Statistical Emulators of Maize, Rice, Soybean and Wheat Yields from Global Gridded Crop Models

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Élodie Blanc*

Abstract

This study provides statistical emulators of crop yields based on global gridded crop model simulations from the Inter-Sectoral Impact Model Intercomparison Project Fast Track project. The ensemble of simulations is used to build a panel of annual crop yields from five crop models and corresponding monthly summer weather variables for over a century at the grid cell level globally. This dataset is then used to estimate, for each crop and gridded crop model, the statistical relationship between yields, temperature, precipitation and carbon dioxide. This study considers a new functional form to better capture the non-linear response of yields to weather, especially for extreme temperature and precipitation events. In- and out-of-sample validations show that the statistical emulators are able to closely replicate crop yields projected by crop models and perform well out-of-sample. This study therefore provides a reliable and accessible alternative to global gridded crop yield models. By emulating crop yields for several models using parsimonious equations, the tools provide a computationally efficient method to account for uncertainty in climate change impact assessments.

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1. INTRODUCTION

The vulnerability of crops to weather is well known and numerous studies have attempted to estimate the impact of climate change on yields (Challinor *et al.* 2014). These studies generally rely on either process-based crop models (e.g. Rosenzweig and Parry, 1994; Parry *et al.,* 1999; Alexandrov and Hoogenboom, 2000; Butt *et al.,* 2005; Deryng *et al.,* 2014) or statistical techniques (e.g. Blanc, 2012; Blanc and Strobl, 2013; Lobell and Field, 2007; Haim *et al.,* 2007; Schlenker and Roberts, 2009). While process-based crop models are able to capture the effect of weather and other environmental conditions on crop growth and yields at the grid cell or site level, they are computationally demanding and sometimes proprietary, which limits their accessibility. On the other hand, statistical models are more easily applicable but depend on the availability of observations to estimate the impact of average weather conditions on crop yields while controlling for other factors. To benefit from the capabilities of processed-based models while preserving the application simplicity of statistical models, Blanc and Sultan (2015) provide an ensemble of statistical tools emulating maize yields from process-based crop models at the grid cell level globally using a simple set of weather variables. They employ the 'perfect model' approach, consisting of training a statistical model on the output of a process-based crop model, based on the assumption that these output are 'true'. This method has been used in a couple of recent studies by Holzkämper *et al.* (2012) and Lobell and Burke (2010) with the purpose of evaluating the ability of statistical models to predict crop yields out-of-sample. These studies find that statistical models are capable of replicating the out-of-sample outcomes of process-based crop models reasonably well. Oyebamiji *et al.* (2015) expand on these studies by estimating a crop yield emulator at the global level for five different crops but, as in previous studies, only consider one process-based crop model. As the choice of crop model is an important source of uncertainty in climate change impact assessments on crop yields (e.g. Mearns *et al.,* 1999; Bassu *et al.,* 2014), Blanc and Sultan (2015) expanded the scope and applicability of statistical emulators by considering five different crop models. These emulators are based on simulations data from the Inter-Sectoral Impact Model Intercomparison Project (ISI-MIP) Fast Track experiment dataset of global gridded crop models (GGCM) simulations. This project, coordinated by the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig *et al.,* 2013) as part of ISI-MIP (Warszawski *et al.,* 2014), was tailored specifically to compare crop models. Therefore, all GGCMs simulations were driven by bias-corrected climate change projections derived from the Coupled Model Intercomparison Project, phase 5 (CMIP5) archive (Hempel *et al.,* 2013; Taylor *et al.,* 2012). The statistical emulators produced by Blanc and Sultan (2015) provide an accessible tool to estimate the impact of climate change on crop yields while accounting for crop modeling uncertainty by allowing users to emulate yields projections from five different GGCMs. However, the crop yield emulators from Blanc and Sultan (2015) are only available for maize. This study proposes to expand the scope of these emulators to three additional crops: rice, soybean and wheat.

This study also improves the response functions estimated by Blanc and Sultan (2015) by estimating more precisely the response of crop yields to weather. The effect of weather on crop yields is non-linear and is therefore usually modeled in regression analyses by including a quadratic term in the specification (e.g. Blanc, 2012; Schlenker and Lobell, 2010; Grassini *et al.,* 2013). However, the symmetrical concave relationship imposed by this functional form might be too restrictive. Blanc and Sultan (2015) find that a fifth order polynomial transformation is well suited to represent the nonlinear relationship between weather and crop yields. However, the polynomial form exhibits behaviors difficult to explain for extreme values of temperature and precipitation. As an alternative, this study applies the fractional polynomial method from Royston and Altman (1994). This approach provides the flexibility and improved fit of a non-parametric model, but with the simplicity of a parametric model.

Data and methods used to statistically estimate relationship between yields and weather variables are presented in Section 2. Results are presented and discussed in Section 3. The models are validated in Section 4. Section 5 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. In this exercise, several modeling groups provided results from global gridded process-based crop models run under the same set of weather and CO2 concentration inputs.

2.1.1 Weather and CO_2

Bias-corrected weather data used as input into each crop model are obtained from the CMIP5 climate data simulations. Daily weather data generated by three CMIP5 climate models, or General Circulation Models (GCMs): HadGEM2-ES, NorESM1-M, and GFDL-ESM2M. These GCMs are selected to be representative of respectively, high, medium and low levels of global warming (Warszawski *et al.,* 2014).

GCM simulations are provided for the 'historical' period of 1975 to 2005 and the 'future' period of 2006 to 2099. For the future period, one Representative Concentration Pathway (RCP) consistent 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)[1] are considered. Combined with the large range of climate change patterns represented by the three GCMs, this study considers the broadest plausible range of future climate change.

Using daily precipitation, and minimum and maximum temperature produced by each GCM and used as inputs by GGCMs, monthly averages of precipitation (*Pr*) and temperature (*Tmean*)[2] are calculated for each summer month. For ease of reference, in this study 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.

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

[2] Mean temperature is calculated as $Tmean = (Tmin + Tmax)/2$.

2.1.2 Crop Yields

Crop yields are obtained from GGCMs members of the ISI-MIP Fast Track experiment. Due to data limitations, simulations from five crop models are selected: the Geographic Information System (GIS)-based Environmental Policy Integrated Climate (GEPIC) model (Williams, 1995; Liu *et al.,* 2007), 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; Smith *et al.,* 2001; Lindeskog *et al.,* 2013), 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). For each of these GGCMs, model simulations considering the effect of CO_2 concentrations are selected in order to account for the CO_2 fertilization effect, which plays an important role on biomass production. In this study, only simulations assuming no irrigation are considered in order to capture the effect of precipitation on crop yields.

All GGCMs estimate annual crop yields in metric tons per hectare (t/ha) at a 0.5×0.5-degree resolution (about 50km^2). Although they differ in their representation of crop phenology, leaf area development, yield formation, root expansion and nutrient assimilation, they all account for the effect of water, heat stress and CO_2 fertilization, and assume no technological change. A more detailed description of each model's processes is provided by Rosenzweig *et al.* (2014). As mentioned in Blanc and Sultan (2015), caveats are associated with each model leading to divergences and GGCM-specific periodic patterns of yield projections.[3]

Crop models simulate yields from 1975 to 2005 for the 'historical' period and 2006 to 2099 for the 'future' period. As only one RCP scenario is selected for each GCM, the panel is constructed over the consecutive period 1975–2099 without distinction (i.e. one historical scenario and one future scenario for each GCM). In the final sample, grid cells for which there are less than 10 yield observations after data cleaning are omitted.

2.1.3 Sample Summary Information and Statistics

The size characteristics of the panel dataset are summarized in **Table 1**. Samples have on average 18 million observations covering over nearly 60,000 grid cells globally. However, sample sizes vary by crop and GGCM, with simulations for maize and wheat being the most extensive. Simulations from pDSSAT for rice and PEGASUS for rice and soybean are not available. Additionally, simulations for wheat by the pDSSAT model are only available for the HadGEM2 GCM, hence the reduced sample size.

Summary statistics for crop yields by GGCM and GCM are presented in **Table 2**. Global average crop yields are generally the smallest for the LPJmL model and the highest for the PEGASUS model—although this model provides simulations for maize and wheat only. The

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[3] 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

range of simulated yields vary greatly across models, with the pDSSAT model simulating maize yields of up to 34.9 t/ha compared to a maximum of 9.7 t/ha projected by the LPJ-GUESS model. For rice, soybean and wheat, the smallest maximum yields are projected by the GEPIC model with 11.3 t/ha, 5.8 t/ha and 10.4 t/ha respectively, while the upper bound is projected by the LPJmL for rice (19.5 t/ha), PEGASUS for soybean (18.3 t/ha) and pDSSAT for wheat (34.3 t/ha). Across GCMs, crop yields are on average the largest under the NorESM1_M scenario although the range of projected yields vary greatly depending on the GGCM and crop considered.

Table 1. GGCMs summary information.

Crop	Model	Observations	Grid Cells
Maize	GEPIC	22,293,247	62,005
	LPJ-GUESS	20,665,195	56,620
	LPJmL	22,794,487	62,148
	PEGASUS	13,406,155	51,580
	pDSSAT	15,758,066	51,447
Rice	GEPIC	22,356,067	62,249
	LPJ-GUESS	19,638,299	55,834
	LPJmL	21,874,607	59,169
Soybean	GEPIC	22,277,853	62,115
	LPJ-GUESS	20,189,609	55,585
	LPJmL	22,469,951	61,367
	PEGASUS	9,534,992	43,436
Wheat	GEPIC	22,987,936	63,260
	LPJ-GUESS	19,816,608	55,106
	LPJmL	24,151,787	65,732
	PEGASUS	13,551,266	51,413
	pDSSAT	5,298,321	50,669

Notes: simulations for wheat from the pDSSAT model are only available for the HadGEM2 GCM.

Table 2. Summary statistics for crop yields (t/Ha) by GGCM and GCM.

Crop	Model	GFDL_ESM2M			HadGEM2_ES			NorESM1_M		
		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Maize	GEPIC	1.8	0.0	14.7	1.6	0.0	12.3	1.9	0.0	12.8
	LPJ-GUESS	1.7	0.0	10.3	1.8	0.0	10.8	1.9	0.0	9.7
	LPJmL	1.3	0.0	17.4	1.5	0.0	17.7	1.5	0.0	17.2
	pDSSAT	2.6	0.0	24.1	2.9	0.0	23.9	2.9	0.0	23.8
	PEGASUS	1.8	0.0	34.6	1.7	0.0	34.4	2.0	0.0	34.9
Rice	GEPIC	1.6	0.0	13.6	1.5	0.0	11.3	1.7	0.0	11.3
	LPJ-GUESS	1.1	0.0	16.3	1.1	0.0	18.6	1.3	0.0	17.2
	LPJmL	1.1	0.0	17.1	1.1	0.0	19.5	1.2	0.0	17.8
Soybean	GEPIC	0.9	0.0	5.8	0.9	0.0	5.0	1.0	0.0	5.8
	LPJ-GUESS	0.8	0.0	8.2	0.8	0.0	8.9	1.0	0.0	10.3
	LPJmL	0.7	0.0	13.7	0.8	0.0	13.1	0.9	0.0	15.2
	PEGASUS	1.2	0.0	18.0	1.1	0.0	16.5	1.4	0.0	18.3
Wheat	GEPIC	1.3	0.0	10.4	1.4	0.0	11.0	1.4	0.0	10.8
	LPJ-GUESS	2.3	0.0	17.1	2.3	0.0	15.0	2.4	0.0	14.4
	LPJmL	1.5	0.0	17.0	1.5	0.0	16.3	1.5	0.0	16.2
	pDSSAT				2.1	0.0	34.3			
	PEGASUS	1.2	0.0	25.8	1.0	0.0	26.1	1.2	0.0	27.9

Table 3. Summary statistics for averaged weather variables by GCM.

		GFDL_ESM2M			HadGEM2_ES			NorESM1_M		
Variable	**Unit**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**	**Mean**	**Min**	**Max**
Pr_1	mm/day	3.2	0.0	147.1	3.0	0.0	152.1	3.0	0.0	148.6
Pr_2	mm/day	3.5	0.0	176.0	3.5	0.0	173.6	3.5	0.0	189.0
Pr_3	mm/day	3.5	0.0	127.3	3.5	0.0	112.5	3.5	0.0	102.3
Tmean_1	˚C	21.4	-3.1	45.0	22.8	-3.1	46.6	22.0	-3.3	43.6
Tmean_2	˚C	23.1	0.5	45.1	24.5	0.6	47.0	23.9	0.0	44.8
Tmean_3	˚C	22.4	-1.2	45.5	23.8	-1.3	46.6	22.9	-2.1	44.7

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

Summary statistics for the summer weather variables, *Tmean* and *Pr*, and *CO2* are presented in **Table 3**. For clarity purposes, summary statistics for these variables are averaged over all GGCMs (weather inputs differ slightly by crop model due to different spatial coverage; i.e., a different number of grid cells are represented by each GGCM for each crop). Summary statistics detailed by GGCM are provided in Appendix A. Precipitation is on average the lowest in the first month of summer and the highest in the last month. Temperatures, however peak in the second month of summer. While no clear pattern amongst GCMs is discernable from these statistics in terms of precipitation, temperatures are clearly the highest under the HadGEM2-ES GCM and the lowest under the GFDL-ESM2M GCM. Atmospheric CO_2 concentrations, not represented in this table, do not differ by GCM or GGCM and range from 331 parts per million (ppm) in 1975 to 927 ppm by the end of the century.

2.2 Methods

A statistical model is fitted for each crop to a panel of yields produced by a GGCM. The response functions are then used to predict crop yields. To evaluate the accuracy of the emulator, yield projections from the emulator are then compared to the outcome of the process-based crop models using the same weather inputs—in-sample validation—and using weather from alternative climate change scenarios—out-of-sample validation. The goal of the study is to produce simple equations that emulate crop yields and can be used by others to predict changes in yields based on data from alternative GCMs. By providing emulators for an ensemble of GGCMs, these emulators also allow users to account for crop modeling uncertainty in climate change impact assessments.

Guided by Blanc and Sultan (2015), this study considers a parsimonious specification (labeled *S1*) that includes precipitation and temperature to statistically estimate the determinants of crop yields. This specification includes the monthly average of summer weather variables to be representative of a common growing season.[4] Among various representations of weather

[4] 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.

effects on crop growth, this set of monthly weather variables was found to provide the best compromise in term of predictive ability and simplicity. The specification also includes interaction terms between temperature and precipitation, and between precipitation and CO_2 to account for the CO_2 effect on water use efficiency. For each crop and GGCM, the specification estimated is of the form:

$$Yield_{lat,lon,gcm,y} = \alpha + \sum_{i=1}^{3} \beta_i Pr\_i_{lat,lon,gcm,y} + \sum_{i=1}^{3} \theta_i Tmean\_i_{lat,lon,gcm,y} + \vartheta CO2_{gcm,y} + \sum_{i=1}^{3} \gamma_i Pr\_i_{lat,lon,gcm,y} * Tmean\_i_{lat,lon,gcm,y} + \sum_{i=1}^{3} \gamma_i Pr\_i_{lat,lon,gcm,y} * CO2_{gcm,y} + \delta_{lat,lon} + \rho_{lat,lon,gcm,y} \quad (1)$$

where for each year, *y*, *Yield* corresponds to crop yields simulated by process-based crop models for each grid cell (defined by its longitude, *lon*, and latitude, *lat*) under each climate model, *gcm*; *Pr* and *Tmean* variables correspond to monthly mean precipitation and temperature variables. *CO2* is the annual midyear CO_2 concentration level in the atmosphere; δ is a grid cell fixed effect; and ρ an error term. Following Blanc and Sultan (2015), adjustments to the specification are made for the pDSSAT model to account for soil fertility erosion, and for the GEPIC model to account for 30-yearly input of CO_2.

Specification (1) represents a linear effect of weather and CO_2 on crop yields. However, it has been established in the literature that crop yield response to weather is non-linear. The most common and straightforward method used to represent non-linear effects in regression analyses consist of including a quadratic term for precipitation temperature, precipitation and CO_2. As detailed in **Table 4**, this quadratic transformation is represented by specification *S1sqint*.[5] However, this functional form imposes a constraint of symmetrical relationship. A fifth order polynomial specification, *S1polyint*, is thus considered to allow greater flexibility in the representation of the effect of weather. Yet, odd tail-end behaviors are associated with this representation and, as noted by Blanc and Sultan (2015), the weather effects should be interpreted with caution when considering extreme events. In response, a fractional polynomial specification, *S1fpint*, addresses this issue by relaxing the symmetry constraint but allowing non-parametric flexibility.

Table 4. Specification description.

Specification	Variable non-linear transformations
S1sqint	*Pr, Pr_sq, Tmean, Tmean_sq, CO2, CO2_sq*
S1polyint	*Pr, Pr_sq, Pr_cu, Pr_qu, Pr_qc, Tmean, Tmean_sq, Tmean_cu, Tmean_qu, Tmean_qc, CO2, CO2_sq*
S1fpint	*Pr_p1, Pr_p2, Tmean_p1, Tmean_p2, CO2_p1, CO2_p2*

Note: suffix _sq denotes square terms, _cu cubic terms, _qu quartic terms, and _qc quintic terms, _p1 and _p2 power terms.

[5] For consistency and comparison with the results of Blanc and Sultan (2015), similar specification notations are used.

In its general form, the fractional polynomial model of degree *m* is defined as:

$$Y = \alpha_0 + \sum_{i=1}^{m} \alpha_i X^{(p_i)} + \mu \tag{2}$$

where the parentheses on the power term on *X* imply the following transformation:

$$X^{(p_i)} = \begin{cases} X^{p_i} \; if \; p_i \neq 0 \\ lnX \; if \; p_i = 0 \end{cases} \tag{3}$$

For each repeated power, p_i, the term is multiplied by another *lnX*. To fit a multivariable fractional polynomial model, a closed-test algorithm performs a backward elimination starting from the most complex specification. In this application, the maximum permitted degree *m*=2. Following Royston and Sauerbrei (2008), powers are chosen from among the set {-2, -1, -0.5, 0, 0.5, 1, 2, 3}.

3. RESULTS

Regressions are estimated for the three specifications *S1sqint*, *S1polyint* and *S1fpint* for each crop model and GCM. The power terms used for the specification *S1fpint* are reported in Appendix B, table B1. Results for each regression are presented in Appendix C. The corresponding estimated values for δ (the grid cell fixed effect) are provided in Appendix D.

Regression results show that precipitation and temperature during all the summer months have a significant impact on crop yields from all GGCMs under any of the three functional forms considered. The significant coefficient for the interaction terms between precipitation and temperature, *Pr_x_Tmean*, indicates that the impact of a change in temperature depends on the amount of precipitation and vice versa. However, the representation of the non-linear relationship between weather variables and yields differs between specifications. To facilitate comparison, the average effect of temperature and precipitation, holding covariates at their mean values, are depicted for each crop model and GCM in **Figure 1** and **Figure 2**. The graphs show that the *S1sqint* specification functional form, due to its symmetrical nature, is very restrictive. For instance, it shows a concave effect of precipitation on yields with a turning point at a very high level of precipitation (around 30mm/day). However, such precipitation rarely occurs in the dataset (mean *Pr_2* is around 3mm/day). *S1polyint* and *S1fpint* address this issue by fitting a curve skewed toward low values of precipitation. These specifications capture the skewness of the curve with a generally sharper increase in yields associated with very low precipitation than *S1sqint*. However, the graphs show that *S1polyint* represents an increase in yield for precipitation over 40mm/day. Such tail-end behavior could lead to erroneous conclusions when extrapolating beyond the range of commonly observed precipitation, which is of particular concern when simulating the effects of climate change. The *S1fpint* model provides a solution to the odd tail-end behavior when using a degree-2 fractional polynomial.

The effect of temperature changes in the second summer month, again with covariates held constant at their mean values, are shown in **Figure 2**. Compared to *S1sqint* or *S1polyint*, the *S1fpint* model allows a better representation of the large beneficial impact of a temperature increase when temperatures are low. The quadratic specification *S1sqint* generally has a flatter bell shape, and the polynomial specification *S1polyint* exhibits hard-to-explain tail-end behavior

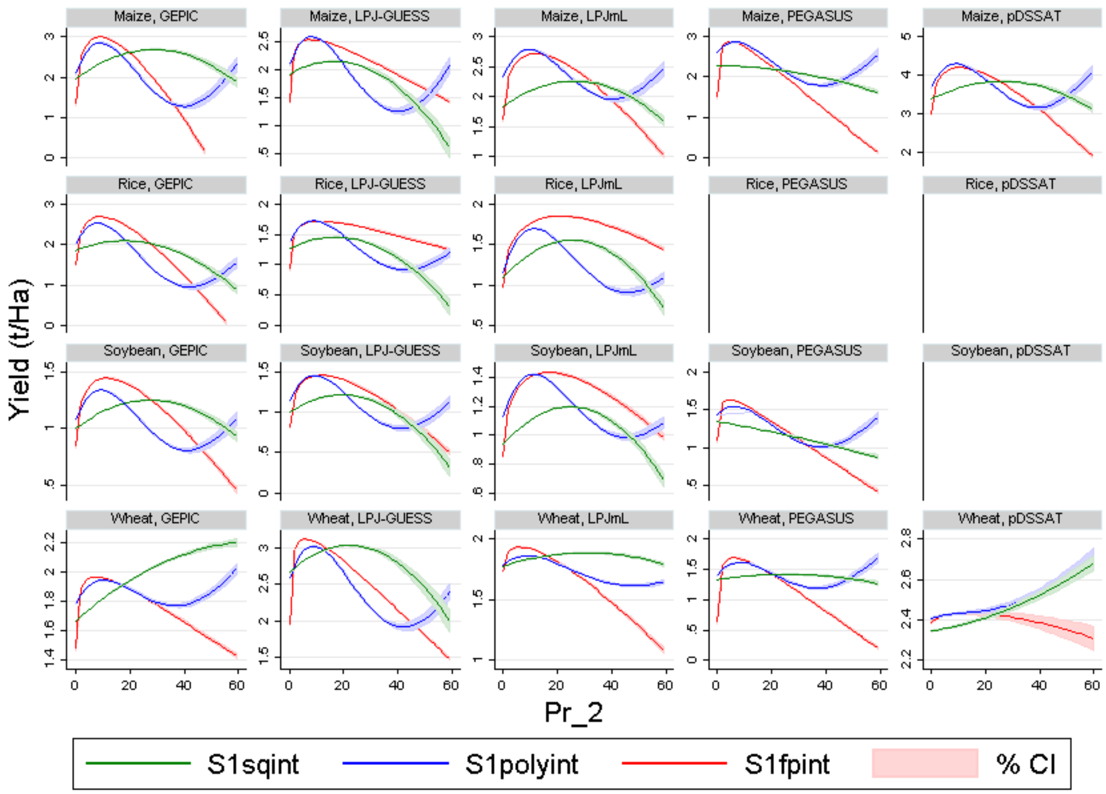

Figure 1. Effect of *Pr_2* on crop yields by GCM for the *S1sqint*, *S1polyint* and *S1fpint* specifications.

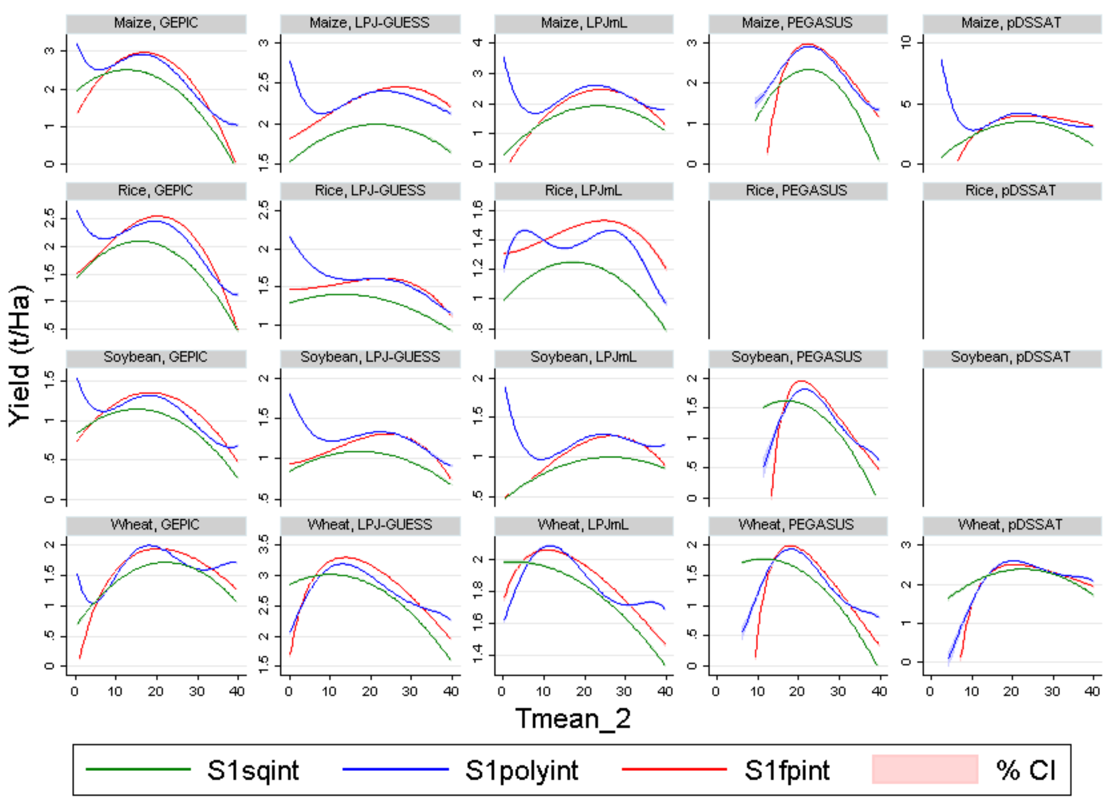

Figure 2. Effect of *Tmean_2* on crop yields by GCM for the *S1sqint*, *S1polyint* and *S1fpint* specifications.
Note: in both figures, covariates are held at their mean values.

for most GGCMs (e.g., an ever-increasing positive effect of temperature on crop yields beyond 45˚C). Graphs of average effects of temperature and precipitation during the first and last months of summer (provided in Appendix E) show similar patterns.

The effect of CO_2 fertilization on crop yields—both direct (as captured by the non-linear representation of CO_2) and indirect (via water use efficiency improvements, as captured by the interaction term between CO_2 and precipitation)—are accounted for in the regression and presented in Appendix E. The estimates indicate a concave relationship between CO_2 and yields for most GGCMs. For the PEGASUS model, CO_2 appears to have a very mild convex but strictly positive effect on yields relationship.

For each crop, GGCM and specification, the root mean square error (RMSE) is calculated to estimate the average error between predicted and 'actual' yields. To account for differences in yield levels between crops and models, the normalized RMSE (NRMSE) is calculated by dividing the RMSE by the difference between maximum and minimum yields. These goodness-of-fit measures are represented in **Figure 3**. The bar graphs show that across crop models, the largest

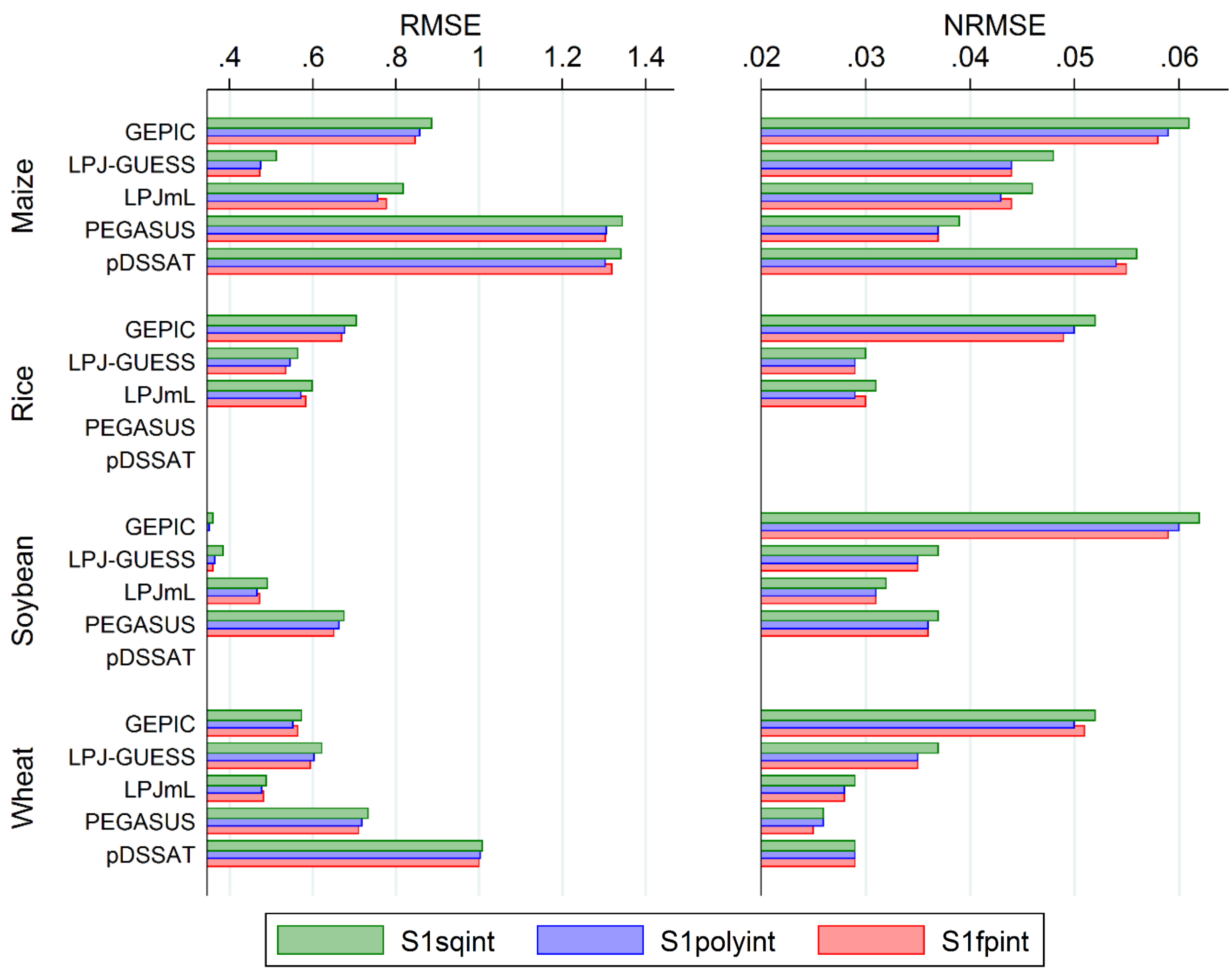

Figure 3. Goodness-of-fit measures by crop, crop model and specification (dependent variable: Yield).

errors in absolute terms are associated with the PEGASUS and pDSSAT models. However, in relative terms, errors are usually the smallest for the PEGASUS and pDSSAT models and the largest for the GEPIC model. Modelling errors are generally larger for maize than for the three other crops, except for soybean for the GEPIC model. When considering functional forms, the average errors between the yields from the statistical models and the crop models are generally the lowest for the *S1fpint* specification. On average, the fractional polynomial functional form reduces errors by 0.04 t/ha for maize and 0.02 t/ha for all other crops compared to a quadratic function. Compared to a higher-degree polynomial function, the gains in goodness-of-fit are less clear-cut, with RMSEs on average higher (by 0.009 t/ha) for the *S1fpint* specification than the *S1polyint* specification for the LPJmL crop model. Overall, this small gain in goodness-of-fit combined with the improved representation of the precipitation and temperature effect on crop yields demonstrates that the fractional polynomial transformation is best suited to the task.

4. VALIDATION

To assess the ability of the statistical models to predict crop yields simulated by GGCMs, in an in-sample forecasting exercise, emulated yields are first compared with GCCM yields based on the full sample. An out-of-sample validation exercise is then conducted by comparing emulated yields based on a partial sample excluding simulation from one climate model, and comparing emulated yields to GGCM yields from the excluded sub-sample. The validation analyses focuses on the preferred specification, *S1fpint*.

4.1 In-Sample Validation

To validate the emulators' prediction accuracy, the within-sample validation exercise is based on yield estimates using the full sample and predictions for each grid cell, year and climate model. Annual crop yields for each crop, GGCM and statistical emulator averaged over the three climate models and all grid cells for the whole globe are reported in **Figure 4**. The dark lines represent simulations from the emulator using the *S1fpint* specification and the lighter lines are representative of the GGCMs' projections. The graphs show that average yields levels differ across GGCMs, despite being driven by the same climate data. On average, however, predictions from the statistical emulators follow the same trend as projections from GGCMs. Some inter-annual yield variability is also captured by the statistical models, although with less accuracy.

To identify spatial patterns of agreements between projections from the two types of models, **Figures 5, 6, 7,** and **8** present the difference (in percentage terms) between crop yield projections from the statistical emulator and the crop models averaged over the period 2090–2099. The maps distinguish between marginal growing area (where yields projections from crop models are less than 1 t/ha) in brown, and more favorable crop growing regions (yields ≥ 1 t/ha) in blue. For both color schemes, lighter shades are representative of better agreement between the emulator and the GGCM. Maps representing actual yield values and differences in levels are provided in Appendix F. For all crops, the figures show that large proportional prediction errors are generally

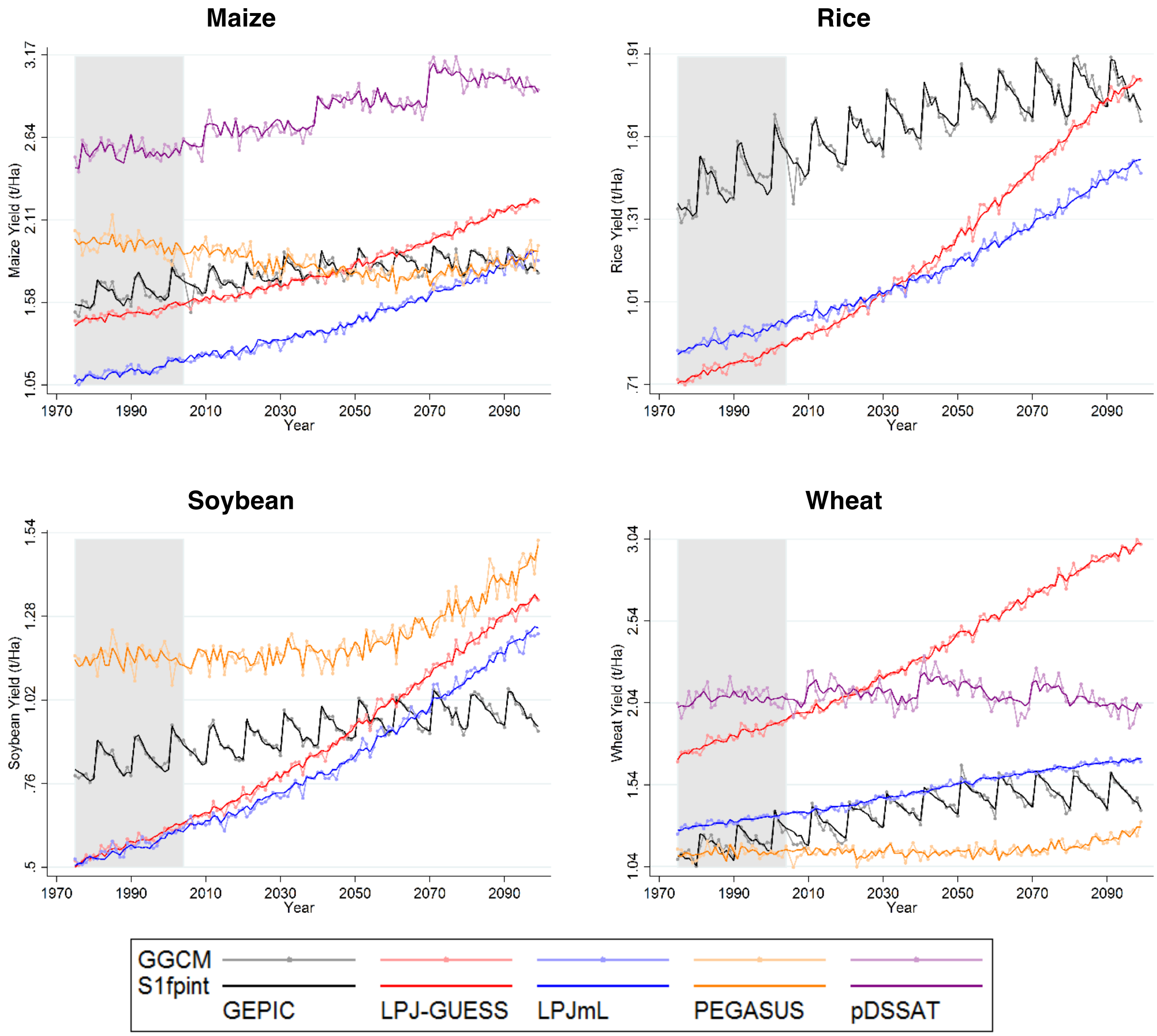

Figure 4. Average crop yield projections from GGCMs and statistical models under the *S1fpint* specification. Note: Shaded areas represents the 'historical' period.

observed in low yield areas, which is an artifact of showing differences in percentage terms, and can be consistent with small absolute errors. For maize, the maps show that the emulator performs relatively well in high yield regions such as the eastern part of the US and Europe where differences are less than 10% for most GGCMs. For PEGASUS, errors between 20% and 50% are observed in the Corn Belt where yields are high, while a higher degree of accuracy is observed in average yield regions such as central Eurasia.

Emulated yields for rice are also close to GGCMs' projections in the eastern US, eastern South America and eastern Asia where productivity is relatively high. For the LPJ-GUESS model, however, high productivity areas are projected in the southeast US, South America and southern Africa and are relatively well captured by the emulator.

For soybean, spatial agreement is also observed between the emulator and GGCM projections in high productivity areas, which differ between GGCMs. Projection differences are on average less than 10% in eastern South America and southern Africa for the LPJ-GUESS model. For PEGASUS, larger agreements are observed in northern Eurasia and Canada, where yields are close to the global average.

Wheat projections from the emulators are also in agreement with those from the GGCMs in areas of relatively high productivity, such as Europe, except for pDSSAT, for which errors are relatively large in this region. For this model, better agreement is found in northern America, where yields are average (around 4 t/ha) and southern South America where yields are high (over 8 t/ha).

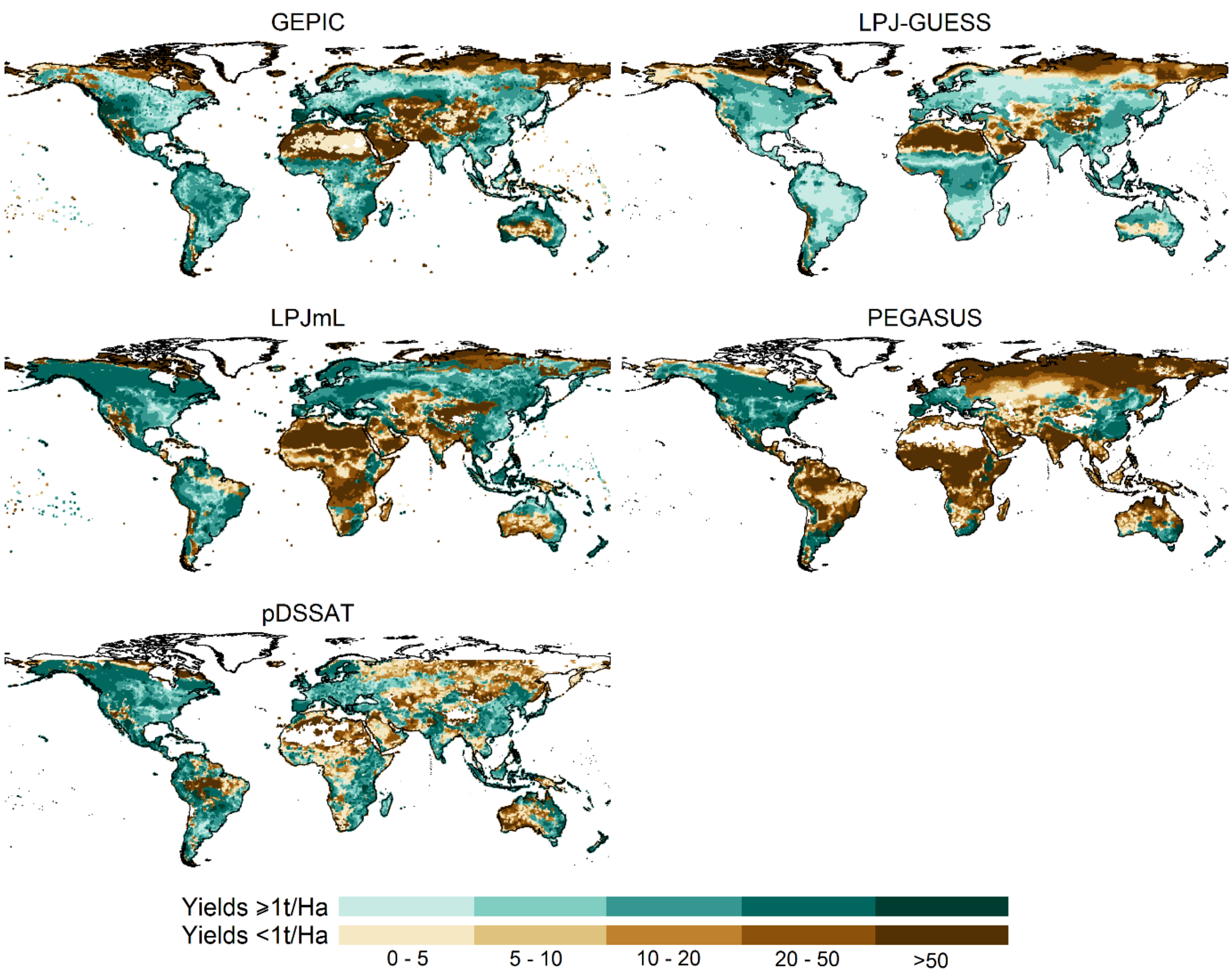

Figure 5. Percentage absolute difference between maize yields from the statistical model (*S1fpint* specification) and GGCMs averaged over 2090–2099.

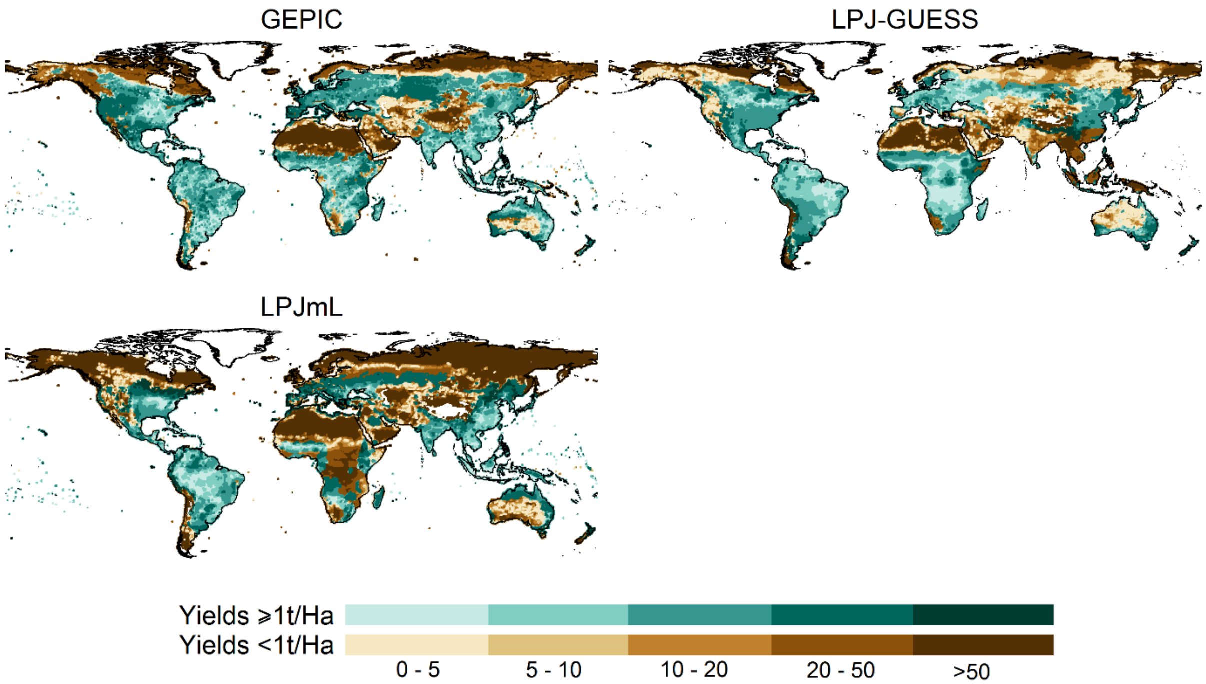

Figure 6. Percentage absolute difference between rice yields from the statistical model (*S1fpint* specification) and GGCMs averaged over 2090–2099.

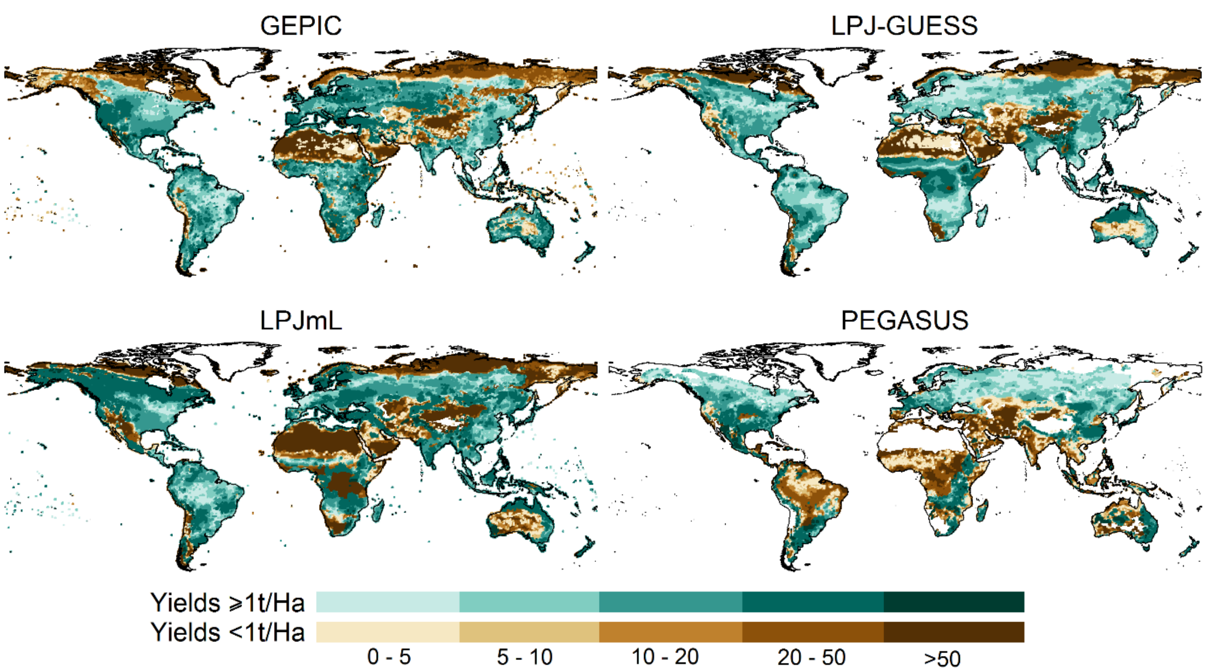

Figure 7. Percentage difference between soybean yields from the statistical model (*S1fpint* specification) and GGCMs averaged over 2090–2099.

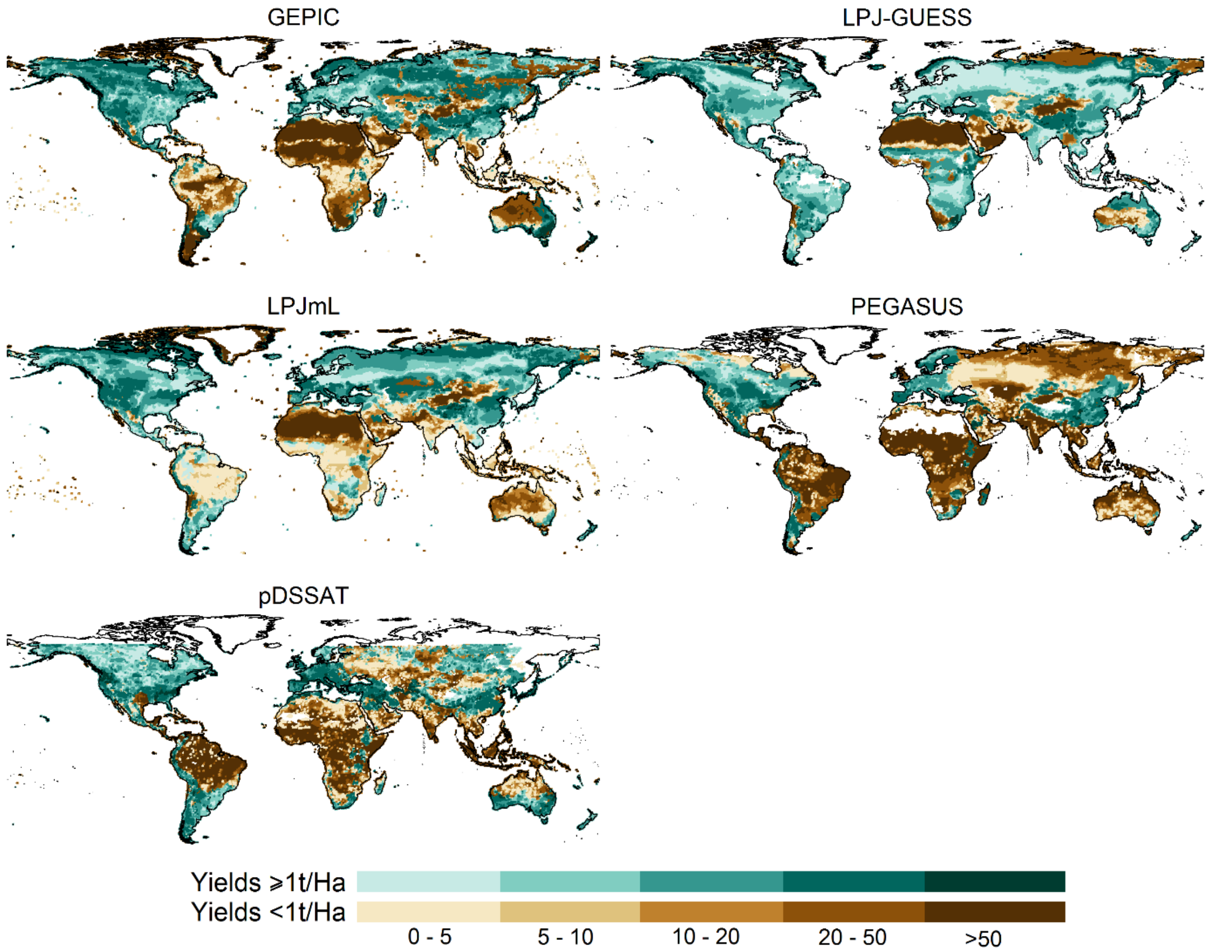

Figure 8. Percentage difference between wheat yields from the statistical model (*S1fpint* specification) and GGCMs averaged over 2090–2099.

4.2 Out-of-Sample Validation

To validate the ability of the emulator to perform under unknown climate change scenarios, an out-of-sample validation exercise is conducted by estimating the regression coefficients using a partial sample that includes data from all but one climate model, and then using these coefficients to emulate yields under weather variables estimated by the excluded climate model. This leave-one-GCM-out validation procedure is implemented three times in order to assess the predictive ability of the emulators for each omitted GCM.

Performance statistics for the out-of-sample validation exercise are reported in Table 2 and compared to the same statistics calculated using the full sample from Section 3. As expected, prediction errors are larger out-of-sample than in-sample but the differences are relatively small. The NRMSEs show a differential of only 0.32 percentage points between the overall out-of-sample and in-sample statistics for maize by PEGASUS. The largest NRMSE differential, 1.26 percentage point, is estimated for maize and GEPIC.

Table 5. RMSE and NRMSE statistics for the leave-one-GCM-out validation using the *S1fpint* specification compared to the full sample (Dependent variable: *Yield*).

Crops	Models	Statistics	GFDL-ESM2M	HadGEM2-ES	NorESM1-M	Overall	Full sample
Maize	GEPIC	RMSE	0.950	1.010	0.826	0.929	0.847
		NRMSE	0.065	0.082	0.065	0.071	0.058
	LPJ-GUESS	RMSE	0.574	0.522	0.531	0.542	0.474
		NRMSE	0.055	0.048	0.055	0.053	0.044
	LPJmL	RMSE	0.816	0.886	0.796	0.833	0.778
		NRMSE	0.047	0.050	0.046	0.048	0.044
	pDSSAT	RMSE	1.456	1.402	1.392	1.417	1.320
		NRMSE	0.060	0.059	0.058	0.059	0.055
	PEGASUS	RMSE	1.342	1.432	1.401	1.392	1.305
		NRMSE	0.039	0.042	0.040	0.040	0.037
Rice	GEPIC	RMSE	0.775	0.744	0.657	0.725	0.671
		NRMSE	0.057	0.066	0.058	0.060	0.049
	LPJ-GUESS	RMSE	0.629	0.564	0.594	0.596	0.536
		NRMSE	0.039	0.030	0.035	0.034	0.029
	LPJmL	RMSE	0.641	0.669	0.571	0.627	0.584
		NRMSE	0.037	0.034	0.032	0.035	0.030
Soybean	GEPIC	RMSE	0.394	0.384	0.342	0.373	0.346
		NRMSE	0.068	0.077	0.059	0.068	0.059
	LPJ-GUESS	RMSE	0.429	0.378	0.382	0.397	0.361
		NRMSE	0.052	0.043	0.037	0.044	0.035
	LPJmL	RMSE	0.508	0.508	0.489	0.501	0.473
		NRMSE	0.037	0.039	0.032	0.036	0.031
	PEGASUS	RMSE	0.733	0.655	0.705	0.698	0.652
		NRMSE	0.041	0.040	0.039	0.040	0.036
Wheat	GEPIC	RMSE	0.609	0.619	0.563	0.597	0.565
		NRMSE	0.059	0.056	0.052	0.056	0.051
	LPJ-GUESS	RMSE	0.727	0.656	0.649	0.677	0.595
		NRMSE	0.043	0.044	0.045	0.044	0.035
	LPJmL	RMSE	0.555	0.570	0.501	0.542	0.483
		NRMSE	0.033	0.035	0.031	0.033	0.028
	PEGASUS	RMSE	0.760	0.767	0.732	0.753	0.711
		NRMSE	0.030	0.029	0.026	0.028	0.025

Note: statistics for pDSSAT and wheat are not available as only simulations for the HadGEM2-ES scenario are available.

To evaluate discrepancies between yield projections from GGCM yields and out-of-sample yields from the emulator over time, **Figure 9** shows time series for each crop, GGCM and leave-one-GCM-out combination. The figure indicates that the emulated crop yields are generally underestimated for the NorESM1-M model when this GCM is excluded from the training dataset. This result is explained by the fact that yield projections under weather conditions from this model are, in most cases, higher than under other GCMs. Conversely, crop yield predictions from the statistical emulators tend to be overestimated when the GFDL-ESM2M model, for which yields are usually the smallest, is excluded from the training sample.

The conclusions from the out-of-sample validation exercise are in line with expectations from statistical analyses, which estimate an average effect. They further highlight the importance of considering the largest ensemble of climate change scenarios possible for the estimation of the emulators. In this regard, the wheat emulator for the PEGASUS model should be used with caution as it is trained on the HadGEM-ES GCM only. As the full sample was designed to encompass the extreme ranges of climate change currently being projected, statistical models estimated using this sample are therefore expected to provide the best predictions of crop yields even under alternative climate change scenarios—which are expected to be within the range of scenarios considered.

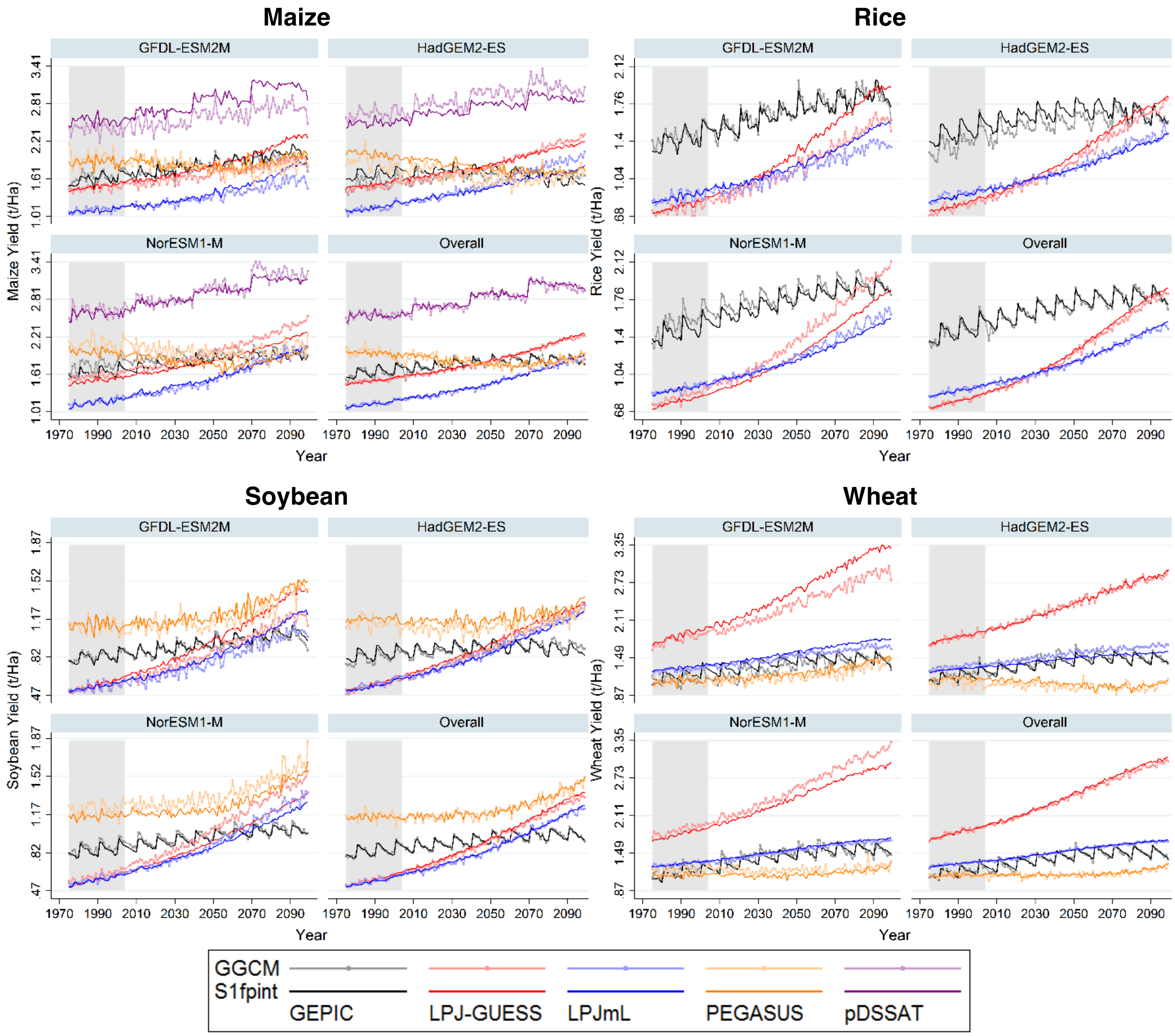

Figure 9. Annual average yield predictions from GGCMs and statistical models (*S1fpint* specification) in the leave-one-GCM-out validation exercise.

5. CONCLUDING REMARKS

This analysis provides simple emulation tools facilitating the assessment of climate change impacts on crop yields. The emulators are constructed based on an ensemble of crop yield simulations from five GGCMs as part of the ISI-MIP Fast Track intercomparison exercise. These GGCMs estimate the impact of weather on crop yields at a 0.5×0.5-degree resolution under various climate change scenarios. Based on a panel of crop yield and weather data at the grid-cell level, crop-specific response functions are estimated for each GGCM.

Building on Blanc and Sultan (2015), this analysis provides estimates for four crops: maize, rice, soybean and wheat. It focuses on a regression specification that include temperature and precipitation only, which is deemed the best compromise in term of predictive ability and simplicity. As an extension to Blanc and Sultan (2015), this analysis compares the traditional non-linear representations of weather effects on crop yields, the quadratic form, and higher degree polynomial with fractional polynomial transformations of weather variables. Fractional polynomial transformations relax the symmetrical relationship constraint imposed by the quadratic transformation while allowing non-parametric flexibility, and addresses the tail-end behavioral issue posed by higher degree polynomial transformations.

The validation exercises show that crop yield predictions from the emulator are reasonably representative of those from the GGCMs, especially with respect to long-term trends. Out-of-sample validations show that, as expected, prediction accuracy is reduced when the training sample excludes yield responses to weather variables outside the range of values used to estimate the model. It is therefore critical to estimate the statistical emulator using the largest sample available, which is designed to encompass the largest range of plausible changes in temperature and precipitation over the twenty-first century.

The crop yield emulators estimated in this study provide an accessible and reliable tool to estimate changes in crop yields under alternative plausible user-defined changes in climate. However, due to GGCM specificities, simulations are more suited to assess long-term trends in yields rather than inter-annual yield variability. The use of the emulator to estimate climate change impact on crop yields should follow the same principles. Also, as shown by the ISI-MIP simulations, the different GGCMs considered in this analysis do not necessarily agree on the extent of the impact of climate change on crop yields even under a similar scenario of climate change. As none of the models is deemed better than another at projecting future crop yields, it is important to consider predictions from many models to account for crop yield modeling uncertainty. By providing yield emulators for several crop models, this study provides a computationally efficient method for researchers to consider modeling uncertainty in climate change impact assessments.

Acknowledgments
We thank Niven Winchester for helpful comments and suggestions. We acknowledge the modeling groups (listed in Appendix A, Table A1 of this paper) and the ISI-MIP coordination team for their roles in producing, coordinating, and making available the ISI-MIP model output. We gratefully acknowledge the financial support for this work from the U.S. Department of Energy, Office of Science under DE-FG02-94ER61937, the U.S. Environmental Protection Agency under XA-83600001-1 and other government, industry, and foundation sponsors of the Joint Program on the Science and Policy of Global Change. For a complete list of sponsors, please visit http://globalchange.mit.edu/sponsors/all.

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APPENDIX A: DATA INFORMATION

Table A1. Modeling group information.

Model	Institution	Modelers' names
GEPIC	EAWAG (Switzerland)	Christian Folberth
LPJ-GUESS	Institutionen för naturgeografi och ekosystemvetenskap (INES), Lunds Universitet (Sweden)	Thomas Pugh, Stephan Olin
LPJmL	PIK (Germany)	Christoph Muller
PEGASUS	Tyndall Centre, University of East Anglia (UK)	Delphine Deryng
pDSSAT	University of Chicago (USA)	Joshua Elliott

Table A2. Summary statistics for maize.

Model	Variables	GFDL_ESM2M			HadGEM2_ES			NorESM1_M		
		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
GEPIC	*Yield*	1.8	0.0	14.7	1.6	0.0	12.3	1.9	0.0	12.8
	Tmean_1	20.5	-5.5	45.1	21.9	-5.3	46.8	21.2	-5.5	43.6
	Tmean_2	22.3	-1.4	45.3	23.7	-1.6	47.3	23.2	-2.1	45.0
	Tmean_3	21.6	-4.0	45.9	22.9	-4.0	46.7	22.2	-5.2	45.0
	Pr_1	3.0	0.0	147.1	2.9	0.0	152.1	2.9	0.0	157.2
	Pr_2	3.3	0.0	176.0	3.3	0.0	174.5	3.3	0.0	189.0
	Pr_3	3.3	0.0	127.3	3.3	0.0	112.8	3.4	0.0	102.3
LPJ-GUESS	*Yield*	1.7	0.0	10.3	1.8	0.0	10.8	1.9	0.0	9.7
	Tmean_1	20.6	-6.4	45.0	22.1	-7.4	46.8	21.3	-6.7	43.6
	Tmean_2	22.5	-3.6	45.3	23.9	-2.9	47.3	23.4	-3.9	45.0
	Tmean_3	21.6	-6.0	45.9	23.1	-5.0	46.7	22.3	-6.3	45.0
	Pr_1	2.9	0.0	147.1	2.8	0.0	152.1	2.8	0.0	135.7
	Pr_2	3.2	0.0	176.0	3.2	0.0	174.5	3.2	0.0	189.0
	Pr_3	3.2	0.0	127.3	3.2	0.0	112.8	3.3	0.0	102.3
LPJmL	*Yield*	1.3	0.0	17.4	1.5	0.0	17.7	1.5	0.0	17.2
	Tmean_1	20.9	-3.8	45.1	22.3	-4.6	46.8	21.5	-4.0	43.6
	Tmean_2	22.7	-1.2	45.3	24.1	-1.4	47.3	23.6	-1.9	45.0
	Tmean_3	21.9	-2.2	45.9	23.3	-2.7	46.7	22.5	-2.7	45.0
	Pr_1	3.0	0.0	147.1	2.9	0.0	152.1	2.9	0.0	157.2
	Pr_2	3.3	0.0	176.0	3.3	0.0	174.5	3.3	0.0	189.0
	Pr_3	3.3	0.0	127.3	3.3	0.0	112.8	3.4	0.0	102.3
pDSSAT	*Yield*	2.6	0.0	24.1	2.9	0.0	23.9	2.9	0.0	23.8
	Tmean_1	22.9	-1.8	44.7	24.2	0.9	46.8	23.4	-2.0	43.6
	Tmean_2	24.3	2.6	44.5	25.7	4.4	45.9	25.0	3.5	44.2
	Tmean_3	23.7	1.3	44.9	25.0	3.3	46.7	24.2	3.6	43.8
	Pr_1	3.5	0.0	147.1	3.3	0.0	152.1	3.4	0.0	157.2
	Pr_2	3.8	0.0	175.6	3.8	0.0	158.5	3.8	0.0	189.0
	Pr_3	3.8	0.0	127.3	3.8	0.0	112.8	3.8	0.0	102.3
PEGASUS	*Yield*	1.8	0.0	34.6	1.7	0.0	34.4	2.0	0.0	34.9
	Tmean_1	23.6	6.1	44.9	24.1	4.8	46.0	23.6	3.7	43.4
	Tmean_2	25.0	9.4	44.5	25.8	10.2	45.9	25.2	10.3	44.7
	Tmean_3	24.3	8.8	44.6	25.0	7.9	46.7	24.2	6.8	44.0
	Pr_1	3.8	0.0	147.1	3.5	0.0	152.1	3.5	0.0	135.7
	Pr_2	4.1	0.0	176.0	4.0	0.0	174.5	4.0	0.0	189.0
	Pr_3	4.1	0.0	127.3	4.0	0.0	112.1	4.0	0.0	102.3

Table A3. Summary statistics for rice.

Model	Variables	GFDL_ESM2M			HadGEM2_ES			NorESM1_M		
		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
GEPIC	*Yield*	1.6	0.0	13.6	1.5	0.0	11.3	1.7	0.0	11.3
	Tmean_1	20.7	-5.1	45.1	22.1	-5.3	46.8	21.3	-5.5	43.6
	Tmean_2	22.5	-1.3	45.3	23.9	-1.3	47.3	23.4	-2.1	45.0
	Tmean_3	21.7	-3.1	45.9	23.1	-3.4	46.7	22.4	-3.9	45.0
	Pr_1	2.9	0.0	147.1	2.9	0.0	152.1	2.9	0.0	157.2
	Pr_2	3.3	0.0	176.0	3.3	0.0	174.5	3.3	0.0	189.0
	Pr_3	3.3	0.0	127.3	3.3	0.0	112.8	3.4	0.0	102.3
LPJ-GUESS	*Yield*	1.1	0.0	16.3	1.1	0.0	18.6	1.3	0.0	17.2
	Tmean_1	20.9	-6.0	45.1	22.3	-6.5	46.8	21.6	-5.5	43.6
	Tmean_2	22.7	-1.6	45.3	24.1	-1.9	47.3	23.6	-2.3	45.0
	Tmean_3	21.8	-3.4	45.9	23.3	-3.9	46.7	22.5	-5.7	45.0
	Pr_1	2.9	0.0	147.1	2.8	0.0	152.1	2.8	0.0	135.7
	Pr_2	3.3	0.0	176.0	3.3	0.0	174.5	3.3	0.0	189.0
	Pr_3	3.3	0.0	127.3	3.3	0.0	112.8	3.3	0.0	102.3
LPJmL	*Yield*	1.1	0.0	17.1	1.1	0.0	19.5	1.2	0.0	17.8
	Tmean_1	21.7	-3.1	45.1	23.0	-3.2	46.8	22.3	-3.0	43.6
	Tmean_2	23.4	0.5	45.3	24.8	-0.8	47.3	24.2	-1.3	45.0
	Tmean_3	22.6	-0.5	45.9	24.0	-2.7	46.7	23.2	-2.4	45.0
	Pr_1	3.1	0.0	147.1	3.0	0.0	152.1	3.0	0.0	157.2
	Pr_2	3.4	0.0	176.0	3.4	0.0	174.5	3.4	0.0	189.0
	Pr_3	3.4	0.0	127.3	3.4	0.0	112.8	3.5	0.0	102.3

Table A4. Summary statistics for soybean.

Model	Variables	GFDL_ESM2M			HadGEM2_ES			NorESM1_M		
		Mean	Min	Max	Mean	Min	Mean	Min	Max	Max
GEPIC	*Yield*	0.9	0.0	5.8	0.9	0.0	5.0	1.0	0.0	5.8
	Tmean_1	20.7	-5.1	45.1	22.1	-5.3	46.8	21.3	-5.5	43.6
	Tmean_2	22.5	-1.1	45.3	23.8	-1.3	47.3	23.4	-2.1	45.0
	Tmean_3	21.7	-3.1	45.9	23.1	-3.4	46.7	22.3	-3.9	45.0
	Pr_1	3.0	0.0	147.1	2.9	0.0	152.1	2.9	0.0	157.2
	Pr_2	3.3	0.0	176.0	3.3	0.0	174.5	3.3	0.0	189.0
	Pr_3	3.3	0.0	127.3	3.3	0.0	112.8	3.4	0.0	102.3
LPJ-GUESS	*Yield*	0.8	0.0	8.2	0.8	0.0	8.9	1.0	0.0	10.3
	Tmean_1	20.7	-6.0	45.0	22.2	-6.5	46.8	21.4	-5.5	43.6
	Tmean_2	22.5	-1.6	45.3	24.0	-1.9	47.3	23.5	-2.3	45.0
	Tmean_3	21.7	-3.4	45.9	23.1	-3.9	46.7	22.4	-5.7	45.0
	Pr_1	2.9	0.0	147.1	2.8	0.0	152.1	2.8	0.0	135.7
	Pr_2	3.3	0.0	176.0	3.3	0.0	174.5	3.3	0.0	189.0
	Pr_3	3.2	0.0	127.3	3.2	0.0	112.8	3.3	0.0	102.3
LPJmL	*Yield*	0.7	0.0	13.7	0.8	0.0	13.1	0.9	0.0	15.2
	Tmean_1	21.1	-3.7	45.1	22.5	-3.5	46.8	21.7	-4.0	43.6
	Tmean_2	22.9	-0.6	45.3	24.3	-0.8	47.3	23.8	-2.1	45.0
	Tmean_3	22.1	-2.0	45.9	23.5	-2.7	46.7	22.7	-2.7	45.0
	Pr_1	3.0	0.0	147.1	2.9	0.0	152.1	2.9	0.0	157.2
	Pr_2	3.3	0.0	176.0	3.3	0.0	174.5	3.3	0.0	189.0
	Pr_3	3.4	0.0	127.3	3.3	0.0	112.8	3.4	0.0	102.3
PEGASUS	*Yield*	1.2	0.0	18.0	1.1	0.0	16.5	1.4	0.0	18.3
	Tmean_1	25.2	8.6	44.7	25.7	9.3	45.5	25.2	9.8	42.8
	Tmean_2	26.2	11.2	44.3	27.1	11.2	45.9	26.4	12.0	44.2
	Tmean_3	25.9	9.4	44.0	26.5	11.7	45.8	25.8	11.5	44.0
	Pr_1	4.5	0.0	147.1	4.1	0.0	152.1	4.2	0.0	149.1
	Pr_2	4.8	0.0	176.0	4.6	0.0	174.5	4.7	0.0	189.0
	Pr_3	4.8	0.0	127.3	4.6	0.0	112.8	4.8	0.0	102.3

Table A5. Summary statistics for wheat.

Model	Variables	GFDL_ESM2M			HadGEM2_ES			NorESM1_M		
		Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
GEPIC	*Yield*	1.3	0.0	10.4	1.4	0.0	11.0	1.4	0.0	10.8
	Tmean_1	20.3	-6.0	45.1	21.7	-8.2	46.8	20.9	-6.7	43.6
	Tmean_2	22.2	-2.1	45.3	23.5	-3.6	47.3	23.0	-2.2	45.0
	Tmean_3	21.4	-4.3	45.9	22.7	-7.3	46.7	22.0	-6.4	45.0
	Pr_1	2.9	0.0	147.1	2.8	0.0	152.1	2.8	0.0	157.2
	Pr_2	3.2	0.0	176.0	3.3	0.0	174.5	3.3	0.0	189.0
	Pr_3	3.3	0.0	127.3	3.3	0.0	112.8	3.3	0.0	102.3
LPJ-GUESS	*Yield*	2.3	0.0	17.1	2.3	0.0	15.0	2.4	0.0	14.4
	Tmean_1	20.1	-6.3	45.0	21.4	-7.9	46.8	20.7	-7.5	43.6
	Tmean_2	22.1	-1.9	45.3	23.4	-3.6	47.3	23.0	-4.0	45.0
	Tmean_3	21.2	-4.2	45.9	22.5	-5.3	46.7	21.8	-6.3	45.0
	Pr_1	2.7	0.0	147.1	2.6	0.0	152.1	2.6	0.0	135.7
	Pr_2	3.0	0.0	176.0	3.0	0.0	174.5	3.0	0.0	189.0
	Pr_3	3.0	0.0	127.3	3.0	0.0	112.8	3.0	0.0	102.3
LPJmL	*Yield*	1.5	0.0	17.0	1.5	0.0	16.3	1.5	0.0	16.2
	Tmean_1	19.9	-10.5	45.1	21.2	-10.4	46.8	20.5	-9.9	43.6
	Tmean_2	21.7	-5.6	45.3	23.1	-5.2	47.3	22.6	-5.7	45.0
	Tmean_3	20.9	-8.9	45.9	22.3	-10.4	46.7	21.6	-10.1	45.0
	Pr_1	2.9	0.0	147.1	2.8	0.0	152.1	2.8	0.0	157.2
	Pr_2	3.2	0.0	176.0	3.2	0.0	174.5	3.2	0.0	189.0
	Pr_3	3.2	0.0	127.3	3.2	0.0	112.8	3.3	0.0	102.3
pDSSAT	*Yield*				2.1	0.0	34.3			
	Tmean_1				25.0	3.3	46.8			
	Tmean_2				26.4	4.2	47.3			
	Tmean_3				25.8	3.2	46.7			
	Pr_1				3.2	0.0	152.1			
	Pr_2				3.6	0.0	174.5			
	Pr_3				3.5	0.0	112.8			
PEGASUS	*Yield*	1.2	0.0	25.8	1.0	0.0	26.1	1.2	0.0	27.9
	Tmean_1	23.2	4.8	44.7	23.8	4.1	45.9	23.3	4.9	43.4
	Tmean_2	24.5	6.1	44.5	25.4	7.2	45.3	24.9	6.7	44.2
	Tmean_3	23.9	6.1	44.6	24.7	6.7	46.0	24.0	6.4	44.0
	Pr_1	3.9	0.0	147.1	3.6	0.0	152.1	3.6	0.0	135.7
	Pr_2	4.2	0.0	176.0	4.0	0.0	174.5	4.0	0.0	189.0
	Pr_3	4.1	0.0	127.3	4.0	0.0	109.1	4.1	0.0	102.3

APPENDIX B: FRACTIONAL POLYNOMIAL TRANSFORMATION

Table B1. Power terms for fractional polynomial transformation used in specification *S1fpint*.

Crop	Model	*Pr_1*		*Pr_2*		*Pr_3*		*Tmean_1*		*Tmean_2*		*Tmean_3*		*CO2*	
		p1	**p2**	**p1**	**p2**	**p1**	**p2**	**p1**	**p2**	**p1**	**p2**	**p1**	**p2**	**p1**	**p2**
Maize	GEPIC	0.5	1	0.5	1	0.5	1	2	2	1	2	3	3	-2	0.5
	LPJ-GUESS	0.5	0.5	0.5	0.5	0.5	1	2	2	2	2	2	3	-2	2
	LPJmL	0.5	1	0.5	1	0.5	0.5	2	2	1	2	1	2	-2	3
	pDSSAT	0.5	1	0.5	1	0.5	1	1	1	0	0.5	0.5	0.5	-0.5	-
	PEGASUS	0.5	0.5	0.5	0.5	0.5	0.5	0	0.5	-0.5	-0.5	0	0	-2	3
Rice	GEPIC	0.5	0.5	0.5	1	0.5	1	2	2	2	2	2	2	-2	2
	LPJ-GUESS	0.5	0.5	0.5	0.5	0.5	1	3	3	3	3	3	3	-1	-0.5
	LPJmL	0.5	1	0.5	1	0.5	1	3	3	2	3	2	3	-2	2
Soybean	GEPIC	0.5	1	0.5	1	0.5	0.5	2	2	1	2	3	3	-2	-0.5
	LPJ-GUESS	0.5	1	0.5	1	0.5	0.5	2	2	2	3	2	3	-2	1
	LPJmL	0.5	1	0.5	1	0.5	1	2	2	2	2	2	2	-2	2
	PEGASUS	0.5	0.5	0.5	0.5	0.5	0.5	-1	-0.5	-2	-1	-2	-1	0	3
Wheat	GEPIC	0.5	0.5	0.5	0.5	0.5	0.5	-1	-0.5	-2	-1	-2	-1	0	3
	LPJ-GUESS	0.5	1	0.5	0.5	0.5	1	0.5	0.5	0.5	0.5	1	1	-0.5	0.5
	LPJmL	0.5	1	0.5	1	0.5	0.5	0.5	0.5	0.5	0.5	1	1	-1	0
	pDSSAT	0.5	0.5	1	1	1	1	0	0.5	-0.5	-0.5	0	0.5	-0.5	-
	PEGASUS	0.5	0.5	0.5	0.5	0.5	0.5	0	0	-0.5	-0.5	-0.5	0	-1	3

See Excel file *Appendix_B_variable_transformations.xls* (available for download on http://globalchange.mit.edu) composed of the following tables:

Table B2. Variable formulas for fractional polynomial transformation.

APPENDIX C: REGRESSION RESULTS

See Excel file *Appendix_C_regression_results.xls* (available for download on http://globalchange.mit.edu) composed of the following tables:

Table C1. Regression results for maize (dependent variable: *Yield*).
Table C2. Regression results for rice (dependent variable: *Yield*).
Table C3. Regression results for soybean (dependent variable: *Yield*).
Table C4. Regression results for wheat (dependent variable: *Yield*).

APPENDIX D: FIXED EFFECTS (Δ) BY SPECIFICATION AND CROP MODEL

See Excel file *Appendix_D_Grid_cells_FE.xls* (available for download on http://globalchange.mit.edu) composed of the following tables:

Table D1. Grid cell fixed effect (δ) by GGCM for maize, specification *S1fpint*.
Table D2. Grid cell fixed effect (δ) by GGCM for rice, specification *S1fpint*.
Table D3. Grid cell fixed effect (δ) by GGCM for soybean, specification *S1fpint*.
Table D4. Grid cell fixed effect (δ) by GGCM for wheat, specification *S1fpint*.

APPENDIX E: TEMPERATURE, PRECIPITATION AND CO_2 EFFECTS

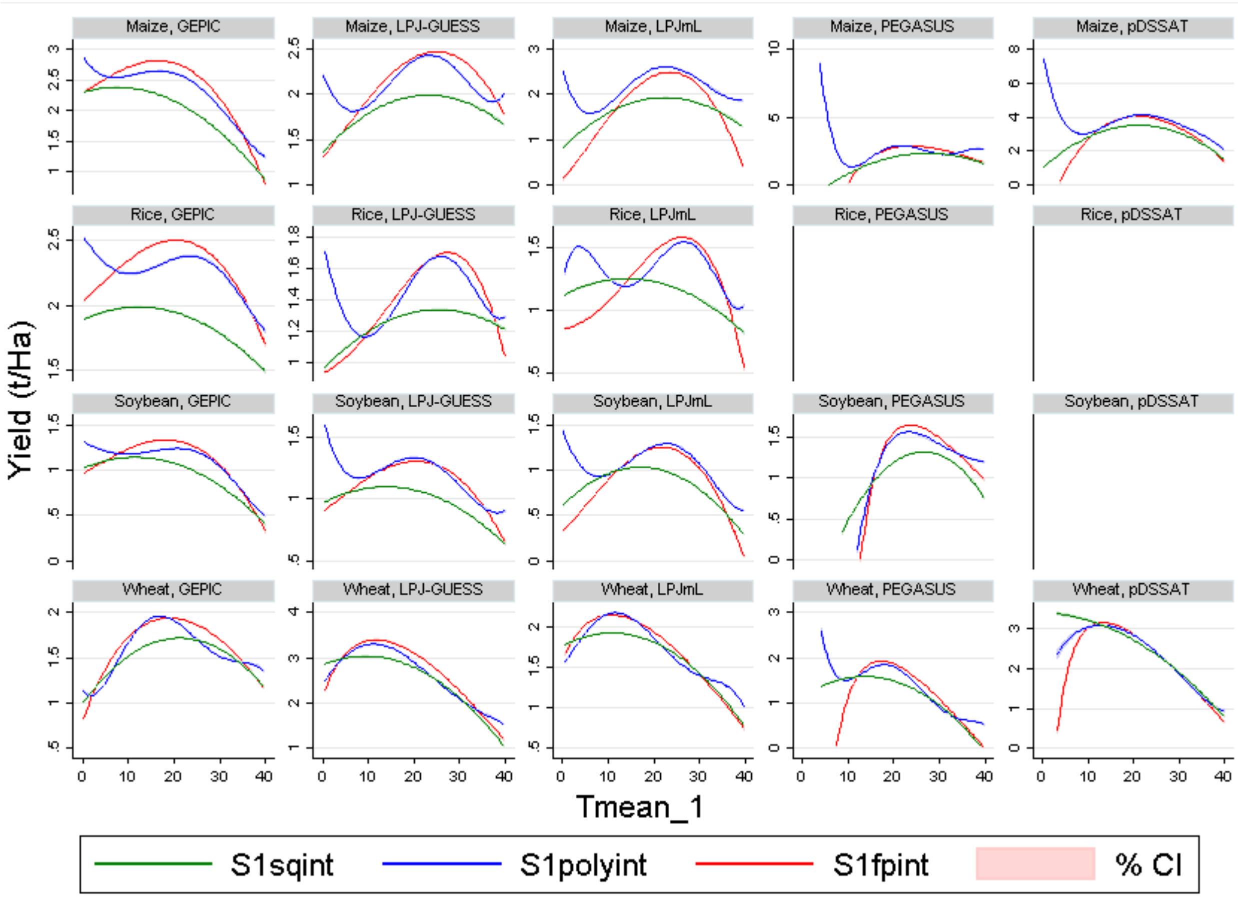

Figure E1. Effect of *Tmean_1* on crop yields by GCM in the *S1sqint*, *S1polyint* and *S1fpint* specification.

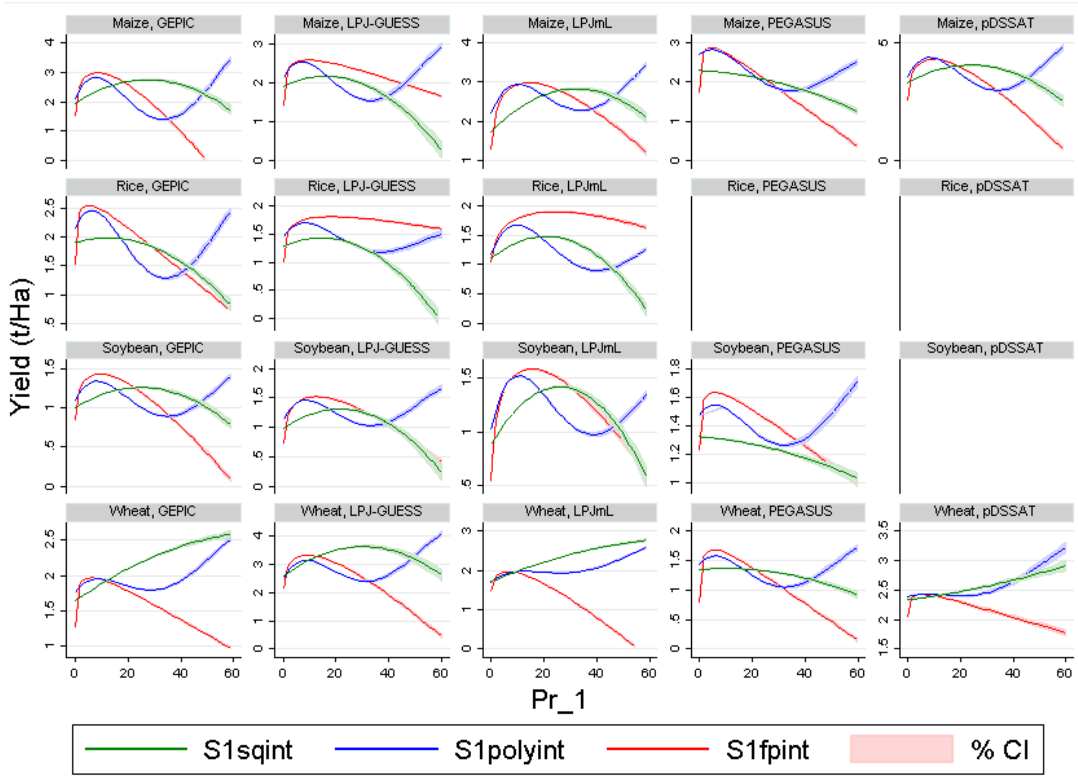

Figure E2. Effect of *Pr_1* on crop yields by GCM in the *S1sqint*, *S1polyint* and *S1fpint* specification.

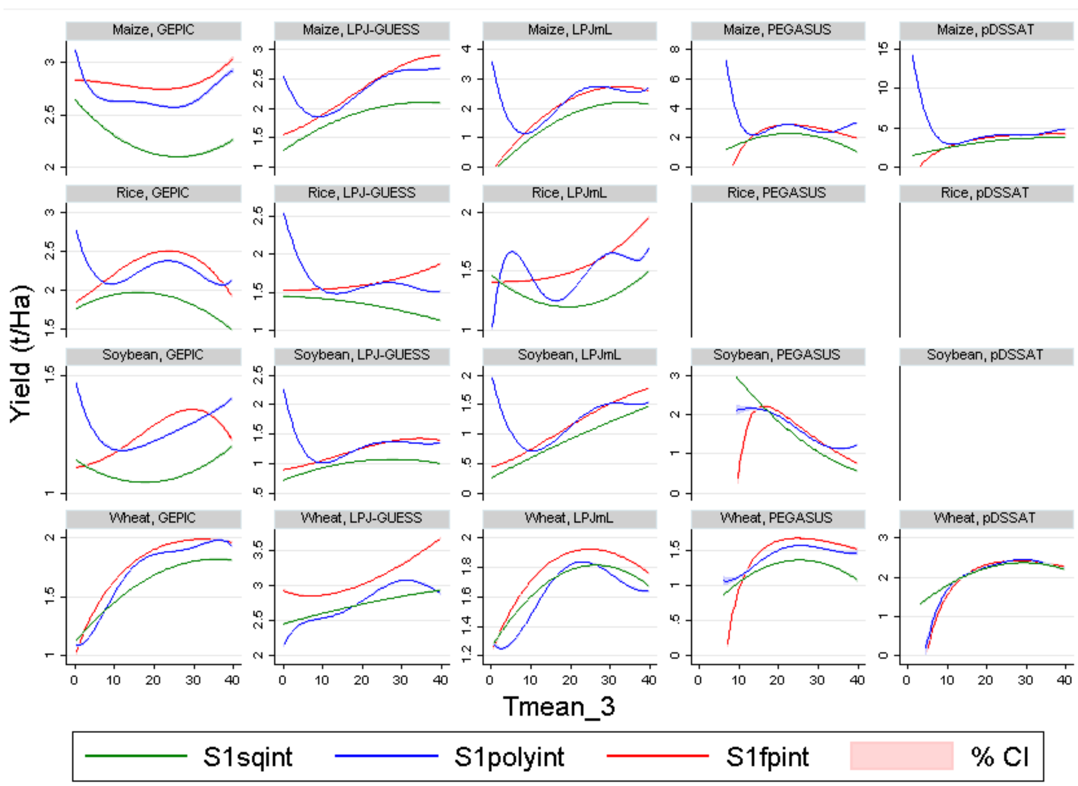

Figure E3. Effect of *Tmean_3* on crop yields by GCM in the *S1sqint*, *S1polyint* and *S1fpint* specification.

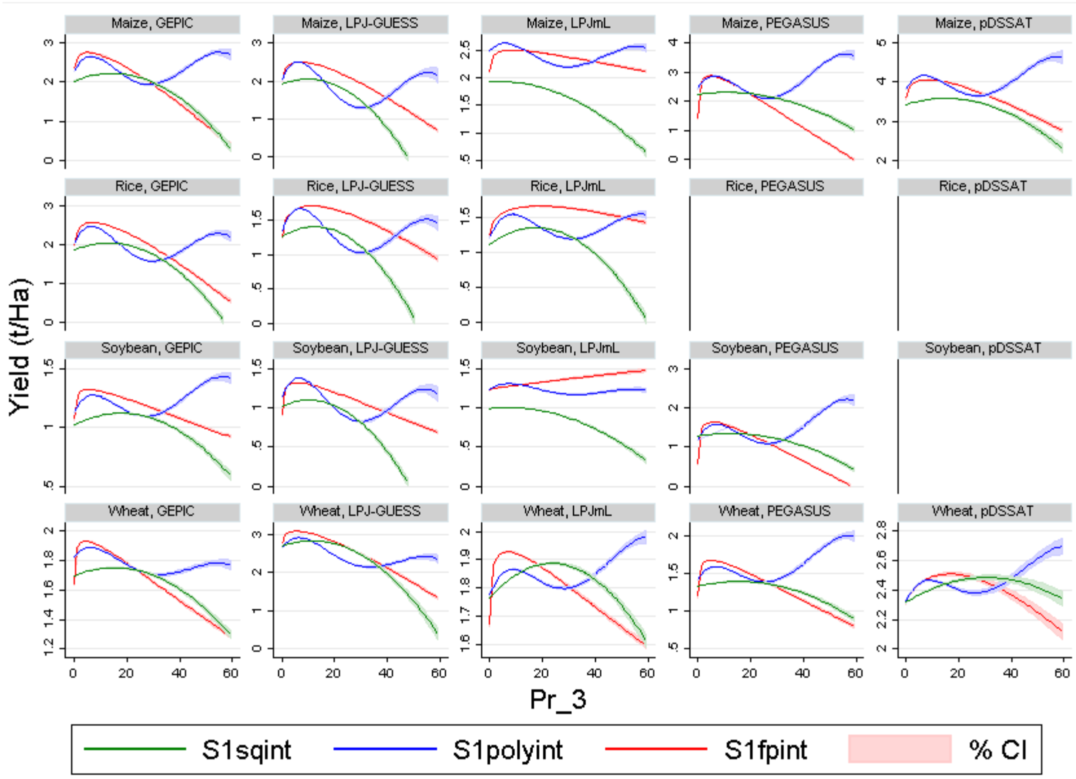

Figure E4. Effect of *Pr_3* on crop yields by GCM in the *S1sqint*, *S1polyint* and *S1fpint* specification.

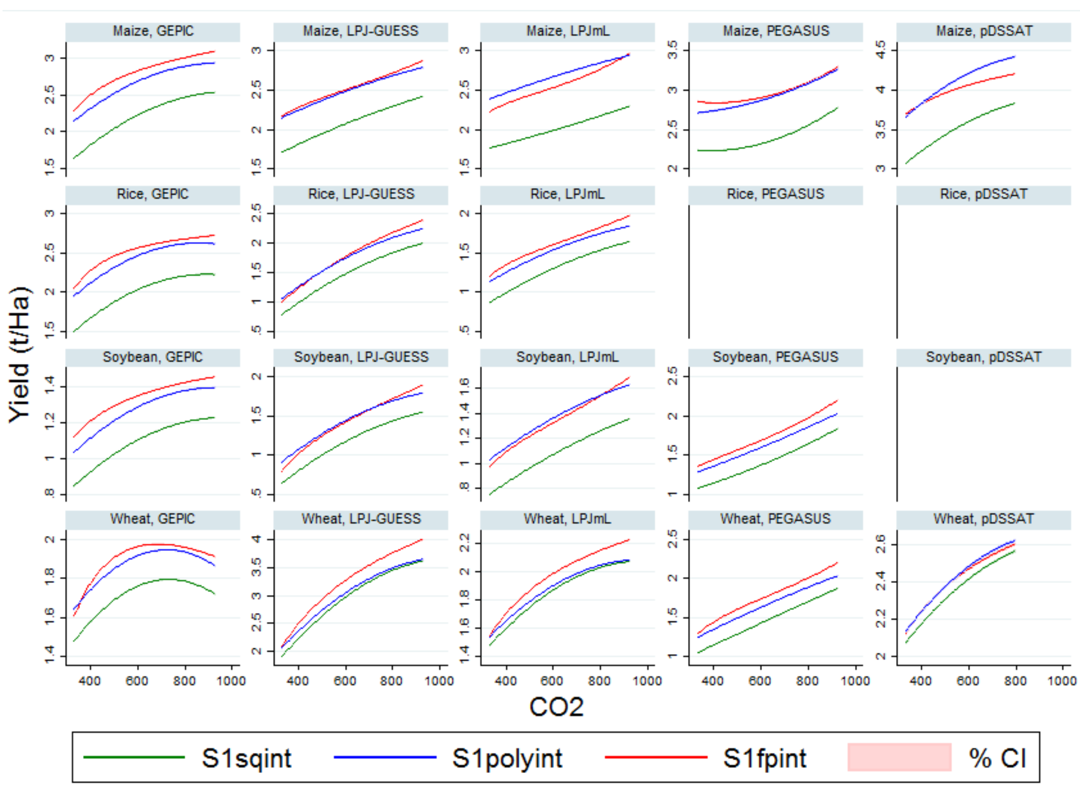

Figure E5. Effect of *CO2* on crop yields by GCM in the *S1sqint*, *S1polyint* and *S1fpint* specification.

APPENDIX F: IN-SAMPLE SPATIAL VALIDATION

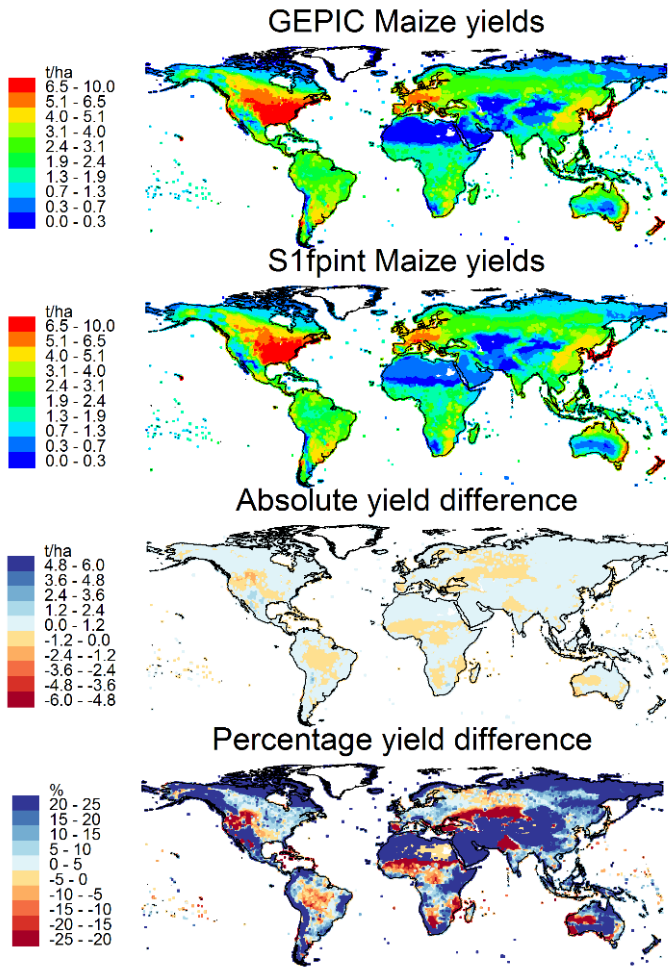

Figure F1. Maize yields averaged over 2090–2099 for the GEPIC and statistical emulators (*S1fpint* specification).

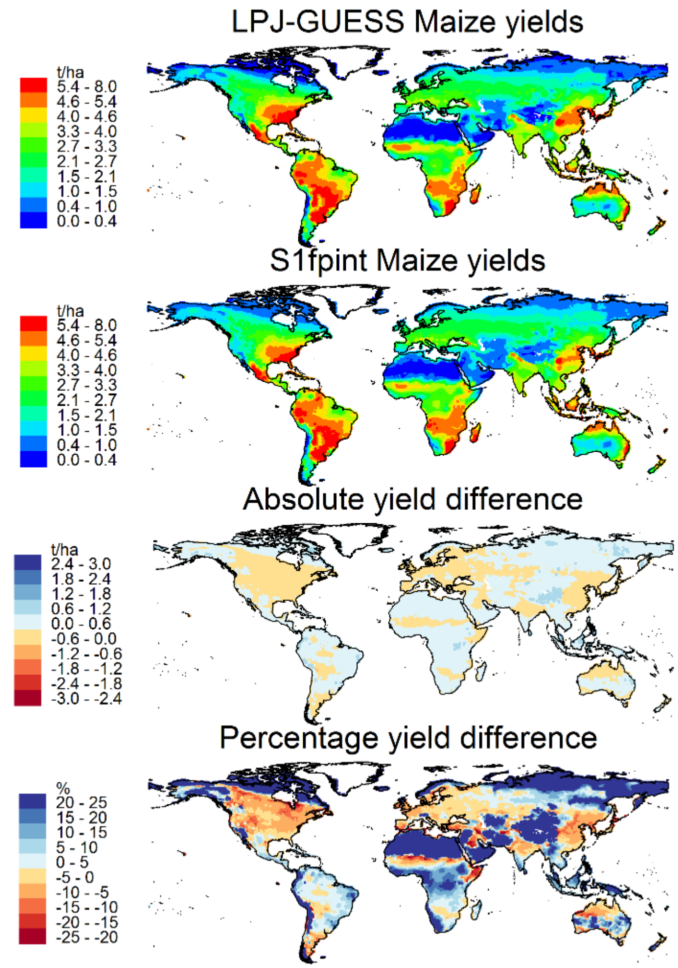

Figure F2. Maize yields averaged over 2090–2099 for the LPJ-GUESS and statistical emulators (*S1fpint* specification).

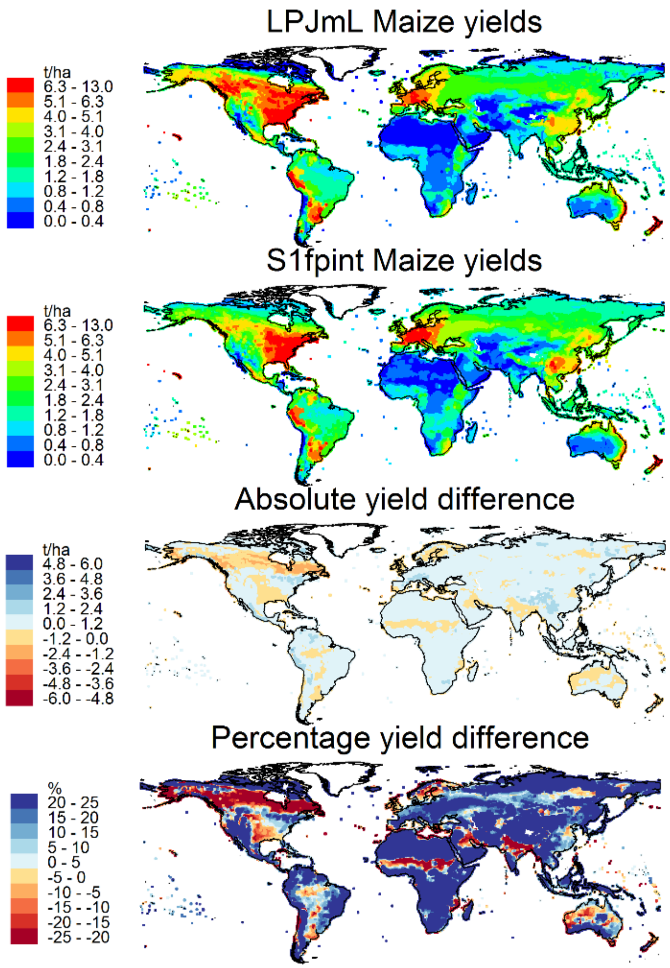

Figure F3. Maize yields averaged over 2090–2099 for the LPJmL and statistical emulators (*S1fpint* specification).

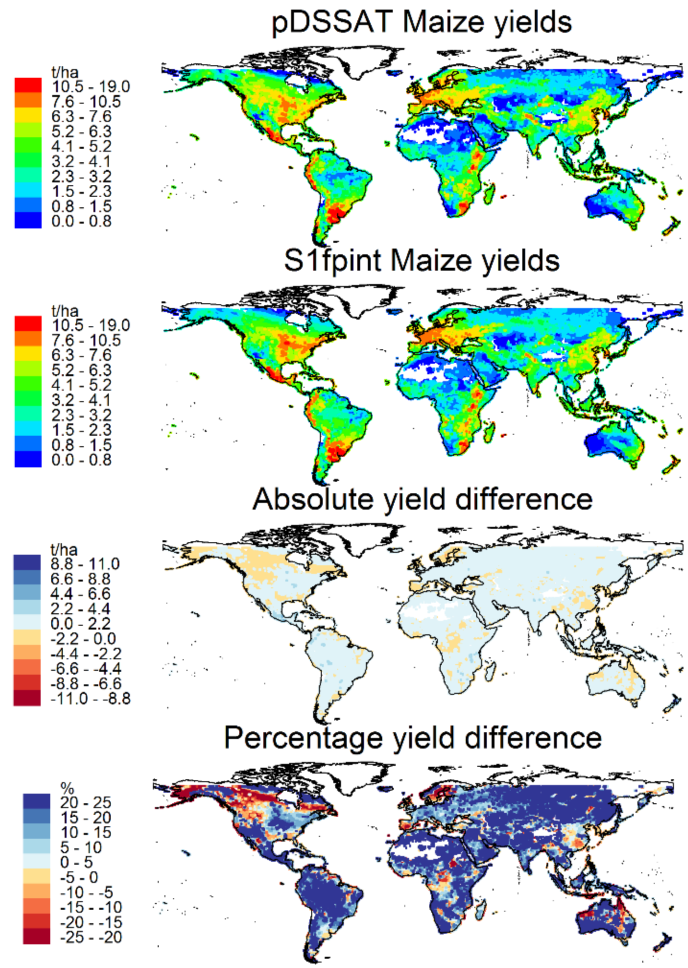

Figure F4. Maize yields averaged over 2090–2099 for the pDSSAT and statistical emulators (*S1fpint* specification).

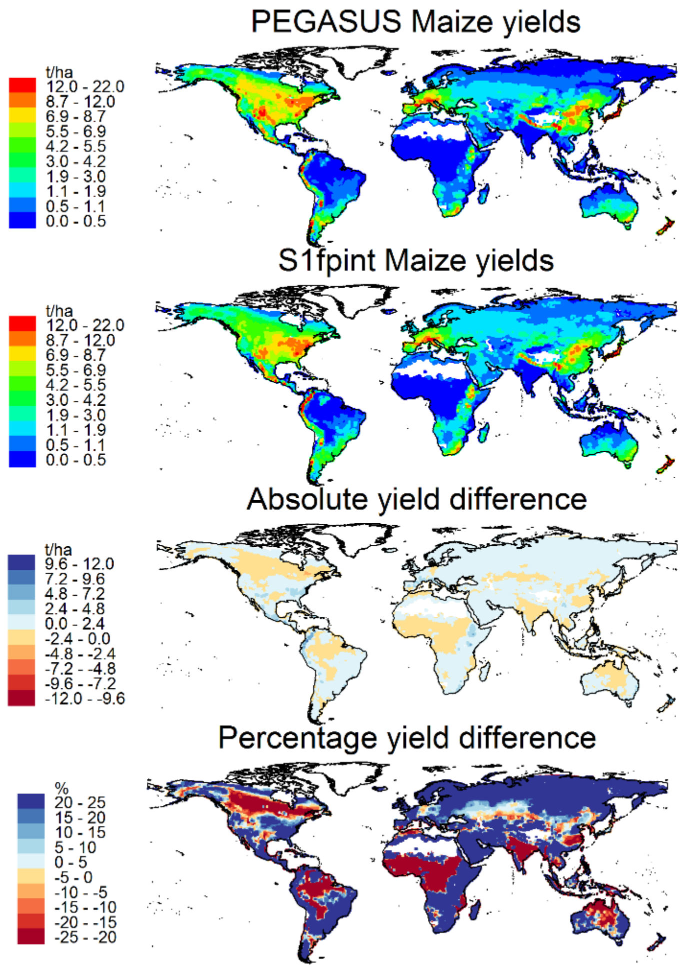

Figure F5. Maize yields averaged over 2090–2099 for the PEGASUS and statistical emulators (*S1fpint* specification).

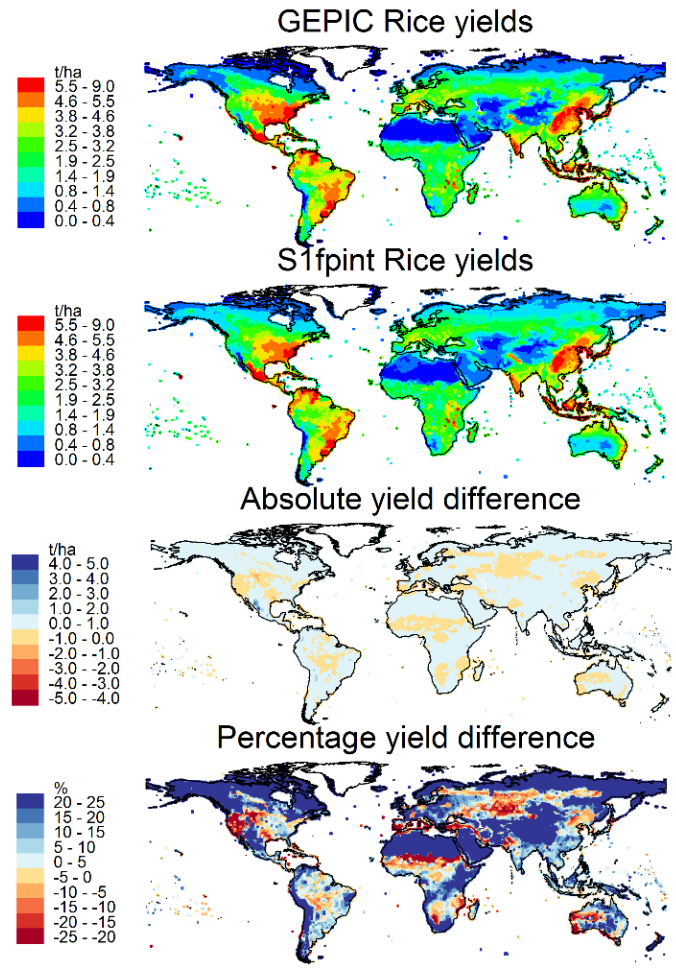

Figure F6. Rice yields averaged over 2090–2099 for the GEPIC and statistical emulators (*S1fpint* specification).

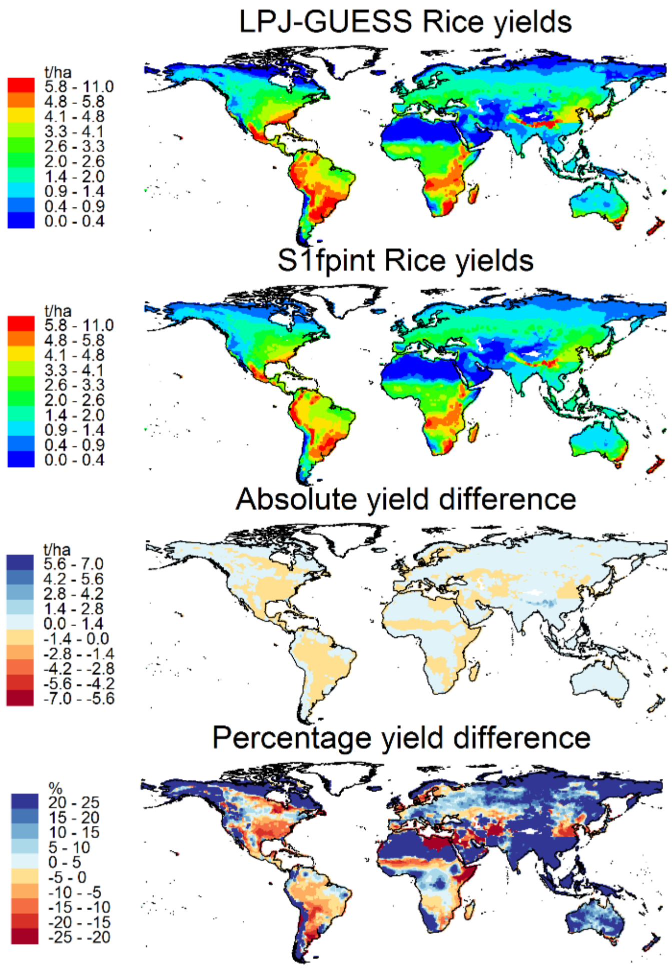

Figure F7. Rice yields averaged over 2090–2099 for the LPJ-GUESS and statistical emulators (*S1fpint* specification).

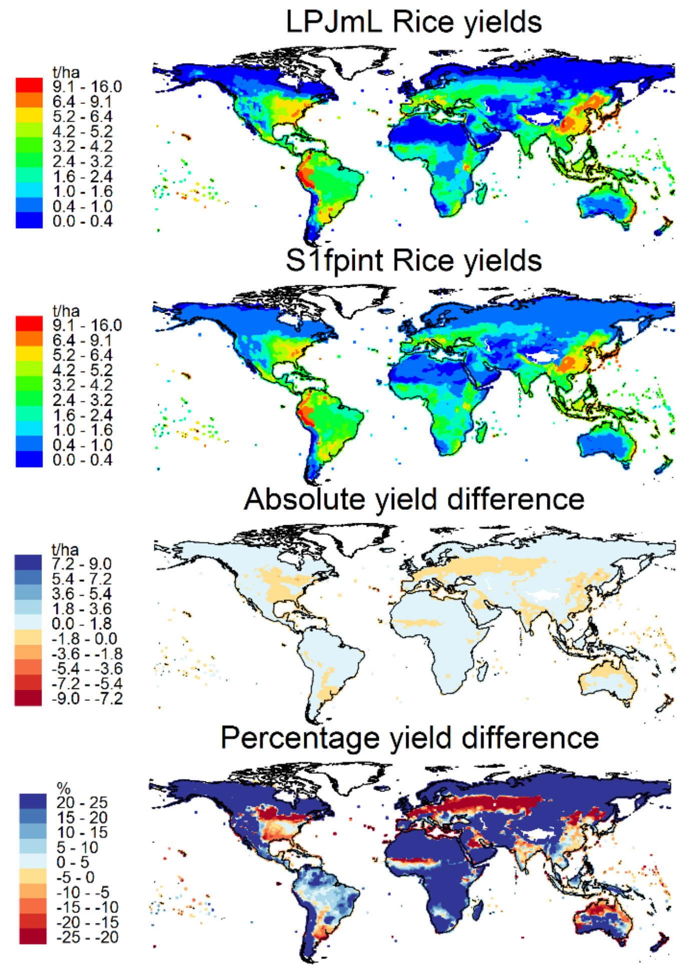

Figure F8. Rice yields averaged over 2090–2099 for the LPJmL and statistical emulators (*S1fpint* specification).

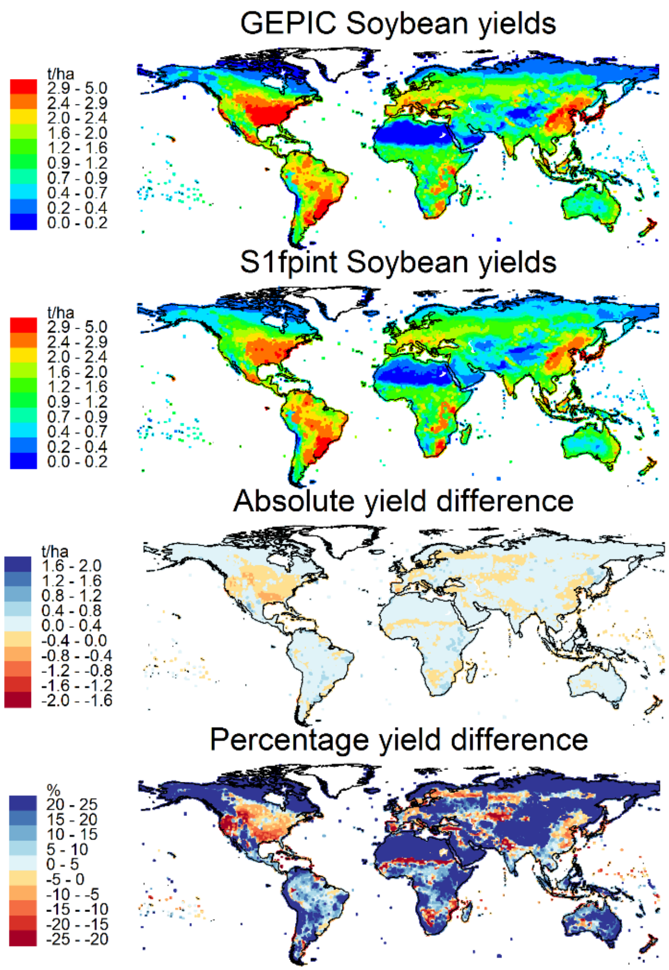

Figure F9. Soybean yields averaged over 2090–2099 for the GEPIC and statistical emulators (*S1fpint* specification).

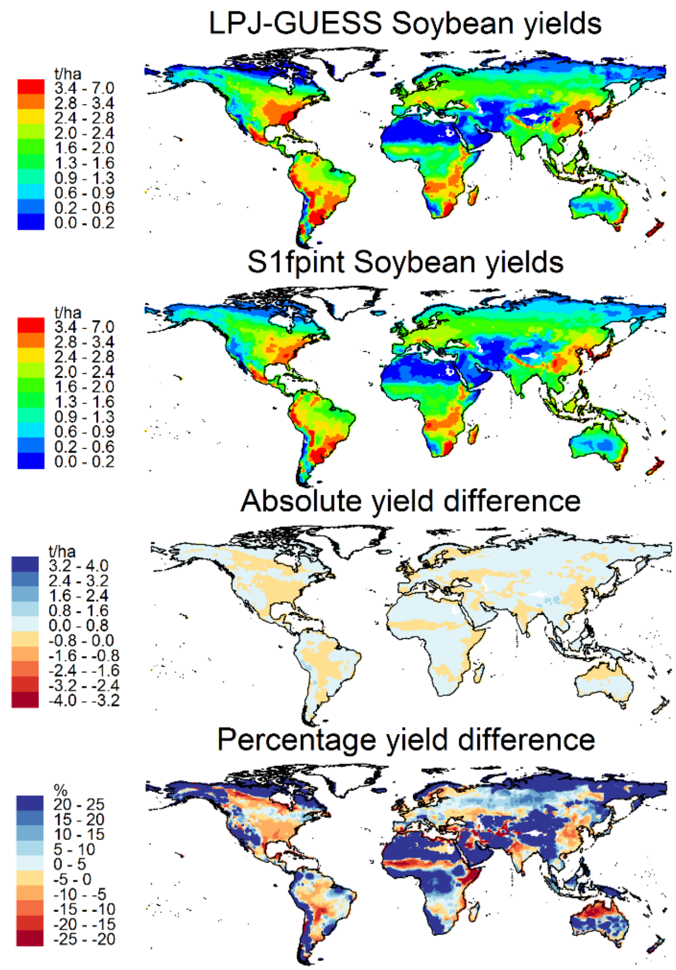

Figure F10. Soybean yields averaged over 2090–2099 for the LPJ-GUESS and statistical emulators (*S1fpint* specification).

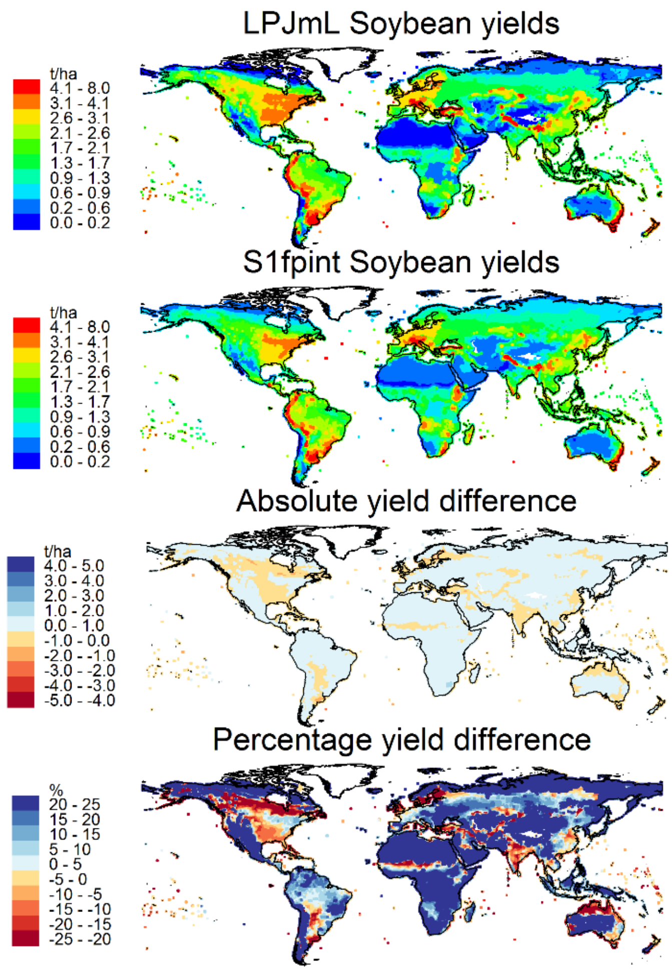

Figure F11. Soybean yields averaged over 2090–2099 for the LPJmL and statistical emulators (*S1fpint* specification).

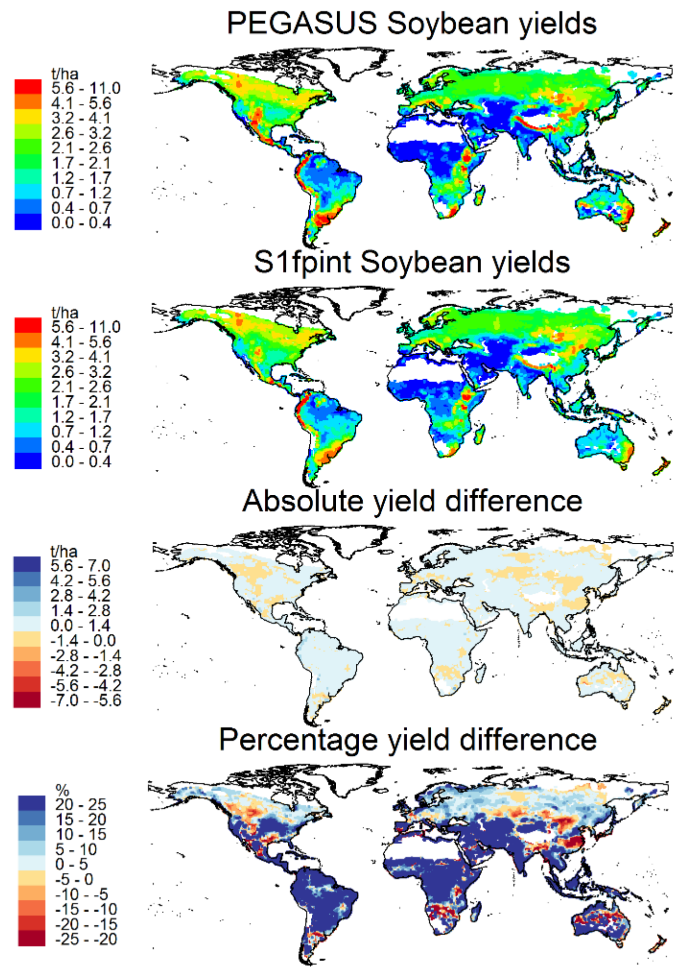

Figure F12. Soybean yields averaged over 2090–2099 for the PEGASUS and statistical emulators (*S1fpint* specification).

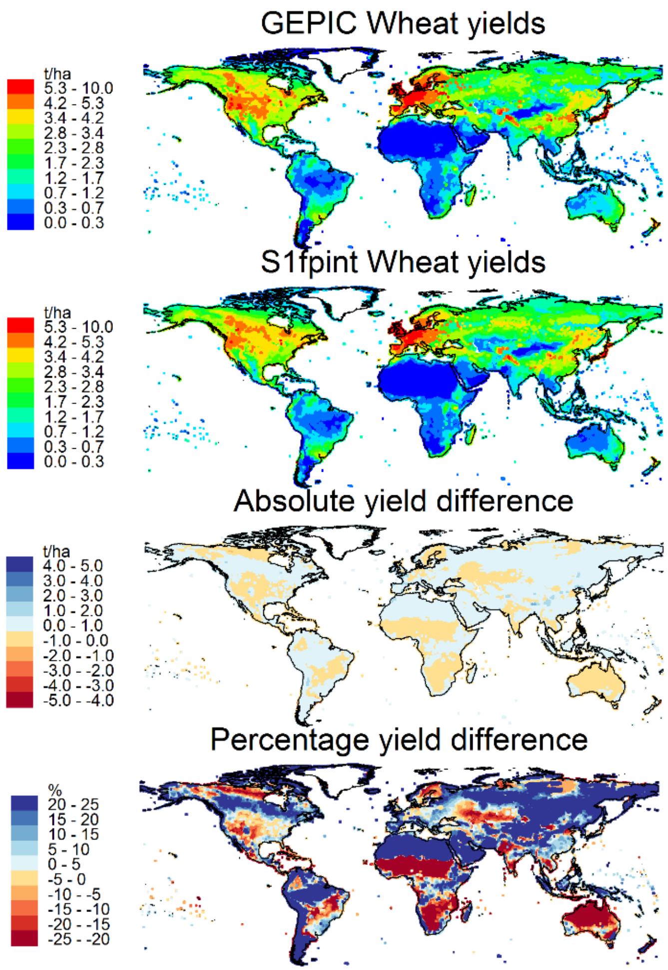

Figure F13. Wheat yields averaged over 2090–2099 for the GEPIC and statistical emulators (*S1fpint* specification).

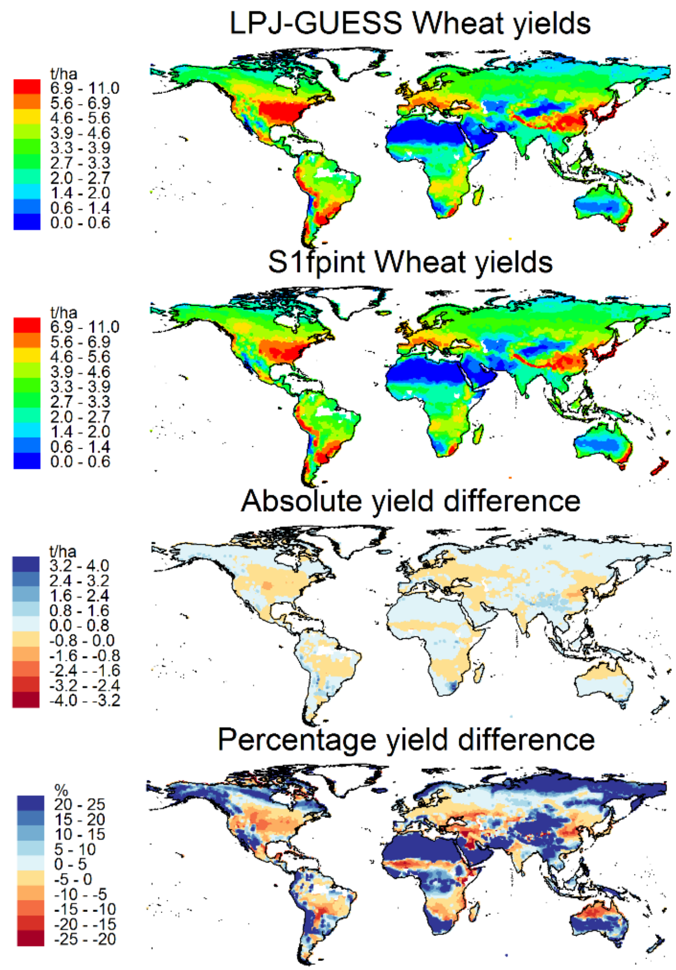

Figure F14. Wheat yields averaged over 2090–2099 for the LPJ-GUESS and statistical emulators (*S1fpint* specification).

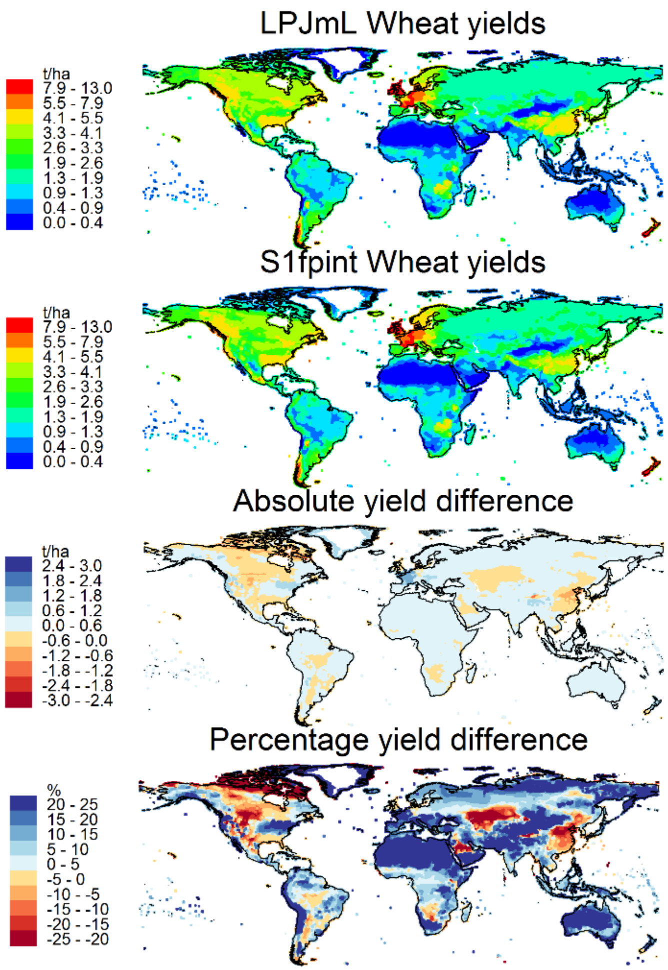

Figure F15. Wheat yields averaged over 2090–2099 for the LPJmL and statistical emulators (*S1fpint* specification).

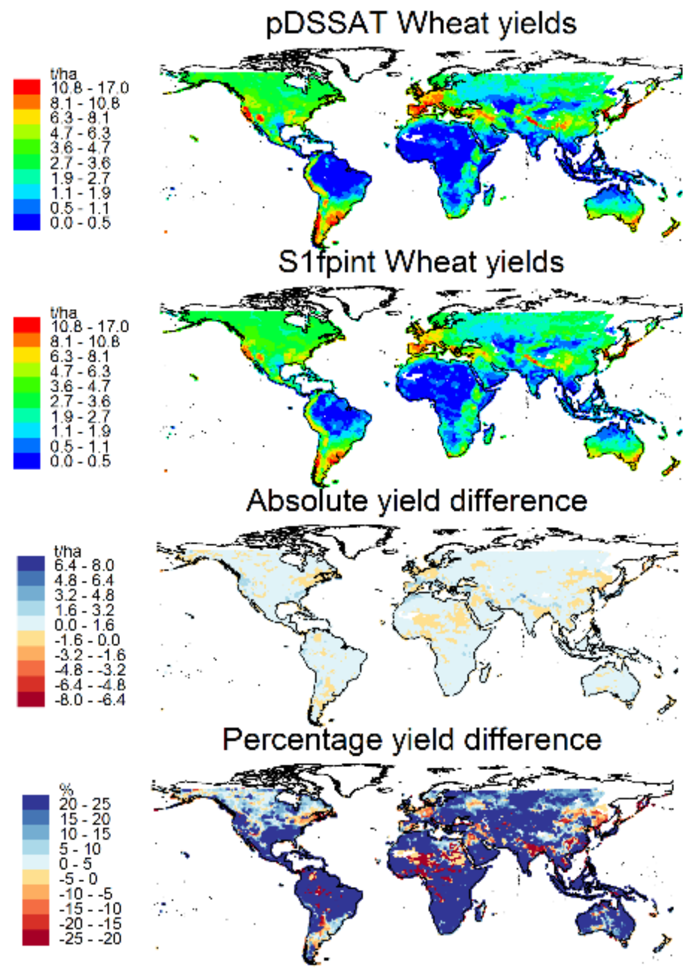

Figure F16. Wheat yields averaged over 2090–2099 for the pDSSAT and statistical emulators (*S1fpint* specification).

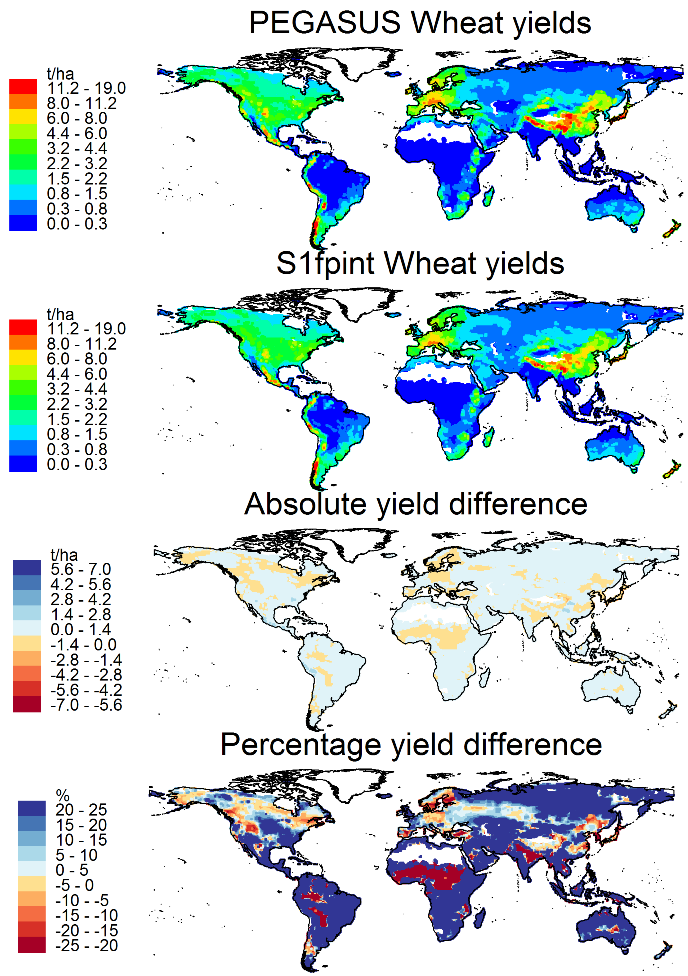

Figure F17. Wheat yields averaged over 2090–2099 for the PEGASUS and statistical emulators (*S1fpint* specification).

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