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Earth's Future

RESEARCH ARTICLE

10.1029/2022EF003190

Key Points:

- Under future climate scenario Representative Concentration Pathway 4.5, average global yields of maize, rice, wheat, and soybean are projected to decrease by 6%–21%
- Implementing adaptive management practices could reduce this loss by 1–13 percentage points relative to maintaining the same practices
- Some areas of the world, such as northern high latitudes, may see future yield increases if adaptation practices are applied

Supporting Information:

Supporting Information may be found in the online version of this article.

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Adaptation Strategies Strongly Reduce the Future Impacts of Climate Change on Simulated Crop Yields

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Abstract Simulations of crop yield due to climate change vary widely between models, locations, species, management strategies, and Representative Concentration Pathways (RCPs). To understand how climate and adaptation affects yield change, we developed a meta-model based on 8703 site-level process-model simulations of yield with different future adaptation strategies and climate scenarios for maize, rice, wheat and soybean. We tested 10 statistical models, including some machine learning models, to predict the percentage change in projected future yield relative to the baseline period (2000–2010) as a function of explanatory variables related to adaptation strategy and climate change. We used the best model to produce global maps of yield change for the RCP4.5 scenario and identify the most influential variables affecting yield change using Shapley additive explanations. For most locations, adaptation was the most influential factor determining the projected yield change for maize, rice and wheat. Without adaptation under RCP4.5, all crops are expected to experience average global yield losses of 6%–21%. Adaptation alleviates this average projected loss by 1–13 percentage points. Maize was most responsive to adaptive practices with a projected mean yield loss of –21% [range across locations: –63%, +3.7%] without adaptation and –7.5% [range: –46%, +13%] with adaptation. For maize and rice, irrigation method and cultivar choice were the adaptation types predicted to most prevent large yield losses, respectively. When adaptation practices are applied, some areas are predicted to experience yield gains, especially at northern high latitudes. These results reveal the critical importance of implementing adequate adaptation strategies to mitigate the impact of climate change on crop yields.

Plain Language Summary Computer simulations are commonly used to predict how crop yield may change under future climate conditions and land management practices. For four major crops (maize, rice, wheat and soybean), we tested different statistical methods to synthesize thousands of computer simulations of crop yield change under future climate into one meta-model which can be used to predict crop yield at any location where that crop is grown. We then predicted the change in crop yield under a likely future climate scenario (Representative Concentration Pathway 4.5) and identified which variables most explained the crop yield change. Considering both adaptive management status (whether or not adaptation practices were applied) and climate factors (average temperature, change in temperature, average precipitation, change in precipitation, CO₂ concentration), we found that adaptation status was the most influential factor determining the predicted yield change for most crops. Managing cropland adaptively in the future can reduce predicted yield losses by 1–13 percentage points relative to maintaining the same management practices. We discuss which types of management practices may be the most useful for different crops, as well as which areas of the world are expected to gain or lose crop yield in the future.

1. Introduction

Food security faces increasing threats from anthropogenic climate change (Wheeler & von Braun, 2013), with current assessment methods predicting between 8 and 80 million additional people at risk of hunger by 2050 (Mbow et al., 2019). While there is general consensus that climate change will undermine food security by causing production losses (Tomoko Hasegawa et al., 2021; Zhu et al., 2021), there is little consensus on the magnitude and even direction of yield response to different climate change factors, as well as the extent to which yield losses can be mitigated by adaptive management. Model projections of yield changes also vary widely from study to study and from region to region, and there is therefore an urgent need to provide reliable large-scale but regionally

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specific estimates inferred from multiple sources of information. This kind of information can help inform stakeholders of expected impact to crops and potential adaptation strategies at local and regional scales.

Typically, future yields are projected using either statistical or process-based models that relate the climate, environment and management practices to plant production and subsequent yield. Projected yields show large variation not only between sites and climate change scenarios but also between crop yield models (Makowski et al., 2015). In order to understand the variation in yield predictions due to model structure, the Agricultural Model Intercomparison and Improvement Project (AgMIP) was founded in 2010 to run and compare process-based agricultural models using standardized inputs (Rosenzweig et al., 2013). AgMIP makes yield predictions using process-based models, but statistical models are also commonly used to predict future agricultural yield (Lobell & Asseng, 2017; Zhao et al., 2017).

Studies assessing the effect of climate change on crop yields typically focus on warming temperatures and precipitation changes. Warming temperatures are expected to decrease global yields of the major staple crops maize, rice, wheat, and soybean by 3%–7% per °C warming on average depending on the crop (Zhao et al., 2017), with broad agreement across field experiments, statistical models, and grid- and point-based process models. While yield losses are typically <10% when averaged at large scales, losses and gains can be much larger at specific sites or grid-points. For example, AgMIP models predict between –60% and +60% local change in plant production by the end of the century for maize, rice, wheat, and soybean (Rosenzweig et al., 2014). More recent work still finds large variations in modeled crop yield sensitivity to climate and other environmental factors (Franke et al., 2020).

Two recent modeling studies identified an important role of water stress on historical and projected yields, finding that water limitation accounts for a greater proportion of yield loss in historical and in near-future periods, with warming becoming relatively more important only at the end-of-century period (Ortiz-Bobea et al., 2019; Zhu et al., 2021). The importance of other environmental effects is not as well understood, such as the effect of CO₂ fertilization on yield, which has been demonstrated to increase yields in ideal conditions, but has mixed effects depending on sites and crop types (Makowski et al., 2020; McGrath & Lobell, 2013; Wilcox & Makowski, 2014). Similarly, many studies find varying effects of different adaptive management strategies, such as using specialized cultivars or irrigation techniques (Parent et al., 2018). These techniques are meant to mitigate yield losses due to climate change by adjusting plant phenology, increasing plant hardiness to extreme temperature or providing deficient water and/or nutrients. In general, adaptive management results in higher yield relative to no adaptive management, although not always (Challinor et al., 2014; Makowski et al., 2020; Wilcox & Makowski, 2014). These previous studies have examined the effects of adaptive management, but have not extrapolated management effects on yield to regional and global scales.

The variability of yield response predictions to climate change published in the scientific literature is very high, and it is therefore necessary to better understand the conditions leading to positive or negative impacts of climate change on the yields of major crops. In this study, we use information from multiple simulations in different locations in order to build global meta-models and use them to map the effect of climate change on crop yields at the global scale, the key novelty being to account for or ignore adaptation of management practices. Meta-models are useful to synthesize large sets of model simulations because the central tendency of crop model ensembles is often more accurate than most individual ensemble members (Bassu et al., 2014) and because they can be used to extrapolate yield values for climate conditions and sites for which no simulation was done with the original crop models (Makowski et al., 2015). Here, we fit different types of meta-models to the largest existing data set of site-level crop model yield projections to answer to following research questions: (a) What distributions of yield losses and gains can be expected on a global scale based on all the available agricultural model simulations? (b) What are the most important factors explaining variability in yield change projections? (c) To what extent are adaptation strategies able to mitigate yield losses? We focus on the staple crops maize, rice, wheat, and soybean, from which humans furnish two-thirds of their calories (Zhao et al., 2017). Our analysis is conducted for the climate change scenario Representative Concentration Pathway 4.5 (RCP 4.5) that projects a warming level between 2.1° and 3.5°C by the end of the century and that is most in line with our current trajectory given stated policies and announced pledges (Arias et al., 2021; IEA, 2021).

2. Methods

2.1. Data Set

A recent literature review gathered 8703 process model simulations of crop yields from 202 studies in 91 countries under 21st century emissions scenarios with a variety of warming levels (Hasegawa et al., 2022). These

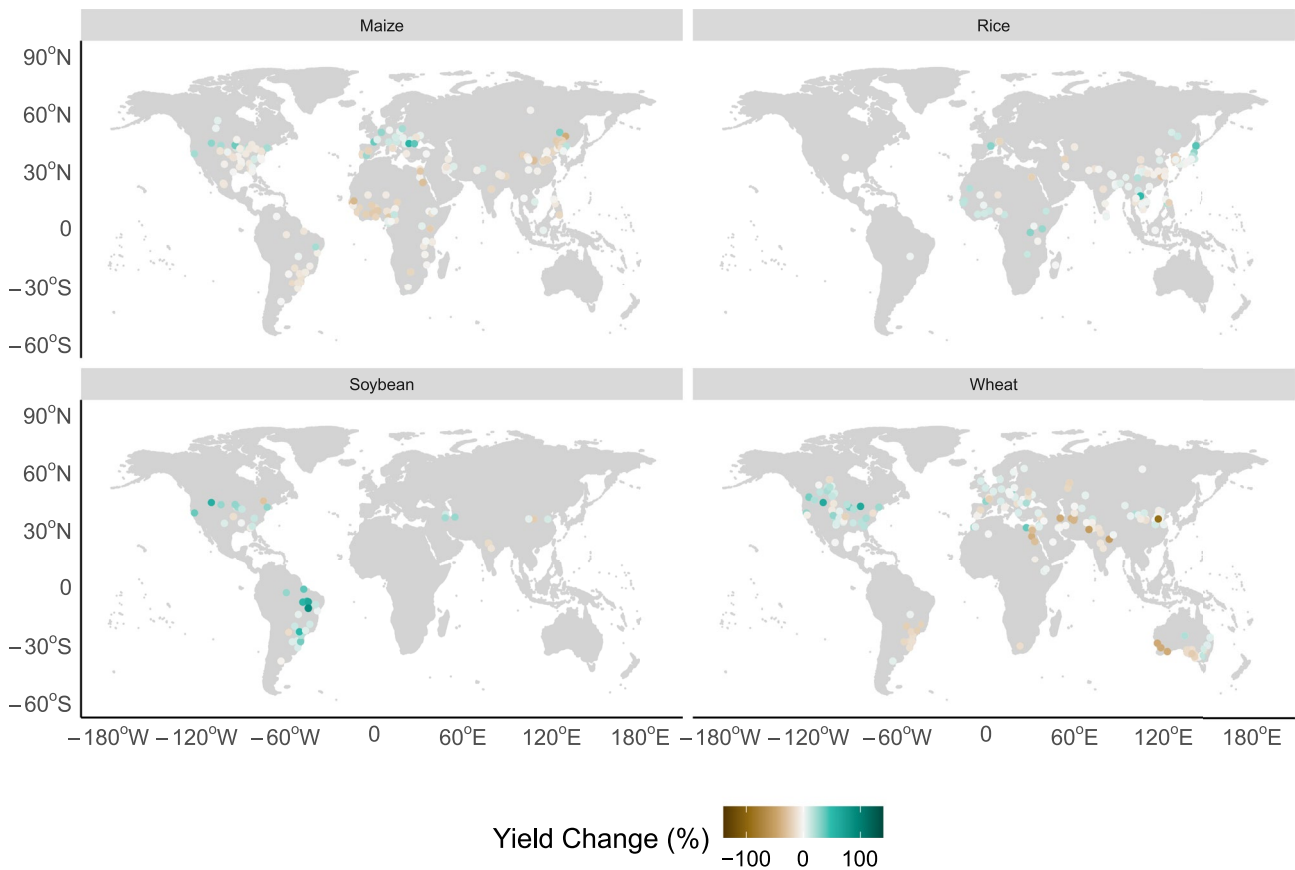


Figure 1. Maps showing locations where future yield was projected for maize, rice, soybean, and wheat. The color of the symbol indicates whether the selected meta-models projected a decrease (brown) or an increase in yield (turquoise) relative to the baseline period under RCP 4.5 in 2060 (yield changes expressed in % change relative to the baseline).

simulations recorded changes in projected yield with temperature in °C, change in temperature from a reference point (i.e., the midpoint [2005] of the current baseline period [2001–2010]) in °C, change in precipitation from the baseline period, average annual precipitation in millimeters (mm), CO₂ concentration in parts per million (ppm), geographical location (Latitude, Longitude), simulation year (both historical and future), and adaptation status. Four crops were represented: maize, rice, wheat, and soybean. The yield is expressed in relative terms, using the grain mass per unit land area for a given projection relative to the baseline period yield to calculate the percentage change in yield from the baseline period.

Adaptation status refers to whether or not any adaptation to land management was simulated. Adaptation includes any simulated change in the timing or amount of fertilizer application; any change in the timing or amount of irrigation determined using indicators of crop growth, climate and soil moisture; the use of nonconventional (e.g., heat-adapted) cultivars; any shift in planting time; soil organic matter management (i.e., compost application or crop residue retention); reduced or no tillage; and other practices (e.g., switching crops, crop rotation, geographic shift, and crop diversification such as agroforestry). Additional details about this data set and access to the data set itself can be found in Hasegawa et al. (2022).

After removing rows with missing values in climate and management predictors, there was a total of 8,501 predictions of yield change for the four crops combined from 370 unique locations, with over 1,000 predictions for each crop except for soybean (Table S1 in Supporting Information S1). For all crops other than soybean, simulations were available on most of the continents: North America, South America, Europe, Africa, and Asia (Figure 1). Simulated yield changes ranged from −100% to +136%, with a mean yield change ranging from −3% for Rice to −16% for Soybean (Figure S1 in Supporting Information S1).

Table 1
Characteristics of the 10 Statistical and Machine Learning Models Used to Predict the Yield Change of Maize, Rice, Wheat, and Soybean

| Model no. | Model type | Predictors | Random effect |
|-----------|------------|---|--------------------------------|
| 1 | RF | Latitude + Longitude | – |
| 2 | GB | Latitude + Longitude | – |
| 3 | RF | $T_{avg} + P_{avg} + \Delta T + \Delta P + CO_2 + \text{Adaptation}$ | – |
| 4 | GB | $T_{avg} + P_{avg} + \Delta T + \Delta P + CO_2 + \text{Adaptation}$ | – |
| 5 | RF | Latitude + Longitude + $T_{avg} + P_{avg} + \Delta T + \Delta P + CO_2 + \text{Adaptation}$ | – |
| 6 | GB | Latitude + Longitude + $T_{avg} + P_{avg} + \Delta T + \Delta P + CO_2 + \text{Adaptation}$ | – |
| 7 | LM | $T_{avg} + P_{avg} + \Delta T + \Delta P + CO_2 + \text{Adaptation}$ | (1 Study reference) |
| 8 | LM | $T_{avg} \times P_{avg} \times \Delta T \times \Delta P \times CO_2 \times \text{Adaptation}$ | (1 Study reference) |
| 9 | LM | 1 | Matern(1 Longitude + Latitude) |
| 10 | LM | $T_{avg} + P_{avg} + \Delta T + \Delta P + CO_2 + \text{Adaptation}$ | Matern(1 Longitude + Latitude) |

Note. RF = random forest; GB = gradient-boosting; LM = linear mixed model. See Section 2.2.1 for definitions of environment variables. (1|Study reference) means that a random effect was included to describe the between-study variability. Matern(1|Longitude + Latitude) means random effects (with Matern covariance function) were included to describe the residual spatial variability.

2.2. Statistical and Machine Learning Meta-Models

2.2.1. Types of Models

We tested multiple types of statistical and machine learning models to find the best model relating the management and climate variables to the predicted yield change. We tested three categories of models: Random Forest (RF), gradient-boosting (GB) models, and linear mixed (LM) models, with and without spatial correlation (Table 1). The first two categories are nonparametric and do not assume linearity, while the third category is more parsimonious and assumes a linear relationship between inputs and outputs. We compared RF and GB models using only spatial location data as predictors (Model 1, 2), using only climate and management variables as predictors (Model 3, 4), and including climate, management, and spatial location as predictors (Model 5, 6; Table 1). Climate and management variables included were the average local area-weighted temperature in degrees Celsius (T_{avg}) measured around the year 2000, the average local area-weighted annual precipitation in mm (P_{avg}) measured around the year 2000, projected global change in temperature from the current baseline period (2000–2010) to the future mid-point year (ΔT), projected annual site-level change in precipitation (ΔP) from the baseline period, the mean CO_2 concentration used for the simulation in parts per million (CO_2), and *Adaptation* as a categorical variable indicating either (a) whether or not an adaptation measure was applied in the models or (b) what type of adaptation measure was applied. Adaptation as a Yes/No variable (a) was used to evaluate model performance, calculate Shapley values (see Section 2.4), and predict future yield change. Adaptation as multiple categorical variables representing different types of adaptation measures (b) was used to plot partial dependence plots (see Section 2.2.2) showing the relative importance of different adaptation measures on the yield change. In case (b), we excluded the adaptation types that had fewer than 25 simulations in the data set for a given crop (Table S2 in Supporting Information S1). Spatial location (longitude, latitude) was included in some of the models tested to account for all spatial factors not explicitly considered, such as the relationship between global and local changes in temperature. We also defined four linear mixed (LM) models. The first LM model estimates the yield using climate and management variables as predictors and the study reference as a random effect (Model 7). The second LM model is similar to Model 7 but also includes all possible interaction effects between pairs of variables (Model 8). Similar to the RF and GB models with spatial location as a predictor (Model 1, 2), we defined a LM model with a spatial correlation term defined using the Matérn correlation function which is used to define the spatial correlation between two points based on their distance (Model 9), and lastly, we defined a LM model with climate and management predictors and a spatial correlation term (Model 10).

All analyses were done in the R Statistical Language (R Version 4.0.4). RF models were fitted using the *ranger* package ($mtry = 2$, number of trees = 1,000; ranger version 0.12.1). GB models were fitted using the *caret* package, choosing the best model of nine parameter combinations (interaction depth = 1, 2, 3 and number of trees = 50, 100, 150; method = “gbm”; caret version 6.0–86). LM models were fitted using the *lme4* package

(lmer function; version 1.1-26), and the LM models with a spatial correlation term were fitted using the *spaMM* package (fitme function; version 3.7.2).

2.2.2. Model Evaluation

For all models, we split the data set by location into a training (75% of data) and a testing data set (25% of data). Two types of data splitting procedures were implemented. First, the data split was done such that test locations were the same as those of the training data set. This type of evaluation is relevant when the meta-models are used to predict yield changes at the same locations as those where the original simulations were performed. In this case, we assessed the capabilities of the meta-models to predict yield changes for various scenarios without any spatial extrapolation. Second, the data was split such that all of the yield predictions in the testing data set were from different locations than those of the training data set. This second type of model evaluation evaluates the capabilities of the meta-models to extrapolate to new locations where no yield simulation is available for training. We performed these two types of random splitting 10 times to calculate means and standard errors of model performance metrics. We calculated three model performance metrics for each meta-model, the root-mean-square error (RMSE), the coefficient of determination (R^2), and the Akaike information criterion (AIC), by comparing the yield change predictions obtained with each meta-model ($Y_{\text{pred},i}$) to the original simulated yield change (Y_i). AIC was calculated as:

$$\text{AIC} = n \times \ln \left(\sqrt{\frac{\sum_{i=1}^n (Y_i - Y_{\text{pred},i})^2}{n}} \right) + 2p \quad (1)$$

where n is the number of predictions and p is the total number of model parameters. We reported the mean and standard deviation of the three model performance metrics for each meta-model using the 10 test datasets. We chose the meta-model with the best performance for each crop using the three metrics defined above (RMSE, R^2 , and AIC in Table S3 in Supporting Information S1) averaged over the 10 test datasets, using the second type of model evaluation (i.e., different locations for testing than those used for training). Here, the model rankings obtained with the three performance metrics were in agreement about the best model for each crop, so we did not have to select one performance metric over another.

Partial dependence plots (PDPs) show the relationship between the yield change and each predictor variable, averaging over the other predictors. This gives a sense of the marginal effect of each predictor on the predicted yield change. To generate our PDPs, we calculated the partial contributions of each predictor variable using the FeatureEffect function (package *iml*, method = "pdp"), and training the model using all the data available.

2.3. Mapping Yield Changes at the Global Scale

We used the best meta-model for each crop to predict global yield changes for different climate and adaptation scenarios. We predicted the yield changes for RCP4.5 (Moss et al., 2010) for the year 2060 (+2°C, 506 ppm CO₂) with and without adaptation practices at the global scale. Yield change predictions were derived for every half-degree grid cell where the relevant crop was grown today, according to the MIRCA 2000 data set of harvested areas around the year 2000 model, using the bias-corrected daily temperature and precipitation from the W5E5 data set (Lange, 2019), also at half-degree resolution, averaged for the period 2001 to 2010 as in Hasegawa et al. (2022).

2.4. Shapley Values

The influence of model predictors in machine learning algorithms can be analyzed using Shapley additive explanations (Lundberg & Lee, 2017), which for any given prediction in a given grid cell, estimates the contribution of each predictor to the deviation of that grid-cell prediction from the mean yield change computed over the whole data set. For the purposes of this manuscript, we will define a yield anomaly as the deviation from the mean yield change in a particular location (i.e., the predicted yield change at a given grid-cell minus average yield change across the data set used to train the model). The Shapley value associated to a given predictor is the contribution of this predictor to a yield anomaly at a given location. A positive Shapley value indicates that the predictor has a positive contribution to the anomaly, while a negative value indicates that it has a negative contribution. Thus,

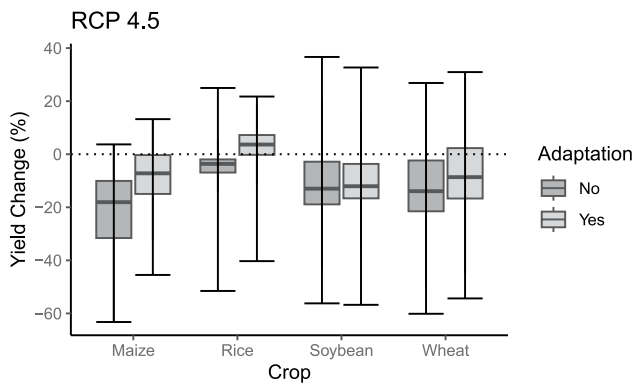


Figure 2. Boxplot summarizing the yield changes (% relative to the baseline) predicted by the selected meta-models for maize, rice, soybean, and wheat for the RCP4.5 climate scenario for the year 2060 (+2°C, 506 ppm CO₂), either with or without adaptation practices applied. The distribution covers all grid cells at the global scale. The box represents the first quartile, median, and third quartile. Whiskers show the minimum and maximum values. The difference in yield change between No Adaptation and Adaptation is significant for all crops ($P < 0.001$).

Shapley values can be used to understand the contributions of each predictor to the predicted yield anomalies. We used Shapley values, calculated using the *DALEX* package (version 2.2.0), to identify the most influential variables for each grid cell's prediction of yield change under the RCP4.5 climate scenario where the relevant crop was grown, assuming either that adaptation practices were applied or not. We considered climate and management factors affecting yield change: (a) annual mean temperature during the baseline period, (b) change in global temperature from the baseline period, (c) change in precipitation from the baseline period, (d) annual precipitation during the baseline period, (e) CO₂ concentration, and (f) crop management adaptation. For each grid cell, we determined the factor that had the largest Shapley value, that is, the largest effect on the predicted yield change anomaly for that grid cell. Using this method, we created global maps highlighting regions where the yield change anomaly is most responsive to temperature, precipitation, CO₂ concentration, or adaptation.

3. Results

Of the 10 statistical meta-models tested, the best models were generally RF and GB models (Tables S3 and S4 in Supporting Information S1). The consistently lower performance of the LM models implies that there are

non-linear relationships in these datasets which LM models cannot capture. For spatial extrapolation (Table S3 in Supporting Information S1), Model 4 (GB) was the highest performing model for maize, while for rice and soybean the best model was Model 5 (RF), and for wheat the best model was Model 6 (GB). Although they were outperformed by RF and GB models, the LM models revealed that adaptation management practices had a statistically significant positive effect on yield changes (Table S5 in Supporting Information S1). For spatial extrapolation, the best maize model was able to explain the greatest amount of variation in the data set ($R^2 = 0.43$), significantly more than the extrapolation performance of the wheat and soybean models (both $R^2 = 0.21$). The rice model extrapolation was very low ($R^2 = 0.12$) although its RMSE was lower than that of other models. In other words, when forced to predict new locations, the statistical models explained at most 43% of the yield change variation in the test data set ($R^2 = 0.12$ – 0.43 ; Figure S2 in Supporting Information S1). Nevertheless, when we split the testing and training datasets such that the testing data set only contained locations from the same half-degree grid cells as the training data set, model performances were higher ($R^2 = 0.33$ – 0.58 ; Table S4, Figure S3 in Supporting Information S1), revealing that the models are better able to predict yield changes for new scenarios at the same sites than to predict new sites. However, it is notable that the maize model was not improved by restricting the testing sites to the same location as the training site, suggesting that the maize data set was large enough to be informative across spatially heterogeneous locations. Further supporting this, among the best meta-models for spatial extrapolation, the best maize model was the only one which did not use latitude and longitude as explanatory variables. It is likely that, for maize, environmental covariates were sufficient to explain the yield change variation across space.

Figure 2 shows a boxplot summary of the global yield changes at each grid cell location predicted by the selected meta-models. Under the RCP4.5 scenario for the year 2060 and +2°C warming, the meta-models predict broad yield losses for maize (mean: -21%; range across locations: -63%, 3.7%), rice (mean: -5.7%; range: -52%, +25%), soybean (mean: -11%; range: -56%, +37%), and wheat (mean: -13%; range: -60%, +27%) when adaptation practices were not applied (Figure 2). Applying adaptive practices increased yields for all crops relative to without adaptation, by 13, 1, and 5 percentage points on average for maize, soybean, and wheat respectively, resulting in reduced net yield losses of -7.5% (mean; range: -45%, +13%) for maize, -10.2% (mean; range: -57%, +33%) for soybean, and -8.1% (mean; range: -54%, +31%) for wheat (Figure 2). With adaptation, rice yields were increased by 7 percentage points relative to without adaptation, resulting in a predicted increase in yield of +1.8% (mean; range: -40%, +22%). The effect of adaptation on yield change was significant for all crops (Table S5 in Supporting Information S1, $P < 0.0001$). There was large spatial variability in yield loss and gain; for example, with adaptive management, rice yields were predicted to increase in South America and parts of China, but not in North America or western Asia (Figure 3). Maize yield losses showed a strong latitudinal gradient, with higher losses at low latitudes, while the other crops had patchier distributions suggesting a more complex spatial

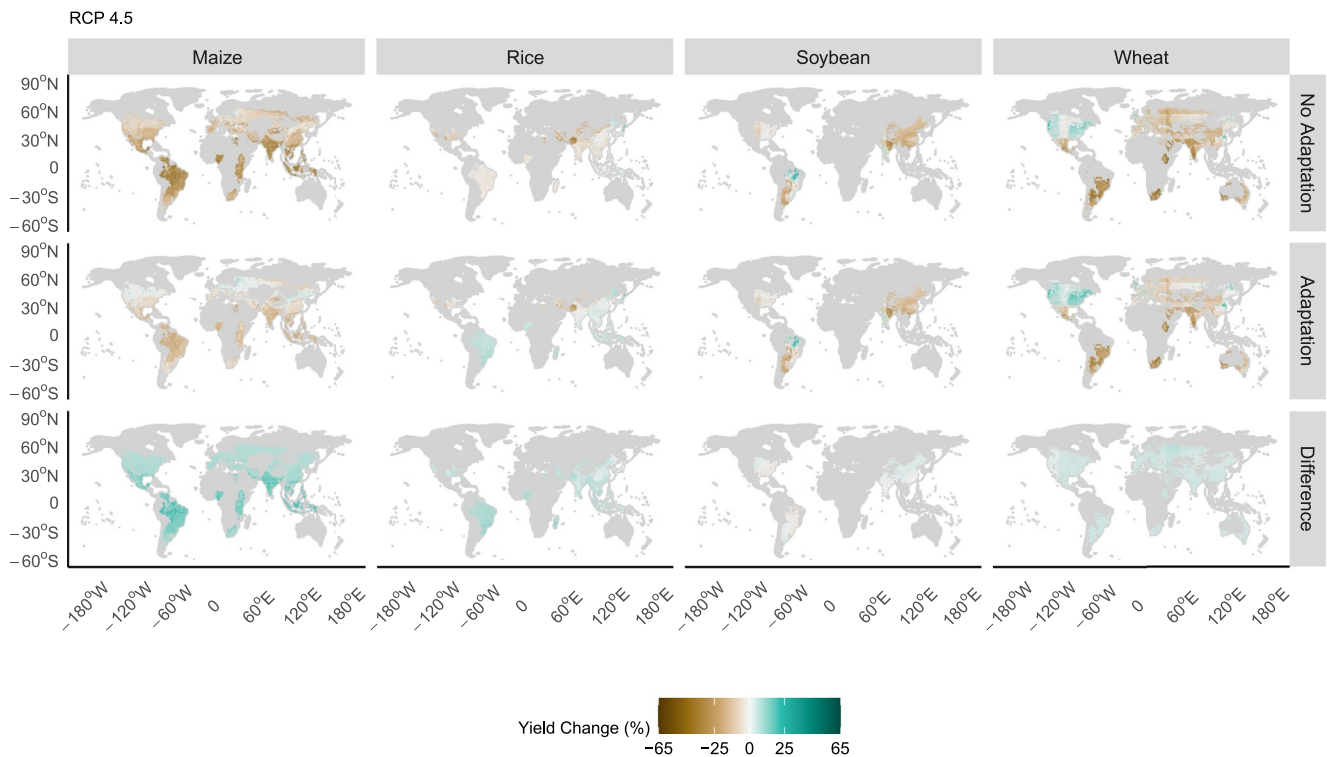


Figure 3. Maps showing the predicted yield changes (% relative to the baseline) of maize, rice, soybean, and wheat for the RCP4.5 climate scenario for the year 2060 (+2°C, 506 ppm CO₂), without adaptation practices (No Adaptation), with adaptation practices (Adaptation), and showing the difference in yield changes from applying adaptation practices (Difference = Adaptation – No Adaptation).

effect for these crops than for maize. For wheat, projected maps showed abrupt changes at some specific latitudes and longitudes, indicative of lack of data in some parts of the world, especially across Eurasia. This suggests that more wheat yield simulations would be useful in this part of the world.

The partial dependence plots show that yield decrease tended to be stronger in locations characterized by high annual mean temperatures during the baseline period and high warming relative to the baseline year (Figure S4 in Supporting Information S1). Conversely, there was relatively little effect of changes in CO₂ concentration for all crops except for wheat, for which yield increased at higher concentrations of CO₂. Latitude and longitude were included in the best model for all crops except maize; the location had non-monotonic effects for these crops, with a tendency toward improved yields at northern high latitudes. Implementing one or more adaptation strategies reduced yield losses but with a distinct impact of different adaptation types. For example, maize yields were improved by irrigation, although they were not as responsive to other adaptation strategies like modifying the cultivar or planting time. Rice yields were responsive to multiple adaptation strategies, especially modifying the cultivar, which was the only crop-specific adaptation strategy that resulted in increased yield (others only reduced yield losses). Wheat was somewhat responsive to adaptive fertilizer use and adaptations that did not fall into the other categories (i.e., “Others”). We did not have enough information to determine the soybean yield response to any specific adaptive strategies, and we similarly lacked the sample size to determine the rice and wheat yield response to irrigation, and the maize yield response to fertilizer use or other adaptive strategies (Figure S4 in Supporting Information S1). There was an interaction between adaptation and warming level, such that the positive effect of implementing adaptation strategies increased with the warming level (Figure S5 in Supporting Information S1).

We used Shapley additive explanations to visualize the contribution of adaptation strategies and climate variables to the yield change anomaly for each grid cell of the RCP4.5 yield change prediction to the year 2060 either assuming that no adaptation practices were applied (Figure 4, Figure S6 in Supporting Information S1) or assuming that adaptation practices were applied (Figures S7 and S8 in Supporting Information S1). In a projection of maize yield without adaptation practices, the lack of adaptation results in a -9 [mean; range: -20, -5.1] percentage

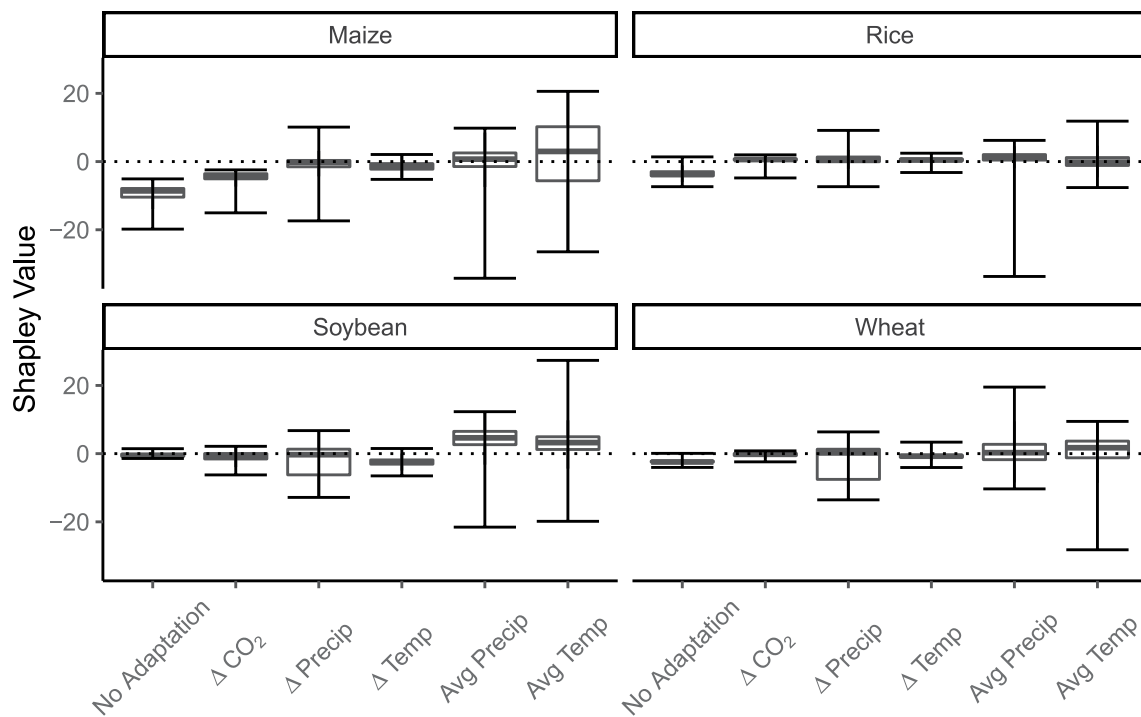


Figure 4. Shapley additive explanation contribution to the predicted yield change (%) for all crops under an RCP4.5 scenario without adaptation. The five predictors considered are absence of adaptation (No Adaptation), change in CO₂ concentration above 390 ppm (Δ CO₂), change in precipitation (Δ Precip), global warming level (Δ Temp), average local precipitation (Avg Precip), and average local temperature (Avg Temp). The box represents the first quantile, median, and third quantile. Whiskers show the minimum and maximum values.

point reduction in the mean predicted yield change. Average temperature also had a large effect, ranging from a 21 percentage point increase to a –26 percentage point decrease in yield change, with higher yield predicted at northern latitudes (Figure 4, Figure S6a in Supporting Information S1). The other crops showed similar general patterns, with the lack of adaptation contributing to yield loss and with other predictors contributing to yield gain or loss depending on the latitude or region (Figures S6b–S6d in Supporting Information S1). For maize, when adaptation practices are applied, they can be seen to contribute to yield gain (Figure S7a in Supporting Information S1).

In order to understand which factor (between adaptation, CO₂ concentration, warming level, annual precipitation, and annual mean temperature during the baseline period) was dominant in each predicted location, we assigned to each grid cell the predictor with the minimum (in the case of predicted yield loss) or maximum (in the case of predicted yield gain) Shapley value. Figure 5 shows that the absence of adaptation was the dominant contributor to yield losses when adaptation practices were not applied, for all crops except wheat where the change in precipitation was also important, and soybean where several climate factors were more important than adaptation practices (Figure S9 in Supporting Information S1). Secondary contributors to yield loss in absence of adaptation differed by crop, with multiple climate factors becoming more important for rice and wheat, and CO₂ concentration change contributing to maize yield loss (Figure S10 in Supporting Information S1). Conversely, Figure 6 shows that the application of adaptation strategies contributed strongly to yield gains, and was the dominant contributor for rice and wheat (Figure S11 in Supporting Information S1). Without applying adaptation strategies, yield gains in regions where adaptation is important are dependent on precipitation changes to improve yields (Figure S12 in Supporting Information S1). For maize, rice, and wheat, yield changes tended to be influenced by adaptation, mean temperature and precipitation during the baseline period, as well as precipitation change, depending on the location. For example, yield gains in these crops were often associated with low average temperature during the baseline period at high latitudes, suggesting that warmer projected temperatures under RCP4.5 could alleviate temperature or temperature-driven growing season length restrictions on crop productivity, resulting in yield gain at high latitude. For wheat, precipitation during the baseline period was a dominant factor explaining yield losses in western North America where precipitation is expected to decline (Figure 5) and yield gains in eastern North America where precipitation is expected to increase (Figure 6). Soybean had different drivers than the other crops; soybean yield loss was most affected by the projected precipitation change and warming level, and yield

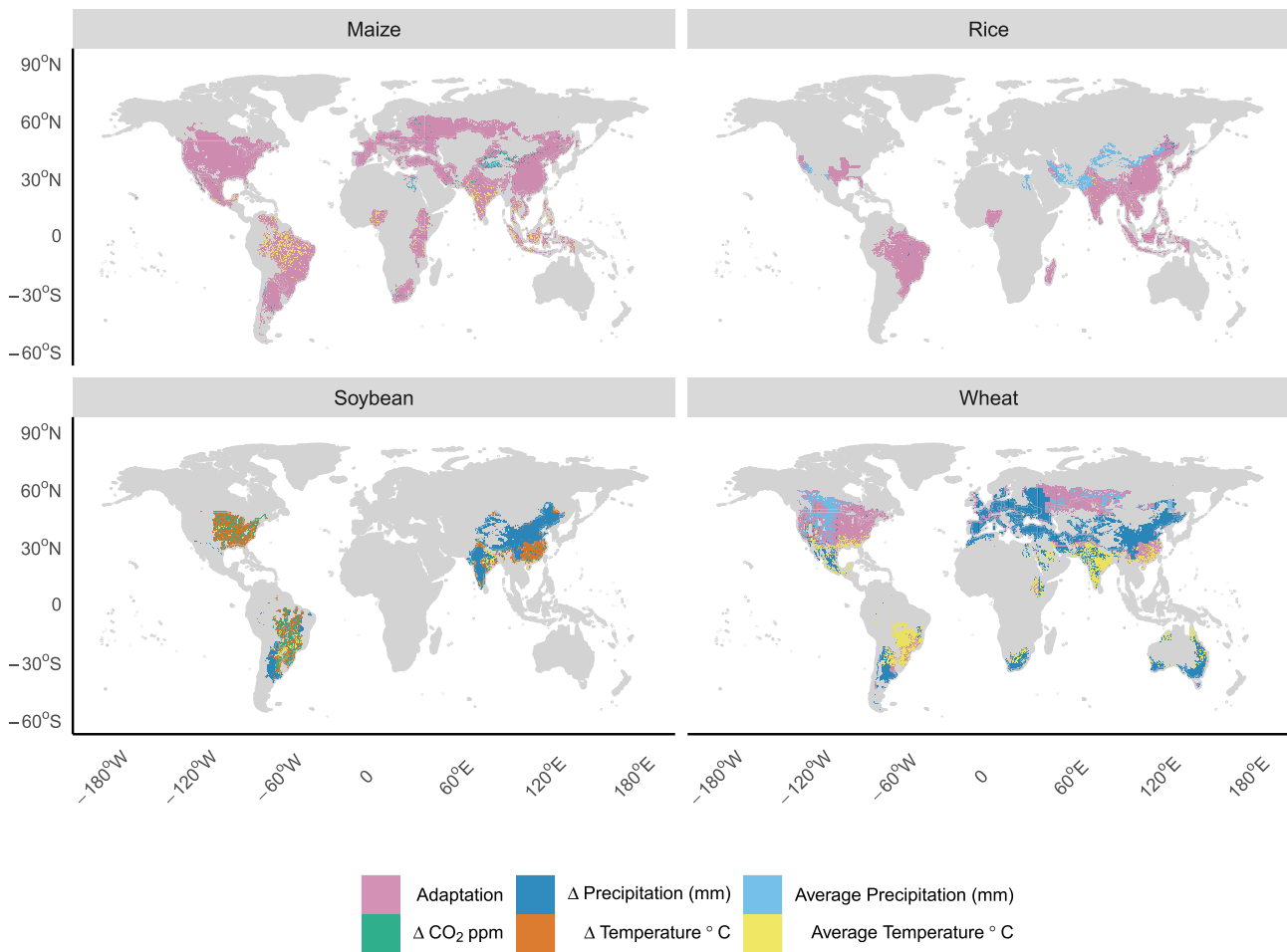


Figure 5. Maps colored to indicate the greatest contributors to the yield losses predicted under an RCP4.5 scenario without adaptation: absence of adaptation (pink), change in CO₂ concentration above 390 ppm (green), change in precipitation (dark blue), warming level (orange), average precipitation (light blue), and average temperature (yellow). The greatest contributors to yield losses other than adaptation are shown in Figure S10 in Supporting Information S1.

gain by the average temperature and precipitation during the baseline period (Figures S9 and S11 in Supporting Information S1).

4. Discussion

The meta-models we developed here for each of the four major crops are informed by climate, management and location factors to map yield changes under the +2°C, +116 ppm RCP4.5 scenario in 2060. Our meta-models were only able to explain a portion of the variability in yields simulated by the original crop models. This is due to the very high variability of simulations between crop models reported in the literature. Even when these models are calibrated with the same data and used with the same input variables, the differences between the simulations obtained with different crop models is generally very large, which explains why our meta-models cannot explain more than half of the variability of the simulations (Bassu et al., 2014; Makowski et al., 2015). However, our meta-models were able to capture the effects of several key factors, in particular the effects of different adaptation strategies. Our study focused on a single scenario, that is, RCP4.5 in 2060. We have chosen this scenario because it seems to be the most realistic given the current socio-economic context (Arias et al., 2021; IEA, 2021). However, the meta-models developed in this study are not contingent on this scenario; they have been trained with a very large database including yield simulations obtained with different climate change scenarios covering a wide range of temperature, precipitation, and CO₂ concentration changes (Hasegawa et al., 2022). They are therefore very generic and could be easily run for any other climate change scenario. To facilitate their reuse, we have made the meta-models and analysis scripts freely available (see Data Availability Statement Section).

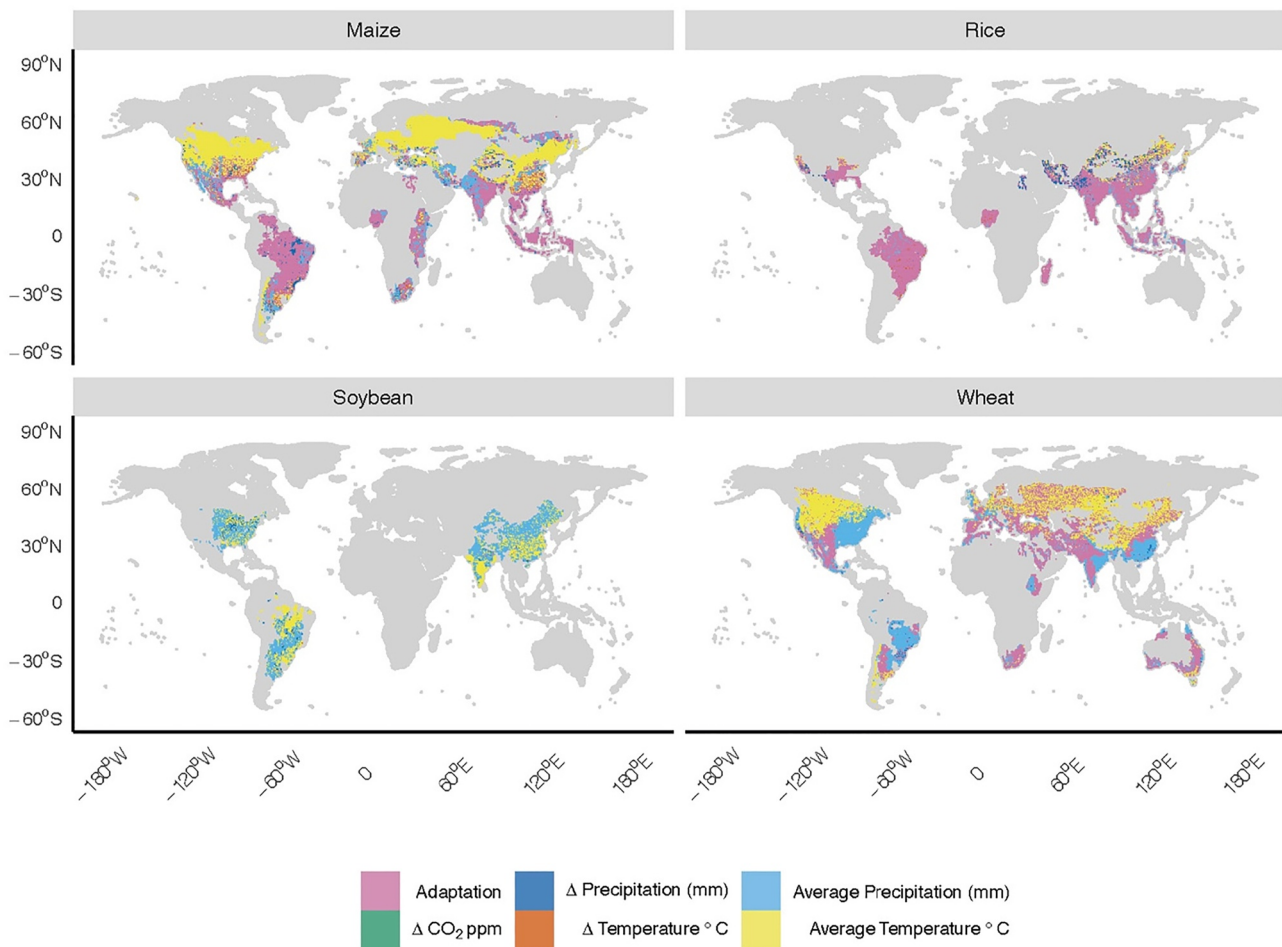


Figure 6. Maps colored to indicate the greatest contributors to the yield gains predicted under an RCP4.5 scenario with adaptation: application of adaptation strategies (pink), change in CO₂ concentration above 390 ppm (green), change in precipitation (dark blue), warming level (orange), average precipitation (light blue), and average temperature (yellow). The greatest contributors to yield gains without adaptation are shown in Figure S12 in Supporting Information S1.

Results clearly reveal that adaptation practice is a dominant factor with a strong, and previously overlooked, impact on global yield change predictions. If we assume that the effect of temperature change is constant, then without adaptation, each degree-Celsius increase in global mean temperature would, on average, reduce global yields of maize by 10%, wheat by 6.5%, rice by 2.8%, and soybean by 5.4%. These are close to the per degree-Celsius estimates of global yield reduction made by Zhao et al. (2017) of 7.4% for maize, 6.0% for wheat, 3.2% for rice, and 3.1% for soybean, although these estimates were based on local rather than global changes in temperature. This study gives a unique view into what particular adaptation practices could prevent these yield losses. We found that maize has the greatest potential of yield loss reduction by adaptation, and that irrigation practices were predicted to be more important relative to the other adaptation practices in the data set (e.g., adaptive cultivars, planting time). Wheat saw some predicted yield benefit from both adaptive fertilization and other management practices, while rice yields were mainly influenced by the choice of cultivar. In addition to benefits from improved yield, some adaptation-related management practices can have co-benefits for soil health and soil carbon (Lessmann et al., 2022). While the management practices that increase yield are often not the same as those meant to increase soil C storage, there is evidence that some practices (e.g., reduced tillage, cover cropping, crop diversification, organic amendments) can improve both yield and soil C stocks (Cooper et al., 2016; Lal, 2006; Smith et al., 2008).

After adaptation, temperature and precipitation during the baseline period, as well as local precipitation change were the most influential climate factors on projected global yield for most crops. Ortiz-Bobea et al. (2019) found that projected yields were primarily impacted by temperature (heat stress), followed by precipitation

(water stress). Recent studies have also demonstrated the compound or synergistic effects of heat and water stress on crops (Beillouin et al., 2019; Lesk et al., 2021). In this study we also found temperature and precipitation to be influential, especially on maize and wheat yield (Figure 4), although predicted yield changes were not always related to heat and drought. In fact, yield gains projected for high-latitude regions (Figure 3) which are most influenced by temperature (Figure 6) are rather due to an alleviation of cold limitation on productivity. A recent update of the Global Gridded Crop Model Intercomparison (GGCMI) based on the Coupled Model Intercomparison Project (CMIP) Phase 6, compared to the earlier GGCMI run with CMIP Phase 5 atmospheric forcing, predicted higher sensitivity to warming but less of a CO₂ fertilization effect (Franke et al., 2020; Müller et al., 2021). Our study observed both sensitivity of crop yield to average temperature during the baseline period (and specifically warming in the case of soybean), but little sensitivity to CO₂, except as a negative contributor to the predicted yield of the C4 crop maize which is not expected to benefit from CO₂ fertilization as C3 crops would. This is possibly because elevated CO₂ reduces transpiration and increases leaf temperature, which may negatively affect photosynthesis and yields in models (Long et al., 2006). However, CO₂ fertilization effects can be difficult to compare across modeling studies that simulate many different levels of CO₂ increase.

One major limitation of this study and its predecessors (Aggarwal et al., 2019; Challinor et al., 2014) is that crop model results are not fully documented, making it difficult to know what types of adaptation practices were implemented beyond broad categories. For example, adaptations through fertilizer application could modify the timing of application, the amount of fertilizer, the type of fertilizer, application method, and other characteristics. Depending on the study, any of these different adaptations may be considered, but all will be presented as a change in fertilizer use. As a result, a wide variety of interventions are considered together and their effects averaged in our grouping into adaptation practice categories. Yet, we know from experimental studies that small modifications in land management can have large effects on productivity (Bai et al., 2018; Sandén et al., 2018). It is therefore difficult for us to say what specific adaptation practices may prevent yield loss. Second, most models do not simulate extreme events well, such as temperature and precipitation extremes (Heinicke et al., 2022; Schewe et al., 2019; Sun et al., 2021), and similarly do not represent pest, weed, or disease spread among crops, so it is relatively unknown how these major avenues of crop failure may amplify each other in the future. A related limitation stems from the translation of process models to meta-models. Meta-model predictions such as the ones made here aggregate the process-model-simulated climate into specific indices such as the climate scenario or the change in climate from the baseline period. This has the effect of, for example, averaging over seasonal variability (and extremes) and their effects on yield predictions. Lastly, as can be seen in Figure 1, some parts of the world are not as well-represented in the simulations compared to mid-latitudes, and as a result the predicted yield change estimates in these regions may not be as trustworthy as they are in other regions, particularly for rice in South America, soybean in East Asia, and Northern Eurasia.

Every time crop model predictions are updated, negative climate impacts are projected to emerge earlier in this century (before 2040; (Jägermeyr et al., 2021)). One can argue that we already see impacts of climate change on crop yield, particularly in reference to compound events that resulted in large, unexpected yield losses (Ben-Ari et al., 2018; Ciaïis et al., 2005). Although previous work and our study support the importance of climate variables such as temperature and precipitation in determining future yields, our study's main finding is the potential for adaptation practices to mitigate yield losses, especially in vulnerable low-latitude regions where yields are otherwise expected to decline with continued human-induced climate change. We further identified an interaction effect between adaptation and warming, suggesting that adaptation practices will become increasingly important to preserve crop yields at higher warming scenarios (Figure S5 in Supporting Information S1). Identifying the specific management practices for each crop and region that can mitigate yield losses is therefore a research priority. At the same time, it is important to consider the social and economic consequences of implementing certain management practices. For example, irrigation may be useful where maize is grown (Figure S4 in Supporting Information S1), but if water resources are limited then it is important to consider the resource and energy trade-offs of using local water sources, treating, or desalinating water. Because of the great diversity in adaptive land management practices and ways of implementing them, best practices for a particular location will likely be found in collaboration with local and Indigenous knowledge and stakeholders (Makondo & Thomas, 2018; Nkomwa et al., 2014). In this way, sustainable development goals (sdgs.un.org) related to maintaining agricultural yield such as reducing hunger and poverty can be met along with those related to climate action, sustainability, equity, and justice.

Data Availability Statement

The authors will maintain the meta-models and analysis code used in this paper as a publicly available Github repository at <https://github.com/rabramoff/ProjectYield>. The first release of this repository has been deposited in Zenodo and is available here: <https://github.com/rabramoff/ProjectYield/releases/tag/v0>, and can be cited as Abramoff et al. (2023). The data used in this paper is publicly available from Hasegawa et al. (2022) and the linked figshare repository (<https://doi.org/10.6084/m9.figshare.14691579.v4>).

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