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RESEARCH

A comparison of climate drivers' impacts on silage maize yield shock in Germany

Federico Stainoh[1] · Julia Moemken[1] · Celia M. Gouveia[2,3] · Joaquim G. Pinto[1]

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Abstract

Extreme weather events have become more frequent and severe with ongoing climate change, with a huge implication for the agricultural sector and detrimental effects on crop yield. In this study, we compare several combinations of climate indices and utilized the Least Absolute Shrinkage and Selection Operator (LASSO) to explain the probabilities of substantial drops in silage maize yield (here defined as "yield shock" by using a 15th percentile as threshold) in Germany between 1999 and 2020. We compare the variable importance and the predictability skill of six combinations of climate indices using the Matthews Correlation Coefficient (MCC). Finally, we delve into year-to-year predictions by comparing them against the historical series and examining the variables contributing to high and low predicted yield shock probabilities. We find that cold conditions during April and hot and/or dry conditions during July increase the chance of silage maize yield shock. Moreover, a combination of simple variables (e.g. total precipitation) and complex variables (e.g. cumulative cold under cold nights) enhances predictive accuracy. Lastly, we find that the years with higher predicted yield shock probabilities are characterized mainly by relatively hotter and drier conditions during July compared to years with lower yield shock probabilities. Our findings enhance our understanding of how weather impacts maize crop yield shocks and underscore the importance of considering complex variables and using effective selection methods, particularly when addressing climate-related events.

1 Introduction

Extreme weather and climate events have become more frequent and severe under ongoing climate change (Diffenbaugh et al. 2017). This leads to strong impacts on the agricultural sector where unusual climate conditions can result in significant yield losses, from farm to global scale (Trnka et al. 2014; Lesk et al. 2016; Mäkinen et al. 2018; Cottrell et al. 2019; Vogel et al. 2019). Moreover, extreme weather events also exert influence on market dynamics by altering domestic prices and trade balances (Chatzopoulos et al. 2020). In Europe, droughts and heat waves reduced cereal yields on average by 9% and 7.3%, respectively, whereas non-cereal yields lessened by 3.8-3.1% during the same set of events in the last 5 decades (Brás et al. 2021). Specific events such as the summer heatwaves of 2003 or 2018 caused widespread losses in the agricultural sector along the continent (García-Herrera et al. 2010; Beillouin et al. 2020; Zhu et al. 2021). Crop yield losses can be associated with single variable extremes, such as high temperatures (Ribeiro et al. 2019), or with a combination of either successive or temporally synchronized events (acquainted in the literature as "compound events", Ribeiro et al. 2020; Bevacqua et al. 2021). In a world where the population is expected to increase to up to 10 billion by 2050 (United Nations 2022), gaining deeper insights into the meteorological drivers responsible for agricultural losses becomes critical if we aim to fulfil the projected nutritional demand (Tilman et al. 2011).

There are two main approaches to studying the impact of weather and climate anomalies on crop yield. The first one is using crop simulation models that, with adequate complexity, can be effectively utilised to evaluate the causal relationship between crop yield and climate anomalies in specific regions. However, some physiological responses to weather and climate extremes are not considered (Barlow et al. 2015). Additionally, extreme weather events are some-

✉ Federico Stainoh
federico.stainoh@kit.edu

1 Institute of Meteorology and Climate Research Troposphere Research (IMKTRO), Karlsruhe Institute of Technology (KIT), Karlsruhe, Germany

2 Instituto Português do Mar e Atmosfera (IPMA), Lisbon, Portugal

3 Instituto Dom Luiz (IDL), Faculty of Sciences, University of Lisbon, Lisbon, Portugal

times linked to indirect impacts on crop yield, which are not represented in models, for instance, throughout pests and disease outbreaks (Ziska et al. 2011). The second approach is statistical modelling. This methodology uses observed yield data, typically from trials (e.g. Mäkinen et al. 2018) or governmental statistics databases (e.g. FAO 2024) and establishes a regression-like link with climate drivers (Zampieri et al. 2018). A common approach within statistical modelling is to strictly focus on climate drivers of significant drops in crop yield. These studies can reveal previously unforeseen causes of yield shock (Ben-Ari et al. 2018) and disentangle the most frequent climate drivers of historical losses (Webber et al. 2020). Therefore, statistical modelling bridges gaps inherent in process-based crop models (Gornott and Wechsung 2016; Zampieri et al. 2018; Webber et al. 2020).

Usually, statistical models are built by considering a great number of variables, and thus, the interpretation of the results can become challenging. This is further evident due to the likelihood of spurious correlation caused by existing co-linearity between variables (Dormann et al. 2013). The definition of weather and climate predictors requires previous knowledge of the vulnerability of the affected system (Smith 2011) since, for example, not every variable necessarily leads to crop losses, thus we use the term "drivers" like in the IPCC (2023). In some cases, it might even have a positive contribution (van der Velde et al. 2012). Many studies utilize aggregated variables like average temperature and total precipitation (Beillouin et al. 2020; Webber et al. 2020), whereas other studies consider statistical-based threshold variables (Zhu et al. 2021; Schmitt et al. 2022). Statistically-based variables facilitate the comparison of weather extremes across different locations by quantifying and standardizing the intensity and frequency (Zampieri et al. 2017). The added value of considering more complex or simple variables has not yet been disentangled (Ben-Ari et al. 2016).

This study investigates the impact of several climate drivers for the specific case of silage maize in Germany. We consider a set of different groups of variables (by both using simple, frequency and cumulative-based variables, as well as a combination of them). We explicitly focus on significant losses in silage maize yield (referred to in this study as "yield shock", using the 15th percentile as threshold). We employ the Least Absolute Shrinkage and Selection Operator (LASSO; Tibshirani 1996), a parametric method which additionally serves as a second filter of variables. We compare the climate drivers of yield shock and the model accuracy using the Mathews Correlation Coefficient, a classification-model performance metric. Lastly, we dive into the causes of historical yield loss by analysing the contribution to high/low probabilities of yield shock during historical losses of silage maize. Thus, our specific aims are:

1. To identify the most relevant climate drivers for silage maize yield shocks
2. To examine the added value of using several sets of climate drivers.
3. To estimate the contribution of weather and climate drivers to high probabilities of yield shock.

This research aims to contribute to the understanding of the meteorological influence on crop yield shocks in silage maize and offers insights into the effectiveness of various variable sets in predicting yield losses. The paper is structured as follows: Data used, data preparation and climate indices are introduced in Section 2. The statistical model development with LASSO along with the introduction of predictive skill is presented in Section 3. Outputs and results of models are presented in Section 4. Finally, we conclude with a summary and a thorough discussion in Section 5.

2 Data

2.1 Crop data

We extract crop yield data from the Statistical German Office database "Regionaldatenbank Deutschland" (https://www.regionalstatistik.de/genesis/online/table/41241-01-03-4). We use the silage maize yield data for the period 1999 to 2020 at the district level (or "Landkreis"), also equivalent to NUTS3 resolution (https://ec.europa.eu/eurostat/web/nuts/background). First, we filter only those locations where data has less than 10% (2 years) of missing values. As a second step, we standardize the series, using the following Eq. 1:

$$y_{DetStd} = \frac{y_{obs} - y_m}{y_m} \tag{1}$$

where y_{DetStd} is the detrended and standardized yield, y_{obs} is the observed yield and y_m is the modelled yield obtained by a locally weighted polynomial regression (LOWESS; Cleveland 1979). LOWESS is a non-parametric regression method that fits multiple low-degree polynomials to localized subsets of the data (in our case, fractions of 20% of data). Detrending and standardization are done for each location separately (see Fig. 1b). Finally, we categorize the data into two groups: one indicating a substantial drop in yield labelled as "yield shock" and the other denoted as "no yield shock". Other studies refer to this as "yield failure" (Webber et al. 2020), "yield loss" (Ben-Ari et al. 2018), "crop yield extreme" (van Oort et al. 2023) or "bad years" (Vogel et al. 2021). The data is categorized using the 15th percentile from the total sample as a threshold (i.e. if $y_{DetStd} < 15th percentile \rightarrow yieldshock$;

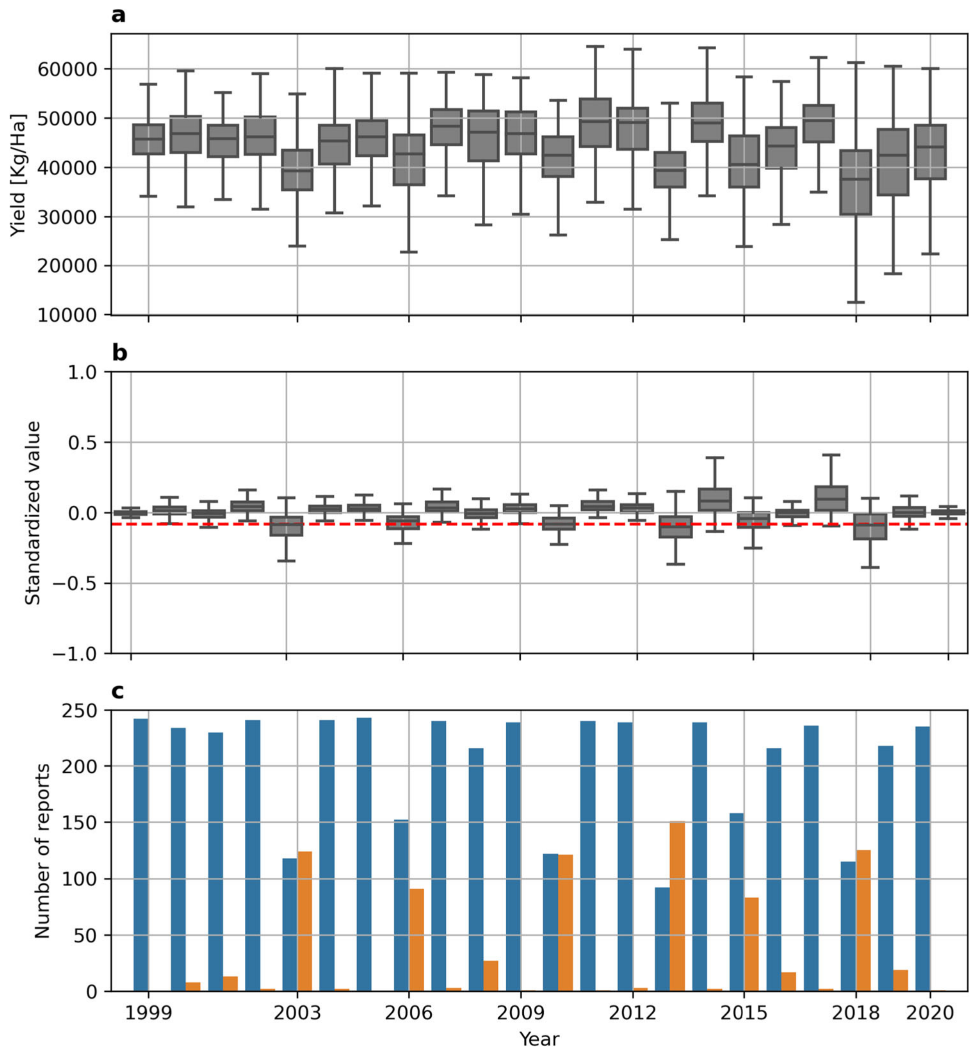


Fig. 1 Silage maize yield sample transformation. (a) Year-to-year distribution of silage maize yield for the entire sample, (b) year-to-year distribution of standardized yield, horizontal red line corresponds to the global 15th percentile (c) number of "yield shock" (orange bars) and "no yield shock" (blue bars) per year

Fig. 1b red line). This threshold is chosen based on previous literature (Ben-Ari et al. 2018). The transformation results in a series of reported yield shock/ no yield shock, as is illustrated in Fig. 1c. We do not discriminate by district. In total, our sample includes 5324 observations.

2.2 Meteorological data and climate indices

We use the ensemble version of the meteorological observational dataset E-OBS version 23.0 (Cornes et al. 2018). E-OBS is a gridded observational dataset based on interpolated European meteorological station data. For our study, we use maximum temperature, minimum temperature and total precipitation for the period 1998 to 2020 with daily temporal and 0.1° spatial resolution. We compute a total of 11 climate indices (Table 1), which are partially based on previous literature (Vogel et al. 2019; Schmitt et al. 2022) and attempt to represent the most studied weather and climate extreme events (drought event, extreme precipitation, cold and high temperatures). We are particularly interested in comparing the impact of frequency (e.g. *number of warm days*) and magnitude (e.g. *cumulative heat*) of unusual weather conditions apart from the most commonly used variables (average temperatures and cumulative precipitation). All percentiles are calculated using 1998-2020 as the base period. In case of "number of wet days", percentiles are computed using only days with precipitation above 1mm. For the 'cumulative-precipitation-based' variables, we compute monthly total precipitation and standardize them within the same months of the studied period by fitting a Gaussian distribution. This process results in a 'Standardized Precipitation' (SP) similar to the widely-known Standardized Precipitation Index (SPI, McKee et al. 1993), with the distinction of accumulating one month in question. The 'standardized precipitation during wet months' and the 'standardized precipitation during dry months' are derived by adjusting the original SP values. We considered the range April-September, based on the standard growing cycle of silage maize.

Table 1 List of climate indices

Variable	Short name	Description
Total precipitation	PP	Monthly total precipitation
Number of dry days	PPlt1	Number of days with precipitation below 1mm
Number of wet days	PP90p	Number of days with precipitation above the wet days-based 90th percentile
SP during dry months	SPltn05	Monthly standardized precipitation when the value is below -0.5
SP during wet months	SPgt05	Monthly standardized precipitation when the value is above 0.5
Mean maximum temperature	TX	Monthly mean maximum temperature
Number of warm days	TX90p	Number of days with daily maximum temperature above the monthly 90th percentile
Cumulative heat	TX90pDD	Cumulative daily maximum temperature during warm days
Mean minimum temperature	TN	Monthly mean minimum temperature
Number of cold nights	TN10p	Number of nights with daily minimum temperature below the monthly 10th percentile
Cumulative cold	TN10pDD	Cumulative daily minimum temperature during cold nights

Among the considered variables, co-linearity becomes evident (Fig. 2 displays the matrix correlation between climate indices for each month). In the endeavour of distinguishing the predictive capability of simple and complex variables and diminishing spurious correlation, we create 6 different groups of predictors (Fig. 3): A "simple group" (*Simple*, Fig. 3a) that consists of total precipitation, mean maximum temperature and mean minimum temperature; a frequency based-variables group (*Frequency*, Fig. 3b) that considers the number of warm days, number of cold

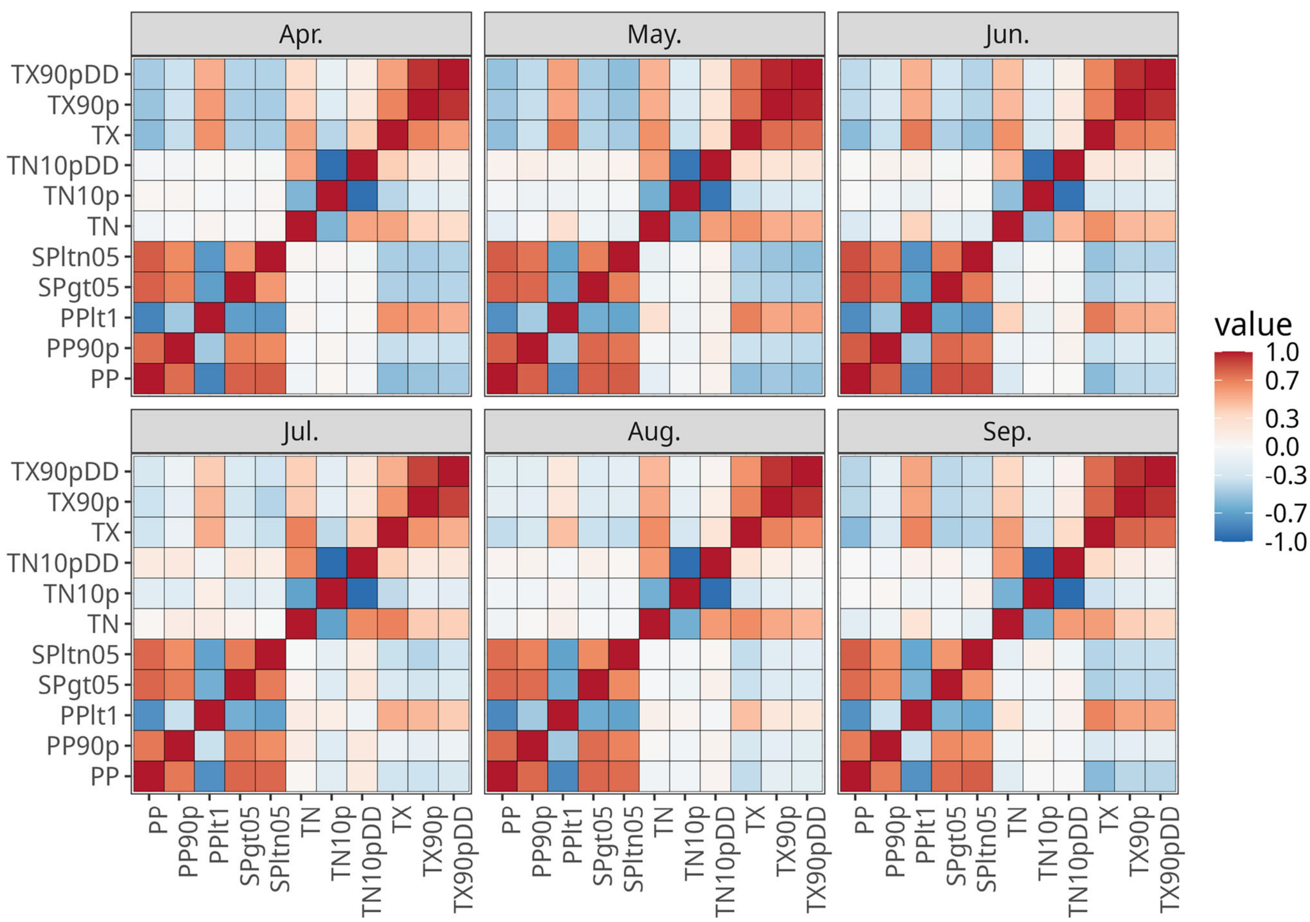


Fig. 2 Spearman correlation between climate indices for each month (in panels)

Fig. 3 Set of selected variables of each group (by panel) prior to modeling. The considered variables appear in blue squares, while the not-considered variables in blank

nights, number of wet days and the number of dry days; a cumulative-based variables group (*Cumulative*, Fig. 3c) that contemplates accumulated heat, accumulated cold, SP during wet months, and SP during dry months; and a group using all the variables together (*All*, Fig. 3d). Additionally, we include two groups using a "Step-wise" variable reduction method. The Step-wise algorithm refers to a method for selecting the best subset of predictors by iteratively adding or removing predictors based on a specific criterion (usually based on information criterion or statistical test), with the goal of finding the "best" model with a reduced number of variables. Step-wise requires the computation of a "null model" (a model with no predictors) and a "full model" (a model with all predictors). In our case, these are based on a logistic regression model (Log version in Eq. 2 and linear version in Eq. 3).

$$p(Y) = \frac{e^{\beta_0 + \sum_{j=1}^{k}(\beta_j X_j)}}{1 + e^{\beta_0 + \sum_{j=1}^{k}(\beta_j X_j)}} \tag{2}$$

$$ln(\frac{p(\mathbf{Y})}{1 - p(\mathbf{Y})}) = \beta_0 + \sum_{j=1}^{k}(\beta_j X_j) \tag{3}$$

where $p(Y)$ is the probability of yield shock, β_0 is the estimated intercept of the model, and $\beta_1 ... \beta_k$ are the estimated coefficients for the $X_1 ... X_k$ predictors. Coefficients are calculated using the maximum likelihood equation (see chapter 4 from James et al. 2021, for more information). The model selection is made using a "Bayesian Information Criterion", in which models are compared by both considering their log-likelihood function and a penalty term based on the number of predictors to avoid overfitting (see chapter 6 from James et al. 2021, for a detailed explanation). We employ the "Forward" mode of Step-wise to obtain the fifth group (*Forward*, Fig. 3e) and the "Backward" mode for the sixth group (*Backward*, Fig. 3f). The whole variable-reduction procedure is estimated using all the available data (as in Tredennick et al. 2021). From the 66 variables, 18 predictors remain in both the Forward group and the Backward group.

3 Methodology

3.1 Modeling with LASSO

For this section, all variables are first re-scaled to [-1,1], to keep them in the same unit range whilst maintaining their distribution (Ali et al. 2014). The data is randomly split in 70% for training and 30% for validation.

We use LASSO to estimate the influence of climate indices on yield shock. LASSO is a regression and regularization method that seeks to find the best model while balancing the coefficient values. For this, coefficients are estimated by both minimizing a negative log-likelihood function and a penalty term (4):

$$S(\beta_0, \beta_1^k) + \lambda \sum_{j=1}^{k} |\beta_j| \tag{4}$$

where S is the negative log-likelihood function, λ is the tuning parameter and $\lambda \sum_{j=1}^{k} |\beta_j|$ is the penalty term (see Wang et al. 2015, for detailed equations). The key feature of LASSO is that parameters can be shrunk to zero, which means that LASSO can also work as a "variable selection" method.

We use the *glmnet* package from R software to perform LASSO (Friedman et al. 2021) and calculate the parameters of the logistic regression (2) and (3). The tuning parameter λ is usually defined by cross-validation. For that, we employ a customized cross-validation called "leave-one-year-out" cross-validation (Wang et al. 2020; Tredennick et al. 2021). The procedure consists of building a model by removing all observations from a particular year and considering a range of possible values for λ. Then, we calculate the model's accuracy, validating it against the "unknown" year. This procedure is repeated each year (in this case, 22 years, i.e. 22 folds). It is computed by using the function *cv.glmnet*, which has two main outputs: The $Lambda.min$ that is the tuning parameter that minimizes the cross-validation error, and the $Lambda.1se$, which suggests the most regularized model within one standard deviation from the $lambda.min$. We estimate all our models using the $lambda.1se$ to maintain a complexity-predictability balance.

3.2 Comparison of variable importance between groups

To estimate the relevance of the climate drivers explaining silage maize yield shock, we perform a qualitative analysis by comparing the coefficient values of the predictors of each model. When considering the log version of Eq. 3, the estimated coe- fficients are related to the linear increase/decrease of the Logit value. We explicitly focus on the variable importance rank.

3.3 Comparison of predictive skill between sets of variables

To compare the performance of each set of variables, we use the Mathews Correlation Coefficient (MCC; Matthews 1975) to estimate the predictive skill on the validation data. The MCC is a symmetric coefficient for assessing binomial or classification model performance. This metric has the advantage of being sensitive to imbalanced data and thus considering broader data distribution scenarios, providing more comprehensive information than other metrics (Chicco et al. 2021). MCC is calculated using the values obtained from a confusion matrix (Fig. S1):

$$MCC = \frac{TPxTN - FPxFN}{\sqrt{(TP+FP)(TP+FN)(TN+FP)+(TN+FN)}} \tag{5}$$

where TN refers to true negatives (actual negatives that are correctly predicted negatives), TP refers to true positives (actual positives that are correctly predicted positives), *FP* refers to false positives (actual negatives that are wrongly predicted positives) and FN refers to false negatives (actual positives that are wrongly predicted negatives). MCC increases when either $TPxTN$ increases or $FPxFN$ decreases. This means that a high model performance requires high numbers of both TP and TN, while having low numbers of both FP and FN. An MCC equal to 1 implies a perfect model, whereas an MCC equal to -1 means that the model does not hit any single value. A value close to 0 means a performance similar to random guessing.

To build the confusion matrix, we require a threshold to split the predicted probabilities. The tentative choice is usually 50%. This means that if the predicted probability of the estimated model were to be above (below) 50%, then the obtained value would be labelled as "yield shock" ("no yield shock"). However, 50% may be biased, especially in the presence of imbalanced data. Instead, we calculate MCC for each model considering a set of 20 thresholds, ranging from 0 (or 0%) to 1 (or 100%), that are equally segmented ($threshld = 0, 0.05, 0.1, 0.15, ...1$). When seeking to obtain conclusions for a more "pessimistic" ("optimistic") view, a threshold closer to 0% (100%) should be considered.

3.4 Identification of key climate drivers leading to historical yield shock

Finally, we select the best model according to the MCC (previous subsection) and investigate climate drivers' contribution to historical silage maize yield losses. At an initial examination, we calculate the predicted probabilities by year using the validation data and compare them with the reported observations (illustrated in Fig. 1c). In the second step, we rank the years from the worst year (high probabilities of yield shock) to the best years (low probabilities of yield shock) by averaging the predictions by year. Then, we select the six worst years (referred to later on as "bad years") and the 6 best years (referred to as "good years") by considering the average predicted probabilities. Finally, we quantify and compare the contribution of the variables to the predicted high and low yield shock probabilities. For this, we use the "log" version of the logistic regression (3), and we calculate the individual contribution to the predicted Logit value from each predictor (6).

$$Contribution_{l,k} = \beta_k * \hat{x}_{l,k} \tag{6}$$

where $Contribution_{l,k}$ is the contribution for each observation l and each predictor k, and $\hat{X}$ is the data for each predictor and observation.

4 Results

4.1 Comparison of variable importance between groups

In this section, we analyse the general pattern of the meteorological variables that explain yield shock probabilities.

Figure 4 illustrates the coefficient values obtained for each model. The name of the models corresponds to the predefined set of predictors. When the colour is red (blue), an increase in the value of the corresponding variable leads to a higher (lower) yield shock probability. Coefficients which are either null or not included are not displayed in colours. The coefficient values are presented in Table S1, sorted by decreasing absolute value. First of all, we observe a diminishment of a total number of predictors in comparison to the original inputs (Fig. 3). The approach with LASSO reduces the total number of variables from 18 to 11 in group *Simple*, 24 to 7 in *Frequency*, 24 to 11 in *Cumulative*, 66 to 21 variables in group *All*, 18 to 14 in *Forward* and 18 to 15 in *Backward*.

Overall, the six groups agree on two sets of conditions. The first one is that hot-dry conditions during July and August increase the probability of yield shock. The primary predictor for the six groups is maximum temperature-related variables in July. This is illustrated in a positive coefficient of TX (i.e. higher maximum temperature, higher probability of yield shock), TX90P (i.e. higher number of warm days, higher probabilities of yield shock), and TXD90pDD (i.e. higher cumulative heat, higher probabilities of yield shock) in groups *Simple*, *Frequency*, and *Cumulative*, respectively. Groups *All* and *Forward* select TX90p in July as the most important variable. The group *Backward*, on the other hand, chooses TX in July as the most important variable (second most relevant variable in group *All* and third in group *Forward*). In addition, in the same month, we observe that reduced precipitation increases the probability of yield shock. This is shown in the negative coefficient of PP (i.e. the less precipitation, the higher probabilities of yield shock) in groups *Simple* and *Backward* and SPltm05 (i.e. the more negative the value of SP, the more the probabilities of yield shock) in group *Cumulative* and in the positive coefficient of PPlt1 (the higher the number of dry days, the higher the probabilities of yield shock) in groups *Frequency*, *All* and *Forward*. Lastly, hot and dry conditions in August increase the probability of yield shock, though the importance of predictors in this month has a lesser extension.

As a second general pattern, cold temperatures during April increase the probability of silage maize yield shock. The key variables change depending on the group, but the predictors show similar patterns. In group *Simple*, we observe a negative coefficient of TX in April, whilst in group *Frequency*, it is illustrated in the positive coefficient of TN10p (i.e., the more number of cold nights, the highest the probability of yield shock). In groups *Cumulative*, *All*, *Forward* and *Backward*, the negative effect of cold temperatures in April is illustrated by a negative coefficient of TN10pDD (i.e. the more cumulative cold, the higher the probabilities of yield shock). We also observed this pattern in May (particularly with TN10pDD) but to a lesser extent.

4.2 Comparison of predictive skill between set of variables

In the next step, we compare the performance of the predicted probabilities between the set of variables. Figure 5 illustrates the performance skill obtained with MCC for all models throughout the different thresholds. As a general observation, the MCC is positive for all models and thresholds, which means that the six model performances are better than random guessing. Moreover, a peak in performance in the six groups is observed when the probability threshold is between 20% and 30%, depending on the model. Therefore, our approach performs better under more "pessimistic" considerations than a balanced threshold choice (50%). The hybrid groups (*All*, *Forward* and *Backward*) present superior

Fig. 4 Coefficient values by variable group (in each panel). The coefficient names (y-axis) refer to the variables in Table 1. Variables either excluded from the group or not selected by LASSO do not have coefficient value at all (blank spaces)

Fig. 5 Mathews correlation coefficient (MCC) for each variable group (by color). The threshold (x-axis) chosen to determine the confusion matrix is in percentage

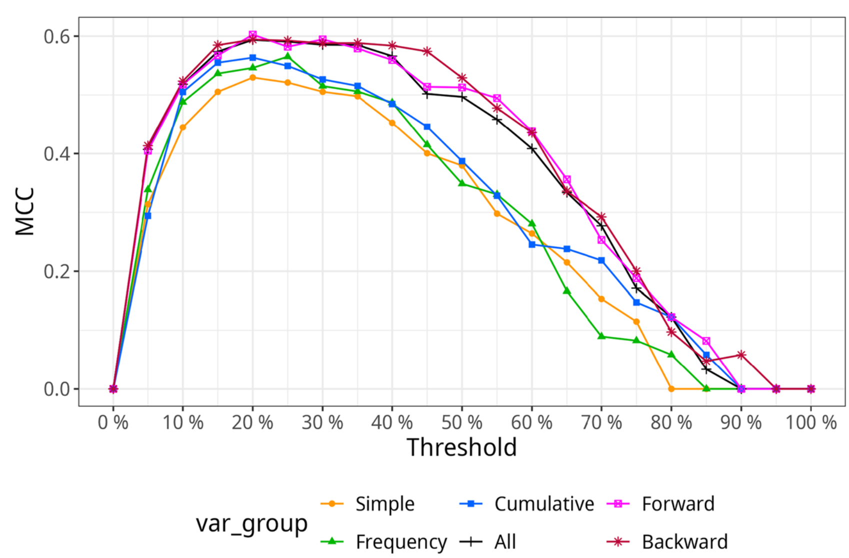
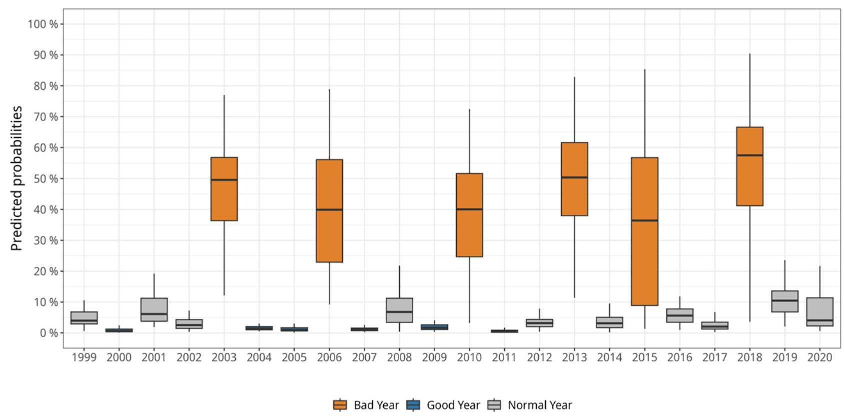


Fig. 6 Year-to-year distribution of the predicted probability in group *Backward*. Orange-coloured boxplots correspond to the 6 "bad years" and blue-coloured to the 6 "good years"



predictive skills than the other groups (*Simple*, *Frequency* and *Cumulative*)). This becomes evident when considering thresholds between 30 and 80%. The group *Backward* (red line in Fig. 5) is the one with the overall highest performance, though the difference can be considered negligible.

4.3 Year-to-year prediction

Since the model obtained using group *Backward* outperforms the others, we conduct the remaining analysis using only this group. Figure 6 displays the year-to-year distribution of predicted probabilities of yield shock. The years with higher and lower probabilities match the reported observations of yield shock in Fig. 1. We observe that 2003, 2006, 2010, 2013, 2015 and 2018 are the years with the highest predicted yield shock probabilities (orange-coloured boxplots in Fig. 6, "bad years"), as well as the ones with the largest numbers of reported yield shock (orange bars in Fig. 1). The year 2018 is the one with the highest predicted probabilities. On the other hand, the years 2000, 2004, 2005, 2007, 2009 and 2011 (blue-coloured boxplots in Fig. 6, "good years") have the lowest predicted yield shock probabilities (This is also true for group *All* and *Forward*, Figures S2 and S3). Therefore, we make composites of the variable contribution using these two sets of years to compare the variables contributing to lower or higher probabilities.

The comparison between the variable contribution to the predicted probabilities is presented in Fig. 7. The variables in the x-axis are sorted by variable importance (as in Table S1 for group *Backward*). If the values are positive (negative), then the corresponding variable contributed to increasing (decreasing) probabilities of yield shock. The most noticeable difference is observed in temperature-based variables in July and in April. For TX and PP in July (first and second variable), the contribution during "Bad years" is mostly positive (i.e. higher logit values), whereas for the "good years", this is negative. For TX90P (fourth variable), the overall contribution during "good years" is entirely negative, whereas during "bad years" is close to 0. Furthermore, the distributions reveal a relatively positive contribution of TN10p during April. For the remaining variables, there is no apparent difference between "bad years" and "good years". These patterns are also observed for groups *All* and *Forward* (Figs. S4 and S5 with their corresponding variable importance rank).

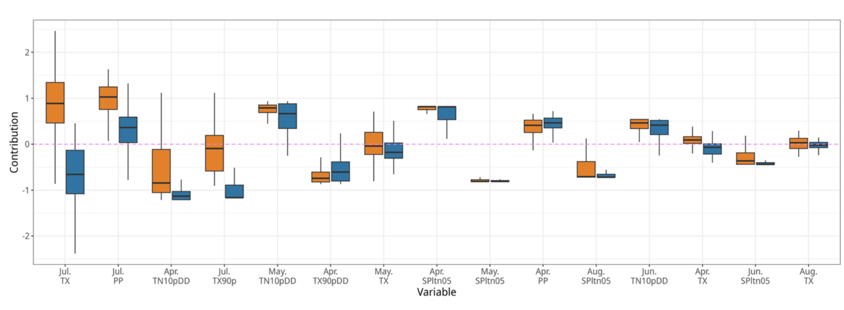


Fig. 7 Composite distribution of the variable contribution to the predicted probabilities in *Backward* group. The variables in x-axis are organized by absolute coefficient values (as in Table S1). The dashed-horizontal violet line indicate a "null contribution". Composites were made using the 6 "bad years" (orange-coloured boxplots) and the 6 "good years" (blue-coloured boxplots)

5 Summary and discussion

This study identified the weather and climate drivers for years of silage maize yield shock in Germany. We sought the key climate drivers associated with substantial drops in yield (here defined as “yield shock” by using a 15th percentile as threshold), found the best combination of variables in terms of predictive skill, and investigated the meteorological drivers of historical yield shock years. The main conclusions are as follows:

1. Silage maize yield shock is triggered by cold conditions during April and hot and dry conditions during July.
2. A pre-set of mixed variables (considering both simple and complex variables) exhibits superior predictive skill.
3. High-yield shock probability years are mainly characterized by relatively hotter-dryer conditions during July compared to low-yield shock probability years and cumulative cold temperatures during April.

We find that higher temperatures and lower precipitation in July are the most relevant factors in determining yield loss in silage maize. Specifically, the number of warm days is the most important variable among the July-based indices. Our result is aligned with the global-based study from Vogel et al. (2019) but disagrees with previous reports in Germany (Gornott and Wechsung 2016; Schmitt et al. 2022). Both studies considered a set of different weather and climate drivers and focused on general crop yield variability. The study from Gornott and Wechsung (2016) found that silage maize has a clearer negative impact of higher evapotranspiration (calculated as a function of maximum and minimum temperature) during August-October. On the other hand, Schmitt et al. (2022) showed a clear impact from drought by using soil moisture data, apart from phenological time-based aggregation. Additionally, distinguishing between the direct impact of high temperature, evapotranspiration, and water shortage is not straightforward. Extreme heat causes increasing vapour pressure deficit, soaring soil water demand by increasing carbon assimilation rate and transpiration rates, thus reducing future water supply (Lobell et al. 2013). Both temperature and precipitation should be taken into account when the prediction of yield shock is the main objective. A possible alternative to overcome this issue is by considering combined indices (e.g. Zampieri et al. 2017), which allows for both the reduction of possible spurious correlation and study of the impact of temperature and precipitation as a compound-event driver. The negative impacts of hot and dry conditions can be alleviated through irrigation, making it an essential tool for developing efficient adaptation strategies. Irrigation for maize is not a common practice in Germany (Peichl et al. 2018; Zhao et al. 2015), although it can significantly increase yields and in some cases is the most important factor in terms of management (Huynh et al. 2019).

As a secondary set of explanatory variables and predictors, anomalous low temperatures during April increase the probability of silage maize yield shock. Most of the weather-agriculture-related research focuses on temperature and drought while giving less relevance to other weather and climate extremes such as frost, low temperature or floods (Cogato et al. 2019). However, maize is also sensitive to seedlings, requiring warm and humid conditions in the soil for growing (Stone et al. 1999; Bechoux et al. 2000). Therefore, yield loss can be driven by low temperatures that do not necessarily fall below the freezing point (Sánchez et al. 2014; Vogel et al. 2019). One strategy that farmers use to avoid cold stress in maize is by delaying the planting date (Parker et al. 2017), although late planting tends to reduce yield by shortening the growing season (Baum et al. 2019).

The results from the MCC revealed that a combination of more complex and simple variables outperforms models with more traditional ones. The Step-wise selection model reduced the number of considered variables drastically, giving a coherent model with high prediction skills. Even though the capability of Step-wise prediction is widely criticized, it can be a powerful algorithm if it is supported by information criterion (Whittingham et al. 2006). These results cast light on the relevance of considering complex variables and using adequate variable selection methods to enhance predictability skills.

When analysing the model’s performance in specific years, we find that predicted probabilities matched the historical yield shock observations well. The six years with the highest predicted probabilities are 2003, 2006, 2010, 2013, 2015 and 2018. This also aligns with the results from Webber et al. (2020) for silage maize. Despite all the predictors from the model, the strongest contribution to high probabilities of yield shock comes from temperature-based variables in July and cumulative cold in April.

Further considerations can be made for future research. First of all, we do not split our sample by region. It is known that crop yield response to environmental conditions also relies on farm management (Zampieri et al. 2017). In Germany, the northeastern region is characterized by a high proportion of sandy soils (Gebauer et al. 2022), which reduces soil moisture, especially under drought conditions. However, as Zhu et al. (2021) mentioned, aggregation implies a compromise between data sample and spatial resolution. Another possibility for future work is to take disaggregated data into account (e.g. Iizumi and Sakai 2020). Furthermore, our selection of variables diminished co-linearity but did not eliminate it. More advanced techniques for addressing spurious correlations, such as those discussed by Dormann et al. (2013), should be considered in future research. This study mainly focuses on the added value of variable selection, and we encourage the trials of more complex variables to disentangle the impact of climate drivers on crop yield.

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Author Contributions FS, JM, CMG and JGP conceived and designed the study. FS performed the data analysis, made the figures and wrote the first paper draft. All authors discussed the results and contributed with manuscript revisions.

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Data Availability No datasets were generated or analysed during the current study.

Declarations

Competing Interests The authors declare no competing interests.

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