Over Half of the Negative Crop Yield Variability Explained by Anthropogenic Indicators

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Abstract

High crop yield variation between years, impacted for example by extreme weather shocks and by other shocks on the food production system, can have substantial effect on food production. This, in turn introduces vulnerabilities within global food system. To mitigate the effects of these shocks there is a clear need for understanding how different adaptive capacity measures link to the crop yield variability. While existing literature provides many local scale studies on this linkage, no comprehensive global assessment yet exists. We assessed reported crop yield variation for wheat, maize, soybean and rice for time period 1981-2009 by measuring both yield loss risk (variation in negative yield anomalies considering all years) and changes in yields during only dry shock and hot shock years. We used machine learning algorithm XGBoost to assess globally the explanatory power of selected gridded anthropogenic indicators (i.e., adaptive capacity measures; such as Human Development Index, irrigation infrastructure, fertilizer use) on yield variation on 0.5 degree resolution, within climatically similar regions to rule out the role of average climate conditions. We found that the anthropogenic indicators explained 40-60% of yield loss risk variation whereas the indicators provided noticeably lower (5-20%) explanatory power during shock years. On continental scale, especially in Europe and Africa the indicators explained high proportion of the yield loss risk variation (up to around 80%). Assessing crop production vulnerabilities on global scale provides supporting knowledge to target specific adaptation measures, thus contributing to global food security.

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Key Points:

- Anthropogenic indicators can explain up to 60% of variation for the negative crop yields
- Less than 20 % of variation of crop yield anomalies during temperature or soil moisture shocks can be explained by anthropogenic indicators

Abstract

High crop yield variation between years, impacted for example by extreme weather shocks and by other shocks on the food production system, can have substantial effect on food production. This, in turn introduces vulnerabilities within global food system. To mitigate the effects of these shocks there is a clear need for understanding how different adaptive capacity measures link to the crop yield variability. While existing literature provides many local scale studies on this linkage, no comprehensive global assessment yet exists. We assessed reported crop yield variation for wheat, maize, soybean and rice for time period 1981-2009 by measuring both yield loss risk (variation in negative yield anomalies considering all years) and changes in yields during only dry shock and hot shock years. We used machine learning algorithm XGBoost to assess globally the explanatory power of selected gridded anthropogenic indicators (i.e., adaptive capacity measures; such as Human Development Index, irrigation infrastructure, fertilizer use) on yield variation on 0.5 degree resolution, within climatically similar regions to rule out the role of average climate conditions. We found that the anthropogenic indicators explained 40-60% of yield loss risk variation whereas the indicators provided noticeably lower (5-20%) explanatory power during shock years. On continental scale, especially in Europe and Africa the indicators explained high proportion of the yield loss risk variation (up to around 80%). Assessing crop production vulnerabilities on global scale provides supporting knowledge to target specific adaptation measures, thus contributing to global food security.

1 Introduction

The recent developments of population growth, urbanization, economic development, and climate change continue to cause significant pressure on the global food system (FAO, 2019). Food systems are vulnerable to systemic and environmental disruptions which can stem from anthropogenic factors such as shocks in food trade systems or environmental conditions such as unfavorable weather conditions (Cottrell et al., 2019). Short term supply shocks such as abrupt drop in the production quantities or crop yields can result in food scarcity which has propagating effects through global markets (Distefano et al., 2018). On longer term, especially small holders who produce around a third of global food (Ricciardi et al., 2018) face myriad of systemic factors hindering adaptation options, e.g., limited economic and financial resources, lower socioeconomic and educational status or unavailability of appropriate technologies (Cohn et al., 2017). Thus, to increase resilience within food production systems, it is important to identify areas most vulnerable to different disruptions.

The key drivers of food production shocks are extreme weather events together with geopolitical and economic events (Cottrell et al., 2019). However, the importance of these drivers is characterized by regional variation; for example, food production in South Asia suffers mostly from hydrological extremes (e.g., droughts and floods), whereas geopolitical and economic crises are the main shock drivers in Sub-Saharan Africa (Cottrell et al., 2019). All these shocks impact food security and especially the most vulnerable communities through food availability (Cottrell et al., 2019), food prices (Chatzopoulos et al., 2020) and quality of food (Fahad et al., 2017). To ensure better mitigation to the shocks, and thus more resilient food systems, it is important to better understand the key factors and the geographical features influencing the responses to these shocks.

Climatic conditions have been shown to be key factors in crop yield variation, explaining approximately 20-60% of the global crop yield variation (Ray et al., 2015; Vogel et al., 2019). However, we lack comprehensive understanding of the other key factors and the potential of human actions to mitigate crop yield losses. Findings from existing studies indicate that anthropogenic indicators related to socio-economic level and food production factors have potential to explain part of this gap. These studies have been focusing especially on droughts and climate change adaptation, suggesting that from vulnerability and adaptive capacity perspective, indicators such as high level of economic activity measured as gross domestic product (Simelton et al., 2009, 2012), human capital (e.g. (Antwi-Agyei et al., 2012; Gbetibouo et al., 2010) or increased irrigation (Fuss et al., 2015; Müller et al., 2018; Troy et al., 2015) seems to correlate well with lower vulnerability or less volatile crop yields. For fertilizer use, key crop production factor, the studied effects have been mixed. Using national scale data Simelton *et al.* (2012) and Kamali *et al.* (2019) found that fertilizer use was linked with lower vulnerability to droughts. On the other hand, Müller *et al.*, (2018) found in a global grid scale modelling study that while higher fertilizer use may lead to lower relative yield variability during years with good yields due to rising mean yields, years with adverse weather conditions do not experience benefit from additional nutrient inputs. Studies with unequal effects and varying spatial scales show that there is potentially high subnational heterogeneity in both yield variation as well as anthropogenic indicators. While the previous studies have been conducted on diverse spatial scales (from villages to country and global level), only one global study (Simelton et al., 2012) is linking multiple anthropogenic and production related indicators to crop yield variation, done using national scale data.

In this study, we shed light on the abovementioned vulnerability issue and its implications for resilience by focusing on crop yield variation and anthropogenic indicators on a subnational scale. More specifically, we examine 1) to what level long-term averages of selected anthropogenic indicators (see Data and methods) can explain negative crop yield variation, and 2) how well the anthropogenic indicators explain geographical differences in crop yield anomalies in responses to heat and drought shocks. We utilized XGBoost algorithm to create regression models where the response variable was observed crop yield data disaggregated to grid-level, and the explanatory variables were mostly subnational or higher resolution anthropogenic indicators; a considerable enhancement from using national scale data as done in existing studies. We used these global gridded datasets to study the relationship between anthropogenic indicators and the yield variation of four key crops: wheat, maize, soybeans and rice. The wheat, maize, soybean and rice are globally major staple crops covering 65% of global calorie intake (Tilman et al., 2011), with soybeans used also extensively as feed for livestock (Hartman et al., 2011). In addition, these crops cover slightly more than 25% of global food trade in terms of monetary values (MacDonald et al., 2015), thus having impact also on food security through global trade networks and for providing income for farmers.

2 Data and methods

In this study, we focus on six key societal and crop production related indicators: i) Human Development Index, ii) governance effectiveness, iii) fertilizer use (nitrogen, phosphorous and potassium), iv) water stress, v) irrigation and vi) agricultural suitability for growing crops (see Table 1). Here we refer to these socio-economic and food production indicators as "anthropogenic indicators" as they represent the human dimension controlling crop production. Unlike e.g. climatic factors, these can potentially be influenced and controlled by human actions and policies.

To study the differences among distinct climatic systems, we split the data into six geographical areas using Holdridge Life Zones that are based on three key climatological factors controlling crop production (precipitation, biotemperature, and aridity) (Holdridge, 1947; Holdridge, 1967; Kummu et al., 2021). We combined the original 38 Holdridge Life Zones into six zones with similar climatic characteristics: "Cool", "Temperate", "Steppe", "Arid", "Sub tropical", and "Humid tropical" (see Fig. S1). We then analysed the association between crop yield anomalies and the six indicators on 0.5 degree (~60 km at the equator) grid cell resolution with a gradient boosting regression algorithm XGBoost (T. Chen & Guestrin, 2016). This was used for three cases: *yield loss risk* for years 1981-2009 and *shock factor*-cases for "hot" and "dry" years. Data and methods are described in more detail below.

2.1 Data

2.1.1 Crop yield data

For the crop yield and harvested area data, we used rasterised (0.5 degree resolution) maize, rice, soybean and wheat annual yield and harvested area data (Ray et al., 2019) for years 1981-2009. The crop data from Ray *et al* (2019) is procured from census observations from around 20'000 political units and gaps within reported data is filled with 5-year averages. The crop yield dataset has been widely used in crop yield variation studies (e.g., Ray *et al* 2012, 2015, 2019, Vogel *et al* 2019).

Table 1 Description of the data used in the study and their sources.

Data name	Abbreviation	Description	Source
Holdridge Life Zones	HLZ	Produced by monthly climate data averaged over 1970-2000 (WorldClim v.2.1)	Kummu *et al* (2021)
Crop yield data			
Crop-specific annual yield and harvested area		Gridded data at 0.5 degree resolution. Data for years 1981-2009	Ray *et al* (2019)
Anthropogenic indicators			
Human Development Index	HDI	Subnational level HDI. 5 arc-minute raster; years 1995-2005	Smits and Permanyer (2019), data gaps filled using method from Kummu, Taka and Guillaume, (2018)
Governance effectiveness	GOV	5 arc-minute raster, national scale; years 1995-2005	WGI (2018)
Water stress	WS	Baseline water stress index 0-1; vector data with HydroBASINS6 resolution (Lehner & Grill, 2013)	Hofste *et al* (2019)
Irrigation infrastructure	WINF	Historical Irrigation Dataset of area equipped for irrigation: 5 arc-min raster, 1995-2005 in 5-year timesteps.	Siebert *et al* (2015)
Fertilizer use	FER	Crop-specific application rates of nitrogen, phosphorus, potassium; 5 arcmin raster, around year 2000	Mueller *et al* (2012, West *et al* (2014)
Suitability index	SI	Crop specific agro-climatic potential yields combined with soil/terrain data (GAEZ v3); 30 arc-min raster	Fischer *et al* (2012)
Temperature and soil moisture data			
Air temperature (°C)		Daily minimum and maximum temperature for years 1981-2009; re-gridded from 0.25 to 0.5 degree	AgMERRA reanalysis dataset by Ruane *et al* (2015)
Daily soil moisture (m^3/m^3)		Soil moisture attained at 12:00 as the daily estimate for soil moisture for years 1981-2009; re-gridded from 0.28 to 0.5 degree	ERA5 re-analysis dataset by Hersbach *et al* (2020)

2.1.2 Anthropogenic indicators

For the socio-economic data we used two indicators: Human Development Index (HDI) at subnational level (Smits & Permanyer, 2019) and national-level governance effectiveness (GOV; WGI 2018, Varis *et al* 2019). The gaps in HDI data were filled by using a method from (Kummu et al., 2018). Both indicators were rasterised to 5 arc-minute resolution spanning over 1990-2015.

To assess the use of water resources we used baseline water stress (WS; Hofste *et al.*, 2019) and area equipped for irrigation (WINF; Siebert *et al* 2015). Baseline water stress, i.e., average water withdrawals per available renewable surface and ground water supplies for the time period 1960-2014, was used as the indicator for local pressure on water use on hydrological subbasin level (HydroBASINS6). For fertilizer use (FER) we included a linear combination of crop-specific gridded application rates for three main fertilizer components: nitrogen, phosphorous and potassium (Mueller et al., 2012; West et al., 2014). These fertilizer fractions were combined using principal component analysis (PCA) with rasterPCA-function from RStoolbox – package (Leutner et al., 2019) in RStudio (RStudio Team, 2019), and the first component (highest variance explained) was used as an explanatory variable in the model. The reference year is mostly year 2000 whereas some data are collected between 1994-2001. Although the dataset provides only a snapshot for fertilizer application rates, to our knowledge there are no globally comprehensive timeseries on gridded fertilizer application rates. Furthermore, while changes in fertilizer application rates for some countries have changed substantially (especially in Southern Asia), the overall trend seems to be less drastic (Lu & Tian, 2017).

Suitability Index (SI) was extracted from FAO Global Agro-Ecological Zones (GAEZ) (Fischer et al., 2012). It aims to capture how suitable areas are to crop-specific cultivation based on different management practices and a set of environmental indicators, such as soil and terrain-slope conditions. Here, we utilized the crop specific global SI-raster with intermediate-level of inputs.

All the indicator datasets were rasterised and aggregated to 0.5 degree resolution (Fig. 1). Due to the lack of comprehensive timeseries data for several of the indicators, we used a raster cell specific average between 1995-2005 (where applicable, see Table 1) as a representative value for the whole time period. This may skew our results as some countries have experienced major economic growth and societal changes within our study period. However, globally the change for several indicators have been relatively modest (see e.g., Fig. S2 for subnational HDI). The selected time period of 1995-2005 represents roughly the middle point of crop yield data (1981-2009). To diminish the impact of outliers, all data were normalized between 2.5 and 97.5% of the respective ranges. The distributions and variable correlations are presented in Fig. S3.

2.1.3 Temperature and soil moisture data

Abiotic stresses caused by extreme climatic events such as prolonged periods of high temperatures (here used as "hot" shocks) or low soil moisture ("dry" shocks) can cause worsening conditions for crop growth through interference of multiple factors such as nutrient and water balance, photosynthesis or assimilate partitioning (Fahad et al., 2017). Here, we utilize air temperature (Ruane et al., 2015) and soil moisture (Hersbach et al., 2020) anomalies to study the links between crop yields and anthropogenic indicators during so called "shock years", as defined below.

To account for the intraday variation in temperature data, the daily temperatures were assumed to follow sine-function so that daily minimum and maximum temperature was the lowest and highest daily value, respectively. The amplitude of the variation was half of the difference between the daily low and high temperatures. For the daily soil moisture, the hourly soil moisture attained at 12:00 in the ERA5 data set was used as the daily estimate for soil moisture. To account for the different soil conditions globally, we standardized and transformed the data to relative soil moisture deficit. This transformation was done for each raster cell by subtracting daily values from the cell specific maximum reported daily soil moisture value for the whole time period and then dividing by the difference between minimum and maximum reported daily soil moistures.

Both temperature (0.25 degrees) and soil moisture (0.28) datasets were re-gridded to 0.5 degree resolution: temperature data were resampled using bilinear interpolation and the soil moisture data with piecewise linear interpolation. We used data from years 1981-2009 for both datasets. More detailed description of the method for temperature and soil moisture data manipulation is shown in Heino *et al.* (2021).

2.2 Methods

The general methodological framework is presented in Fig. 1, while more detailed description of the methods is given below.

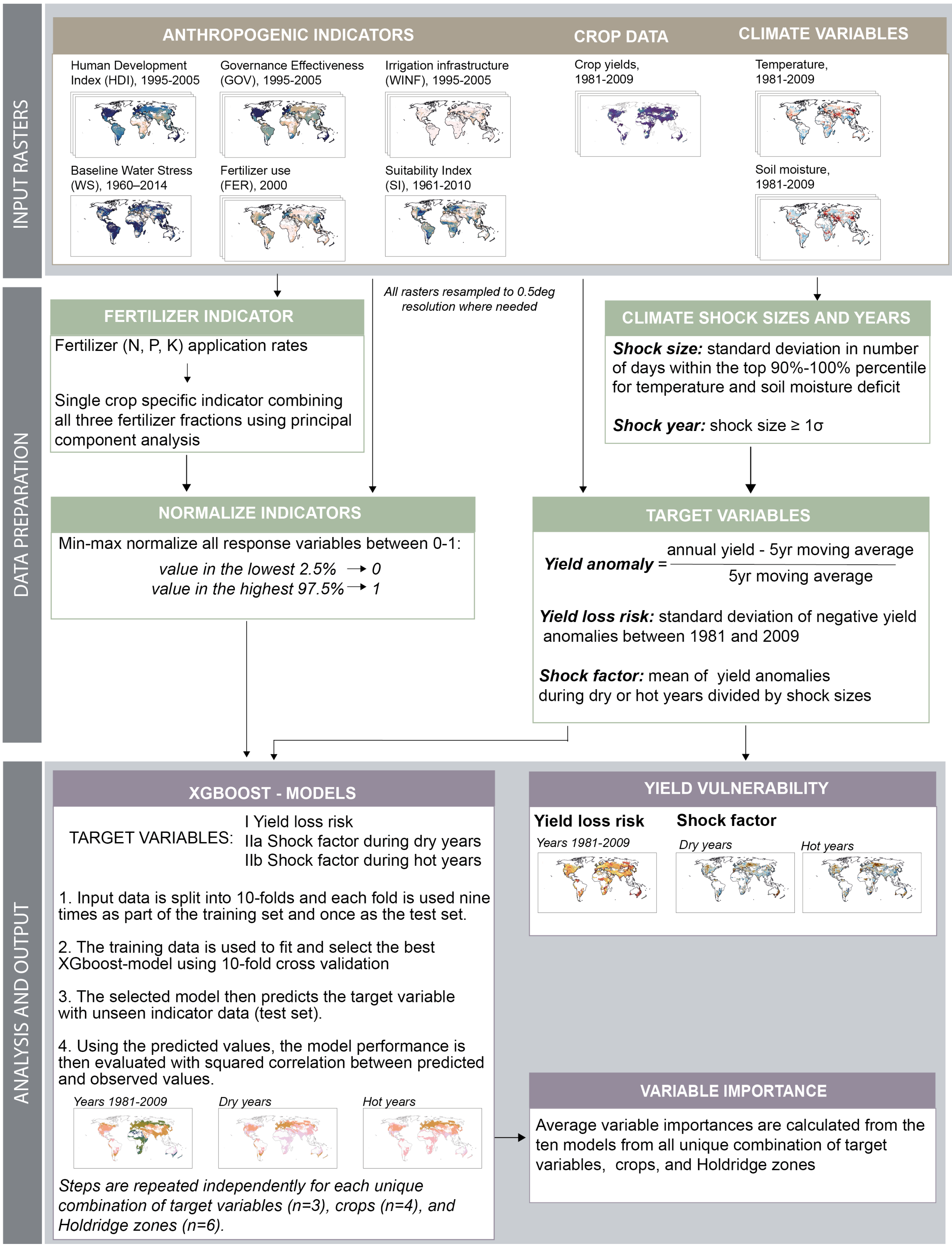

Figure 1 ***Conceptual methodological framework.*** *More detailed descriptions of the data sources and methods can be found in Sections 2.1 Data and 2.2 Methods.*

2.2.1 Yield loss risk

For studying the interannual variation in the yield anomalies, the annual absolute yields for each grid cell were first detrended by subtracting the running 5-year mean from the annual yields. Then these detrended yields were divided by the running 5-year mean of the annual yields to obtain comparable yield anomalies for each grid cell. The prevalence of the yield data is relatively stationary across the whole time-period as most of the grid cells have yield data for almost the whole study period.

The yield loss risk portrays the variation in loss events and is defined here as the standard deviation of negative yield anomalies within each grid cell across years 1981-2009. Higher yield loss risk in a given grid cell depicts larger extent of negative yield anomalies, i.e., higher losses in terms of annual yield. To obtain more representative yield loss risk, we removed all grid cells with less than 15 crop specific observations to limit the potential outliers in areas where extent of crop cultivation varies substantially from year to year. The sample sizes used for each Holdridge zone and crop combination as well as the distribution of the yield loss risk values are shown in Fig. S4.

2.2.2 Shock factor

To study the effect of extreme temperature and soil moisture anomalies on yields, we used two distinct cases: "hot years" denotes years with high temperatures and "dry years" those with very low soil moisture (Fig. 1). The extent of the anomalies was measured within each grid cell that fall above 90th percentile threshold for temperature and soil moisture deficit. Only years when the number of days was over one standard deviation higher compared to the cell specific mean ("hot" or "dry" years) were included in the shock models. Both cases were considered separately, thus a single year can belong into "hot", "dry" or both categories. For more detailed description of calculating the "hot" or "dry" conditions, see Heino *et al* (2021).

Both the temperature and soil moisture conditions have substantial interannual variation. To make the yield effects of the anomalies comparable for each grid cell-year pair, the absolute crop yield anomalies were scaled using the shock size, i.e., standard deviation in the number dry or hot days for a given year. Thus, a grid cell (0.5 degree) with similar crop yield anomalies, a year with higher *temperature or soil moisture* anomaly would receive a lower (closer to zero) value compared to year with lower anomaly. The sample sizes used for each Holdridge zone and crop combination as well as the distribution of the outcome values for "hot" and "dry" cases are shown in Fig. S5 and the unadjusted mean yield anomalies during shock years are presented in Fig. S6.

2.2.3 Modelling setup

We used predictive regression models to study the explanatory power of the anthropogenic indicators on crop yield anomalies. The models were built using gradient boosting algorithm XGBoost (T. Chen & Guestrin, 2016) which implements a non-parametric ensemble machine learning method utilizing weak learners, e.g., decision trees for various regression and classification tasks (Friedman, 2001). Decision tree models are generally well suited to detect non-linear relationships such as crop yields (Leng & Hall, 2020), as well as handle multicollinear variables, and they do not require assumptions on the distributions (e.g., assumption of normality) of the input data. This enables us to use data with non-normally distributed data (see Figs. S3-S5). In this study, the model implementation including model tuning and predictions was done using *xgboost*- and *caret*-packages (T. Chen et al., 2021; Kuhn, 2020) in R software (R Core Team, 2020).

We did three separate analyses looking at the association between crop yield variability and anthropogenic indicators with different outcome variables: yield loss risk and shock factors for "hot" and "dry" years (see Sections 2.2.1 and 2.2.2). For all outcome variables, the regressions were run separately for each Holdridge zone and crops to estimate the importance of the different variables in areas with similar climatic conditions. Holdridge zones with less than 250 observations (i.e., grid cells with data for all indicators) were excluded from the analysis. The performance of the models was assessed using the squared Pearson correlation coefficient (sign preserved) between the observed and predicted outcomes.

Similarity in observation caused by spatial autocorrelation can cause training and test sets to become similar if assigned randomly. This can lead to overly optimistic performance estimates, when in reality the good performance comes from overfitting (Meyer et al., 2019). To combat this issue in the training and test sets, we first split the grid points into small batches using global 100 x 100 hexagon grid with majority of hexagons covering 40-50 adjacent grid cells. All the grid cells within a single hexagon are assigned to the same training or test sets. We then used a nested cross-validation (CV) where first the outer CV splits the data into 10 folds with no overlapping grid points and uses each fold once for evaluating the model chosen in the inner CV loop. The outer cross-validation loop feeds nine folds to the inner CV that performs also 10-fold cross-validation to tune the hyperparameters using grid search with default settings in *caret*-package. The hyperparameter combination with the lowest root mean squared error was chosen. Accordingly, for each Holdridge zone, the outcome variable in a given grid cell was predicted using one of the 10 chosen models that did not use said grid point in the training phase.

To analyse the importance of the variables, we used *xgb.importance*-function from *xgboost*-package (T. Chen et al., 2021). The importance was measured as Gain-values, which indicates how the inclusion of a variable within a certain split of the boosted tree model improves the accuracy of the prediction. Higher Gain-value indicate that the variable was more important for the prediction. Using the variable importance, however, comes with a few caveats. Firstly, the importance does not reveal the actual direction of the relationship between a variable and the outcome variable. Secondly, collinear variables might not have accurate Gain-values as the models can "prefer" one of the collinear variables by putting more weight on the same variable at each split while disregarding the other collinear variables (T. Chen et al., 2018). To supplement the variable importance and to measure the direction of the relationships, we utilize accumulated local effects –visualization (ALE) that provides a method to assess the marginal effects different indicators have on the outcome variables (Apley & Zhu, 2020).

3 Results

3.1 Yield loss risk

We found substantial geographical distinctiveness when assessing the yield loss risk on each grid cell (Fig. 2). For wheat, the strongest negative anomalies occur in a major wheat producer country Australia, as well as North-eastern China and various parts of Africa (Fig. 2a). For maize and rice, the spatial pattern is somewhat similar, as largest risks occur in North-eastern Brazil, Southern Africa, Morocco, Middle East and parts of Central Asia (Fig. 2b, d). When comparing the values with the mean yield loss risks of respective Holdridge zones, especially Africa shows several hotspots for wheat, maize, and rice with over 20 percentage points higher risk for yield loss compared to the respective zone's mean value (Fig. S7). For soybean, while having lower yield loss risks, the most vulnerable areas were found in North-eastern China, eastern Europe and central Asia, Ethiopia as well as Uruguay and Northern Argentina (Fig. 2c).

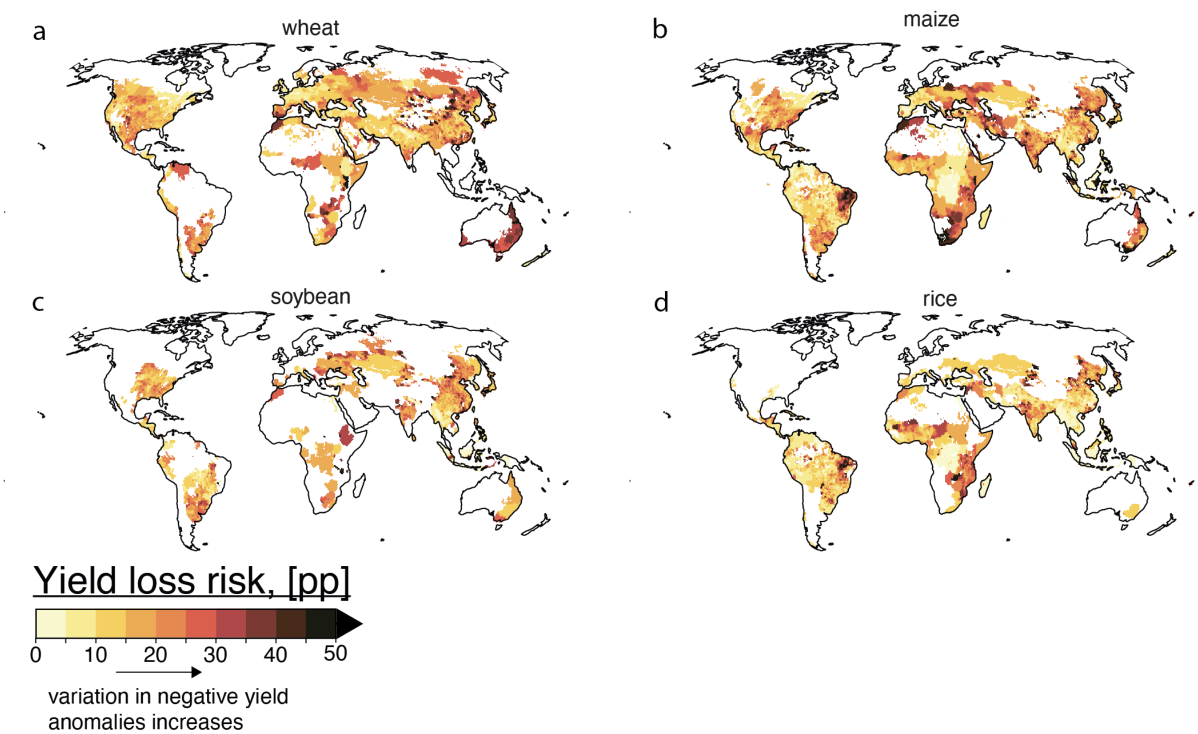

Figure 2 ***Yield loss risk, i.e., standard deviation of negative yield anomalies measured for a. wheat, b. maize, c. soybean, and d. rice****. Increasing yield loss risk indicates that a grid cell has larger negative yield anomalies (i.e., yields lower than 5-year average) during the study period. In other words, areas with higher yield loss risk experience worse negative yield anomalies than areas with lower yield loss risk. White areas indicate no production of the crop in question.*

3.2 Shock factor

When considering only the climatic shock, i.e. dry and hot years (see Methods), our findings highlight those areas with highest crop yield anomaly during shock years (Fig. 3; scaled so that comparable between grid cells; see Methods) are mainly same as those where the yield loss risk is the highest (Fig. 2). For example, the strongest negative yield anomaly for wheat during dry years (Fig. 3a) are found in Australia, similar to the yield loss risk (Fig. 3a). Also, Eastern Europe and Central Asia as well as parts of Midwestern Northern America shows high negative shock factor for wheat (Fig. 3a, b) and maize (Fig. 3c, d). Eastern United States and Southern parts of Latin America have the highest negative impacts in soybean cultivation from both hot and dry shocks. For rice, (Fig. 3g, h) there seems to be much less geographical variation and generally lower negative shock factors than the other crops, in line with previous studies where climatic conditions have been found to have lower effects for rice compared to other crops (e.g., Ray *et al* 2015). When comparing the shock factors to the mean of respective Holdridge zones (Fig. S8), all the studied crops show similar geographical patterns as in absolute shock factor values (Fig. 3) indicating that the mean effect across each of the climatic zones is rather minor (Fig. S9).

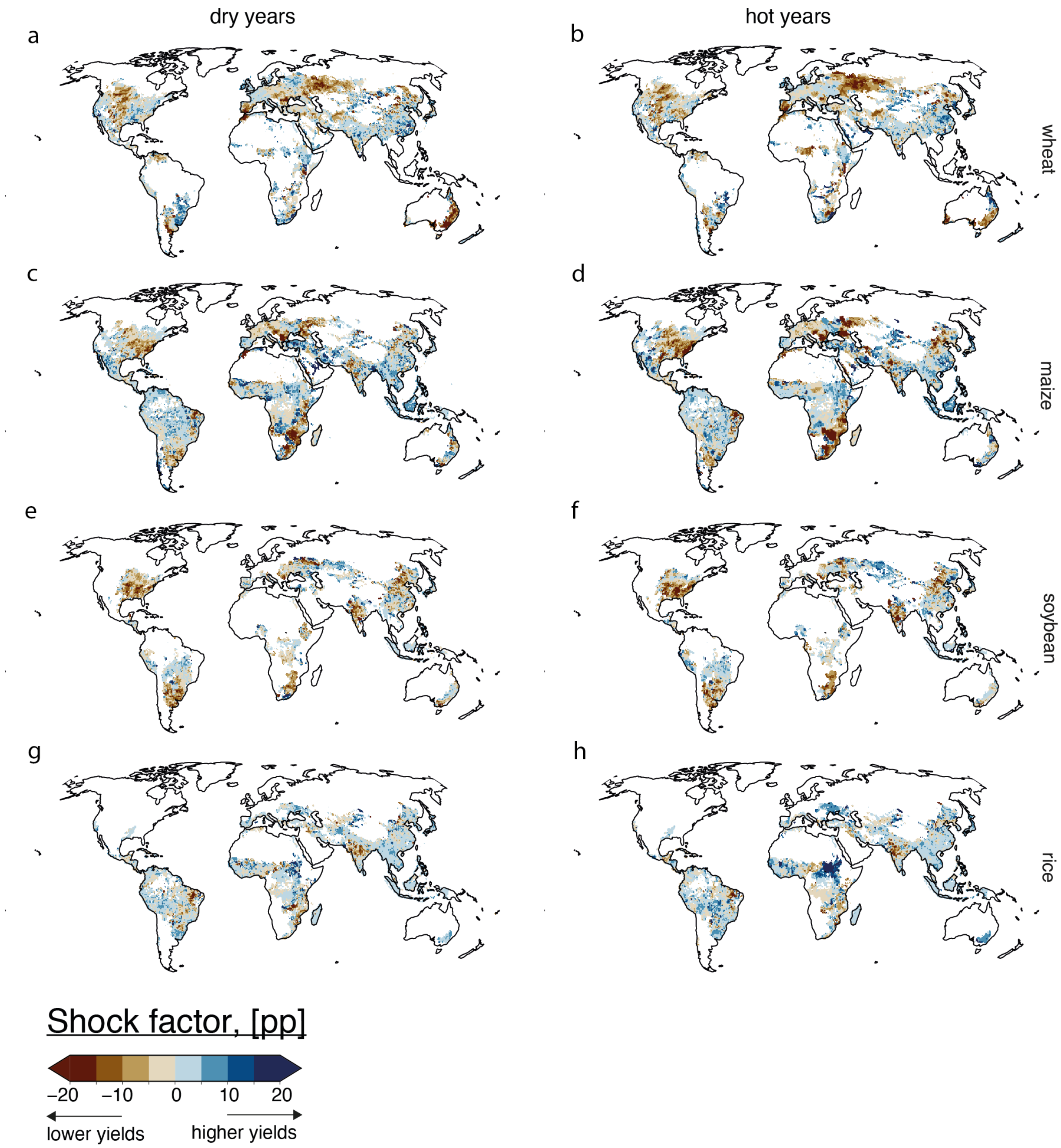

Figure 3 ***Mean yield anomalies during shock years adjusted by shock size.*** *The sign of the shock factor indicates whether the mean yields for shock years are higher (positive values; blue) or lower (negative values; brown) than the running 5-year mean yield. The size of the shock factor indicates how large the shock size adjusted yield anomaly is during shock years. Dry years are those when number of days with soil moisture deficit in the >90th percentile is more than 1 standard deviation from the long-term mean. Hot years indicate that the number of days when number of days with air temperature in the >90th percentile is more than 1 standard deviation from the long-term mean.*

3.3 Explanatory power of anthropogenic indicators

Anthropogenic indicators had substantially higher explanatory power in *yield loss risk* -case compared to when only shock years, either "dry" or "hot", were examined (Fig. 4). This applies to all the studied crops and Holdridge climate zones. For the yield loss risk-case, the explanatory power of the models across both the crops and Holdridge zones seem to be quite clustered, whereas for the shock cases, especially hot years have somewhat larger range of values with regards to the explanatory power of the models (e.g., Cool, Temperate, Steppe and Subtropical zones: Fig. 4a, b, c, e). The mean explanatory power for yield loss risk varied generally between 40-60%, depending on climate zone (Fig. 4) and crop (Fig. 5), whereas the mean explained variation in shock years was substantially lower, around 5 to 20%.

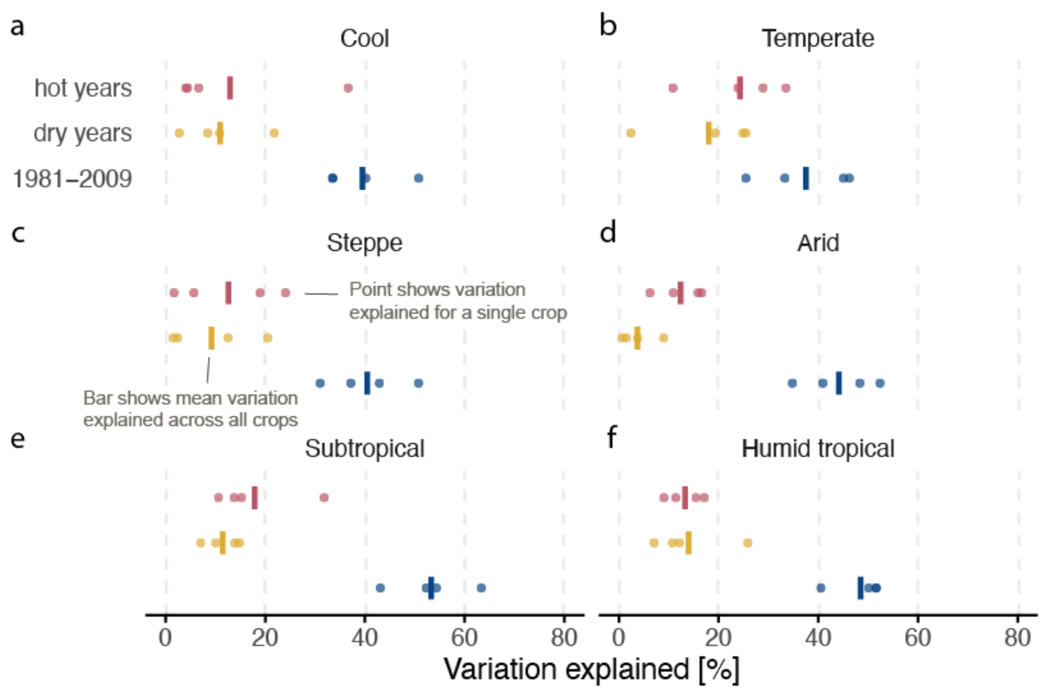

Figure 4 Variation explained within different Holdridge zones. Blue colour represents yield loss risk -case for years 1981-2009, and yellow and red colours represent shock factor -cases for dry and hot years, respectively (see Methods). Each point represents variation explained by models for single crop and horizontal bars represent the mean explanatory power across all crops. Explained variation is measured as the squared Pearson's correlation coefficient between the observed and predicted outcome.

The explanatory power for yield loss risk in years 1981-2009 was rather similar (in average around 40-50%) across all crops (Fig. 4). The best model performance in explaining the yield loss risk was observed in Subtropical and Humid tropical climate zones (ca 50-55% on average), and lowest in Cool and Temperate zones (around 40%) (Fig. 4). In terms of hot/dry shock years only, the mean shock factors were usually better explained in hot years, the difference to dry years being in average 5-10 percentage points. For the crops, wheat models (Fig. 5a) had the largest mean explanatory power for hot years (around 20%) while the mean value for dry years was around 10% for wheat, maize and soybean and lower for rice (Fig. 5).

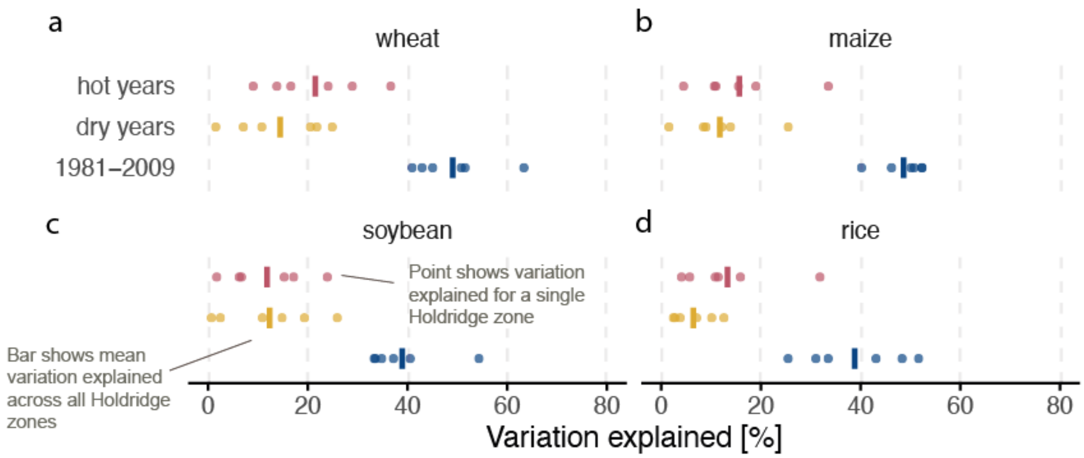

Figure 5 Variation explained for different crops. Blue colour represents yield loss risk -case for years 1981-2009, and yellow and red colours represent shock factor -cases for dry and hot years, respectively (see Methods). Each point represents variation explained by models for single Holdridge zone and horizontal bars represent the mean explanatory power across all Holdridge zones. Explained variation is measured as the squared Pearson's correlation coefficient between the observed and predicted outcome.

Measuring the explained variation for intersections of Holdridge zones and continents shows substantial geographical variation for all the crops in the *yield loss risk* -case (Fig. 6). In majority of Africa, for example, the explained variation was above 50% for all the crops. For the temperate regions in Europe and United States the fitted models explained over 40% of the variation for wheat (Fig. 6a) and maize (Fig. 6d). By contrast, for the majority of the areas, the models captured less than 30% of the variation in mean yield anomalies during shock years. Only wheat (Fig. 6c) and maize (Fig. 6f) models in the Temperate Holdridge zones during hot years performed better, having explanatory power over 40%. The explanatory power was particularly low, for both dry and hot years, for areas in Latin America and East Asia.

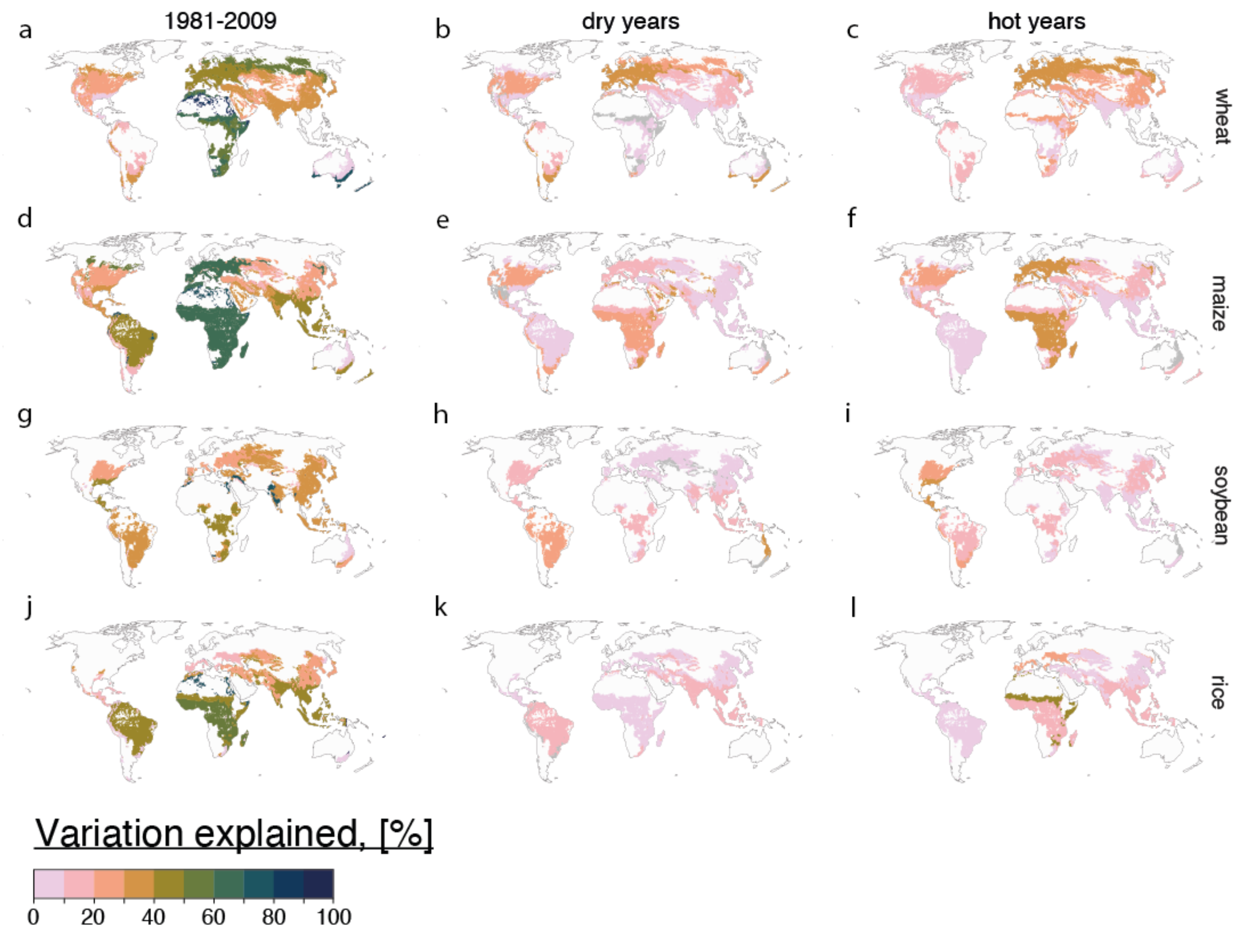

Figure 6 ***Explanatory power of the models within intersection of each Holdridge zone and continents for each crop (n = 37-42).*** *Explained variation is measured as the squared Pearson's correlation coefficient between the observed and predicted outcome.*

3.4 Importance of anthropogenic indicators

On global average, the most important predicting indicators were Human Development Index (HDI), governance (GOV) and fertilizer use (FER) (Fig. 7). However, these indicators, especially FER, also had the highest range in importance values across different crops and climate zones (Fig. 7e). When comparing the shock years to the general yield loss case, some interesting differences were observed: the socio-economic indicators (HDI, GOV) had higher importance in yield loss case than shock years, while for all other indicators, except for WS with no difference, the relationship is the opposite (Fig. 7). The difference is particularly strong in case of GOV, which is much more important in yield loss case than in shock case. This indicates that the importance of different anthropogenic indicators is different in 'normal' conditions than shock conditions.

When assessing the direction of the association between the indicators and the yield loss risk, indicators such as HDI or FER had quite varying impacts within different Holdridge zones (Fig. S10). Quite unsurprisingly, higher fertilizer use seems to contribute to lower yield variability for all the Holdridge zones with the exception for a few areas such as steppe for maize and soybean and subtropical for wheat. For HDI, the relationships between the indicator value and modelled variation were often nonlinear. Increasing of HDI over the 0.5 normalized HDI (i.e., half of the maximum HDI value) seems to yield substantially less variation in yield loss risk (Fig. S10).

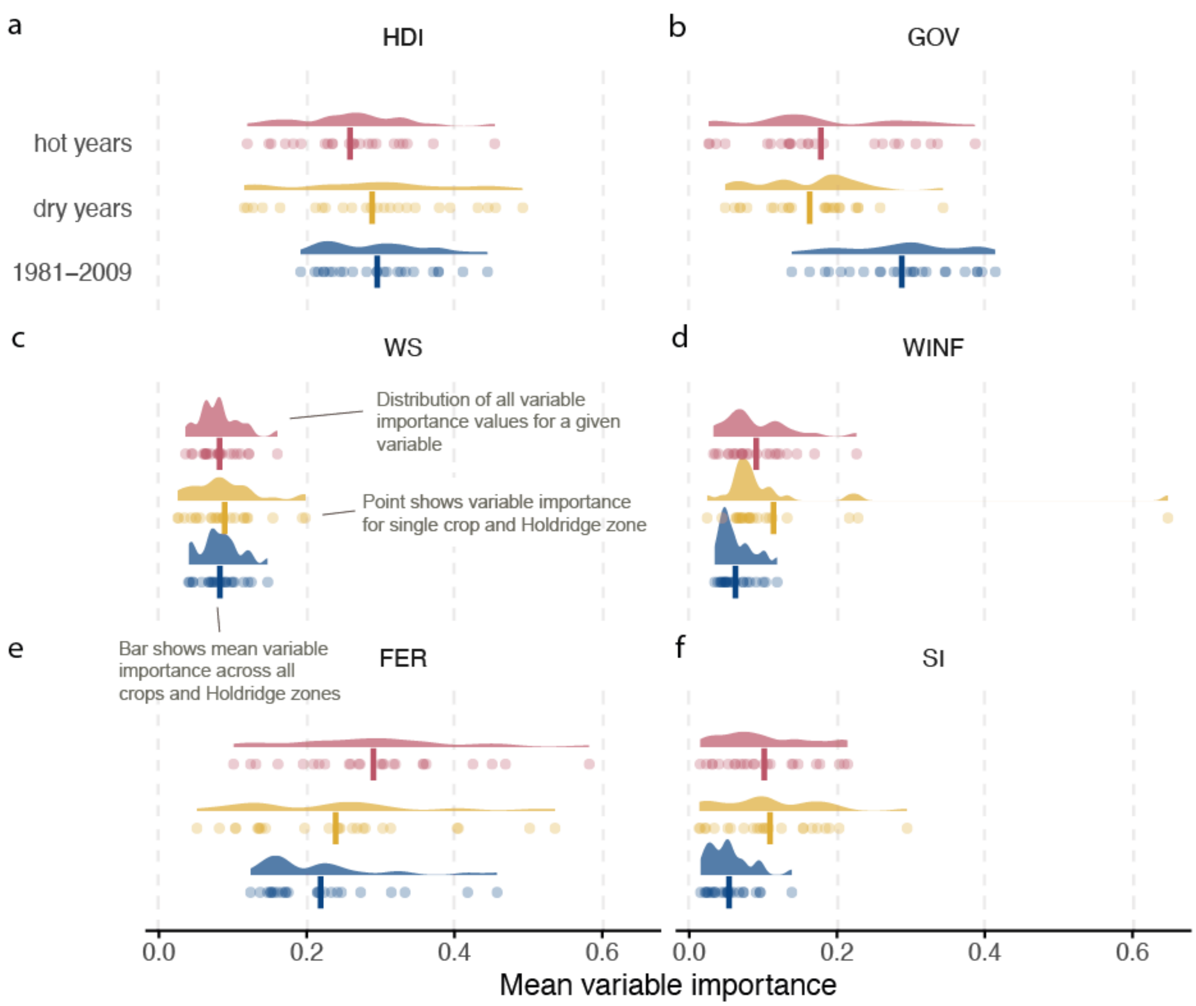

Figure 7 ***Mean variable importance for each indicator.*** *The indicators included are* ***a. Human Development Index (HDI), b. Governance efficiency (GOV), c. water stress (WS), d. irrigation infrastructure (WINF), e. fertilizer use (FER)*** *and* ***f. Suitability index (SI)****. Variable importance is measured as mean Gain-values of models (n=10) for a given crop (n=4) and Holdridge zone combination (n =24). Higher Gain-value indicates that the variable is more important making the prediction. Blue colour represents yield loss risk -case for years 1981-2009, and yellow and red colours represent shock factor -cases for dry and hot years, respectively (see Methods). Each point represents variable importance for single model for a given crop and Holdridge zone, the distribution shows how tightly clustered the variable importance values are, and horizontal bars represent the mean explanatory power across all crops and Holdridge zones.*

4 Discussion and conclusions

4.1 Key findings

We studied crop yield vulnerabilities and their relationship to global socioeconomic indicators with three specific cases. First, we focused on yield variation measured as standard deviation of the negative yield anomalies (*yield loss risk -case*). In the other cases, we considered mean yield anomalies during shock years only (hot years for high temperature and dry years for high soil moisture deficit). Our results suggest that the long-term mean of the selected anthropogenic indicators has substantial explanatory power over the variation of negative yield anomalies within different climatological contexts (Fig 4. and Fig. 6). While the indicators used here are not necessarily directly linked to different adaptation capabilities, they seem to have clear association with the yield variation for most of the studied crops and Holdridge climatic zones.

When using mean yield anomalies during shock years as the target variable, the explanatory power is noticeably lower than in yield loss risk -case (Fig. 3 and Fig. 4). One potential reason for the difference is that the indicators with only a single long-term average for a given indicator cannot capture the potential for adaption measures that are employed on farm level during the shock years. The farm-level management decisions together with sufficient regional diversity in farm characteristics can reduce the regional impacts of climate related shocks (Reidsma et al., 2010). In addition, decision to employ adaptation measures can depend on many factors, such as cultivated crop type (grain or cash crop), education level, access to electricity for irrigation, or access to credit (Alauddin & Sarker, 2014; Bryan et al., 2009; H. Chen et al., 2014). With generic indicators such as HDI we cannot differentiate the actual locations where adaptation methods are utilized.

The most important indicators support the fact that areas with increasing HDI and fertilizer use values have lower negative yield variation which supports also findings of existing studies (Antwi-Agyei et al., 2012; Kamali et al., 2019; Simelton et al., 2012). However, the relationship between different indicators and yield variability is not straightforward in many areas. For example, HDI and yield variation had a convex relationship as areas with low and high HDI have considerably lower yield loss risk compared the "middle-ground" areas (Fig. S10). Studies such as Reidsma *et al.* (2010) and Bharwani *et al.* (2005) suggest that poorer farmers might be better at adapting to climate variability compared to richer farmers who respond more actively to market signals rather than climate signals. Simelton *et al.* (2012), who also observed similar results, hypothesized that farmers in poorer countries relied on more traditional farming and adaptation methods which are no longer utilized when country moves from poor to middle-incoming country, thus increasing drought vulnerability.

Surprisingly, irrigation infrastructure (WINF) was relatively unimportant indicator for the predictions (Fig. 7) even though it has been previously identified as major factor reducing crop yield variation as well as buffer against extreme warm days (Butler & Huybers, 2013; Troy et al., 2015; Vogel et al., 2019). The dataset used here (Siebert et al., 2015) is not crop specific, thus detecting effects of irrigation for a certain crop may be challenging. While we used same irrigation infrastructure extent for all the crops, there are major differences where irrigation is used with a given crop (Portmann et al., 2010), creating noise in the model.

4.2 Limitations and way forward

Assessing the relationship of crop yield anomalies and anthropogenic indicators on a global scale has several challenges. Firstly, comprehensive global timeseries on farm-management practices that span sufficient long time period are non-existent. Using long term mean values for indicators might not be representative for countries that have experienced drastic changes during the study time period. Secondly, we employ a set of rather generic indicators which might not correlate directly with the management practices and decision done in the farms. While generic indicators such as gross domestic product or human development index are generally used as proxies for location specific adaptive capacity, more specific political and socio-economic contexts are needed to measure the impacts of specific interventions (Challinor et al., 2010). However, to our knowledge, comparable data on a global scale at subnational or higher resolution does not exist. Further, crop responses may be highly non-linear compared to each other, (Jackson et al., 2021), thus selecting an arbitrary shock threshold may have very different adaptation implications depending on the crop in question. Also, additional environmental factors such as soil type may have substantial impacts on the results (Folberth et al., 2016) further complicating the relationships.

4.3 Concluding remarks

The global food systems are facing increasing risks as the hot and dry conditions are getting more common (Sarhadi et al., 2018). Further, the increasing shocks can affect multiple crops or crops within different "breadbaskets" simultaneously (Gaupp et al., 2020; Tigchelaar et al., 2018) causing major challenges especially from food security perspective if the lack of production cannot be compensated by trade. From a longer time perspective, climate change is also pushing substantial size of the food production outside of the current. climatic conditions (Kummu et al., 2021). These changes amplify the need for understanding local vulnerabilities across the globe. The results from our high-resolution study indicate the most vulnerable crop production areas to negative crop yield variability, where prioritizing the mitigation efforts could increase the local food security. While the variation in yields cannot be entirely prevented, agricultural policies which support increasing local nutrient availability through nutrient recycling and effective fertilizer use promote resilience towards shocks. In addition, proper social and institutional support as well as understanding local contexts when developing the areas suffering from low education and poverty have important contribution for supporting local food security.

Acknowledgments, Samples, and Data

The authors declare no conflicts of interest relevant to this study.

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Author contributions

PK, MT, MK created initial study design. PK and MH were responsible for the analyses. DKR supplied crop yield data. PK wrote the manuscript with contributions from, MH, MT, VS and MK.

Code availability

All the codes for creating the results in this paper are available at https://github.com/pskinnun/shock_vulnerability

Data availability

All raw data sources are open sourced and available online.

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Earth's Future

Supporting Information for

Over Half of the Negative Crop Yield Variability Explained by Anthropogenic Indicators

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Contents of this file

Figures S1 to S10

Introduction

This supporting information provides additional figures to support the findings of the main text.

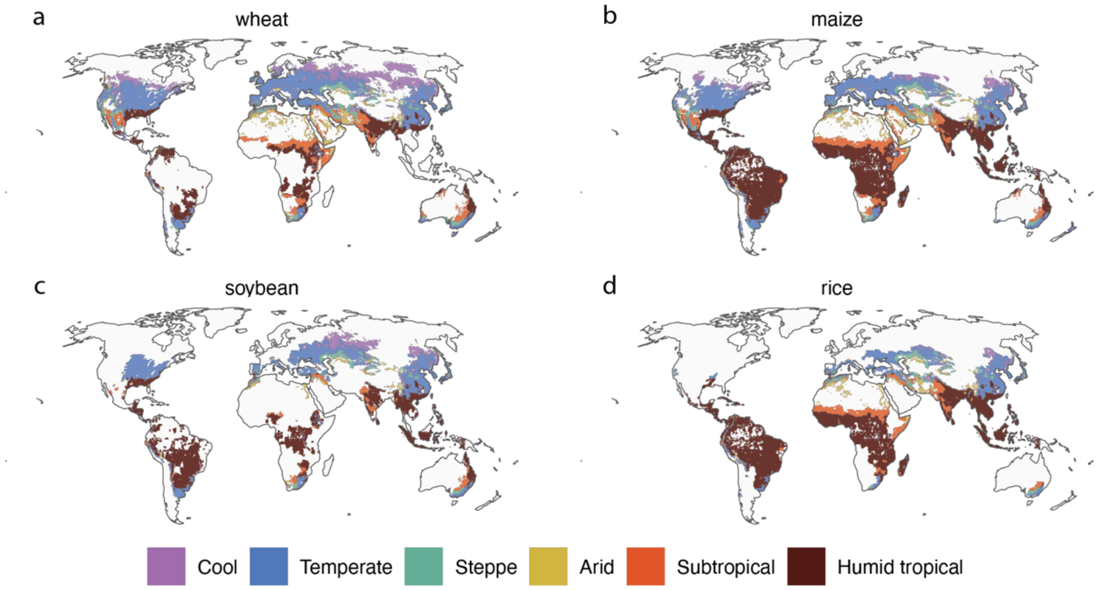

Fig. S1 Holdridge areas intersected with crop growing areas for a. wheat, b. maize, c. soybean and d. rice.

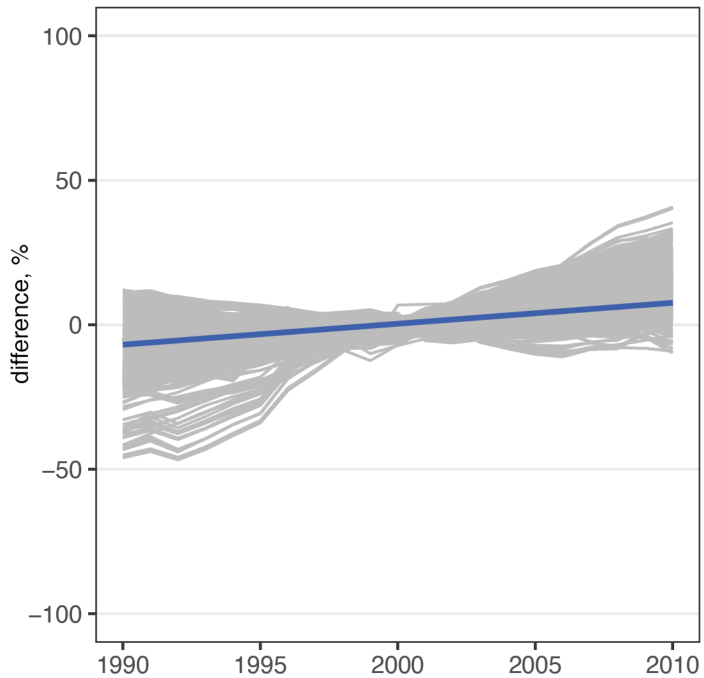

Fig. S2 Difference of subnational Human Development Index (HDI) values (1990-2010) compared to the mean of 1995-2005. We sampled 5000 grid cells from the subnational HDI raster and plotted the timeseries for HDI values for each grid point. Grey lines portray values for the grid cells and blue line depicts linear trend for all the sampled grid cells.

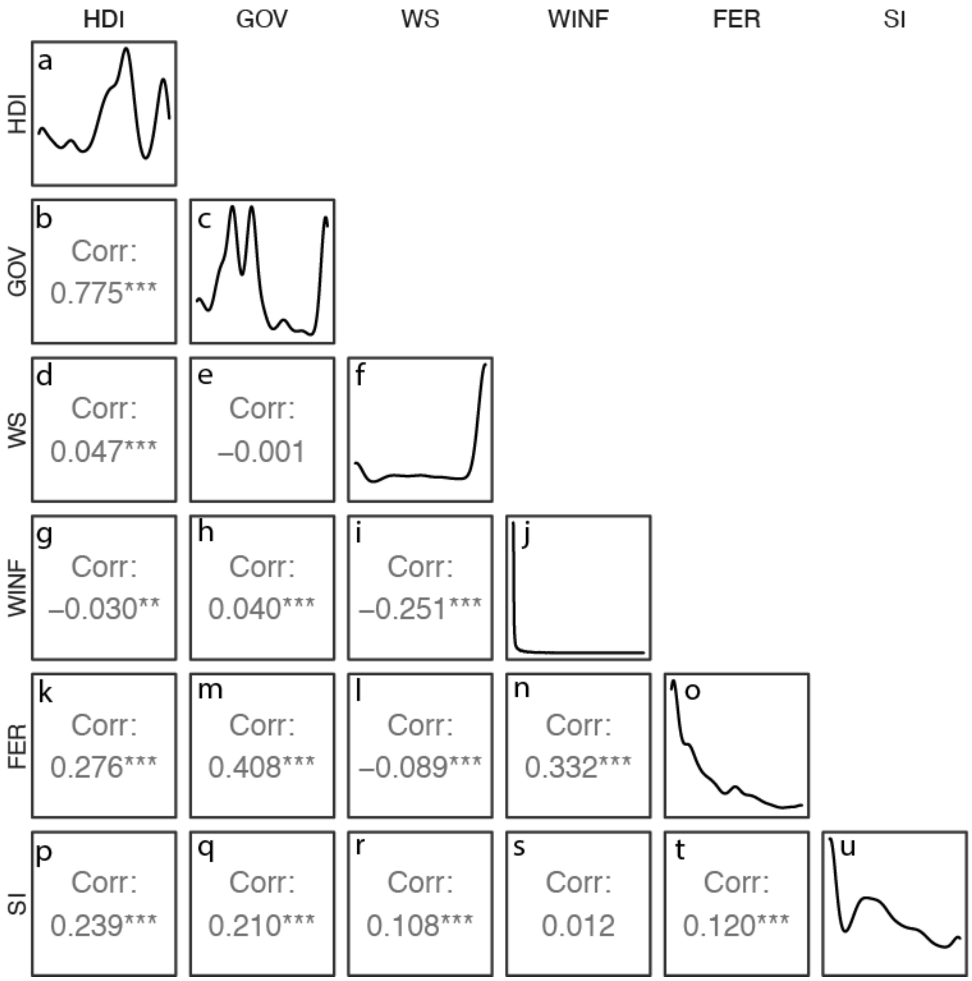

Fig. S3 Distributions (diagonal) and variable correlations for the anthropogenic indicators.

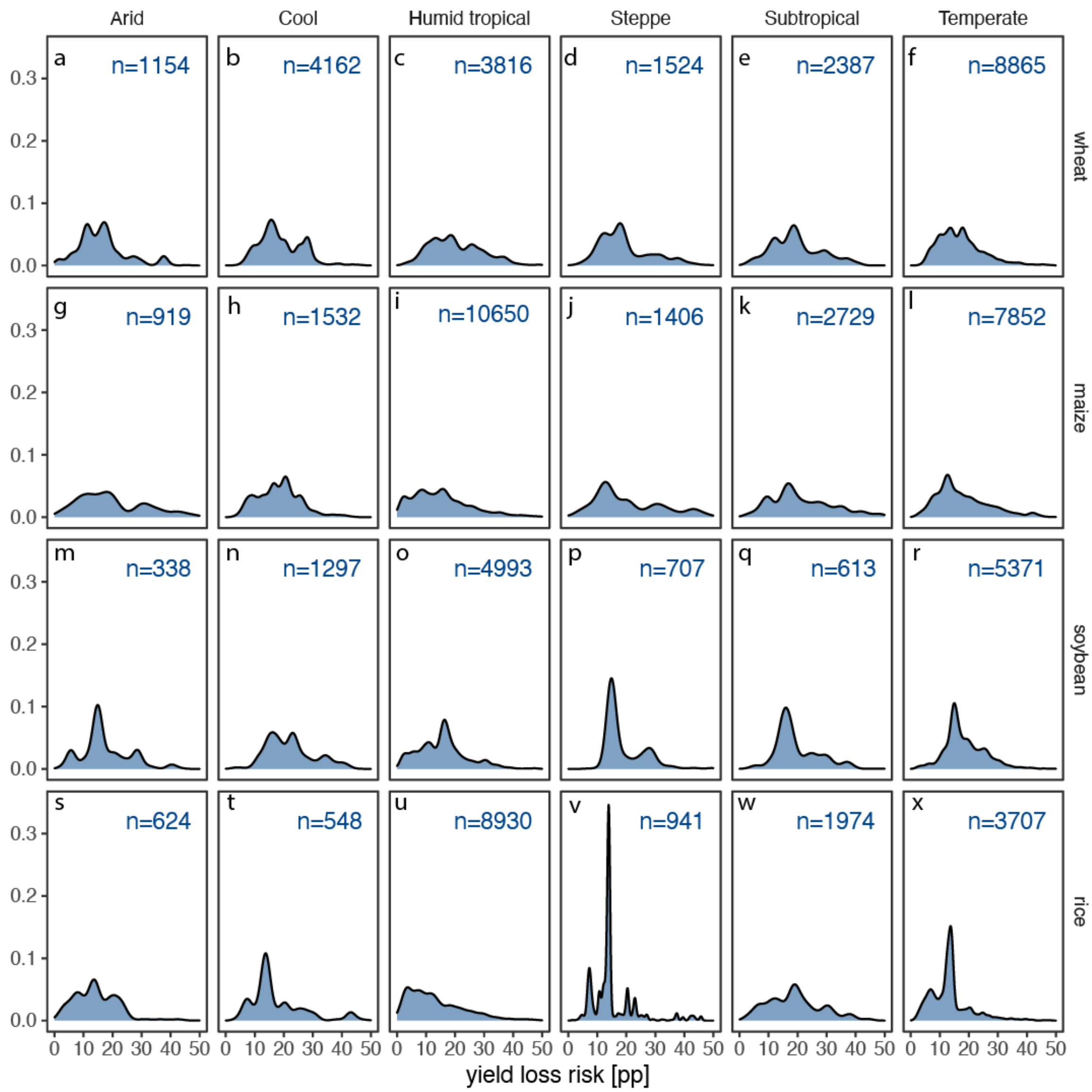

Fig. S4 Distributions and sample sizes (number of cells) used to train the models in the yield loss risk -case. Higher yield loss risk indicates that a grid cell has larger spread in negative yield anomalies (yields lower than running 5-year average) during the study period.

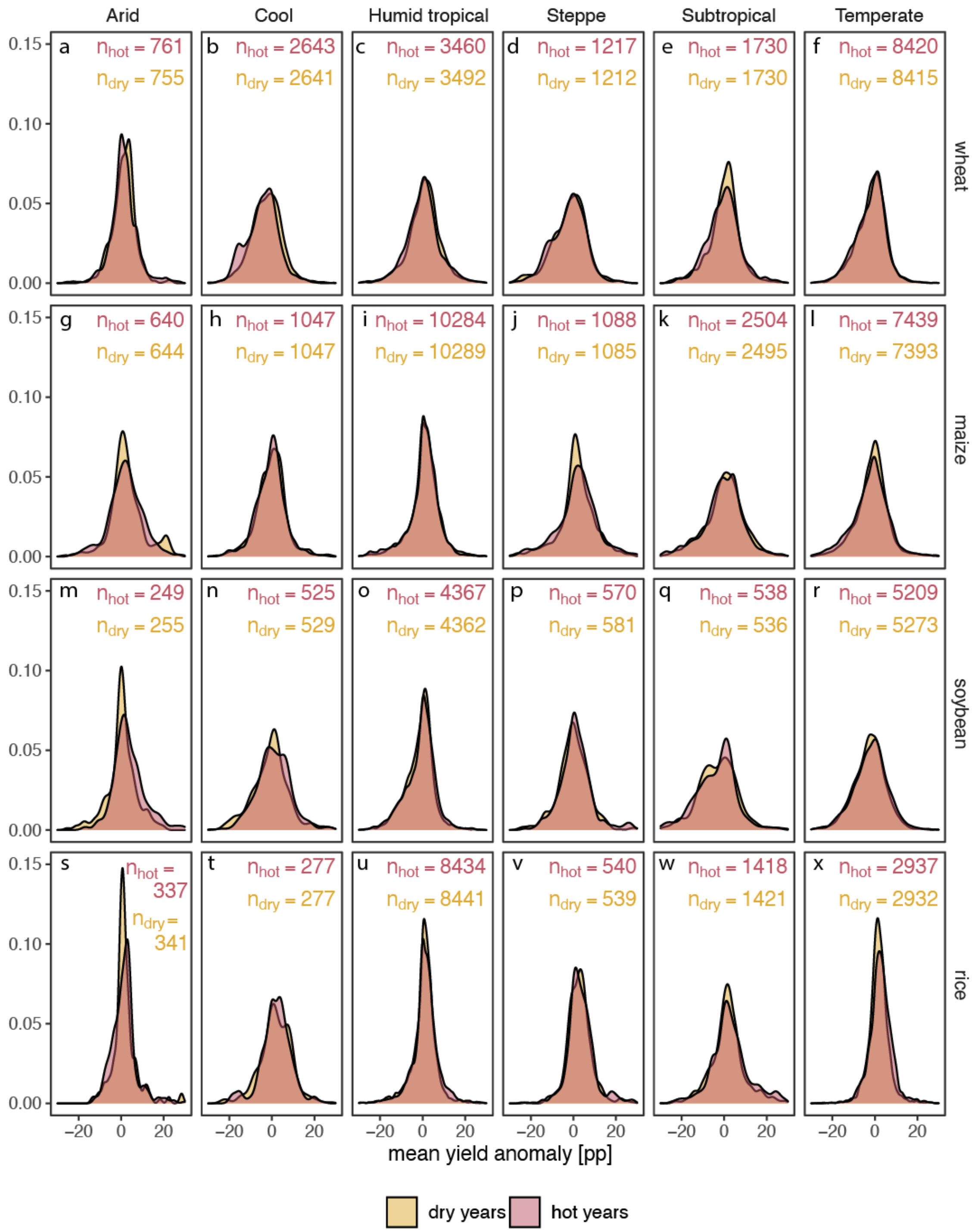

Fig. S5 Distributions and sample sizes (number of cells) used to train the models in the shock factor - cases. Dry years are those when soil moisture deficit is in the >90th percentile is more than 1 standard deviation from the long-term mean (as the number of days). Hot years indicate that the number of days when air temperature is in the 90-100% percentile is more than 1 standard deviation from the long-term mean.

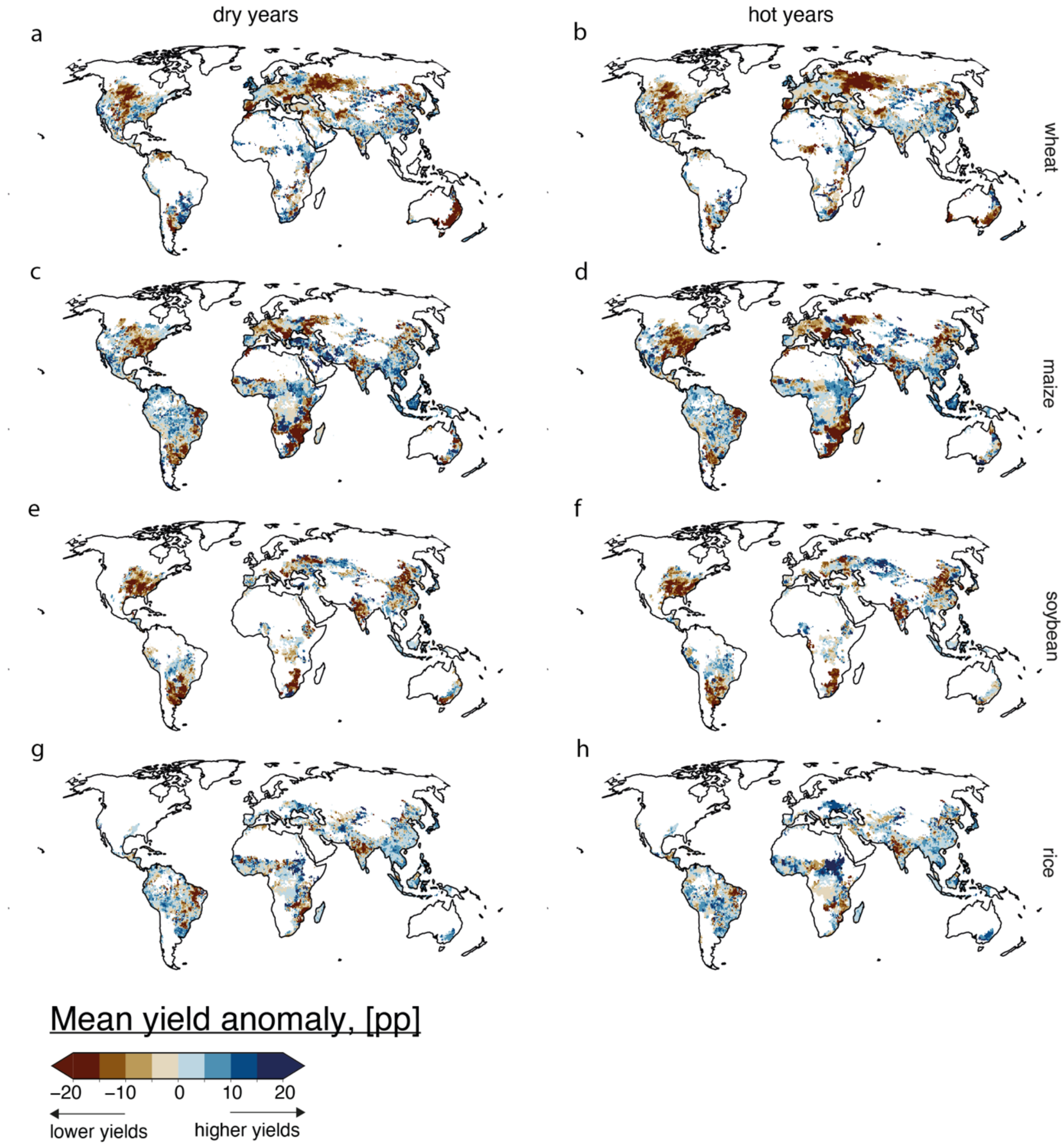

Fig. S6 Mean yield anomalies during shock years. The sign of the yield anomaly indicates whether the mean yields for shock years are higher (positive values; blue) or lower (negative values; brown) than the running 5-year mean yield. Dry years are those when number of days with soil moisture deficit in the >90th percentile is more than 1 standard deviations from the long-term mean. Hot years indicate that the number of days when number of days with air temperature in the >90th percentile is more than 1 standard deviation from the long-term mean.

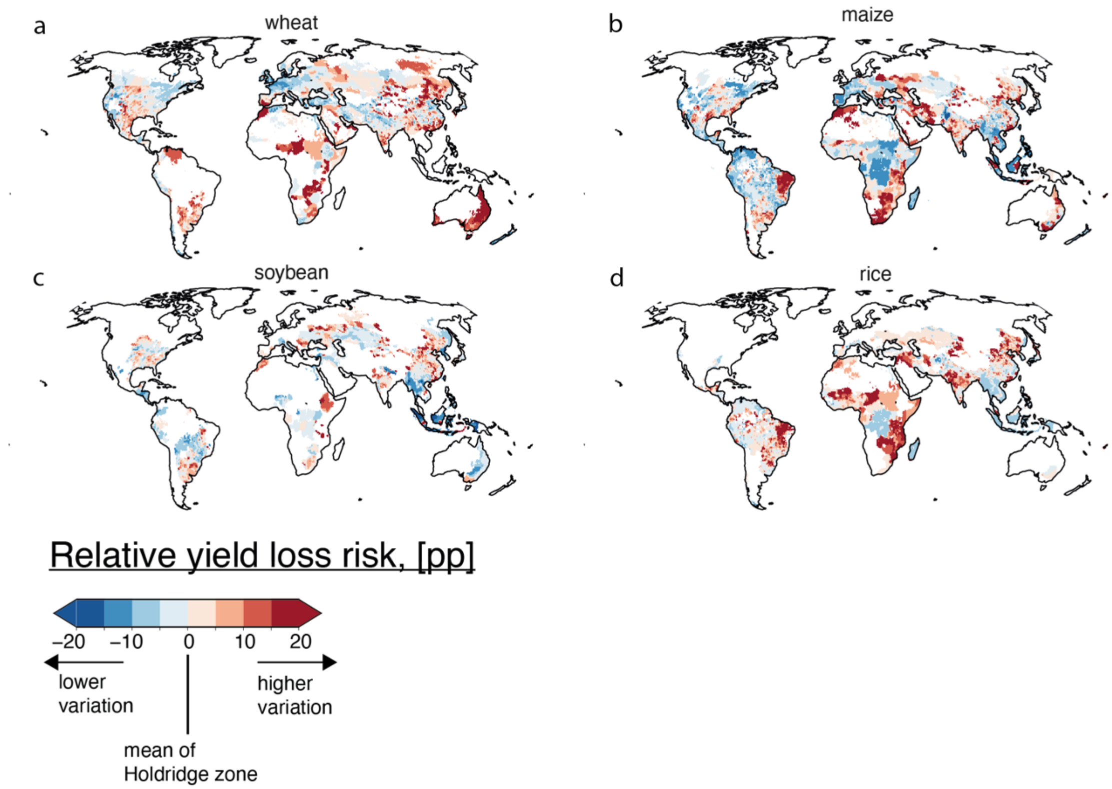

Fig. S7 Difference (as percentage points) between yield loss risk (standard deviation of negative yield anomalies) compared to the mean yield loss risk weighted by mean harvested area for a Holdridge zone for a. wheat, b. maize, c. soybean, and d. rice. Increasing yield loss risk (in red) indicates that a grid cell has larger spread in negative yield anomalies (yields lower than running 5-year average) during the study period compared to the mean yield loss risk of the respective Holdridge zone. Decreasing yield loss risk in (blue) indicates smaller variation in negative yield anomalies compared to the weighted mean of the respective Holdridge zone. Values close to zero indicate that the yields align the Holdridge zone's mean yields over 1981-2009, and white areas indicate no production of the crop in question.

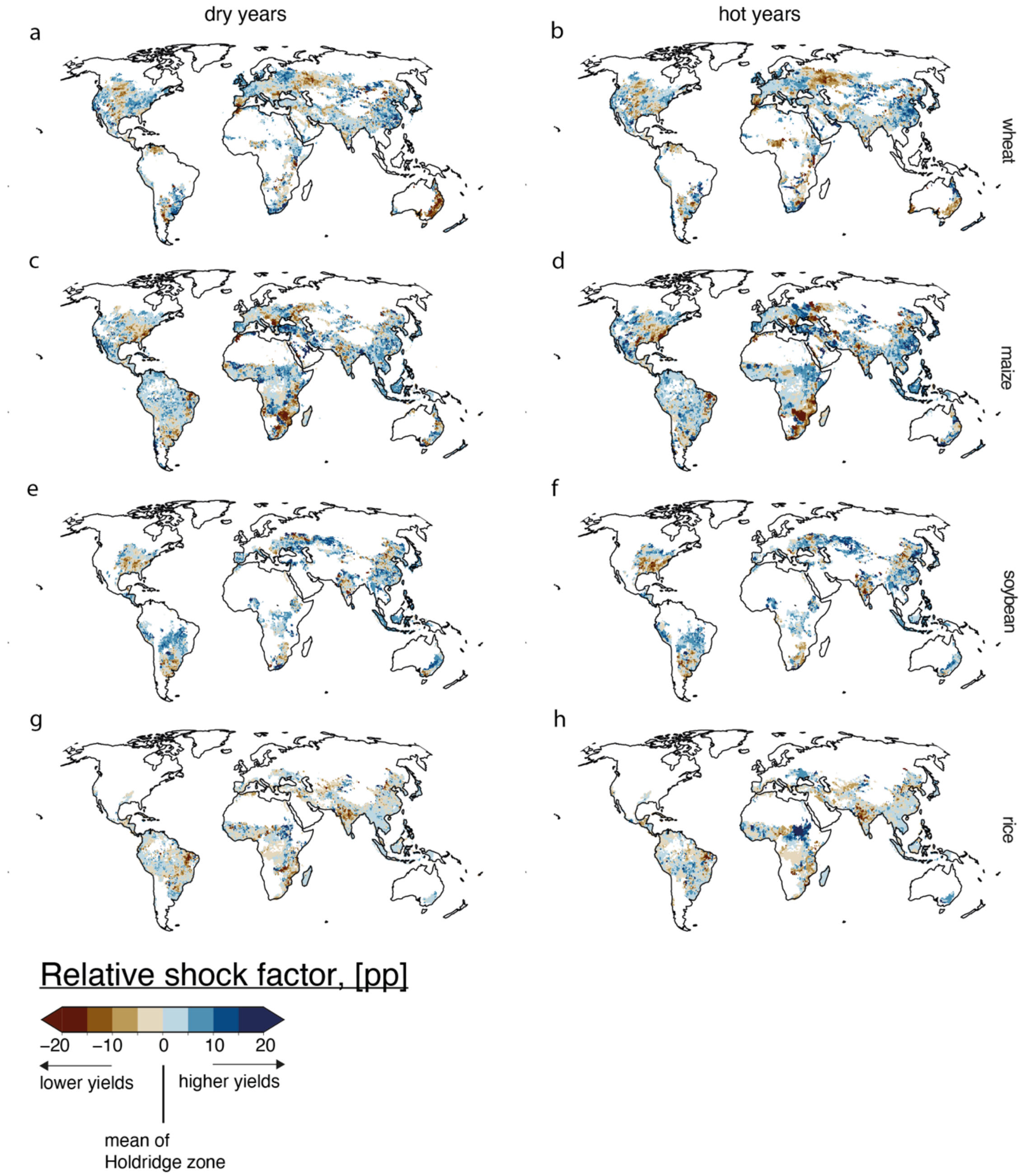

Fig. S8 Difference (as percentage points) in shock factors across shock years. Dry years are those when soil moisture deficit is in the >90th percentile is more than 1 standard deviation from the long-term mean (as the number of days). Hot years indicate that the number of days when air temperature is in the 90-100% percentile is more than 1 standard deviations from the long-term mean. For each grid cell, the mean shock factors are compared to the mean of the whole Holdridge zone. Negative value indicates that the detrended yields normalized by shock sizes are lower than the mean value for a given Holdridge zone. Positive value (blue) indicates that yields during shock years are higher than the mean value for a given Holdridge zone.

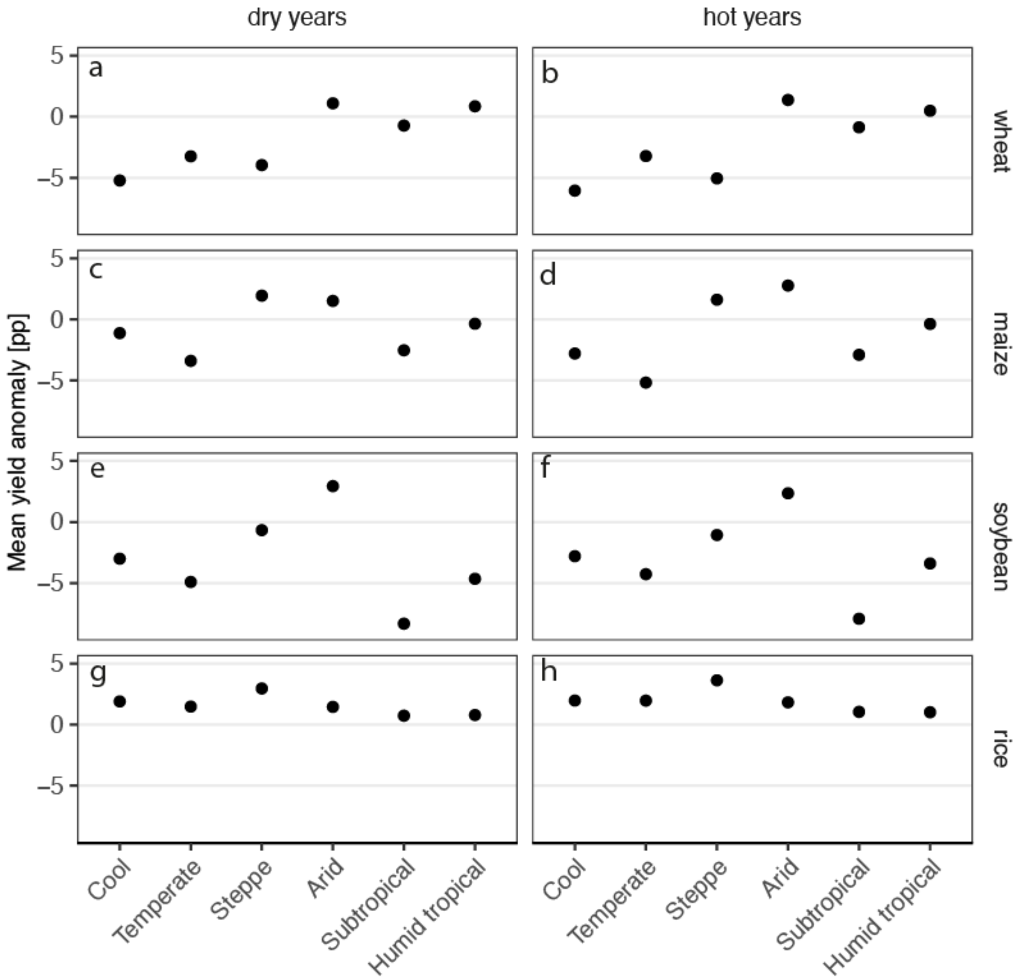

Fig. S9 Mean yield anomalies during temperature ("hot") and soil moisture ("dry") shock years in Holdridge zones. Dry years are those when soil moisture deficit is in the >90th percentile is more than 1 standard deviation from the long-term mean (as the number of days). Hot years indicate that the number of days when air temperature is in the 90-100% percentile is more than 1 standard deviation from the long-term mean.

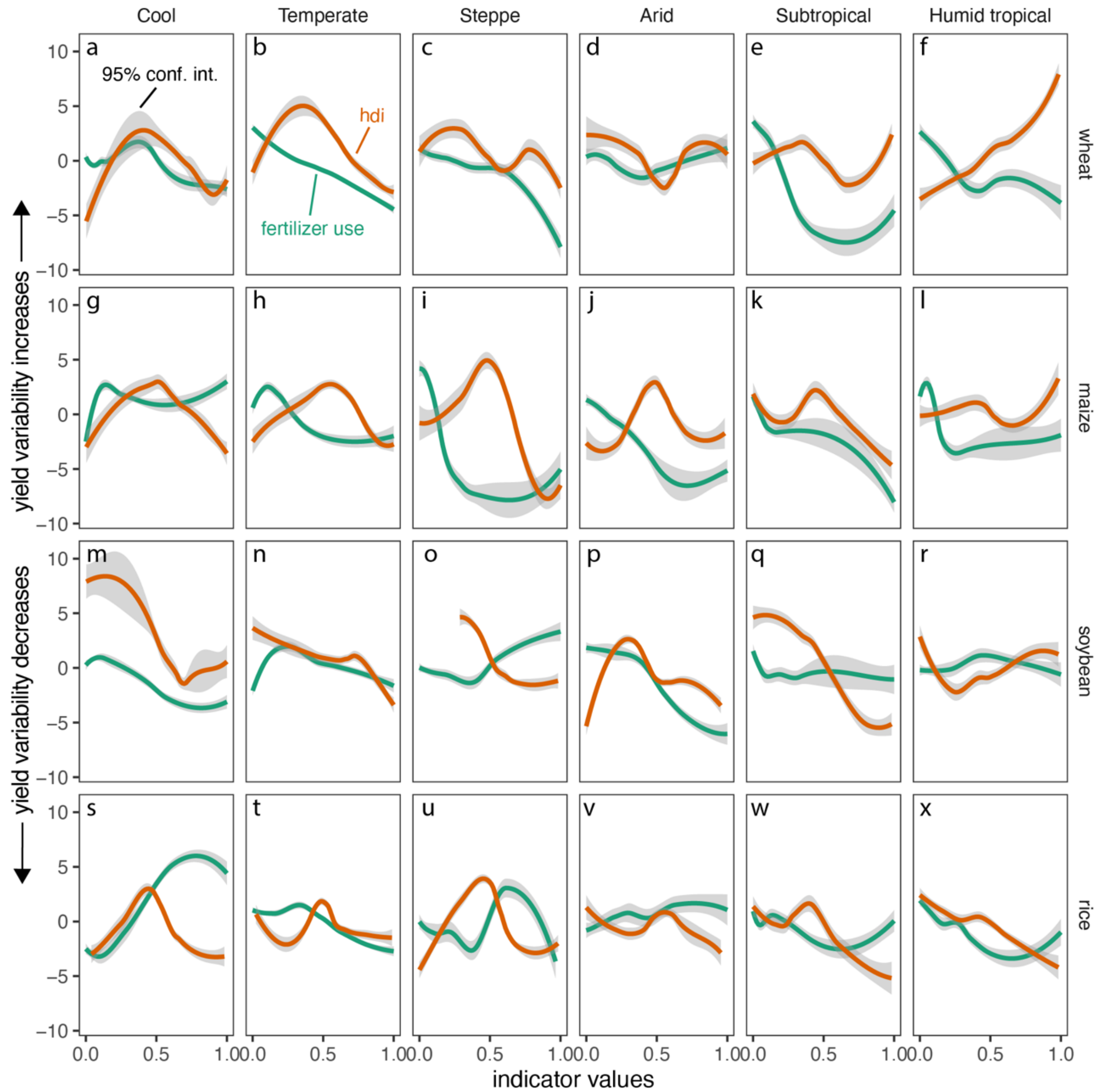

Fig. S10 Main effects for normalized subnational human development index (SHDI) and fertilizer use for assessing the negative crop yield variation at each Holdridge zone from Cool to Humid tropical. The effects are estimated using accumulated local effects -plot (ALE-plot) (Apley & Zhu, 2020) from the 10 models fitted for each crop and Holdridge zone combination aggregated using loess-smoothing. The ALE-plot shows the average marginal effect that the indicator has on the model's outcome variable. The figure shows the magnitude of the effect on yield loss risk (y-axis) with given indicator values (x-axis). The shaded areas indicate 95% confidence intervals.

References

Apley, D. W., & Zhu, J. (2020). Visualizing the effects of predictor variables in black box supervised learning models. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *82*(4), 1059–1086. https://doi.org/10.1111/rssb.12377