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The effect of climate change on crop yield anomaly in Europe

Miriam Schmidt[1,2,*] | **Elizaveta Felsche**[2,3,*]

[1]TUM School of Management, Technical University of Munich, Munich, Bavaria, Germany

[2]Center for Digital Technology and Management, Munich, Bavaria, Germany

[3]Department of Geography, Ludwig-Maximilians-Universität Munich, Munich, Bavaria, Germany

Correspondence
Miriam Schmidt, TUM School of Management, Technical University of Munich, Bavaria, Germany and Center for Digital Technology and Management, Munich, Bavaria, Germany.
Email: miri.schmidt@tum.de

*Miriam Schmidt and Elizaveta Felsche contributed equally to this study.

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Abstract

Every human needs sufficient, safe, and nutritious food to live an active and healthy life. Climate change, especially more frequent extreme climate events, increasingly affects crop yields. Unpredictable losses in crop production pose a high risk to our food systems, thus threatening agricultural producers and consumers worldwide. This study analyzes the effect of climate change on wheat, maize, and barley yield anomalies for the major producing countries in the EU. Applying the Random Forest machine learning model, climate indicators, comprising mean and extreme climate conditions, explain 18% of crop yield anomalies across crops and countries from 1961 to 2020. The predictive power of climate indicators is highest for maize with 24%, followed by barley with 22% and wheat with 3%. However, mean climate indicators are stronger associated with crop yield anomalies than extreme climate indicators. Temperature- and soil moisture–related indicators are more important than precipitation-related indicators. The results reveal a nonlinear relationship between climate indicators and crop yields. Thresholds lead to a sharp decrease or increase in crop yields. Under SSP3-7.0, rising temperatures tend to increase crop yield losses until 2100 without effective adaptation measures. The impact of changing soil moisture–related indicators depends on crop and country. Our study discusses adaptation strategies but also emphasizes the relevance of global mitigation efforts to reduce climate-induced crop risk and to improve our food system's resilience.

KEYWORDS

climate change, climate extremes, crop yields, Random Forest, machine learning

1 | INTRODUCTION

Every human needs sufficient, safe, and nutritious food to meet dietary needs and food preferences for an active and healthy life (FAO, 1996). Climate change, in particular increasing temperatures, changing precipitation patterns, and more frequent extreme events, increasingly affect crop yields in Europe (Ben-Ari et al., 2018; Hernandez-Barrera et al., 2017; Mbow et al., 2019; Nguyen et al., 2018). The extreme drought of August 2022 in the European Union (EU) is estimated to have caused a reduction in maize, soybean, and sunflower yield of −16%, −15%, and −12%, respectively, compared to the 5-year average (Baruth et al., 2022). In the summer of 2018, 40% of the crop areas in Northern and Eastern Europe recorded yields below the 10th percentile for winter wheat and barley (Beillouin et al., 2020). Globalized connected trade markets create structural vulnerabilities amplified by crop production shocks (Burkholz et al., 2019; Rivington et al., 2015). Changes in crop production, storage, and consumption increased global wheat prices by more than 100% in 2007/2008 and 50% in 2010/2011 (Headey, 2011; Schewe et al., 2017). Rising costs for staple crops limit access to food for basic needs (Wheeler et al., 2013). Disruptions in European wheat production due to weather-related shocks or other events result in absolute reductions in wheat exports. Consequently, the least developed countries experience significant import losses in staple foods and supply shortages due to their high dependence on globally connected trade networks (Puma et al., 2015; Burkholz et al., 2019). However, not every climate extreme leads to a crop failure; often, a combination of extreme and moderate values in different climate indicators leads to crop reduction (Beillouin et al., 2020; Ben-Ari et al., 2018; Kolář et al., 2014). The factors leading to crop failure are often multivariate and highly interrelated (Frank et al., 2015). Understanding the drivers of crop yield anomalies helps to predict and mitigate crop failures (Lipper et al., 2014).

Previous studies investigated the impacts of climate indicators on crop yield anomalies, mainly focusing on wheat and maize. For wheat in Europe, climate indicators explain 28% to 63% of the variance in yield anomalies (Vogel et al., 2019; Beillouin et al., 2020; Ray et al., 2015; Frieler et al., 2017). For maize, climate conditions predict between 25% and 68% of crop yield anomalies (Vogel et al., 2019; Beillouin et al., 2020; Ray et al., 2015; Frieler et al., 2017). In terms of indicators, previous studies found that unusually warm and cold temperatures and deficit or excess precipitation adversely affect wheat and maize yields across European countries (Vogel et al., 2019; Beillouin et al., 2020; Lüttger et al., 2018; Hernandez-Barrera et al., 2017; Hlavinka et al., 2009; Kristensen et al., 2011). The relationship is nonlinear, with threshold values leading to a sharp decrease in crop yields (Schlenker et al., 2009; Troy et al., 2015). To our knowledge, only one study has investigated the predictability of barley yields (Beillouin et al., 2020), which is the third most-produced crop in the EU (FAO, 2021). Moreover, most studies focused mainly on temperature and precipitation (Vogel et al., 2019; Frieler et al., 2017; Ray et al., 2015), neglecting soil moisture, which can have a significant influence on the growth of the crops (Vogel et al., 2019; Ray et al., 2019). Moreover, as far as we know, only two studies investigated how the indicators impacting crop growth will develop until 2100 given the shared socioeconomic pathways (SSP) (Ben-Ari et al., 2018; Hernandez-Barrera et al., 2017).

This research analyzes the effects of climate indicators on crop yield anomalies in the EU by focusing on three research questions:

1. What is the influence of changes in climate means and extremes on crop yield?
2. What are the most important climate indicators, and how do they influence crop yield?
3. What effect on crop yield anomaly can be expected in the future under the SSP3-7.0?

In our research, we focus on the three most produced crops in the EU: wheat, maize, and barley (FAO, 2021). For each crop, we consider the five major producing countries in the EU: France (FR), Germany (DE), Poland (PL), Spain (ES), and Romania (RO) for wheat; France, Romania, Hungary (HU), Italy (IT), and Poland for maize; and Spain, Germany, France, Denmark (DK), and Poland for barley at the national level. Figure 1 provides an overview of the research domain.

We use climate indicators as input to the Random Forest regressor (Breiman, 2001) and train the model to predict the crop yields for 1961 to 2020. We investigate which climate indicators are most relevant for the crops and countries showing explanatory power. We further analyze how the most important indicators develop given the SSP3 that is simulating the climate given Representative Concentration Pathway (RCP) 7.0 (radiative forcing of $7\,W{\cdot}m^{-2}$ by 2100) (O'Neill et al., 2014) and qualitatively estimate the possible impact on future crop yields.

This research contributes to the Sustainable Development Goals (SDGs) defined by the United Nations (UN) as a call to action for peace and prosperity. The study qualitatively investigates the possible impact of climate change on the most important crops in the EU, thereby contributing to SDG No. 2 to end hunger.

2 | MATERIALS AND METHODS

An overview of the used data sets and the applied methodology is provided in Figure 2. In the following, we introduce the data sets, the used data processing techniques, and the analysis methods.

2.1 | Data

Regarding agricultural data, we use the crop and livestock data set provided by the UN's Food and Agriculture Organization (FAO). The data are present at the national level from 1961 to 2020 for wheat, maize, and barley (FAO, 2021). We follow previous studies that also used the FAO (2021) data (FAO, 2021) to analyze the impact of climate

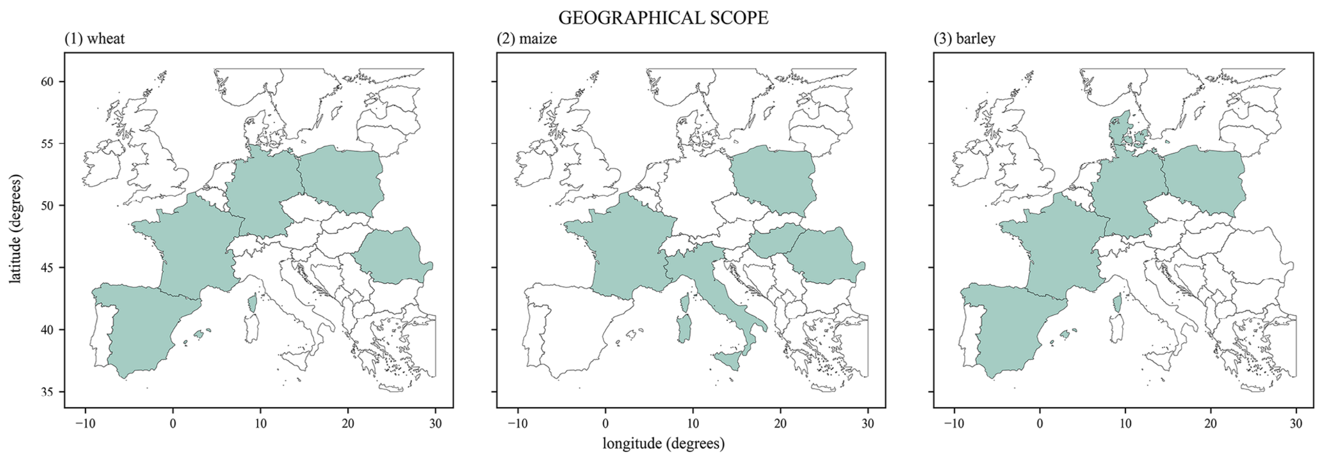

FIGURE 1 Geographical scope of the study: in green, the top five producers of wheat (left), maize (central), and barley (right) are shown.

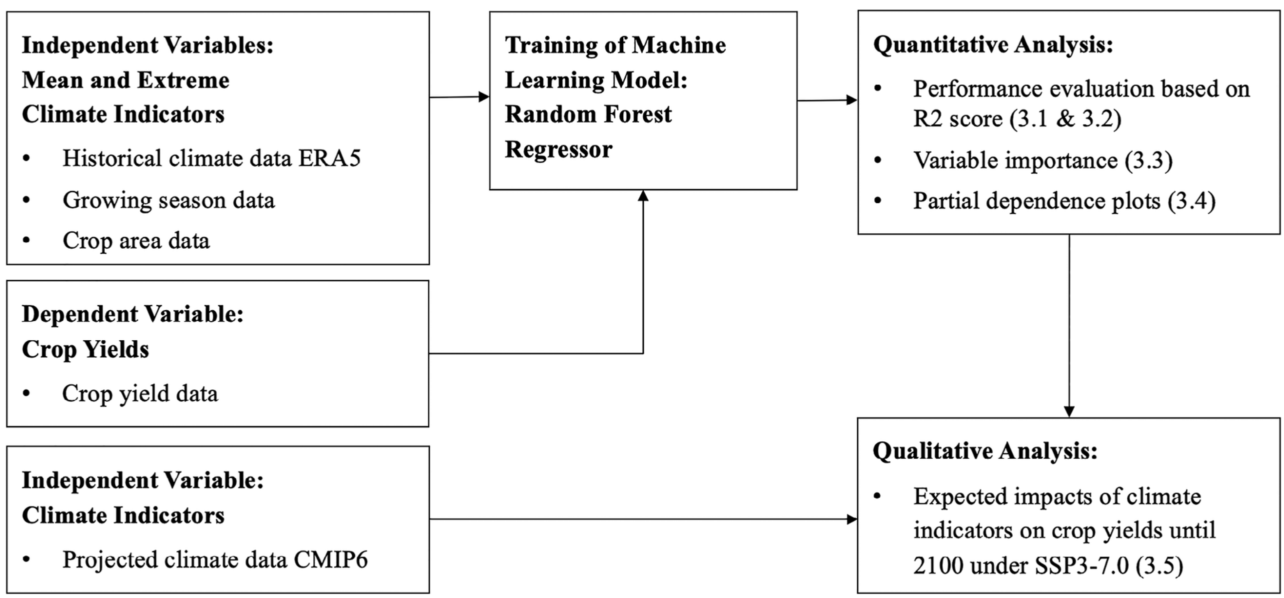

FIGURE 2 Method overview.

indicators on crop yields (Frieler et al., 2017; Lobell et al., 2007; Matiu et al., 2017). We use the crop area data provided by the European Commission Joint Research Centre (European Commission JRC, 2017), which includes the weight ratio of wheat, maize, and barley areas at 25-km grid resolution for the EU from 1975 to 2017. Data for the missing years were filled by interpolation and extrapolation of the nearest value along the time axis. The more comprehensive data set improves mean model performance from an average of 6% to 18% (compare Supporting Information Table S2). Regarding planting start and harvesting end for wheat, maize, and barley, we follow the definition by Sacks et al. (2010). The growing season dates are defined at the national level around 2000.

For climatological data, we use the fifth generation of the European Reanalysis 5 (ERA5), provided by the European Centre for Medium-Range Weather Forecasts Copernicus Climate Change Service (2019). ERA5 is produced by combining large amounts of historical observations into global estimates using advanced modeling and data assimilation systems (Copernicus Climate Change Service, 2022a). The climate data are stored on single levels in a regular latitude–longitude grid with a 30-km resolution. The selected subregion for our analysis lies within the boundaries of 31°North, 30°East, 35°South, and −13°West. Since crop yield data are provided from 1961 to 2020, the same time frame is chosen for ERA5. ERA5 includes temperature-, precipitation-, and soil moisture–related data.

In addition to the historical climate data, the global Climate Model Intercomparison Project 6 (CMIP6) data combine eight climate projections until 2100 (Copernicus

Climate Change Service, 2022b). We chose climate projections from five climate models from 2021 to 2100 to calculate the average temperature-, precipitation- and soil-related climate indicators (ECMWF, 2022): (1) Beijing Climate Center Climate System Model Medium Resolution (BCC-CSM2-MR), (2) Centre National de Recherches Meteorologiques Climate Model Version 6 (CNRM-CM6-1), (3) Australian Community Climate and Earth System Simulator Climate Model Version 2 (ACCESS-CM2), (4) Meteorological Research Institute Earth System Model Version 2.0 (MRI-ESM2-0), and (5) Community Earth System Model 2 (CESM2). The models were selected based on their availability of all three scenarios, SSP1-2.6, SSP2-4.5, and SSP3-7.0, along with the relevant variables essential for our analysis. Given the consistency of trends across all three scenarios (compare Supporting Information Figure S1), we focus on the strongest trend, SSP3-7.0, in the subsequent analysis. The global climate projections follow the SSP3-7.0 (ECMWF, 2022): SSP3 refers to high socioeconomic mitigation and adaptation challenges under a projected RCP 7.0. RCP 7.0 refers to a radiative forcing of 7.0 $W{\cdot}m^{-2}$ by 2100 and is expected to increase the global surface temperature by 3.6°C until 2100 (IPCC, 2021). The projection is a regular latitude–longitude grid whose nominal resolutions depend on the climate model. We use that same subregion with the boundaries of 31° North, 30° East, 35° South, and −13° West.

2.2 | Data processing

We calculated the crop yield anomalies for each crop and country from 1960 to 2020 (FAO, 2021). Technological progress has been a dominating factor for crop yields in the past years, so we detrended the yield to remove the effect (Levers et al., 2016; Huang et al., 2002). Following a recent study on crop yield prediction (Vogel et al., 2019), we applied the Singular Spectrum Analysis (SSA) that decomposes the crop yield time series and reconstructs the technological trend (Goljandina et al., 2013).

We selected temperature-, precipitation- and soil moisture-related climate indicators representing mean and extreme conditions, as shown in Table 1, based on existing literature (Vogel et al., 2019; Frieler et al., 2017; Ray et al., 2015; Beillouin et al., 2020; Lüttger et al., 2018). We calculated the climate indicators for each crop and country from 1960 to 2020 based on the ERA5 data (Copernicus Climate Change Service, 2019), CMIP6 data (Copernicus Climate Change Service, 2022a), growing season dates (Sacks et al., 2010), and crop areas (European Commission JRC, 2017).

The growing season for each crop and country (Sacks et al., 2010) was defined as the period from the month of the first planting day to the month of the last harvest day (compare Supporting Information Table S1). While maize has only one growing season, Sacks et al. (2010) clearly suggested that wheat is cultivated as a winter crop in France, Germany, Poland, Spain, and Romania. Barley is primarily grown as a winter crop in Spain and France, while it serves as a spring crop in Denmark. Since no data were available for barley and maize in Poland, the crop growing season from the geographically closest country was chosen. According to Sacks et al. (2010), barley can be a winter or spring crop in Germany and Poland. According to the major share of cultivated areas, winter barley dominates in Germany (BMEL, 2021) and spring barley in Poland (Statistics Poland, 2021).

The cultivation area for each crop and country was determined based on the data from the European Commission JRC (2017). The climate data were reprojected to match the resolution, projection, and region of the crop area data by nearest neighbor resampling. As suggested by existing research (Frieler et al., 2017; Ray et al., 2015; Lobell et al., 2007), each climate indicator was defined for each grid point and each growing season. We only considered climate data that fell into the crop-growing season. Then, the crop-area weighted average of all climate indicators was taken for each country and each growing season. Only grid points where the crop is grown were included.

2.3 | Random Forest model and R^2 score

The Random Forest regressor (Breiman, 2001) was applied to predict crop yield anomalies for each crop and country. We follow previous studies that suggest using Random Forest to predict crop yields with climate indicators (Vogel et al., 2019; Beillouin et al., 2020; Feng et al., 2018; Hoffman et al., 2018; Leng et al., 2020; Jeong et al., 2016). Additionally, we compared the performance of the Random Forest to other widely used methods of multiple linear regression (Pedregos et al., 2011) and support vector machine (Platt, 1999). The results for Random Forest proved to show higher overall accuracy, which aligns with previous literature (Vogel et al., 2019; Leng et al., 2020; Jeong et al., 2016)

We used the R^2 score as a skill metric to estimate the influence of climate indicators on crop yields. R^2 score or the coefficient of determination represents the proportion of variance of climate anomalies that the climate indicators can explain in the Random Forest model. We applied fivefold cross-validation to ensure the robustness of our results. Since a negative R^2 score implies that the predicted crop yields perform worse than taking the average of all crop yields, only crops and countries with a positive R^2 were considered.

TABLE 1 Climate indicator overview.

Category	Climate indicator	Abbreviation	Unit	Description
Mean temp.	Mean temp.	mean t2m	K	Monthly mean temp. during the growing season
Extr. temp.	Min. temp.	min t2m	K	Monthly min. temp. during the growing season
Extr. temp.	Max. temp.	max t2m	K	Monthly max. temp. during the growing season
Extr. temp.	Cold night frequency	tn10p	Days	Number of days with daily min. temp. below the 10th percentile in a 5-day window during the growing season
Extr. temp.	Warm day frequency	tx90p	Days	Number of days with daily max. temp. over the 90th percentile in a 5-day window during the growing season
Mean precip.	Mean precip.	mean tp	mm (day^{-1})	Monthly mean precip. during the growing season
Extr. precip.	Max. 5-day precip.	rx5day	mm	Max. 5-day precip. during the growing season
Extr. precip.	Max. consec. dry days	cdd	Days	Max. number of consecutive days with less than 1 mm precip. per day
Mean precip.	Mean soil moisture (0–7cm)	mean swvl1	m^3 m^{-3}	Monthly mean soil moisture during growing

Note: Temp. for temperature, precip. for precipitation, extr. for extreme, min. for minimum, max. for maximium, consec. for consecutive.

The Random Forest was used to estimate the R^2 score, including all climate indicators. In a second run, only the mean climate indicators were included in calculating the R^2 score. As suggested by previous studies (Vogel et al., 2019; Lei et al., 2017), the difference between the R^2 score of all climate indicators and the R^2 score of only mean climate indicators can be interpreted as an indication of the relative influence of extreme indicators.

2.4 | Variable importance and partial dependence plots

Climate indicator importance is computed as the mean decrease in impurity (Louppe, 2014) for each crop and country. We calculate the average importance across all cross-validation splits. A higher value implies a greater contribution of the selected variable to the prediction function. Previous research promoted the ranking of individual climate indicators according to their relative importance, in particular, to identify the significance of less studied climate indicators, such as precipitation extremes and mean soil moisture (Vogel et al., 2019; Jeong et al., 2016; Beillouin et al., 2020; Hoffman et al., 2018).

Partial dependence plots visualize the functional relationship between a predictor variable and the response variable, marginalizing over the values of all other input features (Hastie et al., 2008). We calculated the average partial dependence plot across all cross-validation splits. Visualizing partial dependence plots helps to understand functional relationships between climate predictors and crop yields (Vogel et al., 2019; Jeong et al., 2016; Beillouin et al., 2020) and to discover linear or nonlinear responses between climate indicators and crop yield anomalies (Hoffman et al., 2018).

3 | RESULTS

3.1 | Mean and extreme climate indicators explain, on average, 18% of the variance of crop yield anomalies in Europe

We applied the Random Forest regressor to predict the crop yield anomaly. It allowed us to estimate the influence of changes in climate indicators on crop yields. Not all crop-growing countries show a significant influence of climate indicators on crop yield anomalies, as indicated by a negative R^2 score. The Random Forest model has no predictive capacity for wheat in France, Poland, and Spain; maize in Romania, Hungary, and Poland; and Barley in Denmark. Therefore, these crops and countries were excluded from further analysis. Averaged over all countries with significant relationships, our model explains one-fifth (18%) of the variance of crop yield anomalies across all crops using the data from 1961 to 2020 in Europe. The R^2 score ranges between 2% and 43%, depending on crop and region, as shown in Figure 3. The most accurate Random Forest

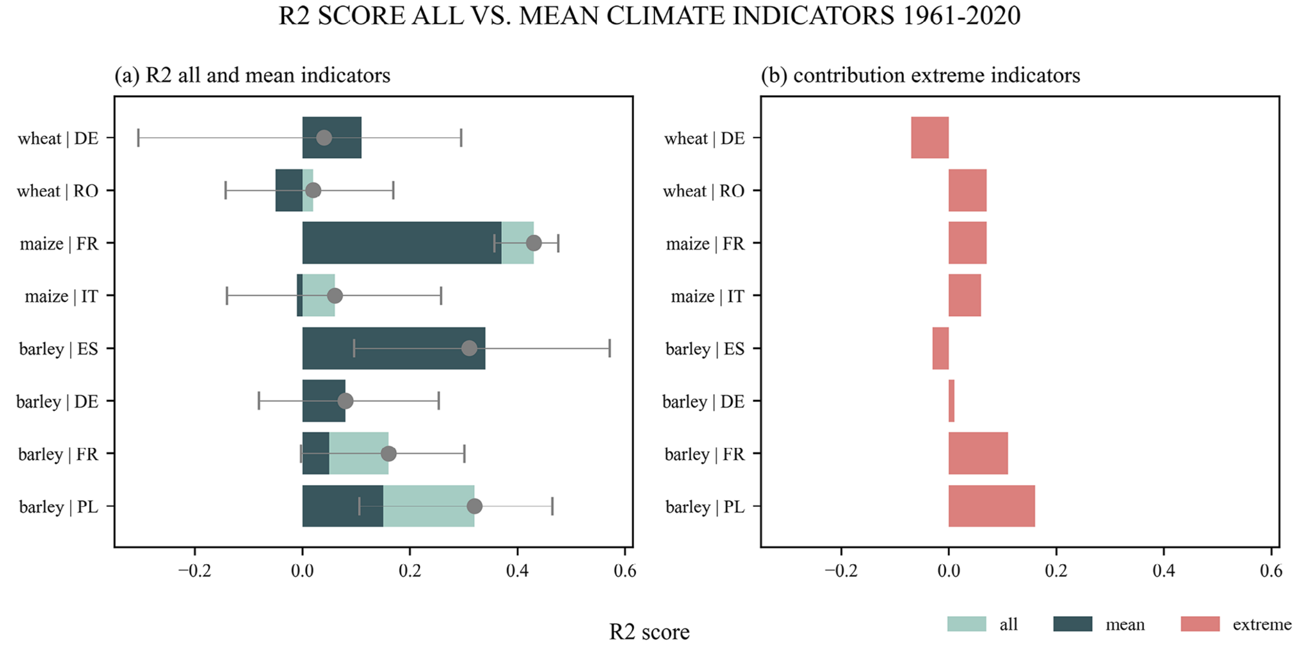

FIGURE 3 R^2 score all vs. mean climate indicators 1961–2020: (a) explained variance (R^2 score) for crop and country based on the Random Forest model that includes all climate indicators (light blue) and only mean climate indicators (dark blue), 5- to 95-percentile range of the R^2 score, including all climate indicators highlighted by the gray line; (b) contribution of extreme indicators calculated as the difference between the R^2 score of the Random Forest model with all climate indicators and only mean climate indicators (red).

model is obtained for maize in France with an R^2 score of 43%, followed by barley in Poland with 32%, and barley in Spain with 31%. On average, maize yield anomalies are explained by 24%, followed by barley with 22% and wheat with 3%.

3.2 | Extreme climate indicators explain, on average, 5% of the variance of crop yield anomalies in Europe

As a next step, we assessed the influence of mean and extreme climate indicators on crop yield anomalies. Therefore, we trained the Random Forest regressor considering all climate indicators and only mean climate indicators. The difference between the training results indicates the relative influence of extreme indicators. Only mean climate indicators predict, on average, 12% of the variance of crop yield anomalies from 1961 until 2020 in Europe. The Random Forest model based only on mean climate indicators explains between 5% and 36% of the yield anomalies depending on the crop and region. The R^2 score decreases by 5% on average, as shown in Figure 3. Extreme climate conditions have the largest influences on barley in Poland and barley in France since the explained variance decreases by 7% and 3%, respectively. However, Figure 3 indicates that the obtained differences are within the error bars, which limits the significance of extreme events. In contrast, extreme climate indicators do not contribute to a higher R^2 score for wheat in Germany and barley in Spain.

3.3 | Temperature- and soil moisture–related climate indicators have the highest predictive capacity for crop yields

The ranking of climate indicators measured by the mean decrease in impurity was used to compare the relative importance of climate indicators. The most important climate variable for each crop and country is temperature or soil moisture, as shown in Figure 4. Across all crops and countries, 42% of the top three climate indicators are related to temperature, 33% to soil moisture, and 25% to precipitation. Our analysis suggests that temperature- and soil moisture–related indicators are more important than precipitation-related indicators in predicting crop yield. Only 17% of climate indicators represent extreme climate indicators, whereas the remaining 83% are mean climate indicators. Thus, mean climate indicators are more important than extreme climate indicators for predicting crop yields. No single climate indicator explains a fraction more than one-third of anomalies in yield across crops and countries. Mean soil moisture in July obtains the maximum variance explained with 28%, for wheat in France.

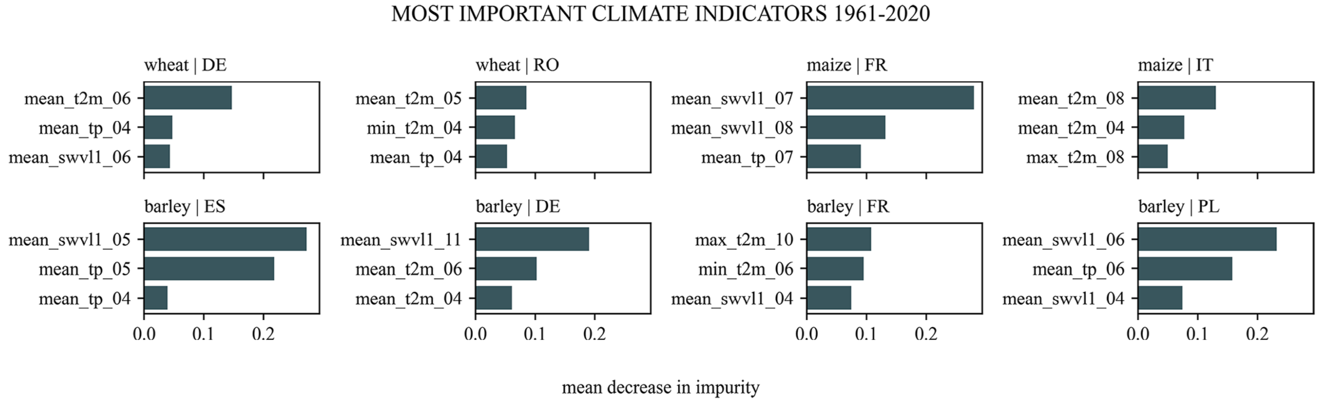

FIGURE 4 Most important climate indicators 1961–2020: mean decrease in impurity for three most important indicators for each crop and country where a positive R^2 score is found. The number after the variable name indicates the month in numerical writing (January—01, etc.).

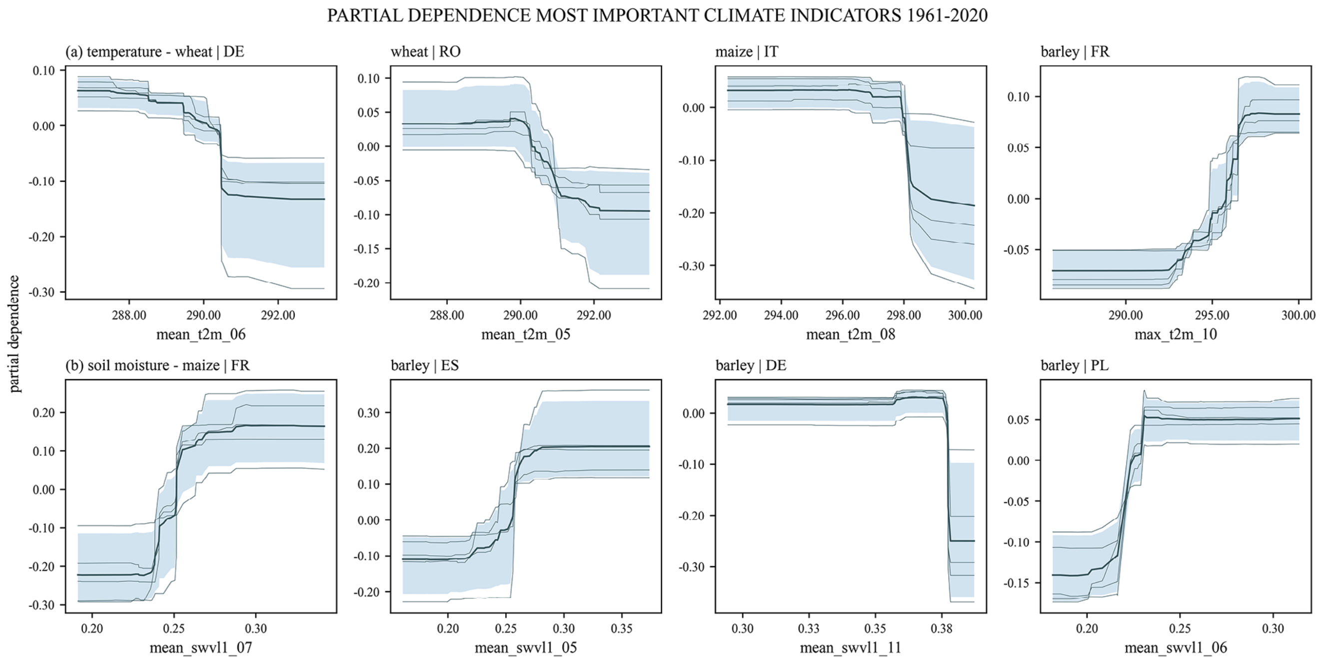

FIGURE 5 Partial dependence most important climate indicators 1961–2020: partial dependence plots highlight the function relationship between crop yields and the most important climate indicators for each crop and country, (a) climate indicators related to temperature and (b) climate indicators related to soil moisture.

3.4 | Temperature and soil moisture extremes can promote and harm crop yields revealing a nonlinear relationship

Partial dependence plots of the most important climate indicators visualize the functional relationship with crop yields and, thus, indicate the correlation between each climate indicator and crop yields. The partial dependence plots for each crop and country's most important climate indicator are shown in Figure 5. We find negative impacts on crop yields from increased temperatures for wheat in Germany, wheat in Romania, and maize in Italy for June, May, and August, respectively. However, for barley in France, an increase in temperatures in October is positively correlated with crop yields. For maize in France in May, barley in Spain in June, and barley in Poland in July, dryer upper soil layers decrease crop yields. Excess soil moisture is also negatively correlated with crop yields, for example, for barley in Germany in November. Our analysis also reveals a nonlinear relationship between climate indicators and crop yields: the partial dependence plots for temperature and soil moisture show threshold-like values

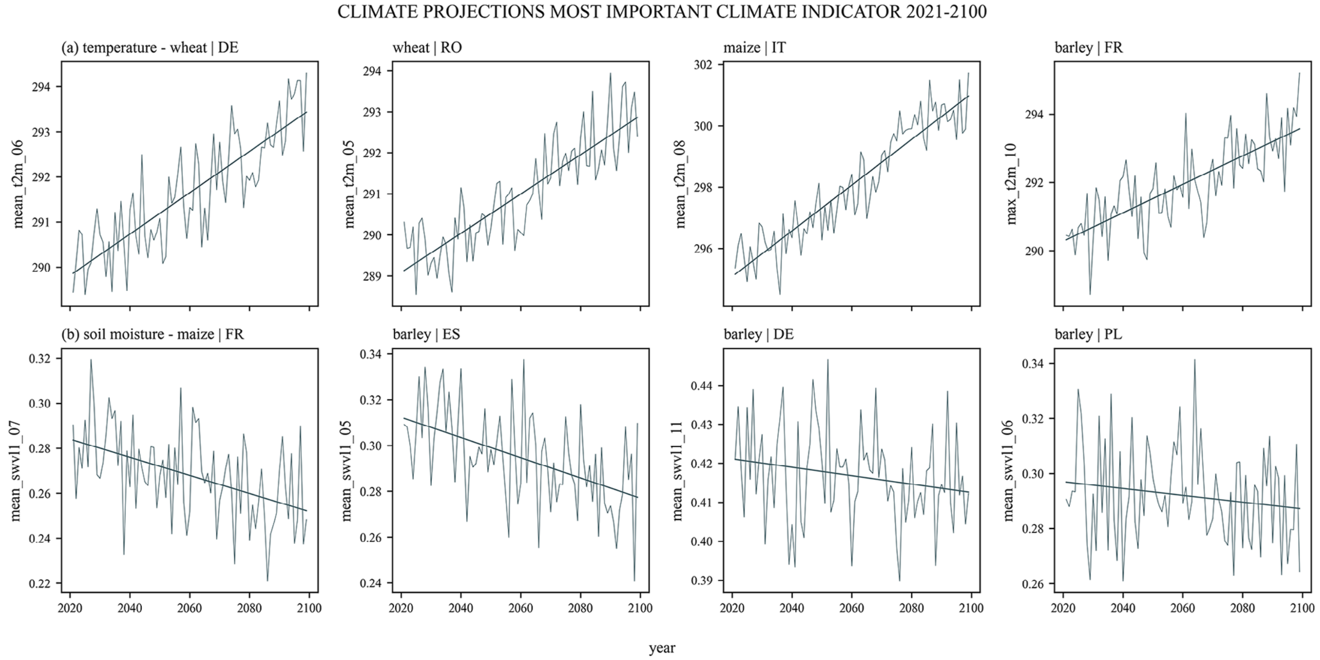

FIGURE 6 Climate projections most important climate indicator 2021–2100: projected development of the most important climate indicator for each crop and country from 2021 until 2100 under SSP3-7.0. The blue line shows the linear trend for each climate indicator.

that lead to a sharp decrease or increase in crop yields when exceeded, as shown in Figure 5. For example, for wheat in Germany, crop yields decrease sharply if the mean temperature in June drops below approximately 290.4 K.

3.5 | Increased heat and drought stress under SSP3-7.0 might fuel an increase in crop losses until 2100

We continue the analysis of the most important climate indicator for each crop and country by calculating the projected anomalies from 2020 to 2100 under the SSP3-7.0 scenario. The possible future climate developments allow us to estimate the influence on crop yields. A positive trend can be observed in all temperature-related indicators from 2021 to 2100, as shown in Figure 6. Warmer temperatures imply that crops are exposed to more heat stress in the future, although warmer temperatures in the fall seasons could lead to stronger crop growth. Soil moisture–related indicators tend to decrease until 2100 under scenario SSP3-7.0, and thus the drought stress to which crops are exposed might increase.

Table 2 shows the correlations between climate indicators and crop yields derived from the partial dependence plots, projected future developments of climate indicators, and their expected impact on crop yields until 2100. Since temperatures are expected to rise, countries that showed a negative correlation between warmer temperatures and crop yields from 1961 to 2020 might experience yield losses more frequently in the future, for example, wheat in Germany, wheat in Romania, and maize in Italy. In contrast, increasing temperatures reduce the risk of cold temperatures until 2100 under SSP3-7.0, for instance, for barley in France in October, and might lead to yield gains. The most important climate indicator for maize in France, barley in Spain, and barley in Poland, the mean soil moisture in spring and summer, is negatively correlated with crop yields. Since the average soil moisture is expected to decrease until 2100 under SSP3-7.0 and, thus, might fall below the threshold more often, crop losses could become more frequent in the future. However, for barley in Germany, the risk of excess soil moisture is decreasing until 2100 under SSP3-7.0 and might lead to yield gains.

4 | DISCUSSION

4.1 | Crop yield explained by climate indicators

All climate indicators predict, on average, 18% of the European yield anomalies from 1961 to 2020. Our research highlights that maize yield anomalies are explained by 24%, followed by barley with 22%, and wheat with 3%. The explained variances presented here are lower than other studies: for maize in Europe, Vogel et al. (2019) found an R^2 score of 47%, Beillouin et al. (2020) of greater than 25%,

TABLE 2 Expected crop yield impact under SSP3-7.0 for the most important climate indicators of each crop and country.

Crop	Country	Climate indicator (CI)	CI condition 1961–2020	Impact on crop yields (CY) 1961–2020	Trend in CI SSP3-7.0 2021–2100	Expected CY impact under SSP3-7.0 by 2100
Wheat	DE	mean t2m 06	Heat	Loss	Increase	Loss
Wheat	RO	mean t2m 05	Heat	Loss	Increase	Loss
Maize	IT	mean t2m 08	Heat	Loss	Increase	Loss
Barley	FR	max t2m 10	Heat	Gain	Increase	Gain
Maize	FR	mean swvl1 07	Deficit	Loss	Decrease	Loss
Barley	ES	mean swvl1 05	Deficit	Loss	Decrease	Loss
Barley	DE	mean swvl1 11	Excess	Loss	Decrease	Gain
Barley	PL	mean swvl1 06	Deficit	Loss	Decrease	Loss

and Ray et al. (2015) of 41%. For barley in Europe, Beillouin et al. (2020) reported an explained variance of 26%. For winter wheat in Europe, Beillouin et al. (2020) and Ray et al. (2015) showed that climate indicators can explain 43% and 36% of crop yield anomaly, respectively. However, research by Vogel et al. (2019) showed that climate indicators only described an insignificant proportion of observed variations in wheat crop yields, likely due to the comparatively long growing season. We show that extreme climate indicators contribute approximately one-third to crop yield anomalies across countries, compared to a fraction of more than half reported by Vogel et al. (2019).

The reported explanatory power of climate indicators also depends on the selected study design and method. The availability of crop yield data at a higher resolution than the country level could be one explanation for the higher R^2 scores achieved by other studies (Beillouin et al., 2020; Ray et al., 2015; Vogel et al., 2019). Our research neglects the impact of local climate on crop yields since the FAO (2021) crop yield data are only available at the national level. Higher resolution data would also increase the training data size for each country. Finally, an analysis with subnational crop yield data might improve the performance of the Random Forest model.

Eighty-two percent of anomalies in crop yield across crops and countries remain unexplained, highlighting the influence of other factors, such as pests and pathogens, crop management practices, and socioeconomic circumstances that influence crop yield (Beillouin et al., 2020; Ray et al., 2015; Vogel et al., 2019). Changes in climate favor large-scale pest and pathogen outbreaks that exacerbate yield losses (Gregory et al., 2009; Deutsch et al., 2018; Bebber et al., 2013). Furthermore, crop management, including fertilizer use, tillage, irrigation, and choice of crop types, can explain another fraction of crop yield anomaly (Mueller et al., 2012; Smith et al., 2007; Vogel et al., 2019; Frieler et al., 2017; Hatfield et al., 2015; Olesen et al., 2011). The inclusion of the factors has been shown to improve model performance (Juroszek and von Tiedemann, 2013). Other economic factors, such as energy and fertilizer prices, also impact the cultivation of crops (Gobin et al., 2010; Tokgoz, 2009). Atmospheric gasses, including CO_2 (Deryng et al., 2014) or ozone (Tai, 2017; Emberson et al., 2018), also interact with crop yields, emphasizing their inclusion in forthcoming crop growth models.

4.2 | Importance of climate indicators for anomalies in crop yields

We analyzed the three most important climate indicators explaining crop yield anomalies for each crop and country. Our research emphasizes that 42% of the climate indicators are related to temperature, 33% to soil moisture, and 25% to precipitation. Previous studies confirm the importance of temperature-related climate indicators: temperature-related indicators correlate stronger with crop yield anomalies than precipitation-related indicators for spring wheat (Vogel et al., 2019), maize (Vogel et al., 2019; Lobell et al., 2007), and barley (Lobell et al., 2007). Furthermore, Beillouin et al. (2020) found that temperature and precipitation explain a higher fraction of anomalies in crop yields than soil moisture across crops in Europe.

Confirming Beillouin et al. (2020), no single mean or extreme climate indicator alone explains a large fraction of yield anomaly across crops and countries. This finding indicates that compound extreme weather events, instead of single climate indicators, might explain crop losses in Europe, as shown by previous studies (Beillouin et al., 2020; Ben-Ari et al., 2018; Kolář et al., 2014).

Vogel et al. (2019), Beillouin et al. (2020), Lüttger et al. (2018), Hernandez-Barrera et al. (2017), Hlavinka et al. (2009), and Kristensen et al. (2011) found that unusually warm and cold temperatures adversely affect wheat and maize yields across European countries. Our study confirms that the relationship exists not only for wheat and maize across European countries but also for barley. In addition, we also found that extreme soil moisture values can harm crop yields.

Our study shows a nonlinear relationship between Europe's most important climate indicators related to temperature and soil moisture and crop yields for wheat, maize, and barley. The finding confirms previous studies from the United States and Denmark: Troy et al. (2015) and Schlenker et al. (2009) describe the nonlinear and threshold-type relationships between precipitation- and temperature-related climate indicators and crop yields for the United States. In addition, Kristensen et al. (2011) found a nonlinear relationship between mean winter temperature and wheat yields in Denmark. Not only do threshold values for temperature and precipitation lead to a sharp decrease or increase in crop yields, but also for soil moisture. However, since our data only include a few samples for extreme values of each climate indicator, the exact threshold values have to be investigated in future studies.

4.3 | Implications for agricultural adaptation strategies

Our results highlight that changes in climate indicators can lead to decreases in crop yields but, under certain circumstances, also promote crop productivity under scenario SSP3-7.0 until 2100. According to the Intergovernmental Panel on Climate Change, food security will increasingly be affected by projected climate change in the future (Mbow et al., 2019). For example, wheat yields are expected to decrease in France and Spain under the future climate projection scenario RCP 8.5 (Ben-Ari et al., 2018; Hernandez-Barrera et al., 2017). However, farmers across Europe are already adapting to climate change. For example, Mbow et al. (2019) and Olesen et al. (2011) already observed changes in sowing and harvesting dates in Europe.

Our research underlines the importance of efficient adaptation strategies for farmers. Since crop management practices also explain a fraction of anomalies in crop yields, adaptation strategies have the potential to reduce the climate risks for crops and improve the resilience of our food system: crop breeding, including new genetic strategies, provides opportunities for improving crop yields that are resistant to precipitation, heat waves, other weather extremes, and shifts in pests and pathogens (Bailey-Serres et al., 2019; Olesen et al., 2011). Also, selecting the most suitable crop type and growing season start for a location can ensure more stable crop yields (Hatfield et al., 2015; Olesen et al., 2011). Several studies showed that irrigation mitigates water stress effects and high-temperature extremes (Frieler et al., 2017; Vogel et al., 2019; Troy et al., 2015). However, water availability poses a long-term challenge, particularly in Southern Europe, and thus, increases the need for more efficient water management systems (Olesen et al., 2011; Iglesias et al., 2015). Besides adaptation practices, mitigation efforts of the agriculture sector can also contribute to reducing the climate-induced crop risk and, thus, ensure food security in the future.

5 | CONCLUSION

In this study, we analyzed the historical and future impacts of mean and extreme climate conditions on wheat, maize, and barley crop yields in Europe using a Random Forest model. Our results underline the importance of considering the impacts of changing mean and extreme climate conditions on crop production and adapting agriculture to climate change to meet food demands in the future. The major conclusions are as follows:

1. Climate indicators, comprising mean and extreme climate conditions, explain 18% of the variance of crop yield anomalies across crops and EU countries from 1961 to 2020. Of those, extreme climate indicators contribute, on average, 58% to the variance of crop yield anomalies.
2. Temperature- and soil moisture–related climate indicators have the highest predictive capacity for crop yields. Temperature and soil moisture extremes can promote and harm crop yields.
3. Increased heat and drought stress under SSP3-7.0 might fuel crop losses until 2100.

The insights into the impact of climate change on crop yields for each crop and country could be helpful for all stakeholders involved in developing effective adaptation strategies, including farmers, agricultural businesses, and policymakers.

A high degree of uncertainty remains in predicting crop yield anomalies. Thus, studies' accuracy can be significantly increased by developing public high-resolution subnational geospatial yield data. It could improve the predicting model performance and provide detailed insights about regional differences. An analysis of the impact of climate change on anomalies in crop yield at the local level would also support more effective decision making for stakeholders from governmental and private institutions concerned with agriculture. To further improve predictions, we suggest including factors such as the usage of pests and pathogens, crop management practices, and socioeconomic conditions.

Ultimately, future research on the impact of climate change on anomalies in crop yield provides the foundation for the SDGs to create a sustainable food system that delivers food security and nutrition for all without harming future generations' economic, social, and environmental bases (Nguyen et al., 2018).

AUTHOR CONTRIBUTIONS

Miriam Schmidt: Conceptualization (equal); data curation (lead); formal analysis (lead); investigation (lead); methodology (equal); project administration (supporting); software (lead); writing - original draft (equal); writing - review and editing (equal). **Elizaveta Felsche**: Conceptualization (equal); project administration (lead); supervision (lead); writing - original draft (equal); writing - review and editing (equal).

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CONFLICT OF INTEREST STATEMENT

We declare no conflict of interest.

DATA AVAILABILITY STATEMENT

All the raw data are publicly available under the sources. Derived data supporting the findings of this study are available from the corresponding author, M.S., on request.

ORCID

Elizaveta Felsche https://orcid.org/0000-0001-6606-091X

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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