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Predicting Agricultural Productivity Under Climate Change Using Crop Yield Emulator

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Tamunotonye M. Braide, Timothy S. Thomas, and Richard D. Robertson

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Authors

Tamunotonye Braide (t.braide@cgiar.org) is a Senior Research Officer in the Foresight and Policy Modeling Unit of the International Food Policy Research Institute, Washington, D.C., USA.

Tim Thomas (tim.thomas@cgiar.org) is a Senior Research Fellow in the Foresight and Policy Modeling Unit of the International Food Policy Research Institute, Washington, D.C., USA.

Richard Robertson (r.robertson@cgiar.org) is a Research Fellow in the Foresight and Policy Modeling Unit of the International Food Policy Research Institute, Washington, D.C., USA.

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International Food Policy Research Institute
1201 Eye Street, NW
Washington, DC 20005-3915 USA
www.ifpri.org

Abstract

This study develops a crop yield emulator as a computationally efficient alternative to the DSSAT process-based model, enabling fast, large-scale assessments of how temperature, rainfall, CO_2, and nitrogen influence crop yields. Implemented using fixed-effects polynomial regression in R, the emulator was trained on DSSAT outputs and validated across seven globally important crops, maize, wheat (spring and winter), rice (indica and japonica), soybeans, sorghum, groundnuts, and potatoes. It showed high predictive accuracy ($R^2 > 0.90$) for most crops, especially spring wheat, groundnut, and potato, and performed reliably under climate scenarios such as RCP7.0. The emulator captured key crop-specific responses, such as maize's sensitivity to heat and nonlinear yield responses to nitrogen inputs. While its performance is slightly lower for maize and Indica rice compared to other crops, it remains a scalable and cost-effective tool for climate scenario analysis. This tool offers valuable support for agricultural decision-making and climate adaptation planning by enabling rapid, data-driven insights into yield outcomes under future conditions.

Keywords: crop yield emulator, DSSAT, climate, nitrogen, CO_2, fixed-effect polynomial regression

Introduction

Climate change presents significant challenges to global agriculture, threatening food security and economic stability, especially in regions that depend on agriculture. Warmer temperatures, changing rainfall patterns, and more frequent extreme weather caused by greenhouse gas emissions put pressure on agricultural systems (van der Wiel & Bintanja, 2021). These changes have reduced crop yields in many regions, complicating efforts to achieve global food security goals (Walsh et al., 2020; Ortiz-Bobea et al., 2021; Lachaud et al., 2022; Thomas et al., 2022a; Chandio et al., 2023; Onyeaka et al., 2024). Higher temperatures increase crop water demands, while excessive or inadequate rainfall causes waterlogging or drought, which negatively impacts productivity (Yadav et al., 2022). Elevated atmospheric CO_2, a major driver of climate change, affects crops differently. C3 crops benefit significantly from elevated CO_2 due to enhanced photosynthesis, while C4 crops show limited response to elevated CO_2. However, under drought conditions, C4 crops may experience indirect benefits, primarily through improved water use efficiency (Bellasio et al., 2023). Nitrogen fertilization improves crop yields and to that extent, it can also be used in some cases to mitigate the adverse effects of climate change, though its effectiveness depends on complex interactions with environmental factors (Zhang et al., 2022). Understanding these complex interactions is critical for developing effective climate adaptation strategies and ensuring sustainable agricultural productivity (Thomas et al., 2022b).

Accurate crop yield predictions are crucial for addressing food security challenges and informing climate adaptation policies. Process-based crop models, such as the Decision Support System for Agrotechnology Transfer (DSSAT), simulate crop growth under diverse environmental conditions (Jones et al., 2003; Hoogenboom et al., 2019, Hoogenboom et al., 2024). However, these models are computationally intensive, making them less practical for large-scale or long-term assessments (Franke et al., 2020). To address this limitation, crop yield emulators, which are statistical models, are designed to replicate the outputs of process-based models, providing a computationally efficient alternative. These emulators enable rapid yield projections across diverse climate scenarios, supporting strategic planning and informed decision-making (Franke et al., 2020). Despite their potential, emulators are often viewed with caution in studies examining the impacts of rainfall, temperature, CO_2, and nitrogen. This stems largely from concerns regarding their ability to accurately capture complex physiological responses compared to process-based models, leading to their relative underutilization in climate impact assessments.

This study addresses this gap in confidence and application by demonstrating that an emulator, trained using DSSAT simulations, can provide high-precision yield projections with minimal loss in accuracy. By evaluating the performance across diverse environmental factors on the crop growth stages, this paper provides the necessary evidence of emulator reliability and computational benefit required for broader adoption in sustainable agriculture, climate adaptation strategies, and support global food security initiatives.

Materials and methods

DSSAT Crop Modeling System

This study used the Decision Support System for Agrotechnology Transfer (DSSAT) crop model (Jones et al., 2003; Hoogenboom et al., 2019, Hoogenboom et al., 2024) to estimate crop yields across diverse environmental scenarios. DSSAT is one of the most extensively validated process-based crop modeling platforms globally, with demonstrated accuracy across a wide range of crops, soils, and climatic conditions. Establishing the emulator on DSSAT simulations rather than observed datasets ensures a consistent, controlled environment to isolate the physiological responses of crops to climate, soil, CO2, and nitrogen management conditions required for robust emulator training. We modeled crop yields for seven crops on half-degree pixels (approximately 50 kilometers at the equator) across most of the world, considering varying combinations of climate, soil, and management factors. This is consistent with the resolution used in prominent global agricultural modeling frameworks, including IFPRI's IMPACT model (Robinson et al., 2015) and the majority of AgMIP (Agricultural Model Intercomparison and Improvement Project) global gridded crop model ensemble simulations (Rosenzweig et al., 2013). The simulations included groundnut, maize, potato, sorghum, soybean, rice (Indica and Japonica), and wheat (spring and winter), resulting in a comprehensive dataset designed for emulator development.

An alternative to crop modeling for building an emulator would be to use agricultural statistics at sub-national level or plot-level data. The former can be problematic because yield growth over time can result from changes in management, atmospheric CO2 changes, or changes in price incentives. The latter, unless it is done over multiple years at multiple sites lacks the ability to control for managerial ability and can often be limited by observed climate ranges. Crop models can isolate management, atmospheric CO2, and productivity changes due to varietal changes, and can be run over a wide range of climate inputs.

The simulations incorporated both historical climate data and future projections. Climatic inputs comprised mean daily minimum and maximum temperatures by month, cumulative rainfall, and four atmospheric CO_2 levels to evaluate CO_2 fertilization effects. Two CO_2 conditions were modeled: one reflecting historical CO_2 levels and another with elevated CO_2 concentrations aligned with the respective Representative Concentration Pathway (RCP) scenarios. The DSSAT weather simulator produce daily weather data consistent with monthly climate aggregates, ensuring realistic environmental inputs for each simulation. Additional key input variables for DSSAT include nitrogen application rates, soil profiles, and farm management practices. The soil profiles used represent 27 distinct soil types from the HC27 Soil Profile Database (Koo and Dimes 2010).

The climate models used in this analysis were developed under the Coupled Model Intercomparison Project (CMIP) in support of the IPCC (Intergovernmental Panel on Climate Change) and its Sixth Assessment Report (AR6). To facilitate finer-scale agricultural modeling, the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP) downscaled the climate data. In this study, we used a baseline climate derived from the Princeton Global Forcings data (Sheffield et al. 2006) and future climates from CMIP6 and ISIMIP3b (Lange 2021). Yield changes from the 2005 baseline climate to the 5 ISIMIP GCMs for 2050. This analysis uses data from ISIMIP3b, which includes five global climate models (GCMs): GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL. These GCMs are run under various emissions scenarios, including SSP585 (Shared Socioeconomic Pathway 585), SSP370, and SSP126, which form the basis for much of the analysis in this study.

Crop Yield Emulator

DSSAT is a comprehensive software suite comprising dynamic growth simulation models for over 45 crops (Jones et al., 2003; Hoogenboom et al., 2019, Hoogenboom et al., 2024). This study focused on 7 globally important crops, developing and employing crop-specific yield emulators, as a computationally efficient alternative to DSSAT. While DSSAT offers simulations of crop growth under various environmental conditions, its high computational demands limit its practicality for some large-scale or long-term assessments. To address this limitation, the emulator was designed using a fixed-effects polynomial regression model implemented in R. With parameter estimates from the regression, yield estimates can be computed in a very small fraction of the time that it would take to run DSSAT, using less memory and processing power. The emulator was designed to replicate DSSAT outputs and predict crop yield responses to climatic factors and nitrogen application. To ensure the analysis focused only on areas where crops were planted, the Spatial Production Allocation Model (SPAM) was used to select pixels with non-zero production. SPAM employs a cross-entropy approach to estimate crop harvested area and yield at a 5-arcmin scale, integrating multiple data sources, such as crop production statistics, land cover maps, irrigated areas and cropping intensity (You et al., 2014). The analysis focused on seven crops, groundnut, maize, potato, sorghum, soybean, rice (*Indica* and *Japonica*), and wheat (spring and winter), selected for their significance for global food security and their representation of both C3 and C4 photosynthetic pathways.

The fixed effect polynomial regression analysis was conducted in two stages. In the first stage, the log of crop yield ($\ln(Y_{it})$) was regressed on climatic variables (rainfall, temperature, and CO_2), using a fixed-effects model to account for unobserved, timeinvariant heterogeneity across observations (Mummolo & Peterson, 2018), with a fixed effect assigned to each pixel. Each pixel had a specific soil type associated with it and due to the way the DSSAT was run, the level of nitrogen fertilizer was held constant in the pixel regardless of climate model used.

The first stage focused on isolating the effects of climate variability on yields, independent of nitrogen application, which remained constant across multiple DSSAT simulations for each pixel. To capture potential non-linear relationships, higher-order polynomial terms were incorporated for all climatic variables, allowing the model to better account for threshold effects such as yield declines from excessive heat or rainfall. The first stage ensured robust estimation of these non-linear effects, as specified in Equation 1:

$$\ln(\mathrm{Y}_{it}) = \beta_0 + \sum_{j=1}^{4} \beta_j{}^{(T)}\, tmax_{it}^{j} + \sum_{k=1}^{4} \beta_k{}^{(R)}\, rain_{it}^{k} + \sum_{m=1}^{3} \beta_m\, \mathrm{CO}_{2it}^{\,m} + \alpha_i + \epsilon_{it} \ldots\ldots\ldots\ldots\ldots 1$$

where $\ln(Y_{it})$ is the log-transformed crop yield for pixel i at time t, $\beta_j{}^{(T)}$ are coefficients for temperature terms, $\beta_k{}^{(R)}$ are coefficients for rainfall terms, $tmax_{it}^{j}$ (for *j* = 1,2,3,4), $rain_{it}^{k}$ (for *k* = 1,2,3,4) are fourth-degree polynomial terms for temperature and rainfall, β_m are coefficients for CO_2 terms, $\mathrm{CO}_{2it}^{\,m}$ (for *m* = 1,2,3) are cubic terms for atmospheric CO_2, α_i captures fixed effects, and ϵ_{it} is the error term.

In the second stage, the estimated fixed effects (α_i) from the first regression were recovered from the first stage regression and used as the dependent variable in a separate model, which regressed them on nitrogen application rates and their cubic polynomial terms as well as on dummy variables representing soil characteristics (texture, fertility, and depth), as detailed in Equation 2. All other management characteristics were identical at all locations, and therefore there were no other potential variables to include in the second stage regression. For nitrogen-fixing crops like soybean and groundnut, the fertilizer variables were excluded since the DSSAT data did not use nitrogen for these crops. For nitrogen-responsive crops, linear regression was used, as shown in Equation 2:

$$\alpha_i = \sum_{j=1}^{3} \beta_j{}^{(T)}\, Texture_{ij} + \sum_{k=1}^{3} \beta_k{}^{(F)}\, Fertility_{ik} + \sum_{l=1}^{3} \beta_l{}^{(D)}\, Depth_{il} + \sum_{n=1}^{3} \beta_n{}^{(N)}\, N_i^n + v_i \ldots\ldots 2$$

Where α_i = is the estimated fixed effect from the first-stage regression (Equation 1), $\beta_j{}^{(T)}$ are coefficients for soil texture, $Texture_{ij}$ is a dummy variable indicating the texture type j for pixel i (e.g. clay, loam, sand), $\beta_k{}^{(F)}$ are coefficients for soil fertility, $Fertility_{ik}$ is a dummy variable indicating the fertility level k for pixel i (e.g. high, medium, low), $\beta_l{}^{(D)}$ are coefficients for soil depth, $Depth_{il}$ is a dummy variable indicating the soil depth category l for pixel i (e.g. deep, medium, shallow), $\beta_n{}^{(N)}$ are coefficients for nitrogen terms, N_i^n (for *n* = 1,2,3) are cubic terms for nitrogen and v_i is the residual error.

Emulator Training and Performance Assessment

To ensure alignment with DSSAT-simulated yields, seven crop-specific yield emulators were developed and trained using data generated by the individual crop models within the DSSAT suite. The emulator was initially trained using the entire dataset[1] comprising a substantial number of observations for each crop, ranging from 203,317 to 576,624. Subsequently, the data were split into training (85%)[2], validation (10%)[3], and testing (5%)[4] subsets to assess both in-sample fit and out-of-sample predictive performance.

The performance of the emulator, a regression model trained to predict crop yields, was evaluated using the following statistical metrics:

- Mean Absolute Error (MAE) (kg/ha and %): Measures the average magnitude of errors between emulator-predicted yields and DSSAT-simulated yields. The MAE percentage expresses the error relative to the mean yield.

$$\mathrm{MAE} = \frac{1}{n} \Sigma_{i=1}^{n} \left| y_i^{DSSAT} - y_i^{Emulator} \right| \quad \ldots\ldots\ldots\ldots 3$$

where y_i^{DSSAT} is the DSSAT-simulated yield, $y_i^{Emulator}$ is the predicted yield from the trained regression model, and *n* is the number of observations.

- Root Mean Square Error (RMSE) (kg/ha and %): Measures average error magnitude, emphasizing larger deviations. The RMSE percentage provides a standardized perspective on error size.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n} \Sigma_{i=1}^{n} \left(y_i^{DSSAT} - y_i^{Emulator} \right)^2} \quad \ldots\ldots\ldots\ldots 4$$

- Coefficient of Determination (R^2): Represents the proportion of variance in DSSAT yields explained by the emulator, with values ranging from 0 to 1 with values closer to 1 indicating strong agreement.

$$\mathrm{R}^2 = 1 - \frac{\Sigma_{i=1}^{n} \left(y_i^{DSSAT} - y_i^{Emulator} \right)^2}{\Sigma_{i=1}^{n} \left(y_i^{DSSAT} - \bar{y}^{DSSAT} \right)^2} \quad \ldots\ldots\ldots\ldots 5$$

where $\bar{y}^{DSSAT}$ is the mean of the observed DSSAT yields.

These statistical metrics approach combining measures of MAE, RMSE and R^2 with an analysis of distributional properties (mean, median, and percentiles) represents the standard for evaluating crop yield emulators and gridded crop models (Chai & Draxler, 2014; Wallach et al., 2018; Franke et al., 2020). By assessing both the magnitude of individual errors and the emulator's ability to replicate the full statistical distribution of

[1] Entire Dataset (100%) is the trained DSSAT-generated data
[2] Train dataset (85%) of the whole dataset
[3] Validation dataset (10%) of the whole dataset
[4] Test dataset (5%) of the whole dataset

the process-based model, we ensure a robust validation that is consistent with the Agricultural Model Intercomparison and Improvement Project (AgMIP) protocols (Rosenzweig et al., 2014).

Results

This study examined the impact of rainfall, temperature, CO_2 levels, and nitrogen application on crop yields, revealing distinct responses that vary by crop and growth stage. The results are presented in key sections. First, the impacts of rainfall and temperature on crop yields were analyzed by identifying crop-specific thresholds, quantifying the percentage change in yield for marginal change and responses across different growth stages (Figure 1, Figure 2). Second, the effect of elevated atmospheric CO_2 on crop yields was explored (Figure 3). The effect of CO_2 across all GCMs under RCP7.0 were summarized in Table 1. Third, the spatial variability of yield changes under elevated CO_2 conditions was evaluated for selected crops, emphasizing regional disparities in climate change impacts and comparing emulator predictions with DSSAT simulations (Figure 4). Fourth, the study evaluated the effects of different nitrogen application rates, highlighting the importance of balanced nutrient management (Figure 5). Finally, the performance of the crop yield emulator was evaluated, demonstrating its accuracy and reliability in replicating DSSAT model predictions (Table 2, Figure 6). The following sections provide a detailed discussion of these results, supported by figures and tables that show key trends and insights.

Impact of Rainfall and Temperature on Crop Yields

Figures 1 and 2 are key to understanding the parameters estimated for the emulator and their implication for how inter-annual variation in weather and climate change will impact yields of these seven crops in any given location. As such, we will begin this section by explaining how to understand them. The analysis was done using the mean daily maximum temperature and total precipitation for every month of the growing season. In our notation, month 1 is the month that the crop was planted, month 2 is the next month and the last month (which may be month 4, 5, or 9, depending on the crop) is the harvest month. The graphs were made so that the end points of each curve represent the 5th and 95th percentiles of the data used to fit the curve. This approach highlights the importance of interpreting results cautiously outside these bounds. The data was representative of the locations where the crop is grown, with climate data representing values from 2005 and projections for 2050. The curve traces out effect on yields relative to the highest level attainable for a given climate variable. For example, Figure 1 shows that maize yields are highest when the mean daily maximum temperature in month 2 of the growing season is around 28°C. However, if the temperature rises to 32°C in month 2, maize yield can only reach 88% of what it would at 28°C. The because the dependent variable in the regressions is the logarithm of yield (Equation 1), to find the impact on yield we would exponentiated each side of the equation, and so the effect of each climate component for each month has a multiplicative effect on yield. We chose not to include interactive terms between temperature and precipitation because when we experimented with it, the increase in explanatory power was small and it lowered the intuition concerning changes in individual values. We also failed to include interactions between the same variable in different months. For example, damage done to the plant by climate in one month might impact the effect of the climate variable on yields in another month. Certainly, neither a crop model nor an emulator is going to perform perfectly under some conditions, and we accept that as a cost of being able to model climate impact efficiently.

Figure 2 shows the marginal changes from the graphs in Figure 1, illustrating the cost or benefit of an additional unit of temperature or precipitation. For example, considering the effect of temperature on maize in Figure 2, using the same reference point as in the example in Figure 1 (month 2 at 28°C), the marginal effect is 0. This means that a slight increase in temperature at a location where the mean daily temperature is normally 28°C leads to no change in yield. However, if the normal temperature is 32°C in month 2, a slight increase as much as 1°C, leads to a reduction in yield of 6%. By knowing the temperature and precipitation levels for all four months before and after climate change, one could estimate the overall impact on yield. This can be done by multiplying the temperature gains or losses of each of the 4 months together with the gains or losses from each of the 4 months of precipitation to get the total change in yield from climate change.

Sorghum is often suggested as a potential substitute for maize in drought-prone areas. This can be seen to some extent when comparing the precipitation graphs in Figure 2, where maize needs much more water in month 1 than sorghum, but sorghum needs more water in month 4. However, sorghum is notably more heat-resilient than maize. At 37°C in month 2, maize experiences a 14% marginal yield loss, but sorghum loses only 4% at the same temperature. Soybeans seem to have a similar temperature preference to sorghum. As shown in Figure 1, sorghum, soybean, groundnut, and Japonica rice all prefer cooler temperatures in month 1. In Month 3, sorghum shows the highest resilience to heat stress, maintaining high yields even at temperatures above 34 °C. In contrast, Month 2 and 4 shows significant yield decline under hotter conditions. Figure 2 shows that both maize and potatoes are very sensitive to high temperatures. Figure 1 further shows that potatoes are sensitive to high temperatures, achieving optimal yields at ~18-24°C. Beyond ~26-28°C, yields decline across all months. This shows that potato is a cool season crop. Groundnuts are in the next tier down in sensitivity, experiencing significant losses to high temperatures across multiple months. Indica rice and Japonica rice exhibit losses similar to groundnuts, but these losses are confined to just one month each.

Winter wheat takes a long time between planting and harvesting, thriving in colder weather during its first three months of growth, as shown in Figures 1 and 2. As spring arrives, winter wheat copes with warmer temperatures much better than spring wheat, with higher temperatures increasing winter wheat yields in some of the months of spring. Similarly, spring wheat also prefers cool weather in the first few months, just like winter wheat. However, the first three months for spring wheat occur in the spring rather than in the fall or early winter.

Rainfall sensitivity varies across crops. Figure 1 and 2 shows that most crops experience either no yield losses or only minor losses during very wet years. Some crops, such as winter wheat in months 7 through 9, have periods where they are not sensitive to either high or low rainfall. Potatoes seem to have the highest sensitivity to insufficient rainfall, meaning that a positive number indicates yield loss when rainfall falls below normal levels. To calculate non-marginal changes, for example, a 50 mm reduction in rainfall from 100 mm to 50 mm in month 2, a trapezoidal approximation is used. The area under the curve between 50 mm and 100 mm is calculated as the average of 1.08% and 0.52 percent which is 0.8%, multiplied by 50 mm, which is 40%.

Figure 1: Crop yield response to rainfall and mean daily maximum temperature.

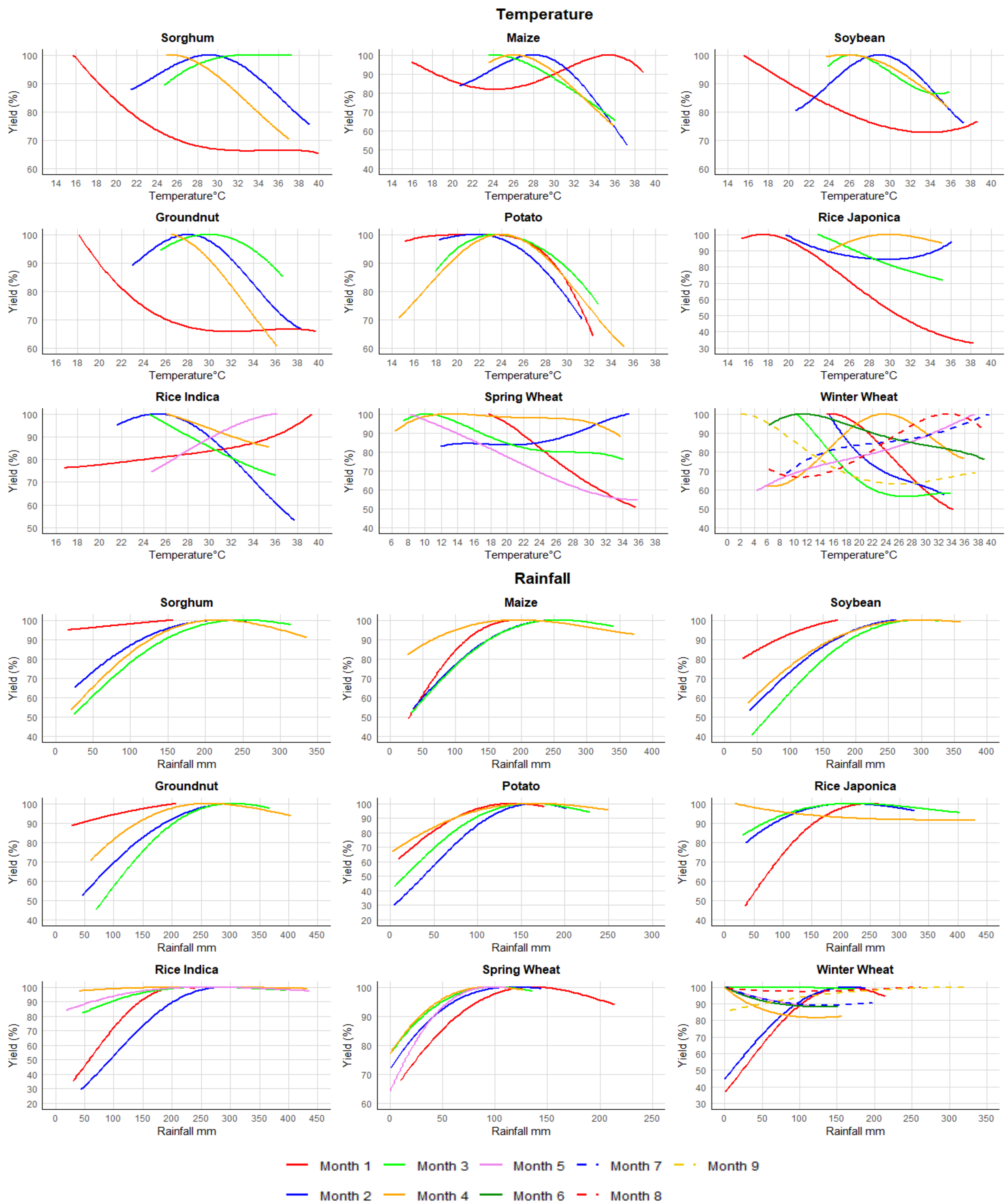
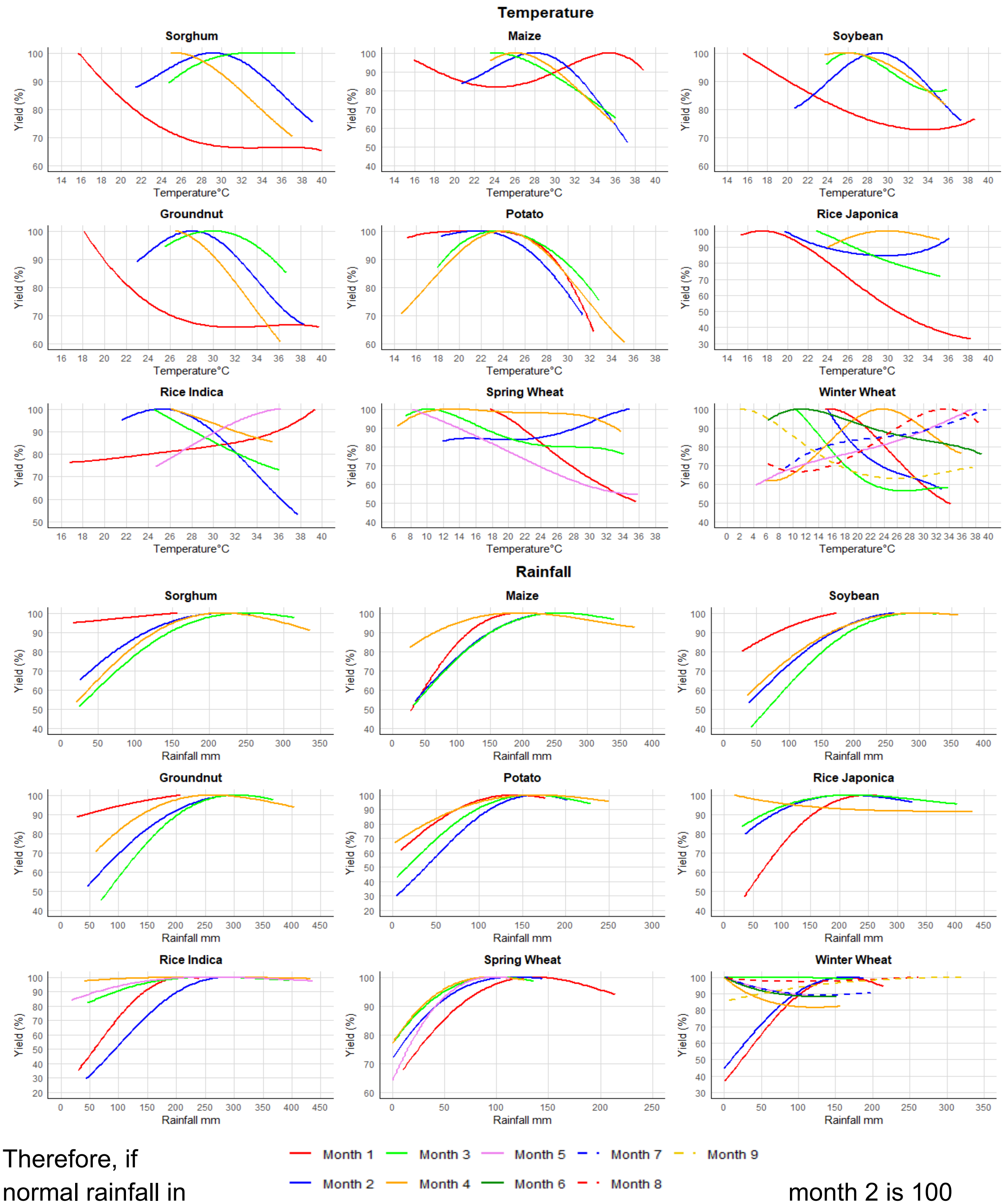


Figure 2: Percent change in crop yield for marginal change in temperature (°C) and rainfall (mm). Yield changes are modeled across the 5th to 95th percentile range for both temperature (°C) and rainfall (mm) in each month.



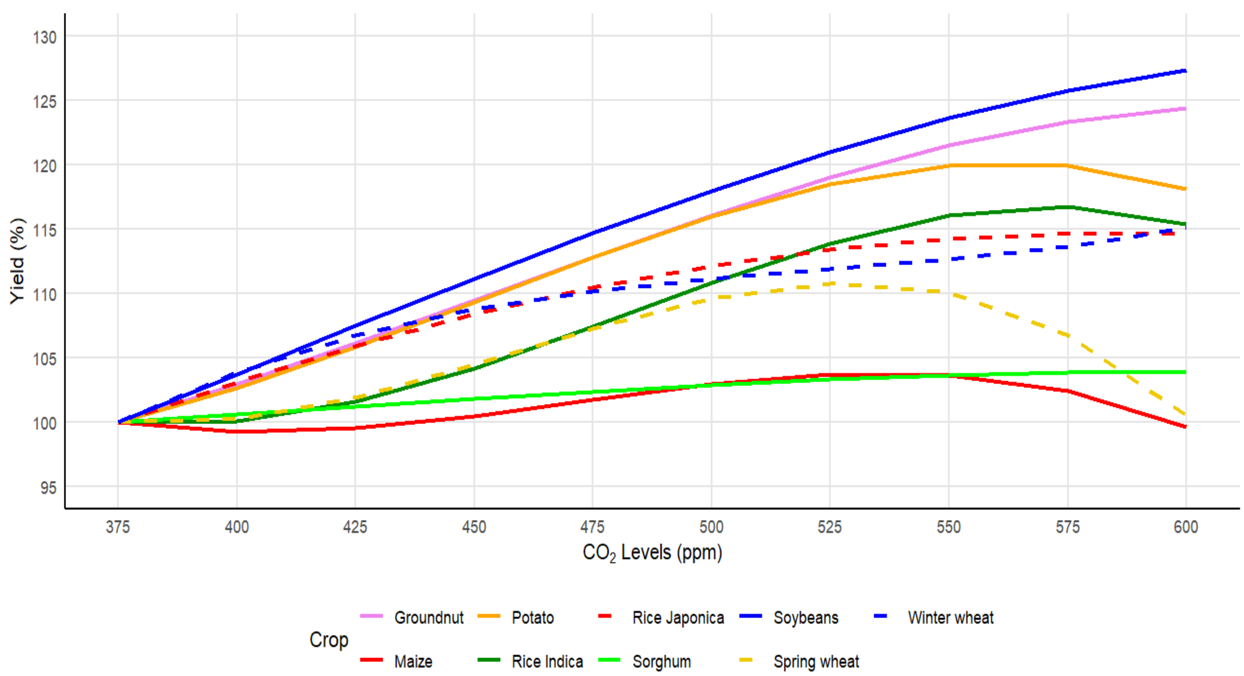
Therefore, if normal rainfall in month 2 is 100 mm and, due to climate change or a dry year the rainfall drops to 50 mm, potato yields will drop by 40%, if all other monthly climate values stay the same.

In terms of rainfall sensitivity, winter wheat and Indica rice rank just below potatoes, both being highly sensitive to drought in months 1 and 2. Maize and Japonica rice are also sensitive to drought, but primarily in month 1. Sorghum, groundnut, and soybeans show sensitivity to drought in month 3, with sorghum also affected in month 4. These results show how rainfall and temperature impact yield responses.

Impact of CO_2 on crop yields

Figure 3 presents the impact of increasing atmospheric CO_2 concentrations (375–600 ppm) on crop yields, using 375 ppm as the baseline (100%). C4 crops such as maize and sorghum are known for their yields not responding much to CO_2 levels, and we see that in the figure. C3 crops do respond to CO_2 levels, and we observe different kinds of responses. Groundnuts and soybeans have the largest yield responses of around 25% increase in yields at the highest level in our analysis. Potatoes show a similar response up through 500 ppm, then they begin to level off, peaking at around 20% boost in yield at 550 ppm. Indica rice peaks at 17% boost in yield at around 575 ppm, where it levels off and possibly declines at CO_2 levels above that.

Figure 3: Yield response of crops to elevated CO_2 levels.



Spring wheat appears to have an optimal yield boost of 11% (relative to the CO_2 levels of 2005, which were 375 ppm) at around 525 ppm, and above 550 ppm, appears to decline (though this could be an artifact of the regression approach used to estimate the effect), showing the same yield at 600 ppm as it did with 375 ppm. This deserves further investigation, especially since winter wheat shows no decline in yield responsiveness, with a 15% gain at the maximum value in our analysis of 600 ppm. The yield response of Japonica rice to CO_2 is very similar to that of winter wheat. It is important to note that in the emulator framework, the CO_2 fertilization effect is estimated as independent (Equation 1), without interaction with temperature or rainfall variables. This implies that the reported CO_2 yield benefits represent average effects across the full range of climate conditions in the training data, rather than conditional effects under specific stress environments. Consequently, the CO_2 effects reported should be interpreted as average responses across the range of simulated conditions, rather than stress-dependent responses. Table 1 presents projected changes in crop yields from 2005 to 2050 under RCP7.0 aggregated to the global level. It shows first the direct impact of climate change on yields ignoring any potential CO_2 fertilization effect, then shows the additional yield accounting for the CO_2 fertilization effect. The values reflect the median value across the 5 climate models used in this study. The table also compares the direct results from DSSAT to results generated by the emulators developed in this paper. The "CO_2 Effect (%)" values represent the relative percentage increase in median yield (kg/ha) for each crop, calculated by comparing yields with and without elevated CO_2. This calculation was performed separately for each crop, consistently resulting in positive CO_2 effect values.

Table 1: Global yield changes (2005–2050) under RCP7.0: CO_2 Effects Across All GCMs

	DSSAT			Emulator		
Crops	**Median Yield Change - No CO_2 (%)**	**CO_2 Effect (%)**	**Net Yield Change (%)**	**Median Yield Change - No CO_2 (%)**	**CO_2 Effect (%)**	**Net Yield Change (%)**
Maize	-14.6	3.38	-11.7	-11.2	2.98	-8.51
Sorghum	-10.1	1.95	-8.33	-9.09	3.09	-6.27
Potato	-6.7	16.4	8.61	-7.35	16.6	8.07
Groundnut	-14.1	18.0	1.34	-12.2	17.7	3.32
Soybean	-8.68	20.9	10.4	-6	19.6	12.4
Indica Rice	-4.63	13.6	8.36	-4.15	13.1	8.42
Japonica Rice	-30.4	17.1	-18.5	-25.8	15.2	-14.5
Spring wheat	-11.8	10.7	-2.43	-6.85	8.69	1.25
Winter wheat	-15.9	12.1	-5.74	-11.2	11.1	-1.37

Note: The table shows the SPAM-weighted median projected global yield changes (%) for major crops from 2005 to 2050 under the RCP7.0 scenario. The values show the median change across all GCMs, both without elevated CO_2 and with the relative yield effect of elevated CO_2, as simulated by DSSAT and predicted by the emulator. The net yield change represents the overall projected yield change under RCP7.0 accounting for both climate and CO_2 fertilization effects.

Table 1 shows that C3 crops, such as soybean, groundnut, potato, rice, and wheat, showed strong positive responses to elevated CO_2. Soybean showed the highest benefit, with yield increases of approximately 21% in DSSAT and 20% in the emulator. Groundnut and potato also showed substantial improvements, with both models estimating gains of about 16–18%. Indica rice showed a CO_2 effect of 14% in DSSAT and 13% in the emulator, while Japonica rice had a higher response, with increases of 17% in DSSAT and 15% in the emulator, despite yield losses in the absence of CO_2. For wheat, the CO_2 fertilization effect was slightly higher in winter wheat, with increases of 12% in DSSAT and 11% in the emulator, compared to spring wheat, which showed increases of 11% in DSSAT and 9% in the emulator. In contrast, C4 crops such as maize and sorghum showed smaller yield increases in response to elevated CO_2, reflecting their lower physiological sensitivity. DSSAT projected yield gains of 3% for maize and 2% for sorghum, while the emulator estimated similar or slightly higher increases of 3% and 3%, respectively. As shown in the net yield change column, elevated CO_2 is projected to fully offset climate-induced yield declines for crops like soybean, potato, and indica rice while maize and sorghum still face net global losses. Japonica rice suffers a large net loss despite CO_2 benefit. Although the emulator differed slightly in its estimation of the CO_2 benefit for each crop, it generally captured the effect across different crop types and climate scenarios.

Pixel-level Yield for Maize and Groundnut under Elevated CO_2 Conditions

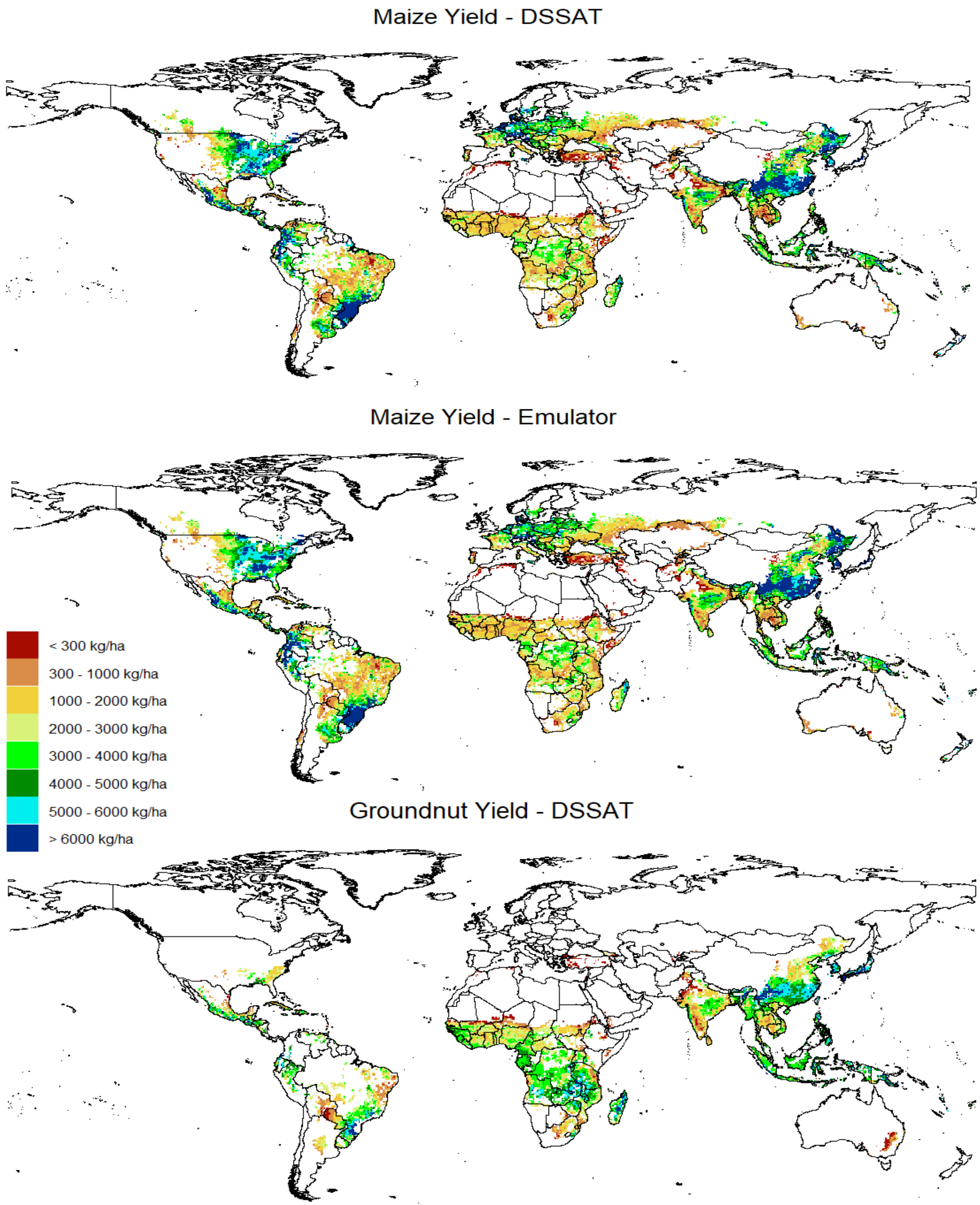
Figure 4 presents global maps of actual yields from DSSAT and predicted yields from the emulator for groundnut and maize under the RCP7.0 scenario, using the IPSL-CM6A-LR climate model for 2050. Yields are displayed with a color-coded legend, ranging from low yield (< 300 kg/ha, shown in red) to high yield (> 6000 kg/ha, shown in blue). For each crop, the top map shows yields simulated by the DSSAT crop model, while the bottom map shows yields predicted by a statistical emulator trained on DSSAT outputs. The same yield class intervals (in kg/ha) are used across all maps to allow for direct visual comparison.

For maize, the emulator closely matched the spatial yield patterns produced by DSSAT, capturing key regional trends, as shown in Figure 4. High-yielding areas, such as China, southeastern Brazil, the United States, Mexico, and parts of Europe, were consistently represented in both maps. Some minor differences were observed, with the emulator slightly overestimating yields in China and the United States and underestimating them in Brazil and Europe. Low-yield regions, including Sub-Saharan Africa, the Middle East, Turkey, and parts of Australia, were also consistently identified by both approaches.

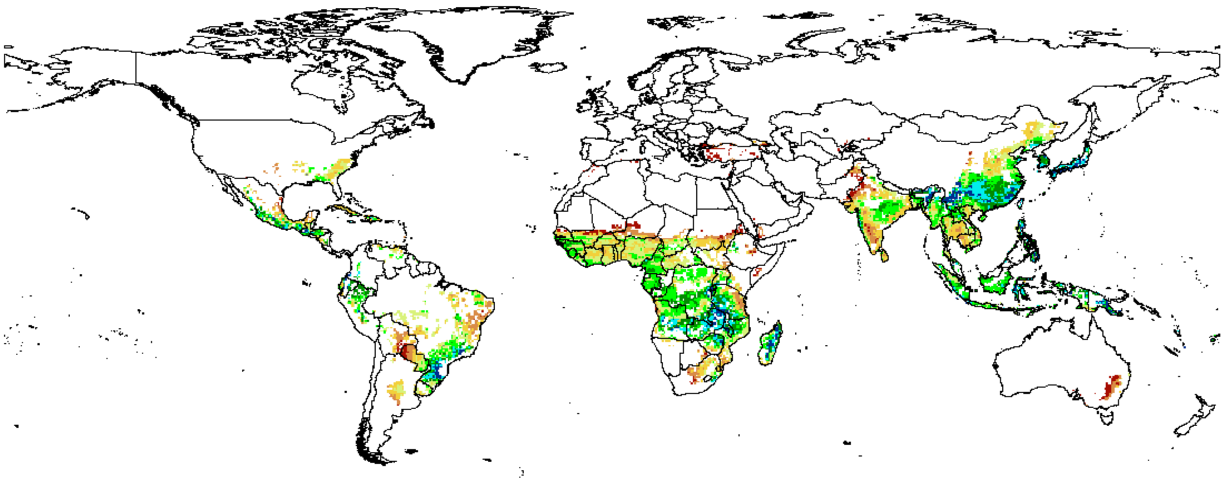
Similarly, for groundnut, the emulator showed strong spatial agreement with DSSAT simulations. High-yielding regions, particularly in Brazil, Southeast Asia (especially China), and parts of East and Southern Africa, were accurately captured. Moderate-yield zones across South America, India, and regions of West, East, and Central Africa were also well represented. Low-yielding areas, including arid zones in northern and southern Africa, Australia, and parts of South Asia, were consistently depicted by both models. Any differences between the emulator and DSSAT remain small and did not affect the overall spatial agreement.

This consistency across both crops demonstrated the emulator's reliability in reproducing DSSAT-derived yield patterns under climate stress. The strong performance of the emulator supported its use as a computationally efficient and robust alternative to process-based models like DSSAT for projecting future crop yields. Its speed and accuracy made it especially suitable for large-scale climate impact assessments and integration into broader agricultural modeling frameworks where both precision and efficiency are essential.

Figure 4: Yield maps for maize and groundnut under elevated CO_2 (RCP7.0 IPSL-CM6A-LR).



Groundnut Yield - Emulator



Impact of Nitrogen on crop yields

Figure 5 presents the yield responses of different crops to increasing rates of nitrogen fertilizer application. Nitrogen is a crucial factor in crop productivity, but its effects vary widely among crop types. We also want to note that particularly at higher levels of nitrogen, the shape of the curve may be due to relatively few observations used in the regressions at that level.

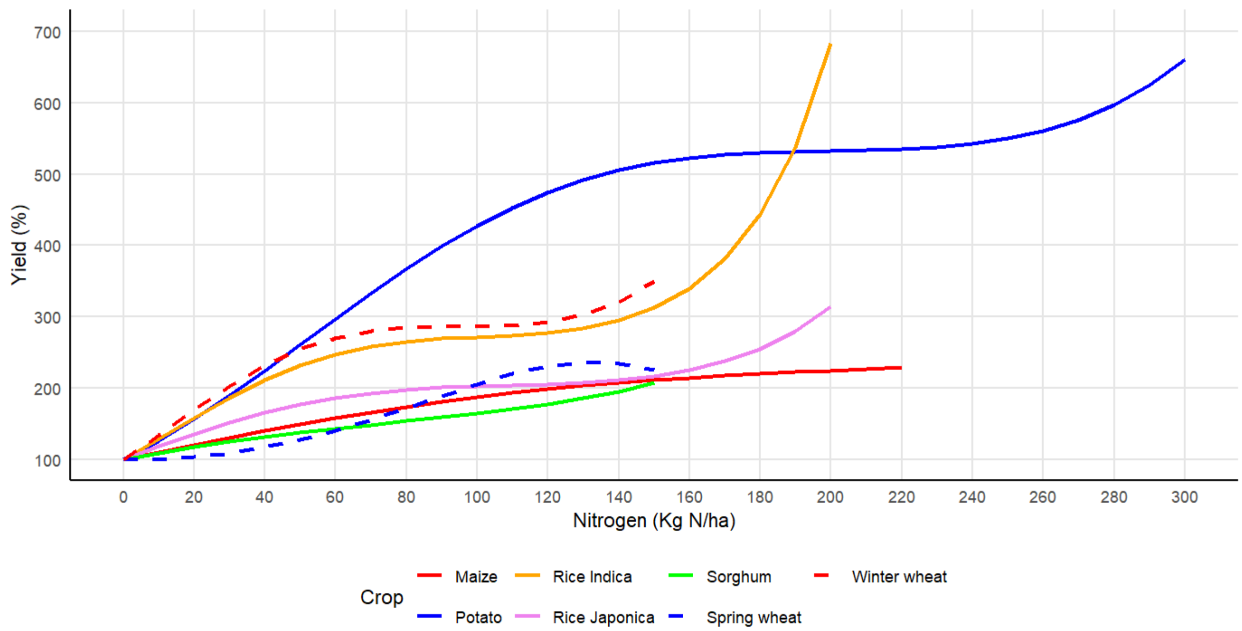
For maize, as shown in Figure 5, the highest marginal yield gains occurred at lower nitrogen rates, with smaller marginal increases at higher levels, as we might expect, as other factors in yield growth besides nitrogen become the limiting factor. Using 0 kg N/ha as the baseline (set at 100%), maize yield at 220 kg N/ha increased by 129%, indicating that optimal nitrogen application more than doubled the yield compared to the baseline. Sorghum also responded strongly to nitrogen, especially between 0 and 150 kg N/ha. This range resulted in a 108% increase over the baseline, more than doubling the yield with added nitrogen.

Potato yields increased in a non-linear form as nitrogen rates increased from 0 to 300 kg N/ha, with yield increasing by 562% compared to the baseline. Indica rice showed a positive yield response from 0 to 200 kg N/ha, corresponding to a 585% increase relative to the baseline. Japonica rice followed a similar pattern, with yield rising by 214% over the baseline at 200 kg N/ha.

Spring wheat exhibited a non-linear response to nitrogen. Yield increased with nitrogen application, peaking at 130 kg N/ha, which represented 236% of the baseline (a 136% increase). However, increasing nitrogen to 150 kg N/ha caused a slight decline in yield, indicating that excessive nitrogen could reduce yield beyond a certain point. Winter wheat responded most strongly to lower nitrogen application rates. At 150 kg N/ha, yield was 250% higher than the baseline.

In addition to nitrogen effects, soil characteristics such as texture, fertility, and depth played a significant role in yield outcomes. Sandy soils generally produced higher yields than clay or loam soils. Across all crops, greater soil fertility and depth were linked to increased yields, except for Japonica rice, which performed better in shallow soils. Regression analyses (see Appendix: Tables B2, B5, B8, B10, B12, B14, B16) confirmed strong interactions between nitrogen levels and soil properties. These findings highlight the importance of tailoring nitrogen management strategies to specific crops and soil conditions to maximize yield while minimizing environmental and economic risks.

Figure 5: Yield response of crops to nitrogen application rates.



Performance Evaluation of the Crop Yield Emulator

Table 2 presents statistical metrics that compare yield predictions from the emulator and the DSSAT model for seven crops, using the entire dataset as well as the validation and test datasets. The metrics include mean absolute error (MAE), MAE percentage, root mean square error (RMSE), RMSE percentage, and R-squared (R^2), which together indicate how closely the emulator matches DSSAT predictions[5].

[5] MAE (%) is calculated as MAE (kg/ha) divided by the mean yield, multiplied by 100. Similarly, RMSE (%) is calculated as RMSE (kg/ha) divided by the mean yield, multiplied by 100.

As shown in Table 2, the performance is reported for the entire dataset (in-sample) and for the validation and test datasets (out-of-sample), allowing for an assessment of both predictive accuracy and model generalizability. For most crops, R^2 values were slightly lower in the validation and test sets compared to the entire dataset, as is expected when evaluating out-of-sample predictions. However, spring wheat and japonica rice maintained consistent R^2 values across all datasets. In general, MAE% and RMSE% were higher in the validation and test sets, reflecting increased variability in out-of-sample predictions.

Overall, the emulator performed strongly, with R^2 values ranging from 0.87 to 0.97 across all crops and datasets, indicating a high level of agreement with DSSAT outputs. Spring wheat showed the best results, achieving R^2 of 0.97 and consistently low MAE% (11%) and RMSE% (17%) across all datasets. Potato and groundnut also demonstrated strong emulator performance. Potato achieved R^2 values of 0.96 for the entire dataset and 0.95 for validation and test sets, with MAE% around 12%. Groundnut recorded R^2 values of 0.93 for the entire dataset and 0.92 for validation and test sets, with MAE% close to 11%, confirming the emulator's reliability for these crops. Sorghum, maize, and soybean also performed well. Sorghum achieved R^2 values above 0.90, with MAE% around 13% and RMSE% near 19%. Maize recorded R^2 values of 0.90 for the entire dataset, 0.89 for validation, and 0.88 for the test set. Soybean showed R^2 values of 0.91 for the entire dataset and 0.90 for both validation and test sets, reflecting consistent emulator accuracy.

Winter wheat also performed robustly, with R^2 values of 0.92 for the entire dataset and 0.91 for the validation and test sets, and MAE% around 14 to 15%. However, RMSE% was higher, approaching 24%, which suggests slightly greater variability in yield predictions. The rice varieties showed relatively higher error margins. Japonica rice maintained a high R^2 of 0.95 across all datasets, while its RMSE% ranged from 29% to 31% and its MAE% from 15% to 16%. Indica rice showed lower R^2 values (0.87–0.88) and higher RMSE% (31%–32%), with MAE% around 18%. This suggests that while the emulator captured general yield trends for indica rice, deviations from DSSAT outputs were more pronounced.

Despite some variation among crops, the emulator consistently performed well across all datasets, demonstrating strong generalizability and minimal risk of overfitting. In summary, the emulator proved to be a reliable and efficient alternative to DSSAT simulations, with particularly strong results for spring wheat, potato, and groundnut, and acceptable accuracy for more challenging crops such as indica rice. These results highlight the emulator's suitability for large-scale agricultural modeling and climate impact assessments.

Table 2: Statistical Metrics Comparing Emulator and DSSAT Yield Predictions Across Datasets.

Crops	Datasets	Mean (kg/ha)	MAE (kg/ha)	MAE (%)	RMSE (kg/ha)	RMSE (%)	R^2
Maize	Entire	3,055	486	15.9	727	23.8	0.90
	Validation	3,051	500	16.4	747	24.5	0.89
	Test	3,067	512	16.7	747	25.0	0.88
Sorghum	Entire	2,448	309	12.6	453	18.5	0.92
	Validation	2,443	320	13.1	471	19.3	0.91
	Test	2,469	323	13.1	471	19.1	0.91
Soybean	Entire	1,841	260	14.1	396	21.5	0.91
	Validation	1,830	268	14.7	410	22.4	0.90
	Test	1,849	272	14.7	410	22.2	0.90
Potato	Entire	3,074	369	12.0	551	17.9	0.96
	Validation	3,080	382	12.4	565	18.3	0.95
	Test	3,093	382	12.4	565	18.5	0.95
Groundnut	Entire	2,795	295	10.6	432	15.5	0.93
	Validation	2,808	309	11.0	453	16.1	0.92
	Test	2,803	307	11.0	453	16.0	0.92
Indica Rice	Entire	1,525	269	17.6	474	31.1	0.88
	Validation	1,526	280	18.4	496	32.5	0.87
	Test	1,522	276	18.1	496	31.9	0.87
Japonica Rice	Entire	437	67	15.4	128	29.2	0.95
	Validation	436	70	16.0	133	30.5	0.95
	Test	448	73	16.2	133	30.7	0.95
Spring wheat	Entire	2,886	304	10.6	483	16.7	0.97
	Validation	2,892	314	10.9	496	17.1	0.97
	Test	2,877	314	10.9	496	17.2	0.97
Winter wheat	Entire	1,662	233	14.0	377	22.7	0.92
	Validation	1,673	245	14.6	401	24.0	0.91
	Test	1,677	244	14.6	401	23.8	0.91

Note: The "Entire" dataset refers to in-sample evaluation, where the emulator's yield predictions are directly compared to DSSAT outputs using all the data. In contrast, the "Validation" and "Test" datasets are used for out-of-sample evaluation to assess how well the emulator generalizes new, unseen data. The validation set is typically used to fine-tune model parameters, while the test set provides an independent assessment of predictive performance.

Table 3: Statistical Metrics Comparing Emulator and DSSAT Yield Predictions for Rainfed Maize across Multiple Regions.

Region	N	Mean (kg/ha)	MAE (kg/ha)	MAE (%)	RMSE (kg/ha)	RMSE (%)
CWANA	25,736	863	197	22.8	299	34.7
ESA	59,005	1,898	315	16.6	430	22.7
LAC	121,952	3,349	553	16.5	815	24.3
SA	36,353	2,677	565	21.1	820	30.6
SEA	45,726	2,880	376	13.1	542	18.8
WCA	77,972	2,056	317	15.4	452	22.0
Rest of orld	209,880	3,953	604	15.3	864	21.9
Global	576624	3055	486	15.9	727	23.8

Note: The results in this table are for the entire dataset.

Table 3 compares the predictions from the emulators to the actual DSSAT values for yields of rainfed maize. The regions with the fewest number of pixels which grow maize have the highest deviations, while the larger regions have deviations similar to what was reported for the world.

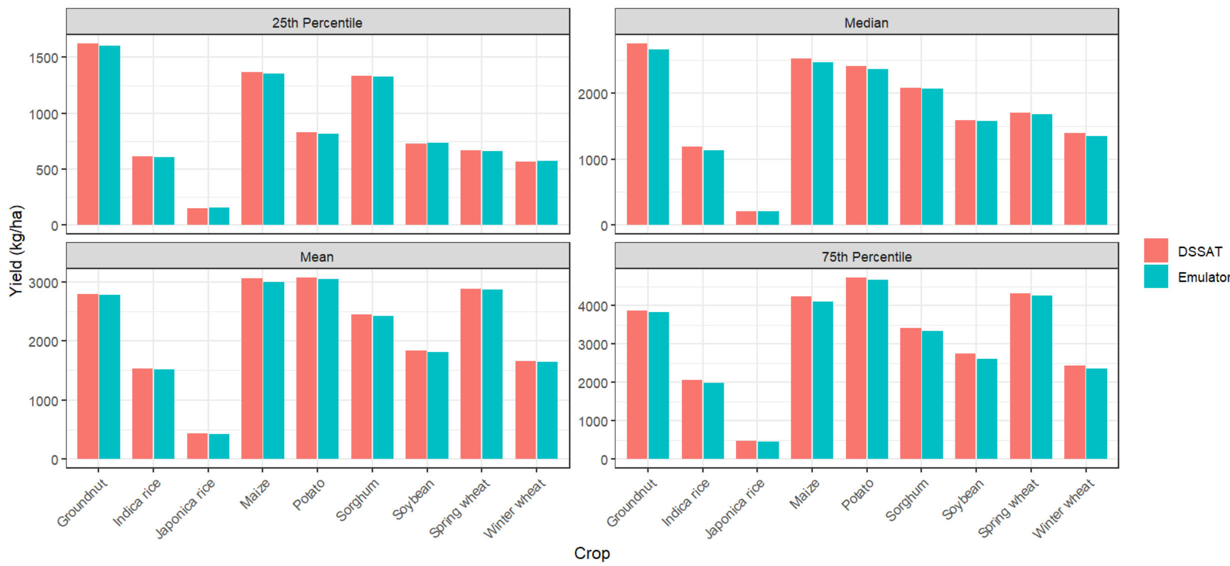
Figure 6 presents a comparative analysis of yield predictions from the emulator and the DSSAT model across multiple crops, using key summary statistics: the 25th percentile, 75th percentile, mean, and median.

The emulator, trained on the entire dataset, shows strong agreement with DSSAT outputs, with the red and blue lines indistinguishable. This alignment is especially close at the 25th percentile, where it is almost exact. At the 75th percentile, the emulator closely mirrors DSSAT predictions, with only minor deviations observed for maize and soybean. These findings suggest that the emulator effectively captures yield variability across both the lower and upper ends of the distribution.

The mean and median values further reinforce the emulator's predictive accuracy. Mean yields align well across most crops, though minor discrepancies are noted for maize. Slight differences in the median values are also observed for groundnut and maize. Despite these deviations, the overall agreement remains high. Visually, Figure 5 shows this consistency, with the emulator's line closely tracking the DSSAT line across all summary statistics. This alignment highlights the emulator's ability to replicate not just point estimates but also the distributional characteristics of DSSAT yield outputs. These visual insights are supported by the statistical metrics in Table 4, which confirm that the emulator preserves both the central tendency and variability of DSSAT predictions.

In summary, Figure 6 shows the strong predictive performance of the emulator. Despite minor differences in a few crops, the emulator exhibits robust and reliable performance, accurately emulating DSSAT yield distributions across multiple crops and statistical measures.

Figure 6: Comparison of Yield Predictions: Summary Statistics of Emulator and DSSAT Predictions.



Note: The emulator line represents the trained entire dataset.

Discussion

This study provides valuable insights into the key climatic factors of crop productivity and demonstrates the use of a crop yield emulator in replicating process-based model outputs. By examining the effects of temperature, rainfall, CO_2, and nitrogen on major crops, and validating emulator results against DSSAT simulations, we provide a practical approach for supporting agricultural decision-making and food security planning.

The results extend existing research by reinforcing well-documented crop sensitivities to environmental conditions, particularly during reproductive phases. For instance, our findings align with Khalifa and Eltahir (2023), Ritchie (2024), Bhat et al. (2024), and Lee et al. (2020) confirming that extreme heat and excess rainfall or drought negatively affect crop development. For example, sorghum is sensitive to early cold, maize to mid-season heat, and potatoes show yield declines above 26°C. Rice varieties differ in heat tolerance, with Japonica being more sensitive than Indica, which supports genotype-specific adaptation strategies noted by Li et al. (2024). Both winter and spring wheat are vulnerable to early heat and excessive rainfall, consistent with findings by Hou et al. (2024) and He et al. (2020).

The study confirms clear yield thresholds in response to temperature and rainfall beyond which productivity drops or plateaus. Most crops benefit from increased nitrogen up to a certain level, after which returns taper or diminish, with variation by soil type. It is likely profit-maximizing levels of nitrogen would be reached long before pure yield-maximizing levels would be reached. Importantly, this study advances crop modeling by demonstrating that well-trained emulators can reliably replicate DSSAT outputs. The emulator performs particularly well for crops such as spring wheat, potato, and groundnut, achieving R^2 values consistently above 0.90 across entire (training), validation, and test datasets. Emulator predictions closely match DSSAT results across climate scenarios, including elevated CO_2, with only minor regional differences. While emulator performance for maize and indica rice was moderate, the model still captured central tendencies effectively, indicating potential for further refinement.

While the fundamental crop sensitivities to temperature and rainfall identified in this study align with results from established process-based models like DSSAT, the primary contribution of the emulator lies in its transformative computational efficiency and scalability. Process-based models such as DSSAT are indispensable for understanding biophysical mechanisms but are computationally prohibitive for the large-scale simulations required for robust uncertainty quantification. For instance, a single global simulation for seven crops across multiple GCMs and RCP scenarios typically requires hours/days of processing on high-performance computing clusters. In contrast, the emulator reproduces these results in seconds to minutes, representing a speed increase of several orders of magnitude. This advantage is not merely a convenience but a fundamental expansion of analytical scope, making previously intractable tasks such as large-scale simulations across thousands of climate realizations, entirely feasible at the global level.

The emulator offers unique advantages for sensitivity analysis and uncertainty quantification. By independently varying temperature, rainfall, CO_2, and nitrogen across their full range of possibilities, the model allows researchers to systematically isolate and measure how much each individual driver contributes to yield variance. Such a comprehensive decomposition of factors would be both cumbersome and prohibitively expensive using process-based models alone. Ultimately, this capacity for rapid uncertainty propagation makes emulators indispensable for policy-relevant risk assessments, providing decision-makers with full probability distributions of potential outcomes rather than just simple average estimates.

Despite its strengths, this study has several limitations that warrant consideration. First, because the emulator was trained exclusively on DSSAT-simulated data, any structural biases or inherent limitations within the DSSAT platform necessarily propagate into the emulator’s predictions. Consequently, the model does not account for farm-level management heterogeneity such as varying tillage practices, irrigation scheduling, or farm size, which significantly influence real-world yields but were not present in the standardized training dataset. Additionally, Equation 1 treats CO_2 as an independent polynomial term without explicit interaction terms for temperature or rainfall. This implicitly assumes that the CO_2 fertilization effect remains constant regardless of climate stress, representing a simplified view of the complex biological dependencies between atmospheric carbon, heat, and moisture availability. We also excluded interactions between both climate variables, interactions which accumulate over time (such as drought or water-logging), and interaction between fertilizer and climate variables (or fertilizer and CO_2 fertilization).

Third, the data we used was created for a particular purpose, which was input into the IMPACT model. It failed to allow different levels of fertilizer at each location, forcing us to compute fertilizer impact from a recovered fixed effect. Finally, it remains unclear how well this emulator framework can integrate broader socio-economic or technological shifts, such as increased mechanization or the adoption of new crop varieties, which will continue to shape agricultural productivity alongside climatic drivers.

In summary, crop yield emulators are promising tools for climate impact research and agricultural policy planning. By accurately replicating complex model outputs, they support a shift toward faster, data-driven modeling approaches that can better inform responses to climate challenges. Ongoing improvements, including the integration of extreme events and enhanced soil and management data, will further enhance their utility for research, policy, and practice.

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Appendix A. DATA INFORMATION

Table A1. Modeling Information

Model	Institution	Modeler
DSSAT	IFPRI	Robertson R.D.

Appendix B. Fixed Effects Polynomial Regression Results

Table B1. Fixed-Effects Polynomial Regression Results for Sorghum Yields Using Entire Dataset: Climate Variables

Variable	Estimate	Std.error	T-statistic	Significance
Tmax1	0.14689	0.02445	6.007713	***
$Tmax1^2$	-0.01335	0.001465	-9.11229	***
$Tmax1^3$	0.000392	3.71E-05	10.5517	***
$Tmax1^4$	-3.79E-06	3.39E-07	-11.1965	***
Tmax2	-1.27813	0.08877	-14.3983	***
$Tmax2^2$	0.069921	0.004646	15.05097	***
$Tmax2^3$	-0.00161	0.000106	-15.2691	***
$Tmax2^4$	1.33E-05	8.85E-07	15.01767	***
Tmax3	0.145426	0.137295	1.059219	
$Tmax3^2$	0.001038	0.007013	0.148017	
$Tmax3^3$	-0.00016	0.000158	-1.02201	
$Tmax3^4$	2.18E-06	1.31E-06	1.65693	.
Tmax4	0.402659	0.09499	4.238983	***

$Tmax4^2$	-0.01052	0.005173	-2.03393	*
$Tmax4^3$	3.64E-05	0.000122	0.298554	
$Tmax4^4$	9.23E-07	1.06E-06	0.873476	
Rain1	0.000292	0.000154	1.899104	.
$Rain1^2$	1.35E-06	1.11E-06	1.214167	
$Rain1^3$	-6.46E-09	2.73E-09	-2.36629	*
$Rain1^4$	5.18E-12	1.98E-12	2.612836	**
Rain2	0.006474	0.000141	45.83045	***
$Rain2^2$	-2.42E-05	7.90E-07	-30.6469	***
$Rain2^3$	3.38E-08	1.62E-09	20.89074	***
$Rain2^4$	-1.54E-11	1.02E-12	-15.0901	***
Rain3	0.008812	0.000222	39.65624	***
$Rain3^2$	-2.99E-05	1.35E-06	-22.2083	***
$Rain3^3$	3.78E-08	2.84E-09	13.33926	***
$Rain3^4$	-1.55E-11	1.70E-12	-9.15721	***
Rain4	0.009088	0.000229	39.7114	***
$Rain4^2$	-3.38E-05	1.29E-06	-26.1727	***
$Rain4^3$	4.52E-08	2.66E-09	17.02269	***
$Rain4^4$	-1.92E-11	1.61E-12	-11.9403	***
CO_2	-0.00124	0.002552	-0.48457	
CO_2^2	3.52E-06	5.48E-06	0.641045	
CO_2^3	-2.79E-09	3.88E-09	-0.71752	
RMSE	0.22904			
Adj R^2	0.925998			
Within R^2	0.428835			
Obs.	399, 762			

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, · $p > 0.1$

Table B2. Regression Results for Sorghum Yields: Nitrogen and Soil Effects Using Extracted Fixed Effects

Variable	Estimate	Std.error	T-statistic	Significance
(Intercept)	6.802667	0.026269	258.962	***
N	0.009064	0.001363	6.650171	***
N^2	-6.73E-05	1.98E-05	-3.39059	***
N^3	2.62E-07	7.94E-08	3.30293	***
Clay	-0.40606	0.014202	-28.5926	***
Loam	-0.19295	0.012159	-15.8683	***
High Fertility	0.218034	0.010954	19.90383	***
Medium Fertility	0.194486	0.009624	20.20928	***

Deep	0.170818	0.010488	16.28741	***
Medium	0.175045	0.014547	12.03311	***
Adj. R^2	0.3036			

*** $p < 0.001$

Table B3. Fixed-Effects Polynomial Regression Results for Soybean Yields Using Entire Dataset: Climate Variables

Variable	Estimate	Std.error	t-statistic	Significance
Tmax1	-0.01327	0.025966	-0.51097	
$Tmax1^2$	-0.00011	0.001572	-0.06833	
$Tmax1^3$	-2.07E-05	4.09E-05	-0.50782	
$Tmax1^4$	5.96E-07	3.86E-07	1.543655	
Tmax2	-2.23602	0.10187	-21.9497	***
$Tmax2^2$	0.124379	0.005398	23.04256	***
$Tmax2^3$	-0.00294	0.000126	-23.3618	***
$Tmax2^4$	2.50E-05	1.09E-06	22.96758	***
Tmax3	1.369409	0.187802	7.291781	***
$Tmax3^2$	-0.04655	0.009961	-4.67302	***
$Tmax3^3$	0.000533	0.000232	2.296014	*
$Tmax3^4$	-3.91E-07	2.00E-06	-0.19552	
Tmax4	-0.29449	0.105246	-2.79811	**
$Tmax4^2$	0.020034	0.005829	3.436727	***
$Tmax4^3$	-0.00054	0.000141	-3.81716	***
$Tmax4^4$	4.90E-06	1.26E-06	3.880436	***
Rain1	0.003241	0.000126	25.72183	***
$Rain1^2$	-1.10E-05	8.07E-07	-13.6228	***
$Rain1^3$	1.50E-08	1.82E-09	8.2528	***
$Rain1^4$	-7.03E-12	1.21E-12	-5.8018	***
Rain2	0.008154	0.000143	56.83886	***
$Rain2^2$	-2.45E-05	7.14E-07	-34.2801	***
$Rain2^3$	2.79E-08	1.29E-09	21.6451	***
$Rain2^4$	-1.05E-11	7.03E-13	-14.899	***
Rain3	0.011913	0.000284	41.96094	***
$Rain3^2$	-3.64E-05	1.54E-06	-23.6409	***
$Rain3^3$	4.36E-08	3.02E-09	14.42195	***
$Rain3^4$	-1.72E-11	1.76E-12	-9.75709	***
Rain4	0.006967	0.000154	45.36854	***
$Rain4^2$	-2.14E-05	7.08E-07	-30.2387	***
$Rain4^3$	2.59E-08	1.28E-09	20.28135	***

$Rain4^4$	-1.03E-11	7.20E-13	-14.3391	***
CO_2	-0.0002	0.002593	-0.07886	
CO_2^2	5.19E-06	5.57E-06	0.931989	
CO_2^3	-5.21E-09	3.94E-09	-1.32309	
RMSE	0.236068			
Adj R^2	0.932628			
Within R^2	0.520934			
Obs.	431001			

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table B4. Fixed-Effects Polynomial Regression Results for Potato Yields Using Entire Dataset: Climate Variables

Variable	Estimate	Std.error	t-statistic	Significance
Tmax1	0.734269	0.099691	7.365426	***
$Tmax1^2$	-0.05368	0.007111	-7.54902	***
$Tmax1^3$	0.00175	0.000219	8.000638	***
$Tmax1^4$	-2.15E-05	2.44E-06	-8.78353	***
Tmax2	-0.37979	0.200498	-1.89425	.
$Tmax2^2$	0.024888	0.013327	1.867476	.
$Tmax2^3$	-0.00065	0.000385	-1.68572	.
$Tmax2^4$	5.27E-06	4.08E-06	1.292639	
Tmax3	1.116717	0.119917	9.312434	***
$Tmax3^2$	-0.05964	0.007298	-8.17207	***
$Tmax3^3$	0.001456	0.000193	7.558915	***
$Tmax3^4$	-1.40E-05	1.87E-06	-7.49121	***
Tmax4	-0.41481	0.031052	-13.3586	***
$Tmax4^2$	0.035685	0.002065	17.27686	***
$Tmax4^3$	-0.00112	5.75E-05	-19.4682	***
$Tmax4^4$	1.15E-05	5.71E-07	20.10199	***
Rain1	0.009599	0.000268	35.75757	***
$Rain1^2$	-5.11E-05	2.25E-06	-22.6851	***
$Rain1^3$	8.99E-08	6.12E-09	14.69841	***
$Rain1^4$	-4.88E-11	4.62E-12	-10.5653	***
Rain2	0.018283	0.000533	34.32075	***
$Rain2^2$	-8.29E-05	4.50E-06	-18.4385	***
$Rain2^3$	1.25E-07	1.18E-08	10.61175	***
$Rain2^4$	-5.94E-11	8.50E-12	-6.98597	***
Rain3	0.014156	0.000318	44.4604	***
$Rain3^2$	-7.33E-05	2.88E-06	-25.4467	***

$Rain3^3$	1.40E-07	8.85E-09	15.85631	***
$Rain3^4$	-8.74E-11	8.12E-12	-10.7603	***
Rain4	0.006185	0.000237	26.1116	***
$Rain4^2$	-2.98E-05	1.92E-06	-15.5017	***
$Rain4^3$	5.13E-08	5.23E-09	9.795826	***
$Rain4^4$	-2.87E-11	4.21E-12	-6.81991	***
CO_2	-0.01622	0.002669	-6.07734	***
CO_2^2	3.97E-05	5.73E-06	6.92144	***
CO_2^3	-2.99E-08	4.05E-09	-7.38096	***
RMSE	0.245225			
Adj R^2	0.952779			
Within R^2	0.537336			
Obs.	386,034			

*** $p < 0.001$, · $p > 0.1$

Table B5. Regression Results for Potato Yields: Nitrogen and Soil Effects Using Extracted Fixed Effects

Variable	Estimate	Std.error	t-statistic	Significance
(Intercept)	-2.01641	0.032505	-62.0342	***
N	0.024789	0.001085	22.84871	***
N^2	-0.00012	1.25E-05	-9.81622	***
N^3	2.05E-07	4.07E-08	5.027317	***
Clay	-0.28179	0.023364	-12.0605	***
Loam	-0.16162	0.019374	-8.34208	***
High Fertility	0.285628	0.016492	17.31915	***
Medium Fertility	0.122076	0.016381	7.452199	***
Deep	0.06178	0.015129	4.083434	***
Medium	0.094279	0.023048	4.090588	***
Adj. R^2	0.333			

*** $p < 0.001$

Table B6. Fixed-Effects Polynomial Regression Results for Groundnut Yields Using Entire Dataset: Climate Variables

Variable	Estimate	Std.error	t-statistic	Significance
Tmax1	0.121888	0.062144	1.96138	*
$Tmax1^2$	-0.01449	0.003287	-4.40682	***
$Tmax1^3$	0.000458	7.49E-05	6.12197	***
$Tmax1^4$	-4.60E-06	6.24E-07	-7.37004	***

Tmax2	-2.48868	0.126054	-19.7429	***
$Tmax2^2$	0.140252	0.006552	21.40612	***
$Tmax2^3$	-0.00337	0.000148	-22.7066	***
$Tmax2^4$	2.91E-05	1.24E-06	23.53402	***
Tmax3	0.019718	0.285713	0.069014	
$Tmax3^2$	0.002825	0.014327	0.197209	
$Tmax3^3$	-7.79E-05	0.000315	-0.24763	
$Tmax3^4$	1.91E-07	2.56E-06	0.074721	
Tmax4	0.278484	0.301655	0.923185	
$Tmax4^2$	0.001514	0.015323	0.098792	
$Tmax4^3$	-0.00032	0.000342	-0.94467	
$Tmax4^4$	4.24E-06	2.83E-06	1.497695	
Rain1	0.001137	8.84E-05	12.8672	***
$Rain1^2$	-2.43E-06	5.16E-07	-4.71282	***
$Rain1^3$	2.41E-09	1.05E-09	2.298832	*
$Rain1^4$	-1.00E-12	6.38E-13	-1.56843	
Rain2	0.008054	0.000128	62.75638	***
$Rain2^2$	-2.30E-05	6.37E-07	-36.0212	***
$Rain2^3$	2.56E-08	1.17E-09	21.92237	***
$Rain2^4$	-9.58E-12	6.61E-13	-14.5055	***
Rain3	0.013527	0.000379	35.73225	***
$Rain3^2$	-4.04E-05	1.99E-06	-20.3059	***
$Rain3^3$	4.73E-08	3.82E-09	12.37603	***
$Rain3^4$	-1.85E-11	2.24E-12	-8.26811	***
Rain4	0.006451	0.000151	42.63287	***
$Rain4^2$	-2.09E-05	6.61E-07	-31.6057	***
$Rain4^3$	2.54E-08	1.16E-09	21.92893	***
$Rain4^4$	-1.01E-11	6.64E-13	-15.2491	***
CO_2	-0.00605	0.002484	-2.4337	*
CO_2^2	1.68E-05	5.32E-06	3.15316	**
CO_2^3	-1.29E-08	3.75E-09	-3.42943	***
RMSE	0.183629			
Adj R^2	0.95019			
Within R^2	0.720191			
Obs.	322465			

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$

Table B7. Fixed-Effects Polynomial Regression Results for Maize Yields Using Entire Dataset: Climate Variables

Variable	Estimate	Std.error	t-statistic	Significance
Tmax1	0.535782	0.030236	17.72027	***
$Tmax1^2$	-0.03984	0.001836	-21.6925	***
$Tmax1^3$	0.001192	4.81E-05	24.79493	***
$Tmax1^4$	-1.24E-05	4.58E-07	-27.0317	***
Tmax2	-1.74854	0.093961	-18.6093	***
$Tmax2^2$	0.094683	0.005128	18.46274	***
$Tmax2^3$	-0.00213	0.000123	-17.307	***
$Tmax2^4$	1.65E-05	1.09E-06	15.13099	***
Tmax3	1.1601	0.134003	8.657258	***
$Tmax3^2$	-0.05302	0.007283	-7.27987	***
$Tmax3^3$	0.001068	0.000176	6.084619	***
$Tmax3^4$	-8.35E-06	1.57E-06	-5.30331	***
Tmax4	0.237297	0.086874	2.731512	**
$Tmax4^2$	0.004192	0.004724	0.887251	
$Tmax4^3$	-0.0004	0.000112	-3.53733	***
$Tmax4^4$	5.00E-06	9.88E-07	5.063141	***
Rain1	0.015099	0.000271	55.80646	***
$Rain1^2$	-7.40E-05	2.27E-06	-32.5673	***
$Rain1^3$	1.46E-07	6.67E-09	21.85363	***
$Rain1^4$	-9.45E-11	5.92E-12	-15.9678	***
Rain2	0.00887	0.00017	52.04989	***
$Rain2^2$	-3.00E-05	9.04E-07	-33.1682	***
$Rain2^3$	3.87E-08	1.77E-09	21.83479	***
$Rain2^4$	-1.64E-11	1.11E-12	-14.7733	***
Rain3	0.009379	0.000285	32.91344	***
$Rain3^2$	-3.22E-05	1.48E-06	-21.709	***
$Rain3^3$	4.24E-08	2.87E-09	14.79612	***
$Rain3^4$	-1.83E-11	1.70E-12	-10.7156	***
Rain4	0.003475	0.000183	18.99721	***
$Rain4^2$	-1.41E-05	7.69E-07	-18.3549	***
$Rain4^3$	2.00E-08	1.26E-09	15.90919	***
$Rain4^4$	-9.05E-12	6.67E-13	-13.567	***
CO_2	-0.02529	0.002806	-9.0136	***
CO_2^2	5.49E-05	6.03E-06	9.099919	***
CO_2^3	-3.89E-08	4.27E-09	-9.10969	***
RMSE	0.284047			
Adj R^2	0.89784			
Within R^2	0.591793			

Obs.	576624			

*** $p < 0.001$, ** $p < 0.01$

Table B8. Regression Results for Maize Yields: Nitrogen and Soil Effects Using Extracted Fixed Effects

Variable	Estimate	Std.error	T-statistic	Significance
(Intercept)	4.634647	0.016294	284.4312	***
N	0.010009	0.000531	18.84145	***
N^2	-4.47E-05	5.56E-06	-8.04252	***
N^3	7.42E-08	1.60E-08	4.647294	***
Clay	-0.71754	0.012202	-58.8073	***
Loam	-0.37972	0.010719	-35.4236	***
High Fertility	0.259825	0.009284	27.98561	***
Medium Fertility	0.127754	0.008674	14.72758	***
Deep	0.182142	0.009132	19.94581	***
Medium	0.180998	0.012848	14.0879	***
Adj. R^2	0.378			

*** $p < 0.001$

Table B9. Fixed-Effects Polynomial Regression Results for Indica Rice Yields Using Entire Dataset: Climate Variables

Variable	Estimate	Std.error	t-statistic	Significance
Tmax1	-0.15908	0.04821	-3.29967	***
$Tmax1^2$	0.010213	0.002978	3.429081	***
$Tmax1^3$	-0.00028	7.58E-05	-3.64863	***
$Tmax1^4$	2.79E-06	6.87E-07	4.059639	***
Tmax2	-0.70522	0.224146	-3.14626	**
$Tmax2^2$	0.046297	0.012068	3.836422	***
$Tmax2^3$	-0.00122	0.000279	-4.38286	***
$Tmax2^4$	1.10E-05	2.36E-06	4.661247	***
Tmax3	-0.72428	0.206478	-3.5078	***
$Tmax3^2$	0.036611	0.011203	3.267886	**
$Tmax3^3$	-0.00085	0.000264	-3.22672	**
$Tmax3^4$	7.43E-06	2.30E-06	3.237625	**
Tmax4	-0.02376	0.163016	-0.14574	
$Tmax4^2$	0.004339	0.009674	0.448486	
$Tmax4^3$	-0.00018	0.000244	-0.75148	
$Tmax4^4$	2.22E-06	2.22E-06	0.997277	
Tmax5	-0.05479	0.062787	-0.87263	

$Tmax5^2$	0.002865	0.003785	0.756897	
$Tmax5^3$	-5.52E-06	9.81E-05	-0.0563	
$Tmax5^4$	-6.73E-07	9.23E-07	-0.7288	
Rain1	0.018119	0.000368	49.28999	***
$Rain1^2$	-7.23E-05	2.73E-06	-26.4825	***
$Rain1^3$	1.08E-07	6.82E-09	15.84239	***
$Rain1^4$	-5.21E-11	5.02E-12	-10.38	***
Rain2	0.016942	0.000323	52.3822	***
$Rain2^2$	-5.23E-05	1.75E-06	-29.9899	***
$Rain2^3$	6.28E-08	3.36E-09	18.67236	***
$Rain2^4$	-2.47E-11	1.97E-12	-12.5667	***
Rain3	0.003262	0.000268	12.17505	***
$Rain3^2$	-1.11E-05	1.01E-06	-10.9664	***
$Rain3^3$	1.44E-08	1.50E-09	9.595767	***
$Rain3^4$	-5.95E-12	7.34E-13	-8.10476	***
Rain4	0.000395	0.000218	1.81223	.
$Rain4^2$	-1.22E-06	8.00E-07	-1.52944	
$Rain4^3$	1.25E-09	1.14E-09	1.097046	
$Rain4^4$	-3.82E-13	5.21E-13	-0.73411	
Rain5	0.002063	0.000164	12.60313	***
$Rain5^2$	-6.87E-06	6.57E-07	-10.4598	***
$Rain5^3$	8.82E-09	1.05E-09	8.432504	***
$Rain5^4$	-3.93E-12	5.44E-13	-7.21753	***
CO_2	-0.03218	0.003789	-8.49395	***
CO_2^2	6.98E-05	8.14E-06	8.578851	***
CO_2^3	-4.86E-08	5.76E-09	-8.43478	***
RMSE	0.268199			
Adj R2	0.906239			
Within R^2	0.70782			
Obs.	290225			

*** $p < 0.001$, ** $p < 0.01$, · $p > 0.1$

Table B10. Regression Results for Indica Rice Yields: Nitrogen and Soil Effects Using Extracted Fixed Effects

Variable	Estimate	Std.error	T-statistic	Significance
(Intercept)	18.20137	0.022881	795.4931	***
N	0.028007	0.000875	32.00246	***
N^2	-0.00027	1.03E-05	-26.1748	***
N^3	8.82E-07	3.40E-08	25.96258	***

Clay	-0.60862	0.019119	-31.8329	***
Loam	-0.19448	0.016737	-11.6198	***
High Fertility	0.31143	0.015442	20.16775	***
Medium Fertility	0.116644	0.01407	8.290263	***
Deep	0.072515	0.012666	5.725403	***
Medium	0.104565	0.01907	5.483166	***
Adj. R^2	0.3921			

*** $p < 0.001$

Table B11. Fixed-Effects Polynomial Regression Results for Japonica Rice Yields Using Entire Dataset: Climate Variables

Variable	Estimate	Std.error	t-statistic	Significance
Tmax1	0.338461	0.034271	9.876068	***
Tmax1^2	-0.01324	0.002132	-6.21025	***
Tmax1^3	0.000125	5.65E-05	2.205192	*
Tmax1^4	4.28E-07	5.41E-07	0.792495	
Tmax2	-0.57625	0.087635	-6.57555	***
Tmax2^2	0.029862	0.005154	5.794346	***
Tmax2^3	-0.00073	0.000133	-5.53177	***
Tmax2^4	7.10E-06	1.26E-06	5.645595	***
Tmax3	1.166624	0.122067	9.557233	***
Tmax3^2	-0.06083	0.007068	-8.60556	***
Tmax3^3	0.001356	0.000178	7.610232	***
Tmax3^4	-1.12E-05	1.65E-06	-6.76721	***
Tmax4	-0.38061	0.075267	-5.05685	***
Tmax4^2	0.029647	0.004343	6.825909	***
Tmax4^3	-0.00084	0.000107	-7.79752	***
Tmax4^4	7.94E-06	9.62E-07	8.249336	***
Rain1	0.012011	0.000328	36.58431	***
Rain1^2	-4.46E-05	2.09E-06	-21.308	***
Rain1^3	6.54E-08	4.84E-09	13.51409	***
Rain1^4	-3.13E-11	3.42E-12	-9.16022	***
Rain2	0.004175	0.000245	17.03231	***
Rain2^2	-1.61E-05	1.25E-06	-12.9224	***
Rain2^3	2.26E-08	2.40E-09	9.414706	***
Rain2^4	-1.00E-11	1.44E-12	-6.96909	***
Rain3	0.002949	0.000287	10.26785	***
Rain3^2	-1.11E-05	1.34E-06	-8.29409	***
Rain3^3	1.55E-08	2.48E-09	6.237962	***

$Rain3^4$	-6.97E-12	1.49E-12	-4.67303	***
Rain4	-0.00076	0.000171	-4.44897	***
$Rain4^2$	2.01E-06	6.35E-07	3.168824	**
$Rain4^3$	-2.22E-09	9.36E-10	-2.37426	*
$Rain4^4$	8.60E-13	4.44E-13	1.938177	.
CO_2	0.003916	0.003614	1.083703	
CO_2^2	-3.70E-06	7.76E-06	-0.47697	
CO_2^3	4.12E-10	5.49E-09	0.075108	
RMSE	0.212905			
Adj R^2	0.932572			
Within R^2	0.445528			
Obs.	203317			

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, · $p > 0.1$

Table B12. Regression Results for Japonica Rice Yields: Nitrogen and Soil Effects Using Extracted Fixed Effects

Variable	Estimate	Std.error	T-statistic	Significance
(Intercept)	-1.63166	0.020819	-78.3756	***
N	0.018226	0.000796	22.89281	***
N^2	-0.00016	9.32E-06	-17.2527	***
N^3	4.91E-07	3.09E-08	15.92122	***
Clay	-0.45793	0.017509	-26.1547	***
Loam	-0.10906	0.015224	-7.16372	***
High Fertility	0.233746	0.014015	16.67809	***
Medium Fertility	0.051263	0.012794	4.006781	***
Deep	-0.06525	0.011406	-5.72052	***
Medium	-0.00368	0.017381	-0.21195	
Adj. R^2	0.2717			

*** $p < 0.001$

Table B13. Fixed-Effects Polynomial Regression Results for Spring wheat Yields Using Entire Dataset: Climate Variables

Variable	Estimate	Std.error	T-statistic	Significance
Tmax1	0.446427	0.056938	7.840595	***
$Tmax1^2$	-0.02466	0.003386	-7.28235	***
$Tmax1^3$	0.000542	8.65E-05	6.267774	***
$Tmax1^4$	-4.38E-06	8.03E-07	-5.45647	***
Tmax2	0.246511	0.025059	9.837331	***

$Tmax2^2$	-0.01771	0.001794	-9.8763	***
$Tmax2^3$	0.000535	5.31E-05	10.07786	***
$Tmax2^4$	-5.65E-06	5.54E-07	-10.1921	***
Tmax3	0.206666	0.013523	15.28248	***
$Tmax3^2$	-0.01751	0.001174	-14.9149	***
$Tmax3^3$	0.000569	4.03E-05	14.1262	***
$Tmax3^4$	-6.44E-06	4.76E-07	-13.5412	***
Tmax4	0.129697	0.012757	10.16683	***
$Tmax4^2$	-0.01033	0.00117	-8.83193	***
$Tmax4^3$	0.000349	4.17E-05	8.367166	***
$Tmax4^4$	-4.29E-06	5.08E-07	-8.43457	***
Tmax5	-0.02366	0.010983	-2.15416	*
$Tmax5^2$	0.001173	0.000913	1.28446	
$Tmax5^3$	-7.52E-05	3.03E-05	-2.48493	*
$Tmax5^4$	1.24E-06	3.45E-07	3.589353	***
Rain1	0.008425	0.000247	34.04154	***
$Rain1^2$	-4.95E-05	2.08E-06	-23.7735	***
$Rain1^3$	1.04E-07	6.63E-09	15.72801	***
$Rain1^4$	-7.20E-11	6.71E-12	-10.7328	***
Rain2	0.007527	0.000233	32.30429	***
$Rain2^2$	-5.95E-05	3.31E-06	-17.9617	***
$Rain2^3$	1.85E-07	1.62E-08	11.42646	***
$Rain2^4$	-1.88E-10	2.36E-11	-7.9637	***
Rain3	0.006484	0.000236	27.4906	***
$Rain3^2$	-5.34E-05	2.92E-06	-18.3161	***
$Rain3^3$	1.62E-07	1.42E-08	11.46532	***
$Rain3^4$	-1.66E-10	2.17E-11	-7.67051	***
Rain4	0.007075	0.000245	28.90531	***
$Rain4^2$	-6.55E-05	3.13E-06	-20.8949	***
$Rain4^3$	2.33E-07	1.51E-08	15.44858	***
$Rain4^4$	-2.71E-10	2.32E-11	-11.6902	***
Rain5	0.01235	0.000348	35.50492	***
$Rain5^2$	-0.00012	5.31E-06	-22.5537	***
$Rain5^3$	4.68E-07	3.23E-08	14.47579	***
$Rain5^4$	-6.24E-10	6.38E-11	-9.7749	***
CO_2	-0.04094	0.002767	-14.7958	***
CO_2^2	9.20E-05	5.94E-06	15.49696	***
CO_2^3	-6.72E-08	4.20E-09	-16.0024	***
RMSE	0.206432			

Adj R^2	0.966406			
Within R^2	0.277801			
Obs.	299697			

*** $p < 0.001$, * $p < 0.05$

Table B14. Regression Results for Spring wheat Yields: Nitrogen and Soil Effects Using Extracted Fixed Effects

Variable	Estimate	Std.error	T-statistic	Significance
(Intercept)	7.048534	0.038683	182.2123	***
N	-0.00143	0.001826	-0.78222	
N^2	0.000168	2.74E-05	6.125599	***
N^3	-8.15E-07	1.15E-07	-7.10486	***
Clay	-0.51674	0.022469	-22.9977	***
Loam	-0.28695	0.019088	-15.0335	***
High Fertility	0.834889	0.015724	53.09711	***
Medium Fertility	0.511344	0.01411	36.23894	***
Deep	0.399413	0.014807	26.97409	***
Medium	0.286734	0.021455	13.36456	***
Adj. R^2	0.3579			

*** $p < 0.001$

Table B15. Fixed-Effects Polynomial Regression Results for Winter wheat Yields Using Entire Dataset: Climate Variables

Variable	Estimate	Std.error	t-statistic	Significance
Tmax1	0.137678	0.025572	5.383945	***
$Tmax1^2$	-0.00439	0.001727	-2.54344	*
$Tmax1^3$	-3.16E-05	5.12E-05	-0.6171	
$Tmax1^4$	1.49E-06	5.59E-07	2.657577	**
Tmax2	0.072436	0.037736	1.91955	.
$Tmax2^2$	-0.01286	0.002627	-4.89623	***
$Tmax2^3$	0.000497	7.96E-05	6.241478	***
$Tmax2^4$	-6.13E-06	8.83E-07	-6.94091	***
Tmax3	0.284823	0.027567	10.33205	***
$Tmax3^2$	-0.02626	0.00197	-13.3279	***
$Tmax3^3$	0.000854	5.87E-05	14.55931	***
$Tmax3^4$	-9.34E-06	6.23E-07	-14.9797	***
Tmax4	-0.15561	0.011813	-13.1729	***
$Tmax4^2$	0.016956	0.001021	16.61465	***
$Tmax4^3$	-0.00059	3.40E-05	-17.3333	***

$Tmax4^4$	6.47E-06	3.85E-07	16.81947	***
Tmax5	0.061454	0.007199	8.536131	***
$Tmax5^2$	-0.00345	0.000637	-5.41354	***
$Tmax5^3$	9.75E-05	2.19E-05	4.456141	***
$Tmax5^4$	-9.41E-07	2.53E-07	-3.71773	***
Tmax6	0.094469	0.007377	12.80498	***
$Tmax6^2$	-0.007	0.000627	-11.166	***
$Tmax6^3$	0.000196	2.04E-05	9.596241	***
$Tmax6^4$	-1.94E-06	2.24E-07	-8.65171	***
Tmax7	0.131334	0.014743	8.907997	***
$Tmax7^2$	-0.00709	0.001011	-7.01121	***
$Tmax7^3$	0.000168	2.87E-05	5.863642	***
$Tmax7^4$	-1.40E-06	2.84E-07	-4.92706	***
Tmax8	-0.07916	0.006595	-12.0033	***
$Tmax8^2$	0.004743	0.000607	7.810346	***
$Tmax8^3$	-6.94E-05	2.10E-05	-3.29554	***
$Tmax8^4$	-3.65E-08	2.40E-07	-0.15212	
Tmax9	0.016591	0.004351	3.812926	***
$Tmax9^2$	-0.00464	0.000476	-9.75173	***
$Tmax9^3$	0.000181	1.79E-05	10.1429	***
$Tmax9^4$	-2.03E-06	2.15E-07	-9.41946	***
Rain1	0.014788	0.000342	43.26677	***
$Rain1^2$	-6.86E-05	2.82E-06	-24.3675	***
$Rain1^3$	1.05E-07	7.05E-09	14.88952	***
$Rain1^4$	-4.83E-11	4.72E-12	-10.2288	***
Rain2	0.012095	0.000305	39.60812	***
$Rain2^2$	-6.00E-05	2.56E-06	-23.4106	***
$Rain2^3$	1.08E-07	6.76E-09	16.04541	***
$Rain2^4$	-6.17E-11	5.23E-12	-11.794	***
Rain3	0.000156	0.000192	0.809664	
$Rain3^2$	-1.49E-06	1.57E-06	-0.94781	
$Rain3^3$	1.69E-09	4.44E-09	0.379842	
$Rain3^4$	7.18E-13	3.97E-12	0.180853	
Rain4	-0.004	0.000204	-19.6123	***
$Rain4^2$	2.50E-05	1.60E-06	15.68923	***
$Rain4^3$	-5.28E-08	4.26E-09	-12.3894	***
$Rain4^4$	3.39E-11	3.22E-12	10.53283	***
Rain5	-0.00188	0.000229	-8.17944	***
$Rain5^2$	8.73E-06	2.15E-06	4.057922	***

$Rain5^3$	-1.63E-08	6.82E-09	-2.3863	*
$Rain5^4$	1.29E-11	6.03E-12	2.148811	*
Rain6	-0.00248	0.000211	-11.7678	***
$Rain6^2$	1.58E-05	2.01E-06	7.877361	***
$Rain6^3$	-3.81E-08	6.56E-09	-5.8056	***
$Rain6^4$	2.73E-11	6.40E-12	4.267401	***
Rain7	-0.00203	0.000137	-14.801	***
$Rain7^2$	1.03E-05	7.75E-07	13.24033	***
$Rain7^3$	-1.44E-08	1.46E-09	-9.87958	***
$Rain7^4$	6.04E-12	7.87E-13	7.679041	***
Rain8	-0.00048	0.00013	-3.70395	***
$Rain8^2$	3.06E-06	6.34E-07	4.828753	***
$Rain8^3$	-5.07E-09	1.11E-09	-4.54874	***
$Rain8^4$	2.49E-12	6.01E-13	4.137872	***
Rain9	0.001262	0.000123	10.2469	***
$Rain9^2$	-3.53E-06	5.64E-07	-6.25858	***
$Rain9^3$	4.11E-09	9.32E-10	4.408331	***
$Rain9^4$	-1.64E-12	4.76E-13	-3.43558	***
CO_2	0.018373	0.003029	6.06482	***
${CO_2}^2$	-3.45E-05	6.51E-06	-5.29799	***
${CO_2}^3$	2.19E-08	4.61E-09	4.74768	***
RMSE	0.240602			
Adj R^2	0.937431			
Within R^2	0.640674			
Obs.	358585			

*** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$, · $p > 0.1$

Table B16. Regression Results for Winter wheat Yields: Nitrogen and Soil Effects Using Extracted Fixed Effects

Variable	Estimate	Std.error	t-statistic	Significance
(Intercept)	0.154989	0.026416	5.86722	***
N	0.032786	0.001246	26.3147	***
N^2	-0.00034	1.82E-05	-18.7475	***
N^3	1.19E-06	7.61E-08	15.67212	***
Clay	-0.43298	0.015138	-28.6031	***
Loam	-0.29006	0.012452	-23.2947	***
High Fertility	0.659881	0.010409	63.39534	***
Medium Fertility	0.471506	0.01011	46.63677	***
Deep	0.269175	0.010162	26.48923	***

Medium	0.146618	0.014568	10.06434	***
Adj. R^2	0.4009			

*** $p < 0.001$