Earth's Future

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Key Points:

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

Supporting Information:

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

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Crop Yield Loss Risk Is Modulated by Anthropogenic Factors

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Abstract High crop yield variation between years—caused by extreme shocks on the food production system such as extreme weather—can have substantial effects on food production. This in turn introduces vulnerabilities into the global food system. To mitigate the effects of these shocks, there is a clear need to understand how different adaptive capacity measures link to 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 the time period 1981–2009 by measuring both yield loss risk (variation in negative yield anomalies considering all years) and changes in yields during "dry" shock and "hot" shock years. We used the machine learning algorithm XGBoost to assess the explanatory power of selected gridded indicators of anthropogenic factors globally (i.e., adaptive capacity measures such as the human development index, irrigation infrastructure, and fertilizer use) on yield variation at a 0.5° resolution within climatically similar regions (to rule out the role of average climate conditions). We found that the anthropogenic factors explained 40%–60% of yield loss risk variation across the whole time period, whereas the factors provided noticeably lower (5%–20%) explanatory power during shock years. On a continental scale, especially in Europe and Africa, the factors explained a 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 put 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 drops in production quantities or crop yields, can result in food scarcity which has propagating effects through global markets (Distefano et al., 2018). In the longer term, smallholders who produce around a third of global food (Ricciardi et al., 2018) in particular face a myriad of systemic factors hindering adaptation options—for example, 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 of 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 during the growing season have been shown to be key factors in crop yield variation, explaining approximately 20%–60% of global crop yield variation (Ray et al., 2015; Vogel et al., 2019). Higher temperatures, increasing soil moisture deficit, or excess water decrease crop yields as the growing conditions move outside of the optimal range for crop production (Ben-Ari et al., 2018; Lesk et al., 2021). However, these effects are not uniform across different countries or crops (Agnolucci et al., 2020; Jägermeyr et al., 2021; Ray et al., 2015; Zhao et al., 2017), and agronomic practices and crop production infrastructure such as irrigation can provide ways to adapt or mitigate the adverse effects (Agnolucci et al., 2020; Siebert et al., 2017).

While the connection between climate and crop yield variation is well established, we lack a comprehensive understanding of other key factors and the potential of human actions to mitigate crop yield losses. Findings from existing studies show heterogeneity for the relationship between anthropogenic factors and crop yield variation, depending on the included factors and areas of interest. Studies focused primarily on droughts and climate change adaptation suggest that from a 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) seem to correlate well with lower vulnerability or less volatile crop yields. Contrastingly, Bryan et al. (2015) and Lamichhane et al. (2020) did not find strong relationships between adaptive capacity and social and other capital indicators.

For fertilizer use, a 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 modeling 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 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 and anthropogenic factors. While previous studies have been conducted across diverse spatial scales (from villages to country and global level), only one global study (Simelton et al., 2012) links multiple anthropogenic and production related factors to crop yield variation using national-scale data. Particularly for large countries such as the United States and China, this scale is too coarse to detect potential relationships accurately.

In this study, we focused on the association between anthropogenic indicators and crop yield vulnerability, and its implications for resilience of global food supply on a subnational scale. More specifically, we examined (a) to what extent long-term averages of selected indicators of anthropogenic factors (see Section 2) can explain negative crop yield variation, and (b) how well the indicators explain geographical differences in crop yield anomalies in responses to heat and drought shocks. We utilized the 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 indicators of anthropogenic factors; 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 factors and the yield variation of four key crops: wheat, maize, soybeans, and rice. The wheat, maize, soybean, and rice are major staple crops globally, covering 65% of global calorie intake (Tilman et al., 2011), with soybeans also used 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 also impacting food security through global trade networks and providing income for farmers.

2. Data and Methods

In this study, we focus on six key societal and crop production related indicators: (a) the human development index (HDI); (b) governance effectiveness (GOV); (c) fertilizer use (nitrogen, phosphorus, and potassium); (d) water stress (WS); (e) irrigation; and (f) agricultural suitability for growing crops (see Table 1). Here, we refer to these socio-economic and food production indicators as "anthropogenic factors," as they represent the human dimensions controlling crop production –unlike for example, 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, 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 Figure S1 in Supporting Information S1). We then analyzed the association between crop yield anomalies and the six indicators on 0.5° (~60 km at the equator) grid cell resolution with a gradient boosting regression algorithm XGBoost (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.

Table 1
Description of the Data Used in the Study and Their Sources and Reference Years

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° resolution. Data for years 1981–2009	Ray et al. (2019)
Indicators of Anthropogenic factors			
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 et al. (2018)
Governance effectiveness	GOV	5 arc-minute raster, national scale; years 1995–2005	WGI (2018)
Water stress	WS	Baseline water stress index 0–1, average of 1960–2014; vector data with HydroBASINS6 resolution (Lehner & Grill, 2013)	Hofste et al. (2019)
Irrigation infrastructure	WINF	Historical Irrigation Data set of area equipped for irrigation: 5 arc-min raster, 1995–2005 in 5-year time steps.	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°	AgMERRA reanalysis data set 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°	ERA5 re-analysis data set by Hersbach et al. (2020)

2.1. Data

2.1.1. Crop Yield Data

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

2.1.2. Indicators of Anthropogenic Factors

For the socio-economic data, we used two indicators: the HDI at a subnational level (Smits & Permanyer, 2019) and national-level governance effectiveness (GOV; WGI, 2018; Varis et al., 2019). The gaps in HDI data were filled using a method from Kummu et al. (2018). Both indicators were rasterized to 5 arc-minute resolution spanning 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 WS—that is, average water withdrawals per available renewable surface and groundwater supplies for the time period 1960–2014—was used as the indicator for local pressure on water use on a hydrological sub-basin level (HydroBASINS6). Area equipped for irrigation (WINF) provided a gridded estimate of irrigation extent averaged over the years 1995, 2000, and 2005. However, the irrigation extent did not differentiate between different crops, and it was used as a proxy of agricultural infrastructure in general. For fertilizer use (FER) we included a linear combination of crop-specific gridded application rates for three main fertilizer components: nitrogen, phosphorus 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—a 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 share of variation absorbed by the first component varied between 74% and 79%, depending on the crop. The reference year is most commonly the year 2000, though some data are collected between 1994 and 2001 (Mueller et al., 2012). Although the data set provides only a snapshot for fertilizer application rates, to our knowledge there are no globally comprehensive time series 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). The suitability index (SI) was extracted from FAO global agro-ecological zones (GAEZ) (Fischer et al., 2012). It aims to capture how suitable areas are for 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 inputs.

All the indicator datasets were rasterized and aggregated to 0.5° resolution (Figure 1). Due to the lack of comprehensive time series data for several indicators, we used a raster cell-specific average between 1995 and 2005 for HDI, GOV, and WINF indicators and single raster cell-specific values for the rest of the indicators (FER, WS, SI) as the representative values 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 (e.g., see Figure S2 in Supporting Information S1 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, we used min-max scaling where all data was scaled between 0 and 1 using 2.5%–97.5% of the respective ranges. Values under the threshold 2.5% received value of 0 and values higher than the 97.5% threshold received value of 1. The distributions and variable correlations are presented in Figure S3 of Supporting Information S1.

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 utilized air temperature (Ruane et al., 2015) and soil moisture (Hersbach et al., 2020) anomalies to study the links between crop yields and anthropogenic factors 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 were the lowest and highest daily values, respectively. The amplitude of the variation was half 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°) and soil moisture (0.28°) datasets were re-gridded to 0.5° 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. A more detailed description of the method for temperature and soil moisture data manipulation is shown in Heino et al. (2022).

2.2. Methods

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

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 de-trended by subtracting the running 5-year mean from the annual yields. Then these de-trended 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 entire study period. While the de-trending method may have some influence

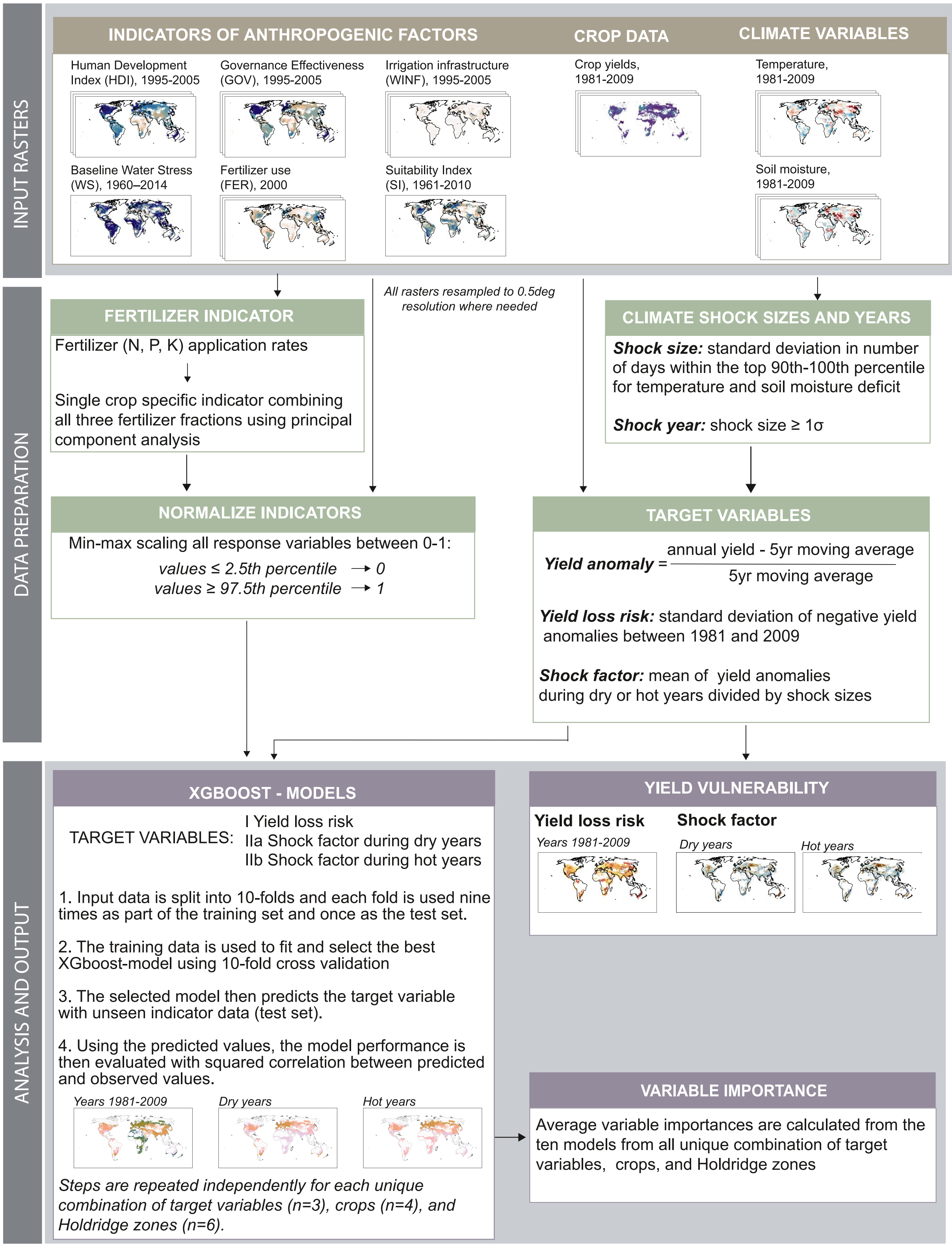

Figure 1. Conceptual methodological framework. More detailed descriptions of the data sources and methods can be found in Sections 2.1 Data and Section 2.2 Methods.

on the level of the crop yield anomalies, previous studies testing different de-trending methods have not found a substantial difference between the methods (Iizumi & Ramankutty, 2016; Müller et al., 2017).

After standardizing the yield anomalies, we calculated yield loss risk, which portrays the volatility of crop yield loss events. The yield loss risk is defined here as the standard deviation of negative yield anomalies within each grid cell across years 1981–2009. Yield loss risk can be considered analogous to downside risk which measures risk and volatility related to financial assets using standard deviation for lower-than-average asset values (see e.g., Ogryczak & Ruszczyński, 1999). Higher yield loss risk in a given grid cell depicts a larger extent of negative yield anomalies—that is, higher losses in terms of annual yield. To obtain more representative yield loss risk, we removed all grid cells with fewer 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 Figure S4 of Supporting Information S1.

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," denoting years with high temperatures, and "dry years," denoting those with very low soil moisture (Figure 1). The extent of the anomalies was measured within each grid cell that falls above the 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 be accounted for "hot," "dry," or both cases; while we consider both cases separately, years with both "hot" and "dry" conditions may experience greater decreases in yields than years with either "dry" or "hot" conditions (Feng et al., 2019; Heino et al., 2022). For a more detailed description of calculating the "hot" or "dry" conditions, see Heino et al. (2022).

Both 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—that is, the standard deviation in the number of dry or hot days for a given year. Thus, in a grid cell (0.5°) with similar crop yield anomalies, a year with a higher *temperature or soil moisture* anomaly would receive a lower (closer to zero) value compared to a year with a smaller 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 Figure S5 of Supporting Information S1, and the unadjusted mean yield anomalies during shock years are presented in Figure S6 of Supporting Information S1.

2.2.3. Modeling Setup

We used predictive regression models to study the explanatory power of anthropogenic factors on crop yield anomalies. The models were built using the gradient-boosting algorithm XGBoost (Chen & Guestrin, 2016), which implements a non-parametric ensemble machine learning method that utilizes weak learners—for example, decision trees for various regression and classification tasks (Friedman, 2001). Decision tree models are generally well-suited to detect nonlinear relationships such as crop yields (Konduri et al., 2020; Leng & Hall, 2020), as well as handle multi-collinear 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 Figures S3–S5 in Supporting Information S1). 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 factors with different outcome variables: yield loss risk, and shock factors for both "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 fewer 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

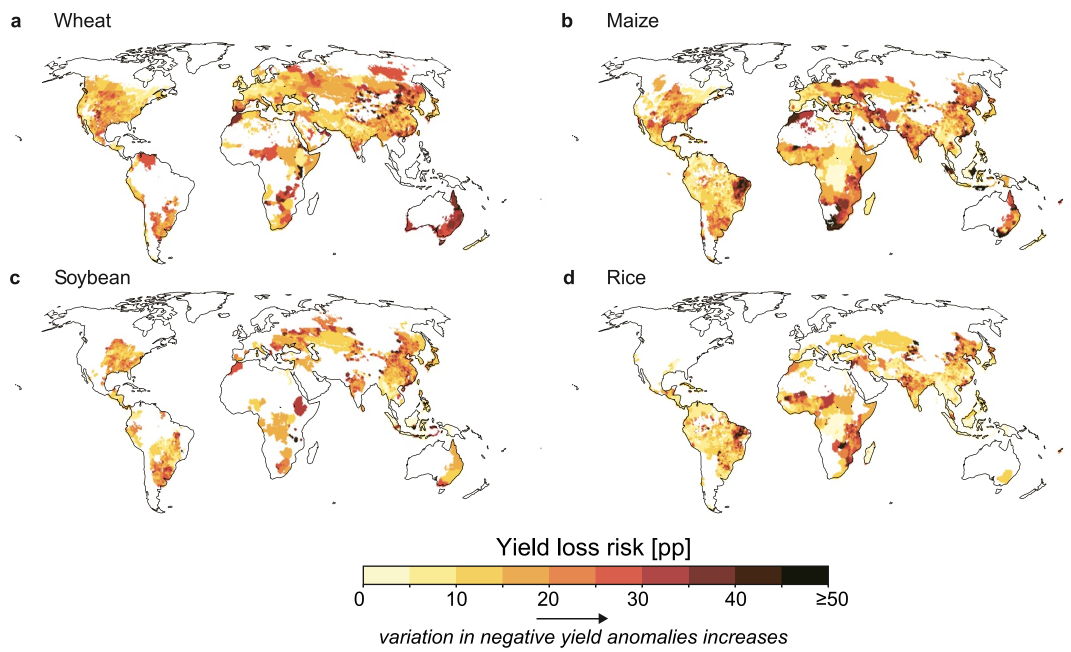

Figure 2. Yield loss risk, that is, standard deviation of negative yield anomalies measured for (a) wheat, (b) maize, (c) soybean, and (d) rice. Increasing yield loss risk indicates that a grid cell has larger negative yield anomalies (i.e., yields lower than 5-year average) during the study period. 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.

the grid points into small batches using a global 100 × 100 hexagon grid with the majority of hexagons covering 40–50 adjacent grid cells. All grid cells within a single hexagon were 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 CV loop feeds nine folds to the inner CV that performs also 10-fold CV to tune the hyperparameters using grid search with default settings in the *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 analyze the importance of the variables, we used *xgb.importance*-function from the *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. A higher Gain-value indicates 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 (Chen et al., 2018). To supplement the variable importance and to measure the direction of the relationships, we utilized accumulated local effects–visualization, which 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 (Figure 2). For wheat, the strongest negative anomalies occur in a major wheat producer country Australia, as well as northeastern China and various parts of Africa (Figure 2a). For maize and rice, the spatial pattern is somewhat similar, as the greatest risks occur in northeastern Brazil, southern Africa, Morocco, the Middle East, and parts of Central Asia (Figures 2b and 2d). When comparing the values with the mean yield loss risks of respective

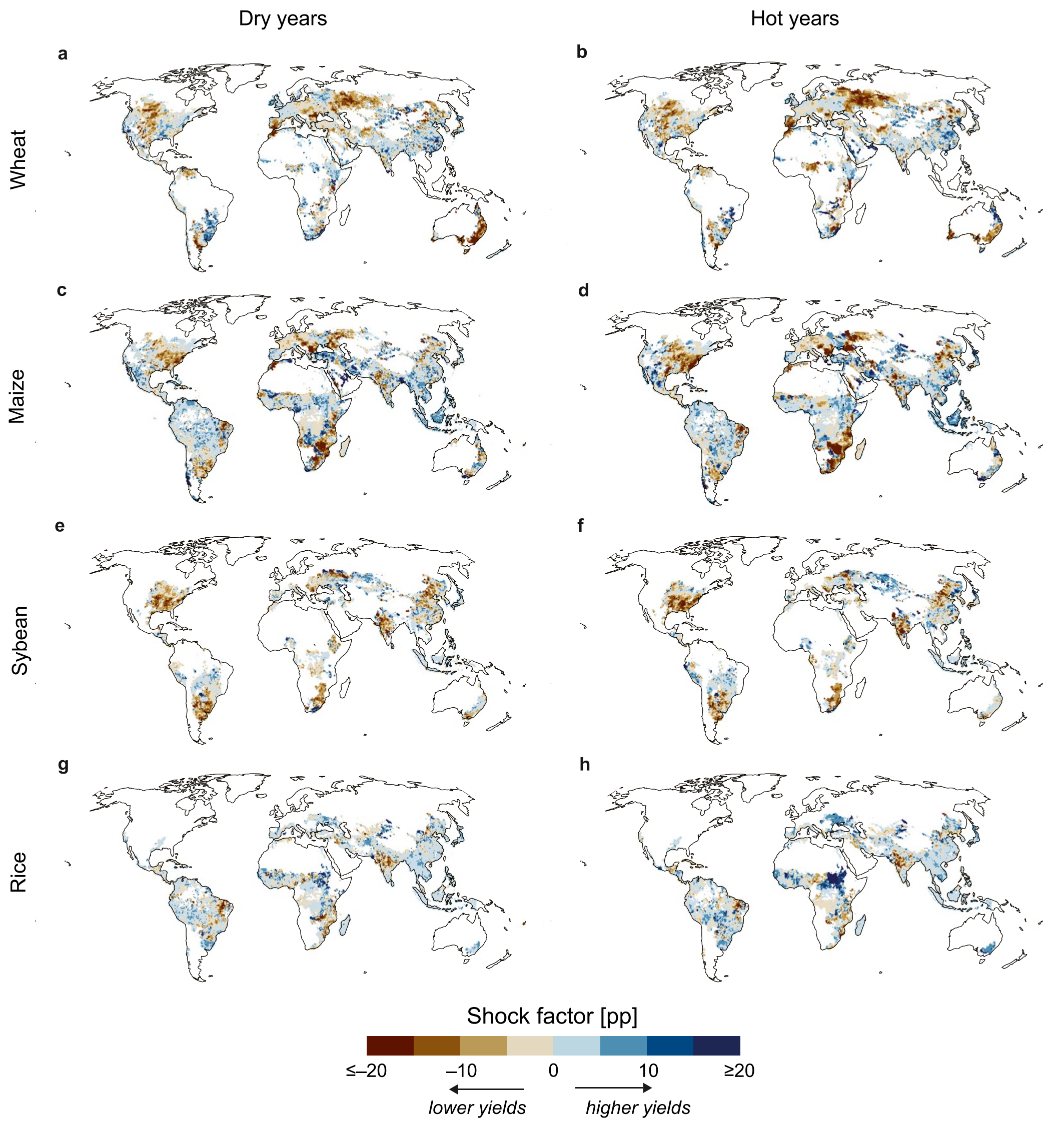

Figure 3. Mean yield anomalies during shock years adjusted by shock size. The sign of the shock factor indicates whether the mean yields for shock years are higher (positive values; blue) or lower (negative values; brown) than the running 5-year mean yield. The size of the shock factor indicates how 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.

Holdridge zones, particularly Africa shows several hotspots for wheat, maize, and rice, with over 20% points higher risk for yield loss compared to the respective zone's mean value (Figure S7 in Supporting Information S1). For soybean, while having lower yield loss risks, the most vulnerable areas were found in northeastern China, Eastern Europe, central Asia, Ethiopia, Uruguay, and northern Argentina (Figure 2c).

3.2. Shock Factor

When considering only climatic shocks, that is, dry and hot years (see Section 2.2), our findings highlight those areas with the highest crop yield anomalies during shock years (Figure 3, scaled so that they are comparable between grid cells; see Section 2.2) are mainly the same as those where the yield loss risk is the highest (Figure 2). For example, the strongest negative yield anomalies for wheat during dry years (Figure 3a) are found in Australia, similar to the yield loss risk (Figure 2a). Also, eastern Europe and central Asia, as well as parts of midwestern

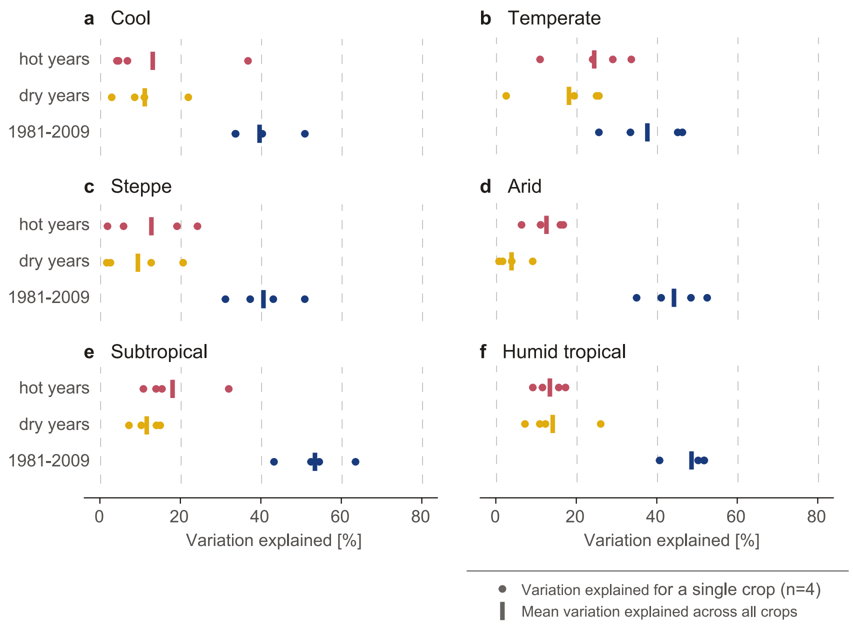

Figure 4. Variation explained within different Holdridge zones. Blue color represents yield loss risk–case for years 1981–2009, and yellow and red colors represent shock factor–cases for dry and hot years, respectively (see Section 2.2). Each point represents variation explained by models for single 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.

North America show high negative shock factors for wheat (Figures 3a and 3b) and maize (Figures 3c and 3d). 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 (Figures 3g and 3h), there seems to be much less geographical variation and generally smaller negative shock factors than other crops, in line with previous studies where climatic conditions have been found to have lower effects for rice compared to others (e.g., Ray et al., 2015). When comparing the shock factors to the mean of respective Holdridge zones (Figure S8 in Supporting Information S1), all studied crops show similar geographical patterns as in absolute shock factor values (Figure 3), indicating that the mean effect across each of the climatic zones is rather minor (Figure S9 in Supporting Information S1).

3.3. Explanatory Power of Anthropogenic Factors

Anthropogenic factors had substantially higher explanatory power in the *yield loss risk*-case compared to only shock years, either "dry" or "hot" (Figure 4). This applies to all 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 seems to be clustered, whereas for the shock cases (particularly hot years) the explanatory power has a somewhat larger range of values (e.g., Cool, Temperate, Steppe and Subtropical zones: Figures 4a–4c and 4e). The mean explanatory power for yield loss risk varied generally between 40% and 60%, depending on climate zone (Figure 4) and crop (Figure 5), whereas the mean explained variation in shock years was substantially lower, around 5%–20%.

The explanatory power for yield loss risk in years 1981–2009 was rather similar (in average around 40%–50%) across all crops (Figure 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%) (Figure 4). In terms of hot or dry shock years only, the mean shock factors were usually better explained in hot years, the difference to dry years being on average 5–10% points. For the crops, wheat models (Figure 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 (Figure 5).

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 (Figure 6). In the majority of Africa, for example, the explained variation was above 50% for all the crops. For the temperate regions in Europe and the United States,

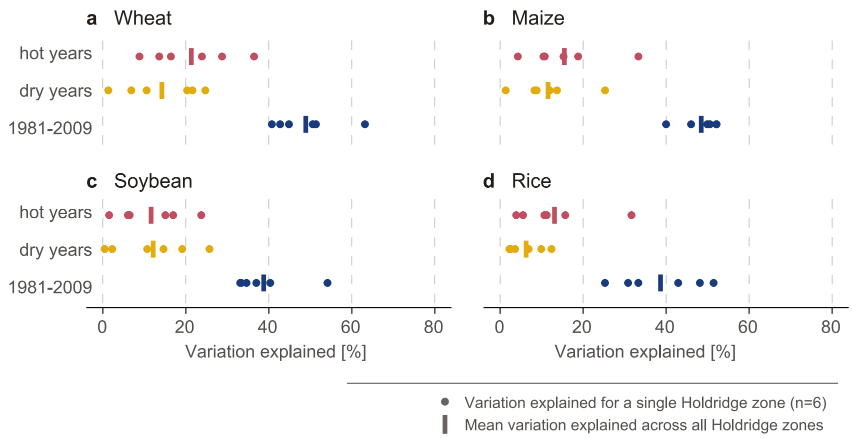

Figure 5. Variation explained for different crops. Blue color represents yield loss risk–case for years 1981–2009, and yellow and red colors represent shock factor-cases for dry and hot years, respectively (see Section 2.2). Each point represents variation explained by models for a single Holdridge zone 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.

the fitted models explained over 40% of the variation for wheat (Figure 6a) and maize (Figure 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 (Figure 6c) and maize (Figure 6f) models in the Temperate Holdridge zones during hot

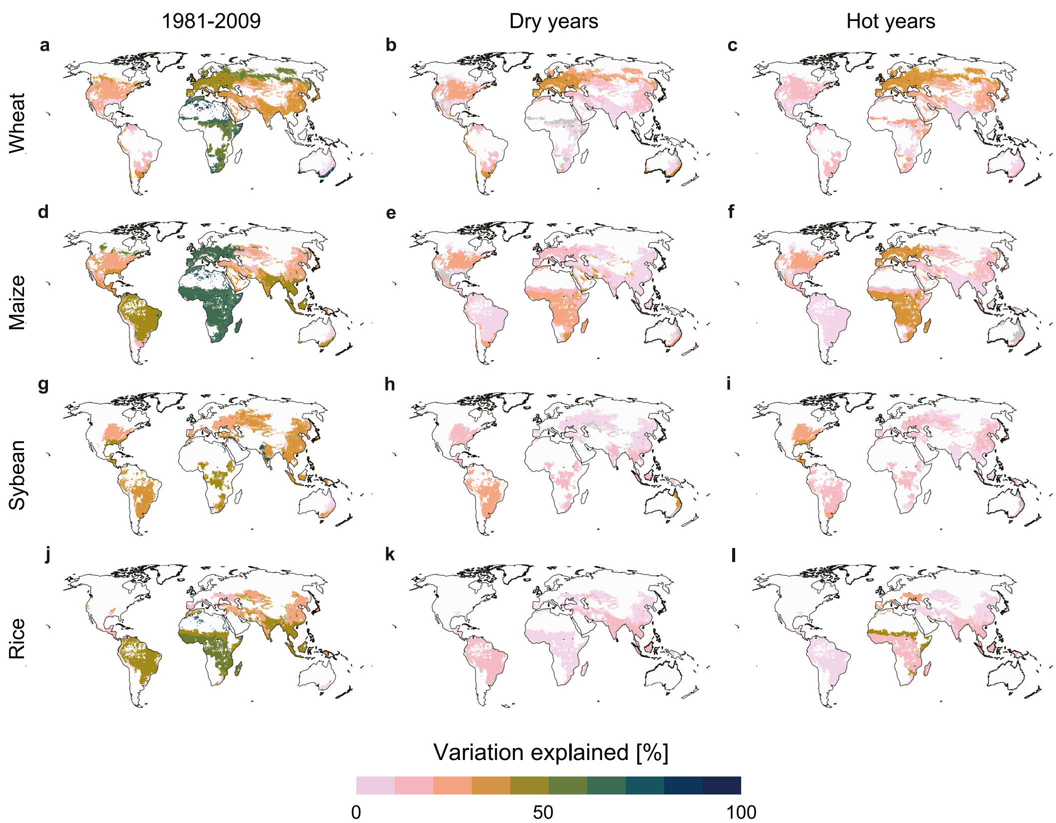

Figure 6. Explanatory power of the models within the intersection of each Holdridge zone and continents for each crop ($n = 37–42$). Explained variation is measured as the squared Pearson's correlation coefficient between the observed and predicted outcome.

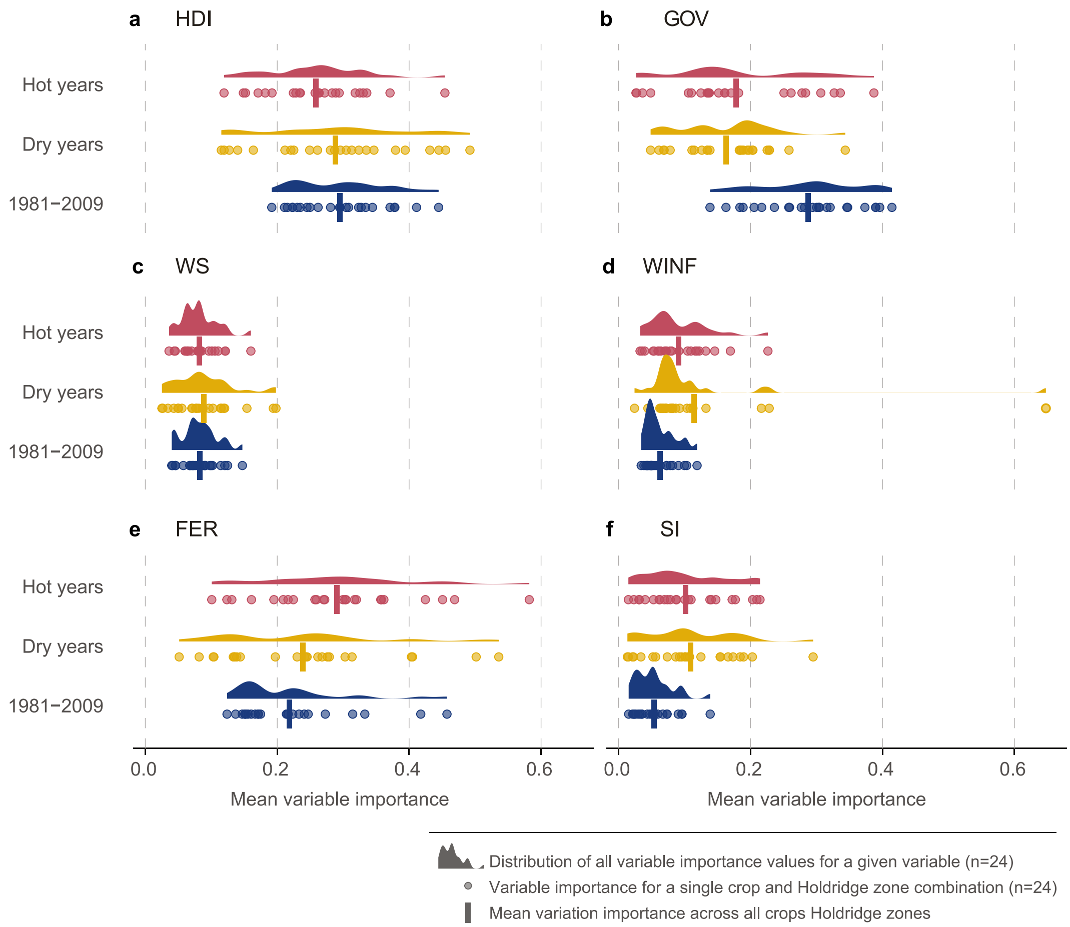

Figure 7. Mean variable importance for each utilized indicator. The indicators included are (a) human development index (HDI); (b) governance efficiency (GOV); (c) water stress (WS); (d) irrigation infrastructure (WINF); (e) fertilizer use (FER); and (f) Suitability index (SI). Variable importance is measured as mean Gain-values of models ($n = 10$) for a given crop and Holdridge zone combination ($n = 24$). Higher Gain-value indicates that the variable is more important in making the prediction. Blue color represents yield loss risk-case for years 1981–2009, and yellow and red colors represent shock factor-cases for dry and hot years, respectively (see Section 2.2). Each point represents variable importance for a 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.

years performed better, having explanatory power over 40%. The explanatory power was particularly low, for both dry and hot years, in areas in Latin America and East Asia.

3.4. Importance of Anthropogenic Factors

On a global average, the most important prediction indicators were HDI, GOV, and fertilizer use (FER) (Figure 7). However, these indicators, especially FER, also had the highest range in importance values across different crops and climate zones (Figure 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 the yield loss case than shock years, while for all other indicators (except for WS with no difference), the relationship is the opposite (Figure 7). The difference is particularly strong in case of GOV, which is much more important in the yield loss case than in the shock cases. This indicates that the importance of different anthropogenic factors 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 (Figure S10 in Supporting Information S1). Quite unsurprisingly, higher fertilizer use seems to contribute to lower yield variability for all the

Holdridge zones, with the exception of a few areas such as steppe for maize and soybean and subtropical for wheat. For HDI, the relationships between the indicator value and modeled variation were often nonlinear. Areas with scaled HDI over the 0.5 seem to yield substantially less variation in yield loss risk (Figure S10 in Supporting Information S1).

4. Discussion and Conclusions

4.1. Key Findings

We studied crop yield vulnerabilities and their relationship with global socioeconomic indicators with three specific cases. First, we focused on yield loss risk measured as a 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 means of the selected indicators of anthropogenic factors have substantial explanatory power over the variation of negative yield anomalies within different climatological contexts (Figures 4 and 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 the yield loss risk-case (Figures 3 and 4). The heterogeneity in the relationship between adaptive capacity and the anthropogenic factors shown in the existing literature (e.g., Antwi-Agyei et al., 2012; Bryan et al., 2015; Kamali et al., 2019; Lamichhane et al., 2020; Simelton et al., 2012) suggests that the differences in how perceived adaptive capacity and crop yield variation are linked differ substantially from region to region. The decision to employ adaptation measures depends 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; Chen et al., 2014). Furthermore, factors such as prices of agricultural inputs or market prices for the cereal and soybean may affect how farmers employ the different adaptation methods available to them during years with adverse conditions.

Our finding that areas with high HDI and fertilizer use resulted in lower negative yield variation supports the findings of many 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 have a convex relationship, as areas with low and high HDI have considerably lower yield loss risk compared to the "middle-ground" areas (Figure S10 in Supporting Information S1). 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 that are no longer utilized when a country develops from a poor-to middle-income country, thus increasing drought vulnerability.

Surprisingly, irrigation infrastructure (WINF) was a relatively unimportant indicator for the predictions (Figure 7), even though it has been previously identified as major factor in reducing crop yield variation as well as a buffer against extremely warm days (Butler & Huybers, 2013; Troy et al., 2015; Vogel et al., 2019). While the irrigation extent used here (Siebert et al., 2015) does not differentiate between crops there are major differences where irrigation is used with a given crop (Portmann et al., 2010). Discrepancies between actual used irrigation intensity and our data set can create noise in the models, thus detecting effects of irrigation for a certain crop may be challenging.

4.2. Limitations and Ways Forward

Climate change is pushing a substantial proportion of food production outside of current climatic conditions (Kummu et al., 2021). Hot and dry conditions become more common (Sarhadi et al., 2018), and shocks are increasingly affecting multiple crops within different "breadbaskets" simultaneously (Gaupp et al., 2020; Tigchelaar et al., 2018). These changes can increase food prices, reduce household incomes and increase risk of malnutrition (IPCC, 2022) highlighting the importance of understanding local vulnerabilities and adaptive capacity regarding food security across the globe. While only a fraction of global population can fulfill their food crop demand with only local production (Kinnunen et al., 2020), the stability of local food production plays an important role—especially if the food scarcity cannot be compensated by trade (Distefano et al., 2018). Yield variation cannot be entirely prevented, but certain agricultural policies may promote resilience against shocks, including those that support increasing local nutrient availability through for example, nutrient recycling and effective fertilizer use. In addition, proper social and institutional support, as well as understanding local contexts when developing areas suffering from low education and poverty, have important contributions for supporting local food security. However, given the complex relationships and nonlinearities between food production, vulnerabilties, and adaptive capacity, more detailed local and regional scale research is needed (Bryan et al., 2015; Challinor et al., 2010; Lamichhane et al., 2020).

4.3. Policy Implications for Food Security

Assessing the relationship of crop yield anomalies and anthropogenic factors on a global scale has several challenges. Firstly, comprehensive global time series on farm-management practices that span sufficiently long time periods are non-existent at a subnational resolution. Using long-term mean values for indicators of anthropogenic factors might not be representative for countries that have experienced drastic changes during the study time period. It is plausible that the models cannot capture the potential for adaptation measures that are employed at a farm level for example, during the shock years. Similarly, a smaller sample size for the years with hot or dry conditions due to the relative rarity of these events can introduce more noise in the models. Management practices such as fertilizer application rates can vary substantially between years, depending on the growing season conditions, market prices for agricultural inputs and crops, and agricultural subsidy schemes.

Secondly, we employed a set of rather generic indicators, which might not correlate directly with the management practices and decisions made at the farm level. While generic indicators such as gross domestic product or HDI 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. Furthermore, crop responses may be highly nonlinear 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. Additional environmental factors such as soil type may have substantial impacts on the results (Folberth et al., 2016) and thus further complicating these relationships.

Conflict of Interest

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

Data Availability Statement

All raw data sources are open sourced and available online. All the codes for creating the results are available at https://github.com/pskinnun/shock_vulnerability.

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