Adaptation strategies strongly reduce the future impacts of climate change on 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 contrasting future adaptation strategies and climate scenarios for maize, rice, wheat and soybean. We tested 10 statistical models, including some machine learning models, to relate the percentage change in future yield relative to the baseline period (2000-2010) to 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 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 loss by 1–13%. Maize was most responsive to adaptive practices with a 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 most able to prevent large yield losses, respectively. When adaptation practices are applied, some areas may 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. We tested different statistical methods to merge the findings of many different computer simulations of crop yield change under future climate into one model which can be used to predict crop yield at any location where that crop is grown. We created and selected the best model for four major crops: maize, rice, wheat and soybean. 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, CO_2 concentration), we found that adaptation status was the most influential factor determining yield change for most crops. Managing land adaptively in the future can reduce yield losses by 1-13% 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.

Key Points.

- Under future climate scenario RCP4.5, maize, rice, wheat, and soybean are expected to decrease in average global yield by 6-21%.
- Implementing adaptive management practices reduces this loss by 1-13% relative to maintaining the same management practices.

- Some areas of the world, such as northern high latitudes, may see future yield increases if adaptation practices are applied.

Keywords. Crop yield, agriculture, crop model, climate change, management, adaptation

1 Introduction

Food security faces increasing threats from anthropogenic climate change (Wheeler and 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 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). Though AgMIP primarily makes yield predictions using process-based models, statistical models are also commonly used (Zhao et al. 2017; Lobell and Asseng 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 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 (Zhu et al. 2021; Ortiz-Bobea et al. 2019). The importance of other environmental effects is not as well understood, such as the effect of CO_2 fertilization on yield, which has been demonstrated to increase yields in ideal conditions, but have mixed effects depending on sites and crop types (McGrath and Lobell 2013; Makowski et al. 2020; Wilcox and 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 provide 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; Wilcox and Makowski 2014; Makowski et al. 2020). 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 predictions of yield responses 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 synthetize 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 dataset of site-level crop model yield projections to answer to following research questions: (1) What distributions of yield losses and gains can be expected on a global scale based on all the available agricultural model simulations? (2) What are the most important factors explaining variability in yield change projections? (3) 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 (IEA 2021; Arias et al. 2021).

2 Methods

2.1 Dataset

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 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), CO_2 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 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 dataset and access to the dataset 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 8501 predictions of yield change for the four crops combined from 370 unique locations, with over 1000 predictions for each crop except for soybean (Table 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).

2.2 Statistical and machine leaning 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 models (LM), with and without spatial correlation (Table 1). 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 (1) whether or not an adaptation measure was applied or (2) what type of adaptation measure was applied. Adaptation as a Yes/No variable (1) was used to evaluate model performance, calculate Shapley values (see 2.4), and predict future yield change. Adaptation as multiple categorical variables representing different types of adaptation measures (2) was used to plot partial dependence plots (see 2.2.2) showing the relative importance of different adaptation measures on the yield change. 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 estimates the yield using climate and management variables as predictors and the study reference as a random effect (Model 7). The second linear mixed 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=1000; 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 dataset by location into a training (75% of data) and a testing dataset (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 dataset. 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 split was done such that all of the yield predictions in the testing dataset were from different locations than those of the training dataset. This second type of model evaluation is relevant to evaluate 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 ($Y_{pred,i}$) to the original simulated yield change (Y_i). AIC is calculated as:

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

where 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 S2) 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 (+2ºC, 506ppm CO_2) 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 dataset of harvested areas around the year 2000 model, using the bias-corrected daily temperature and precipitation from the W5E5 dataset (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 and 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 dataset. 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 – average yield change across the dataset 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, 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: (1) annual mean temperature during the baseline period, (2) change in global temperature from the baseline period, (3) change in precipitation from the baseline period, (4) annual precipitation during the baseline period, (5) CO_2 concentration, and

(6) 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, CO_2 concentration, or adaptation.

3 Results

Of the 10 statistical models tested, the best models were generally RF and GB models (Table S2 and Table S3). For spatial extrapolation (Table S2), Model 4 was the highest performing model for maize, while for rice and soybean the best model was Model 5, and for wheat the best model was Model 6. Although they were outperformed by RF and GB, the LM models revealed that adaptation management practices had a statistically significant effect on yield changes (Table S4). For spatial extrapolation, the best maize model was able to explain the greatest amount of variation in the dataset (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 43% or less of the yield change variation in the test dataset (R^2 = 0.12-0.43; Figure S2). Nevertheless, when we split the testing and training datasets such that the testing dataset only contained locations from the same half-degree grid cells as the training dataset, model performances were higher (R^2 = 0.33-0.58; Table S3, Figure S3), 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 dataset was large enough to be informative across spatially heterogenous locations.

Figure 2 shows the global distributions of the yield changes 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% on average for maize, soybean, and wheat respectively, resulting in reduced net yield losses of -7.5% (mean; range: -46%, +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 4% relative to without adaptation, resulting in a predicted increase in yield of +1.4% (mean; range: -39%, +22%). 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 effect for these crops than for maize.

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). Conversely, there was relatively little effect of changes in CO_2 concentration for all crops except for wheat, for which yield increased at higher concentrations of CO_2. 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 towards improved yields at northern high latitudes. Implementing one or more adaptation strategies tended to reduce yield losses but with a distinct impact of different adaptation types. For example, maize yields were improved by irrigation, although they were not very responsive to other adaptation strategies. 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"), while soybean yields did not improve with any adaptation strategies. In some cases, implementation of a crop-specific adaptation strategy resulted in even greater yield loss, as was the case for soybean and adaptive fertilizer use (Figure S4). 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).

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) or assuming that adaptation practices were applied (Figure S7, Figure S8). In a projection of maize yield without adaptation practices, the lack of adaptation results in a -9% [mean; range: -20%, -5.1%] reduction in the mean predicted yield change. Average temperature also had a large effect, ranging from a 21% increase to a -26% decrease in yield change, with higher yield predicted at northern latitudes (Figure S7a). 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 (Figure S7b,c,d). For maize, adaptation practices can be seen to contribute to yield gain (Figure S8a).

In order to understand which factor (between adaptation, CO_2 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 case of predicted yield loss) or maximum (in 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). 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 S10). 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 gain by the average temperature and precipitation during the baseline period (Figure S9, S9).

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 +2ºC, +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, i.e. RCP 4.5 in 2060. We have chosen this scenario because it seems to be the most realistic given the current socio-economic context (IEA 2021; Arias et al. 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 CO_2 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 code availability section).

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 per degree-Celsius estimates of global yield reduction estimated 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 more important relative to the other adaptation practices in the dataset (i.e., adaptive cultivars, fertilizer application, planting time, others). Wheat saw some 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, Gross, and Robertson 2008).

After adaptation, temperature and precipitation during the baseline period, as well as local precipitation change were the most influential climate factors on 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 (Lesk et al. 2021; Beillouin, Ben-Ari, and Makowski 2019). In this study we also found temperature and precipitation to be influential, especially on maize and wheat yield (Figure 4), although 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 CO_2 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 CO_2. However, CO_2 fertilization effects can be difficult to compare across modeling studies that simulate many different levels of CO_2 increase.

One major limitation of this study and its predecessors (Challinor et al. 2014; Aggarwal et al. 2019) is that model results are not fully documented, making it difficult to know what types of adaptation practices were implemented beyond broad categories. For example, adaptations to fertilizer application could modify the timing of application, the amount of fertilizer, the type of fertilizer, application method, and other characteristics. As a result, a wide variety of interventions are considered together and their effects averaged in our grouping into adaptation practices categories. Yet, we know from experimental studies that small modifications in land management can have large effects on productivity (Sandén et al. 2018; Bai et al. 2018). Second, most models do not simulate extreme events well, such as temperature and precipitation extremes (Sun et al. 2021; Heinicke et al. 2022; Schewe et al. 2019), 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. Lastly, as can be seen in Figure 1, the tropics 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 and soybean in East Asia.

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 (Ciais et al. 2005; Ben-Ari et al. 2018). 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). 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), 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 and Thomas 2018; Nkomwa et al. 2014). In this way, sustainable development goals (https://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.

Code/Data availability

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.

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Tables and Figures

Table 1: Characteristics of the 10 statistical and machine learning models used to predict the yield change of maize, rice, wheat, and soybean. 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. $\boldsymbol{Matern(1|Longitude + Latitude)}$ means random effects (with Matern covariance function) were included to describe the residual spatial variability.

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

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

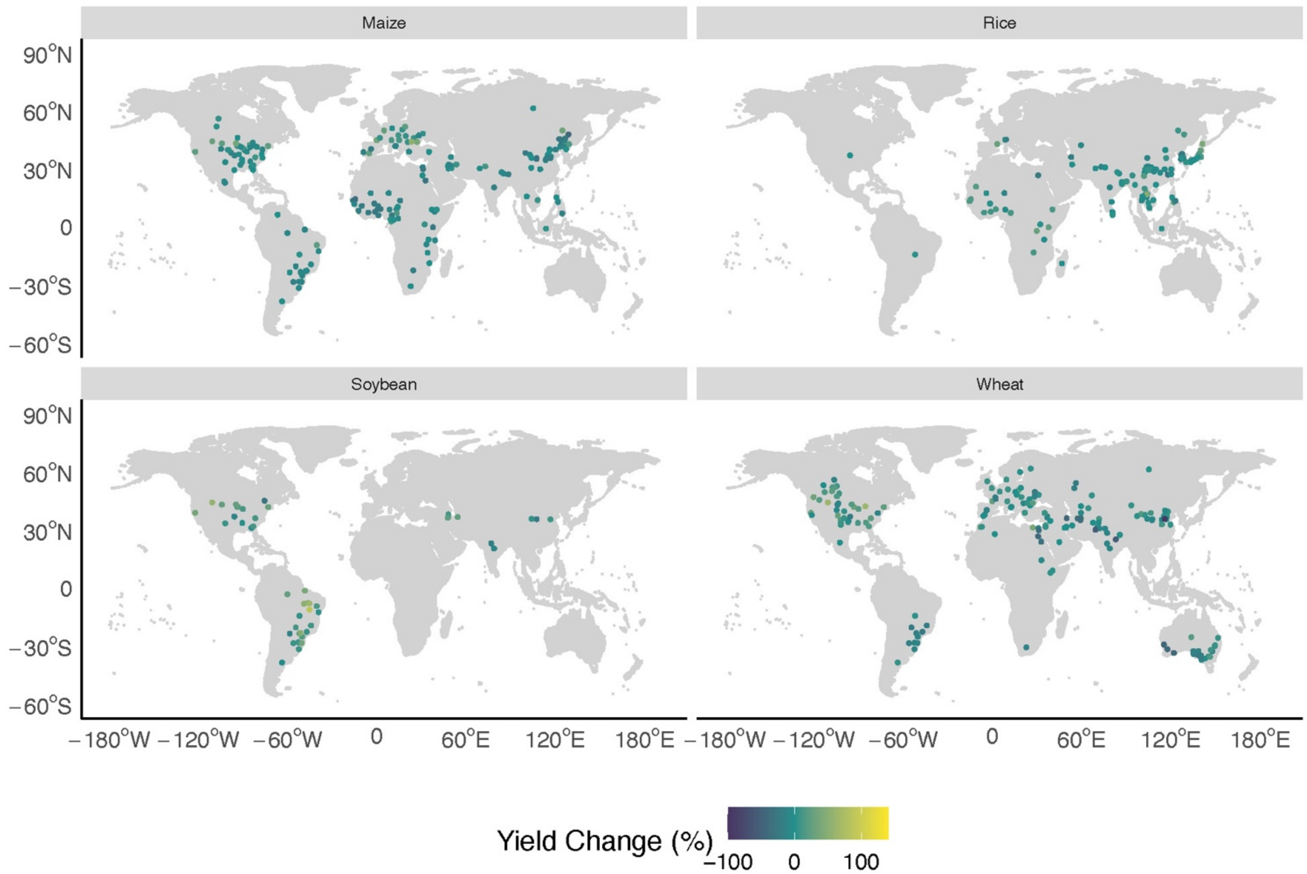

Figure 2: Boxplot summarizing the yield changes (% relative to the baseline) predicted by the selected meta-models for maize, rice, wheat and soybean for the RCP4.5 climate scenario for the year 2060 (+2ºC, 506ppm CO_2), either with or

without adaptation practices applied. The distribution covers all grid cells at the global scale. Box represents the 1st quantile, median, and 3rd quantile. Whiskers show the minimum and maximum values.

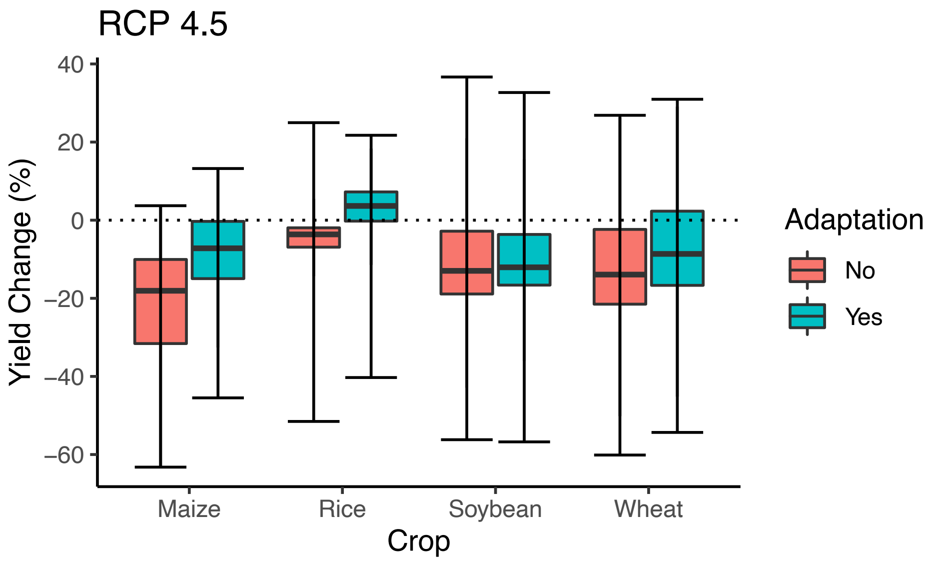

Figure 3: Maps showing the predicted yield changes (% relative to the baseline) of maize, rice, wheat and soybean for the RCP4.5 climate scenario for the year 2060 (+2ºC, 506ppm CO_2), without adaptation practices (No Adaptation), with adaptation practices (Adaptation), and showing the difference in yield changes from applying adaptation practices (Difference = Adaptation – No Adaptation).

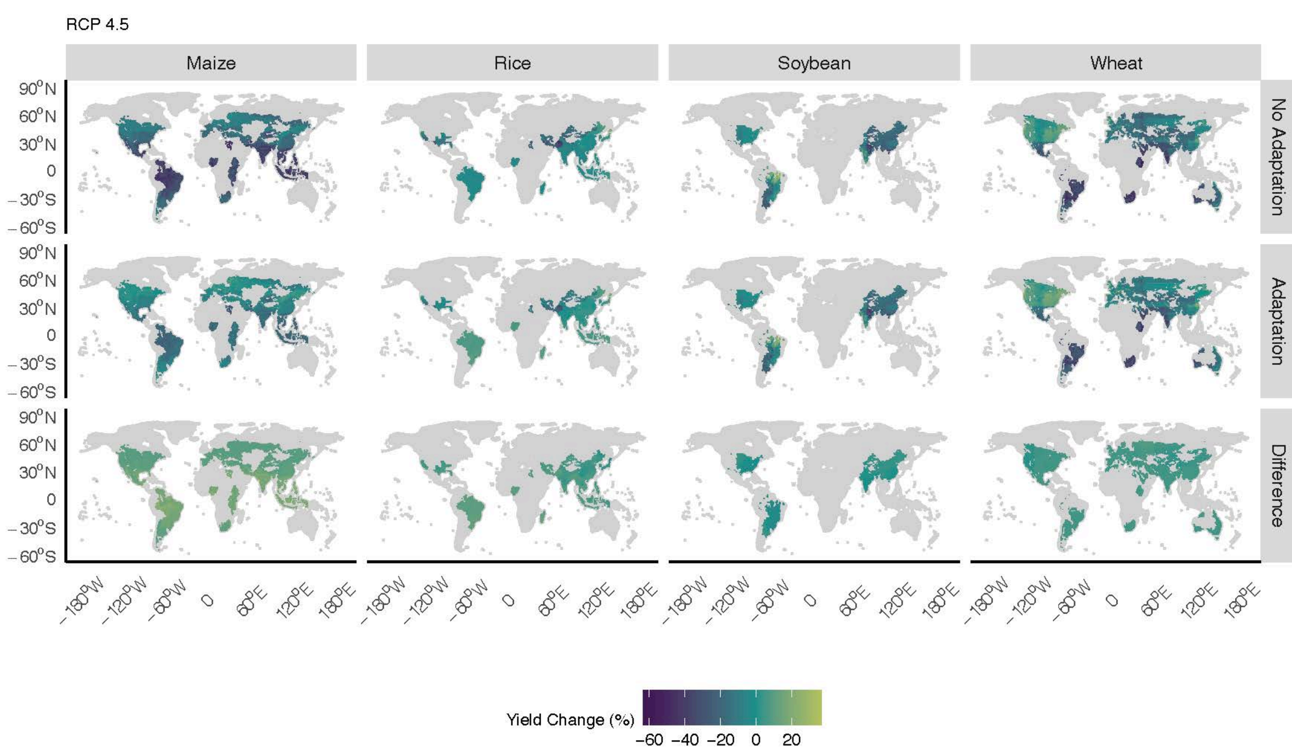

Figure 4: Shapley additive explanation contribution to the predicted yield change (%) for all crops under an RCP4.5 scenario without adaptation. The five predictors considered are absence of adaptation (No Adaptation), change in CO_2 concentration above 390ppm (Δ CO_2), change in precipitation (Δ Precip), global warming level (Δ Temp), average local precipitation (Avg Precip), and average local temperature (Avg Temp). Box represents the 1st quantile, median, and 3rd quantile. Whiskers show the minimum and maximum values.

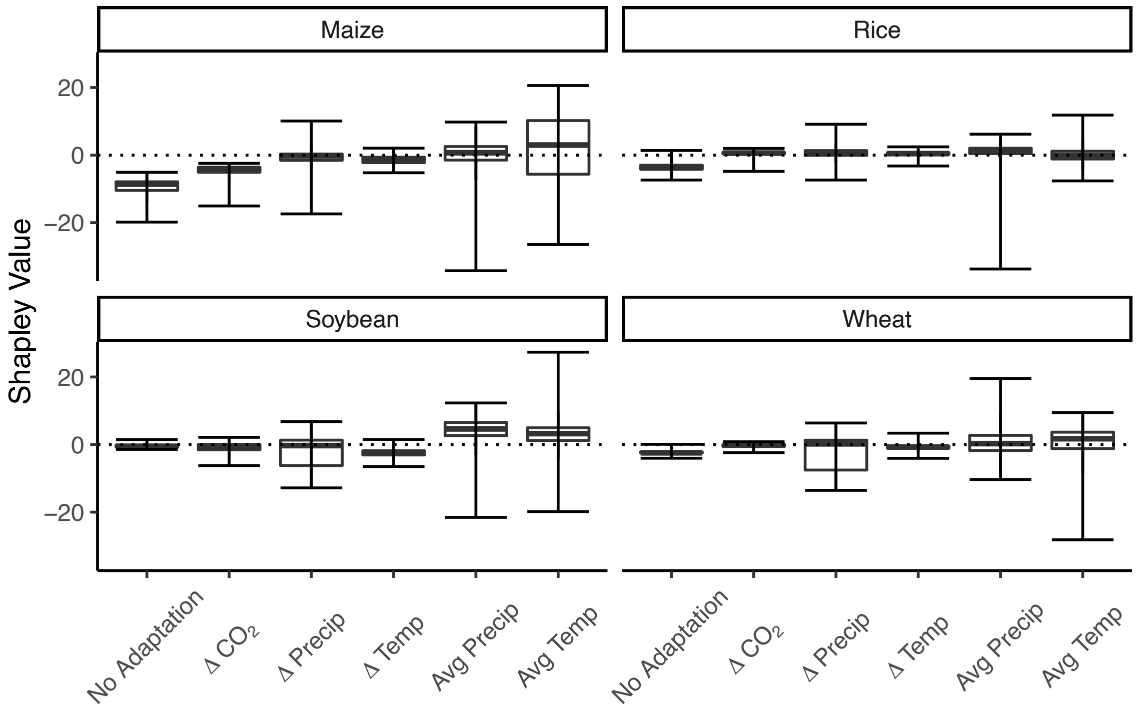

Figure 5: Maps colored to indicate the greatest contributors to the yield losses predicted under an RCP4.5 scenario without adaptation: absence of adaptation (pink), change in CO_2 concentration above 390ppm (green), change in precipitation (dark blue), warming level (orange), average precipitation (light blue), and average temperature (yellow).

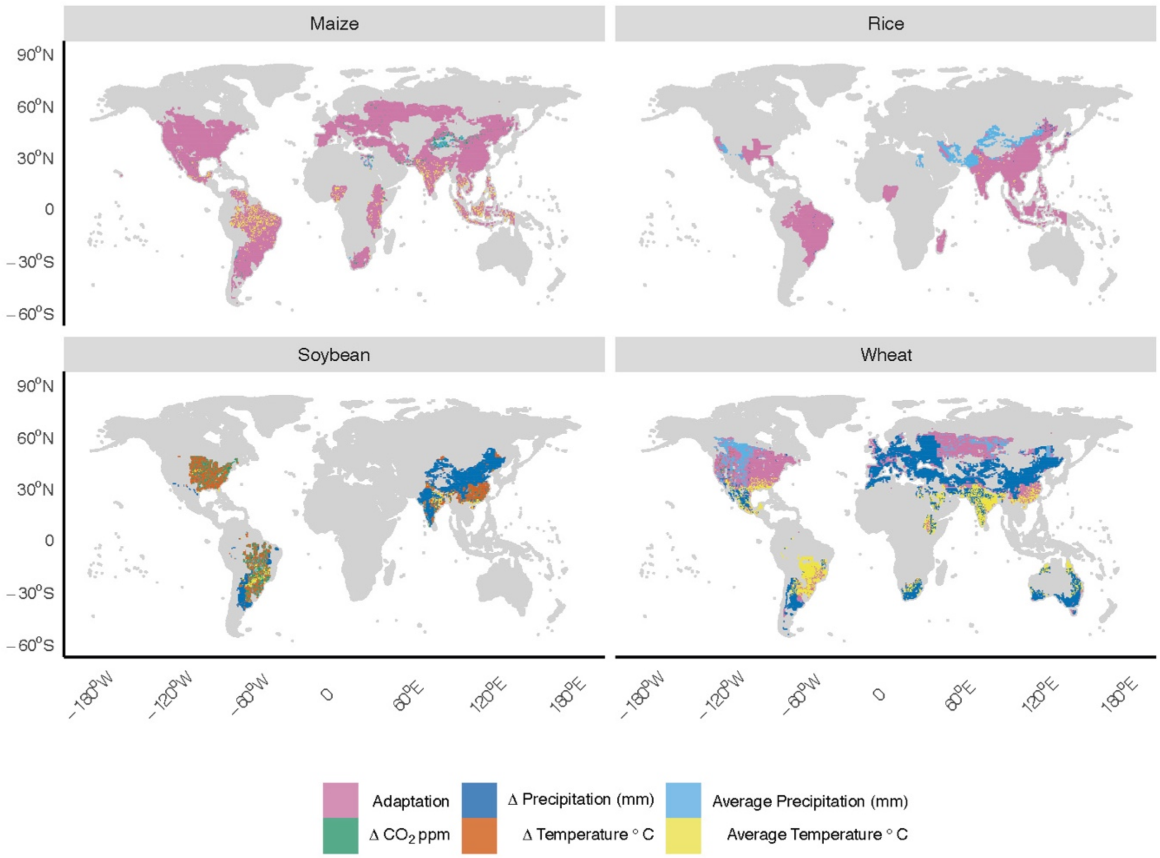

Figure 6: Maps colored to indicate the greatest contributors to the yield gains predicted under an RCP4.5 scenario with adaptation: application of adaptation strategies (pink), change in CO_2 concentration above 390ppm (green), change in precipitation (dark blue), warming level (orange), average precipitation (light blue), and average temperature (yellow).