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No historical evidence for increased vulnerability of French crop production to climatic hazards

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Abstract

Recent adverse weather events have questioned the stability of crop production systems. Here, we assessed the vulnerability of eleven major crops in France between 1959 and 2018 as a function of climate, crafting a novel hazard framework that combines exposure and sensitivity to weather-related hazards. Exposure was defined as the frequency of hazardous climate conditions. Sensitivity of crops was estimated by the yield response to single and compound hazards, using observed yields available at *département* (county) level. Vulnerability was computed as the exposure-weighted average of crop sensitivities. Our results do not reveal any evidence for historically increased vulnerability of French crop production. Sensitivity to adverse weather events, and thus the overall vulnerability, has significantly decreased for six of the eleven crops between 1959 and 2018, and shown no significant decline or remained stable for the other five. Yet compound hazards can induce yield losses of 30% or more for several crops. Moreover, as heat-related hazards are projected to become more frequent with climate change, crop vulnerability may rise again in the future.

1. Introduction

Recent adverse weather events have questioned the stability of crop production systems. Severe yield losses in France and Europe, for example in 2003, 2007, 2016 and 2018 (Beillouin et al., 2020; Ben-Ari et al., 2018; Ciais et al., 2005), caused economic turmoil for farmers, states or insurances.

There is a growing body of literature showing that severe yield losses can occur in Europe under adverse climate conditions (Beillouin et al., 2020; Ben-Ari et al., 2018; Ceglar et al., 2016; Ciais et al., 2005; Gouache et al., 2015). Both the frequency of crop exposure to adverse weather conditions and the sensitivity of crop yields to these can change over time, due to shifting climate or management regimes. The intensity and frequency of heat and drought waves are impacted by climate change (Field et al., 2012; Klein Tank and Können, 2003; Rahmstorf and Coumou, 2011; Samaniego et al., 2018; Sheffield and Wood, 2008; Stott, 2016; Trnka et al., 2011). Moreover, Europe shows faster rates of warming than the global average (Bhend and Whetton, 2013) – for example, during summer 2018, temperatures 3°C warmer than usual prevailed in most places of the continent (Copernicus, 2020). Next to exposure, yield sensitivity to climate may also change over time. This sensitivity depends on several factors such as crop species, cultivars, and crop management practices like sowing dates, irrigation or fertilization, which may evolve temporally (Iizumi et al., 2014; Perronne et al., 2017). It is therefore necessary to simultaneously analyze the temporal evolution of crop exposure to climatic hazards and the sensitivity of yields to these hazards in order to understand the evolution of crop vulnerability.

In addition to its strategic importance for European crop production, contributing 20% of the European Union agricultural grain production, France has the advantage of having long yield time series over more than 60 years. This makes it possible to analyze the frequency of climatic events that can have a negative impact on crop yields. Therefore, we were able to assess the vulnerability of French agricultural crop production to climatic hazards for eleven staple crops (spring barley, maize, spring and winter oats, potatoes, spring and winter rapeseed, sugarbeet, sunflower, spring and winter soft wheat) over the last six decades. Our study is performed at *département* level (administrative division on level 3 of the unified NUTS territory classification, NUTS3; henceforth: department). Specifically, we address four research questions. First, have crop yield losses changed in frequency? Second, which weather hazards are mainly responsible for observed losses? Third, how sensitive is crop production to these hazards? Fourth, has the vulnerability of crop yields changed over time?

2. Material and methods

2.1 Workflow

We applied five steps, separately for each crop (Figure 1). First, we merged crop yield and weather data during the growing season into one combined data base (section 2.2). Second, we calculated trends in yields and defined loss events as harvests substantially below trend-expected values (section 2.3). Third, we applied two machine learning methods to find loss-defining weather variables (section 2.4). Fourth, we derived weather-related hazards based on these variables and observed losses. We calculated the frequency of these hazards and their trends over time (section 2.5). Fifth, we calculated the impact of hazards on yield levels (section 2.6). This last step was performed for three different time frames, 1959-2018, 1959-1988 and 1989-2018 to analyze changes over time.

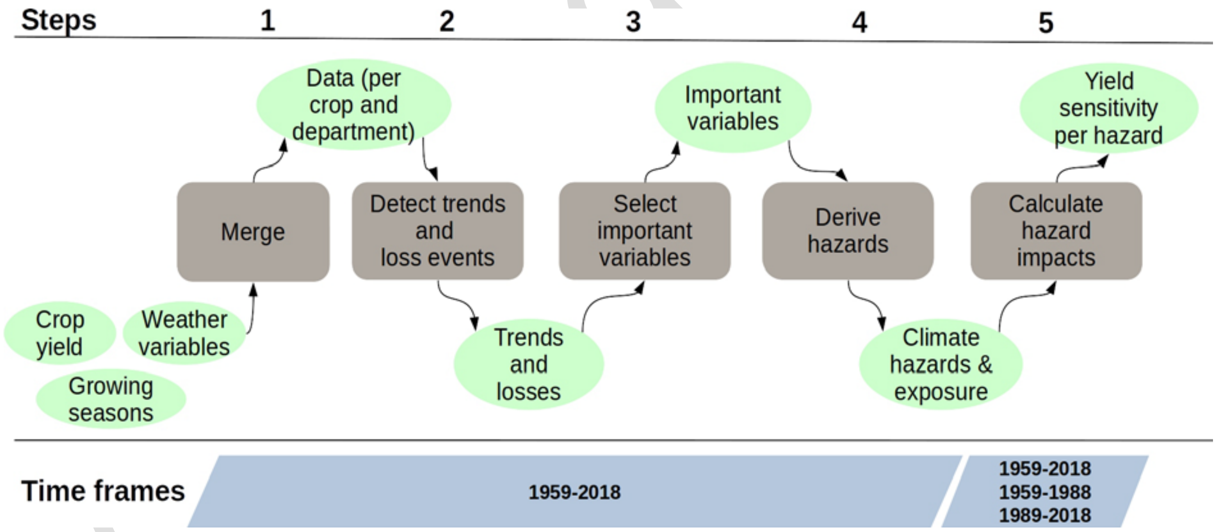


Figure 1: Workflow of the analysis in five steps. Ellipses are inputs and outputs, rounded rectangles denote operations and parallelograms the time frames for which analyses were carried out.

2.2 Input data

2.2.1 Yield data

Yield data from 1900 to 2016 are as described in Schauberger et al. (2018) and were extended by the data for 2017 and 2018. We inspect eleven crops: spring barley, grain maize, oats (spring and winter cultivars separately), potatoes, rapeseed (spring and winter), sugar beet, sunflower and soft wheat (spring and winter). Yields were available on French *département* level (counties or NUTS3 regions). Some values in the statistical yearbooks had to be considered as outliers or reporting errors; these were filtered before further calculations as described in SI Text 1.

For all analyses related to weather hazards, we focus on the period 1959-2018 since SAFRAN weather data are not available before. For studying the frequency of yield loss events, we use yield data since 1900 to illustrate the development over a longer time.

2.2.2 Growing seasons

Sowing and harvesting months were extracted from MIRCA2000 (Portmann et al., 2010) at five arc-minute resolution (around 8 km) and re-mapped to departments. Seasons were assumed as fixed over the full time series and homogeneous across France (Table 1). One season was considered for barley (spring type), maize, potatoes, sugarbeet and sunflower and two seasons for oats, rapeseed and wheat (winter and spring types). Sowing was assumed on the first day of the sowing month and harvest on the last day of the harvesting month, respectively. Double cropping within this set of crops does not occur in France. For potatoes there are several possible varieties (short, middle and long maturation) which were all merged here, as the long-term data of relative shares per department were not available.

Table 1: Growing seasons, data count and harvested areas

Crop	Sowing month	Harvesting month	Yield data points [a]	Departments (out of 76 [b])	Harvested area (kha) [c]
Spring barley	May	September	3,648	65	523.0
Maize	April	September	3,048	53	1,408.2
Spring oats	March	July	3,421	60	41.3
Winter oats	October	July	3,020	54	58.7
Potatoes	April	September	3,746	66	128.0
Spring rapeseed	May	October	501	10	1.7
Winter rapeseed	October	July	2,984	57	1,225.8
Sugar beet	April	October	1,545	28	391.8
Sunflower	May	September	753	15	370.6
Soft spring wheat	March	July	1,838	34	12.6
Soft winter wheat	October	July	3,776	66	4,624.0

[a] *After filtering, SI Text 1*
[b] *There are 76 departments in Köppen-Geiger climate zone Cfb; SI Figure 1*
[c] *Average 2000-2010*

2.2.3 Weather data

We used the SAFRAN mesoscale atmospheric analysis running from August 1958 to December 2018 and produced by Météo France (Quintana-Seguí et al., 2008). SAFRAN provides weather variables at 8 km spatial and hourly temporal resolution. These were aggregated and spatially averaged to monthly variables for each department. Thirteen weather indices with agronomic importance (Barnabas et al., 2008; Ben-Ari et al., 2016; Brisson et al., 2010; Gouache et al., 2015; Luo, 2011) were computed, belonging to three distinct categories: temperature, radiation and water (Table 2). SAFRAN precipitation and temperature are obtained by interpolation from a large sample of weather stations. Solar radiation at surface was calculated using a radiative transfer scheme and the vertical profiles (temperature, humidity, and cloudiness) analysed by the SAFRAN algorithm. We computed potential evapotranspiration (ETP) based on the Penman–Monteith equation.

Variables were checked for sufficient variation and cross-correlation (SI Figure 2). Since days below -17°C and above 34°C did not show reasonable variation due to limited occurrence, these two variables were removed. Moreover, monthly minimum and maximum temperatures were highly correlated with mean temperatures such that only the latter were kept for all analyses. The monthly water balance of precipitation minus potential evapotranspiration was highly correlated with precipitation such that we did not include this composite variable. For each crop, only the weather variables during its growing season were considered. This resulted in a maximum of 80 weather variables per crop: e.g. for winter wheat there is a 10-month growing season with 8 monthly variables.

Since the year 1958 is incomplete in SAFRAN data, our hazard analysis only starts in 1959.

Table 2: Weather variables, on monthly basis; discarded variables due to low variation or high correlation with others are written in italic font.

Variable group	Variable	Unit	Value range	Used?	Symbol (x=month)
Temperature	*Number of days with Tmin below -17°C*	*Days/ month*	*0 ... 6.5*	*No*	
	Number of days with Tmin below 0°C	Days/ month	0 ... 31	Yes	D^{0}_{x}
	Number of days with Tmax between 0°C and 10°C	Days/ month	0 ... 31	Yes	$D^{0..10}_{x}$
	Minimum temperature	*°C*	*-10.3 ... 22.2*	*No*	
	Mean temperature	°C	-7.9 ... 26.4	Yes	T^{m}_{x}
	Number of days with Tmax above 30°C	Days/ month	0 ... 27.0	Yes	D^{30}_{x}
	Number of days with Tmax above 34°C	*Days/ month*	*0 ... 15.9*	*No*	
	Maximum temperature	*°C*	*-6.0 ... 33.7*	*No*	
Radiation	Shortwave surface incoming radiation	W/m^2	14 ... 339	Yes	R_x
	Potential Evapotranspiration[a] (ETP; Penman-Monteith)	mm/day	0.2 ... 7.1	Yes	ETP_x
	Precipitation amount	mm/day	0 ... 19.1	Yes	Pr_x

Water availability	Fraction of days per month with precipitation > 0.1 mm	None	0..1	Yes	D^{Pr}_{x}
	Precipitation – Evapotranspiration	*mm/day*	*-6.9..18.3*	*No*	

[a] *ETP is also strongly influenced by temperature, so classification is subjective*

2.3 Detecting yield trends and loss events

Absolute yields in tonnes per hectare (t/ha) were de-trended to obtain deviations from a temporal trend (i.e. yield anomalies). For each department, a time trend was fitted by local regression (LOESS) with a span width of 0.66, in line with Ben-Ari et al. (2018). A yield loss was defined as a yield anomaly at least 10% lower than expected, with 'expected' being the LOESS-interpolated trends calculated separately for each crop and department. Yield loss events constituted 17-28% of the data, depending on the crop.

2.4 Selecting important weather variables

A selection of crop-specific important weather variables was performed by applying two variable filters (SI Text 2). Afterwards, two inference methods were applied to select important variables among the remaining ones: a binomial logit Lasso regression (Least Absolute Shrinkage and Selection Operator) with cross-validated choice of λ and Random Forests (RF; Breiman (2001)). In-sample and out-of-sample (OOS) validation were applied, omitting each year in turn from the training data, which provides a robust estimate of model performance for predicting occurrence of yield loss using independent data. Performance was measured with the AUC (Area Under the Receiver-Operator-Curve) as an established measure for dichotomous outcomes (Makowski et al., 2009). An AUC of 1 is tantamount to a perfect classification while a value of 0.5 denotes a performance equal to flipping a coin, that is, no better than pure chance. For each crop species, the method (Lasso or RF) with the higher out-of-sample AUC was chosen for variable selection; in case of ties Lasso was preferred. Important variables were derived as described in SI Text 3.

This multi-step selection of variables ensured that only those climatic variables were selected that provided robust evidence of a statistical association with crop yield losses in major agricultural areas of France. The models (Lasso or RF) were only used to select important variables; all further calculations were based on non-parametric, model-independent methods (next sections) and observed data to avoid model assumptions. Lasso and RF were implemented in R 3.3.2 (R Core Team, 2016), using packages *glmnet* and *randomForest*.

The yield data have an underlying spatio-temporal structure, i.e. yields may be correlated across space and time. Temporal auto-correlation in regression analysis usually requires the correction of confidence intervals, if predictions are made or when coefficients are interpreted. Yet, in our study, we use the Lasso and RF models only to select variables for further consideration in the hazards concept, thus nullifying the need for robust standard errors. Our cross-validated choice of the regularization parameter lambda in Lasso, where each year was omitted in turn, additionally reduced temporal correlations. Regarding spatial correlation, we explicitly aim for identifying variables and hazards relevant for major production areas in France, such that a putative bias in selection is not considered to undermine our results. Nonetheless, to test the robustness of variable selection, we applied it also to selected 'representative' departments(SI Text 4).

2.5 Deriving the exposure of crops to climate hazards

In this study, we define vulnerability by separately assessing exposure to climatic hazards and yield sensitivity (i.e. crop reponse) when these hazards occur. Though vulnerability may encompass social dimensions like the adaptive capacity (Krishnamurthy et al., 2014), we focus only on physiological dimensions and assume the adaptive capacity as constant within the study time frame (see discussion).

Yield-reducing hazards were defined as events where the value of one weather variable falls within a harmful range, characterized by increased odds of observing yield loss (Figure 2). These ranges were derived as follows. First, the values of each selected weather variable, e.g. the number of days above 30°C in July, were discretized into 50 equi-spaced bins (between the min and max observed values) and the fractions of crop loss events observed in these bins were calculated. Second, the 50 calculated loss fractions were interpolated by a spline curve, weighted by observation counts. A function relating odds of yield loss (O) to each considered weather variable was then derived from the smoothed curve (equation 1 in Table 3), following the definition of odds in statistics; see also Ben-Ari et al. (2018). We calculated the analogous loss odds for the prior share of losses in the database (i.e. the total frequency of losses during the whole time period considered) as reference case (equation 2). Third, loss-inducing ranges were defined as those ranges of observed weather variables where yield loss odd ratios (LOR, equation 3) were larger than 2, indicating an at least doubled chance to suffer from losses. Fourth, hazards (H) were defined as weather conditions associated with these loss-inducing ranges (equation 4). In the example (Figure 2), since a LOR > 2 is associated with more than 7.4 days of T_{max} above 30°C in July, the event “at least 7.4 days of T_{max} above 30°C in July” defines one hazard H. A specific exposure E was then calculated for each hazard H as the frequency of H in all data (equation 5). Equations 1-5 are calculated separately for each crop and weather variable, but across departments and time.

Table 3: Equations 1-5

Nr	Equation	Description
1	$O_l^w = \dfrac{f_l(w)}{1 - f_l(w)}$	O_l^w = loss odds and $f_l(w)$ = smoothed fraction of observed losses for w = value of a weather variable
2	$O_p = \dfrac{f_p}{(1 - f_p)}$	$f_p = \frac{\#Losses}{\#Data}$, i.e. the prior share of losses

3	$LOR^w = \frac{O_l^w}{O_p}$	O_l^w are loss odds from eq. 1 and O_p prior odds from eq. 2; LOR is then the loss odds ratio
4	$H^w \coloneqq \{w \mid LOR^w \geq 2\}$	H^w as loss-inducing hazards and w = value of a weather variable
5	$E_{H^w} \coloneqq \frac{\#Data\ with\ H^w}{\#Data}$	E_{H^w} as exposure to hazards and #Data = the number of data rows (in the numerator only those where weather is 'hazardous' according to eq. 4 are counted)

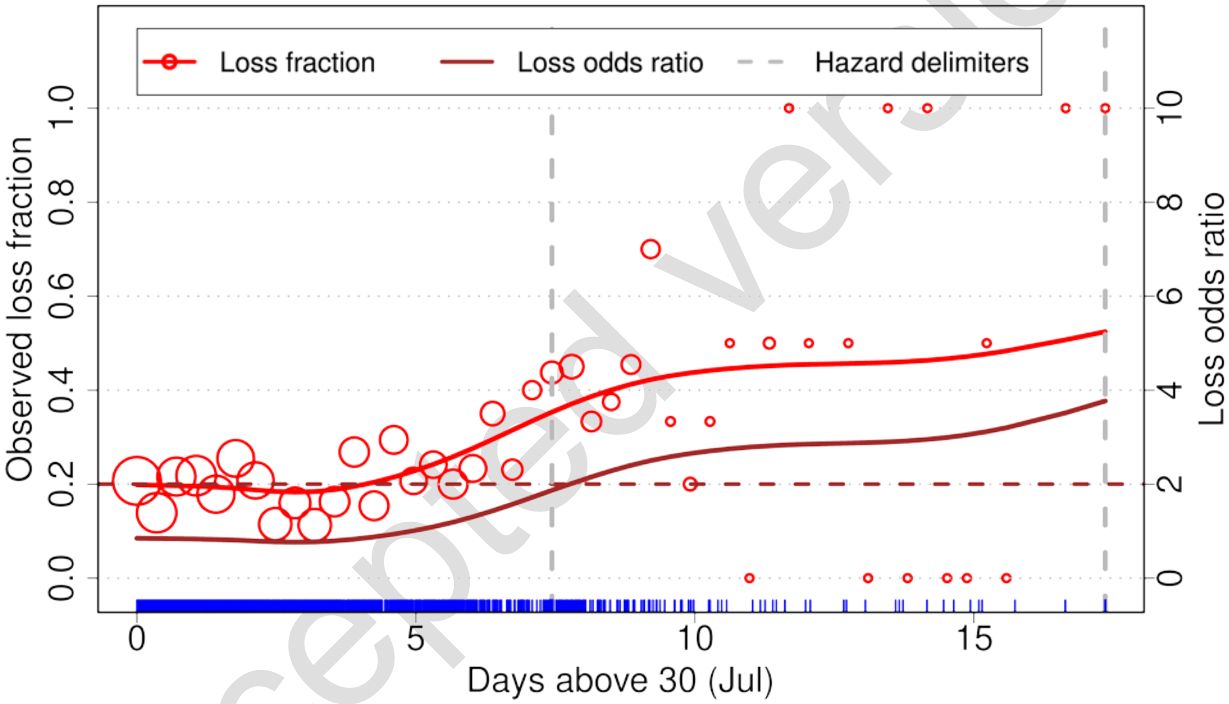


Figure 2: Definition of yield hazards, illustrated with the example of days with T_{max} above 30°C in July for spring wheat. Red circles denote observed loss fractions (loss count over total observations) per discretized x value; circle size is log-proportional to observation count. The red curve is a spline interpolation of these loss fractions, with fractions weighted by data count. The solid brown line denotes the odds ratio of losses (LOR, eq.3, right y axis); the dashed horizontal brown line is the hazard definition threshold of odds ratio >= 2. The blue rug at the bottom denotes data density. The dashed vertical grey lines indicate the range of values of the considered weather variable defining the hazard; here: if there are more than 7.4 days above 30°C in July, this is detrimental for spring wheat, as the loss odds increase substantially. The loss fractions in the right margin frequently assume extreme values (0 or 1) due to data scarcity in this high temperature range – which justifies the weighting of the spline interpolation by observation count.

2.6 Calculating hazard impacts: sensitivity and vulnerability

For each hazard H, yield sensitivity (S) was estimated as the observed yield reduction in the case the hazard occurs. Yield reduction was defined as the difference between the median yields (as ratios to trend-expected yields) without and with the hazard event (equation 6). To estimate the uncertainty of S we used a bootstrapping approach which accounts for the spatial correlation between departments (SI Text 4).

$$S_{H^w} := median(Y_{H^w}) - median(Y_{not\ H^w}) \qquad \textbf{(eq. 6)}$$

with S_{H^w} the sensitivity of yields, $Y = \frac{Yield}{Expected.Yield}$, i.e. the attained yield percentage, where $Y_{not\ H^w}$ refers to yield cases without 'hazardous' weather conditions, while Y_{H^w} refers to yield cases with weather hazards. S < 0, therefore, denotes a loss due to hazards.

Vulnerability (V) to hazards was calculated as the accumulated impact of all hazards as exposure-weighted mean yield losses (equation 7). V can be interpreted as the expected (i.e. annual average) yield loss due to all weather hazards across the considered time period. Uncertainty of V was estimated with bootstrapping analogously to S.

$$V = \frac{\sum_{H^w} E_{H^w} * S_{H^w}}{\sum_{H^w} E_{H^w}}$$

(**eq. 7**), with V as vulnerability, E_{H^w} the exposure to hazardous weather from eq. 5 and S_{H^w} the sensitivity to hazards from eq. 6

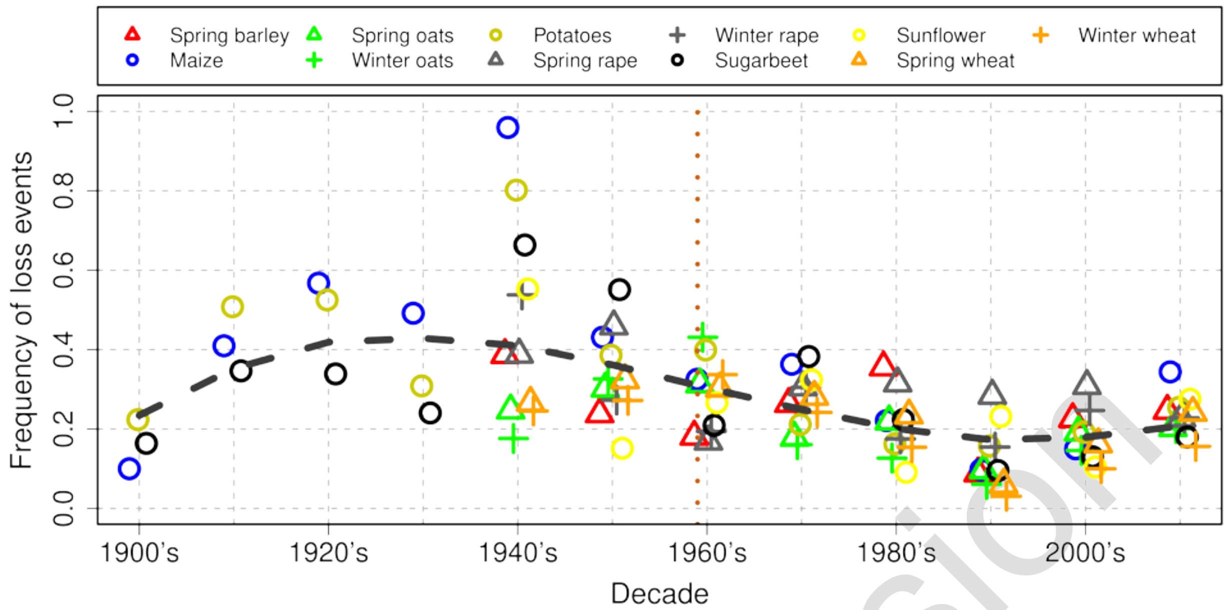
E, S and V were calculated independently over 1959-2018 and two sub-periods 1959-1988 and 1989-2018. Interactions of hazards were studied by calculating E and S for all pairs of jointly occurring hazards. A change in frequency of interactive hazards between the two successive periods was also assessed.

3. Results

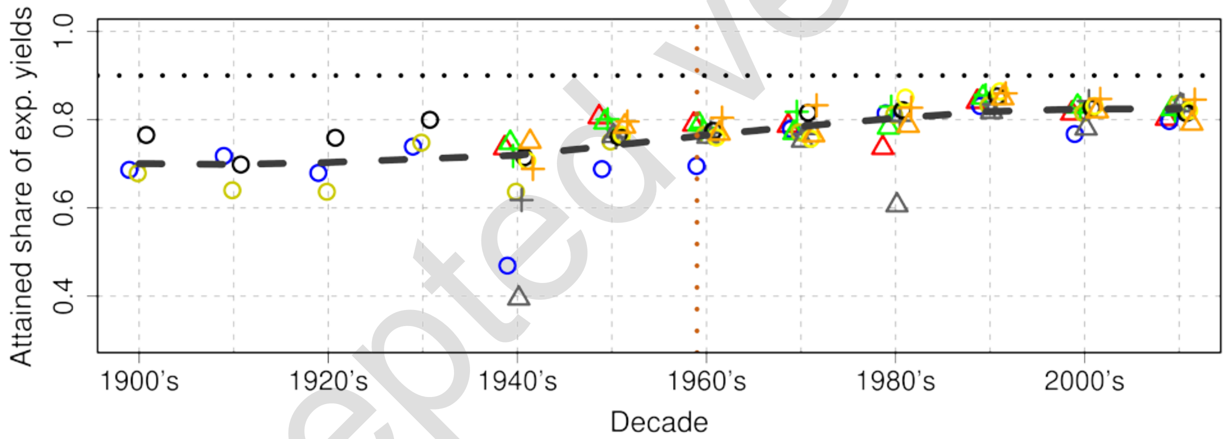
3.1 Yield losses declined in frequency and magnitude since 1920

The frequency of loss events (defined as at least 10% below trend-expected yields) has changed over time (Figure 3a). The decade 1940-49 shows a high frequency of loss events for maize, potatoes, sugarbeet, sunflower and winter rape. There was a downward trend of losses since 1920 (data for season-specific crops start in 1943), halving the number of departments affected by losses from approximately 40% in the 1920's-40's to less than 20% around 1990. Recent decades since 1990 have, however, seen no further decline in crop yield losses. For several crops, loss frequency has rather increased since then. Notwithstanding, the average magnitude of losses in relation to expected yields (i.e., the expected loss percentage in case a loss of at least 10% occurs) has continuously decreased over time (Figure 3b), and has become similar across crops in recent years (approximately -18% in the 2010s). Although 2016 was a remarkably bad year for winter wheat (Ben-Ari et al., 2018), we did not observe a clear signal in loss fractions in the 2010s since the other years of the decade were statistically compensating and because the severe yield losses observed in 2016 were limited to certain regions and crop species.

Losses tended to co-occur across crops and departments (SI Figure 3). Between crops, those with the same seasonality (e.g. spring oats and barley) show losses in the same year and department in approximately half of all cases. Simultaneous losses were also frequently observed for the two different season types of the same crop (e.g. spring and winter oats). For all eleven crops, losses mostly occurred in small clusters encompassing few French departments, but some events affected more than 50% of departments, indicating substantial losses in a larger region (SI Figure 3b).



(a)



(b)

Figure 3: Evolution of yield losses over time, defined as yields at least 10% below trend-expected yields. (a) Frequency of yield losses per decade, relative to all harvest events in that decade. (b) Expected shortfall, i.e. the attained percentage of trend-expected yields if a loss event occurs. For (a) and (b), the grey dashed line is the spline interpolation between the means across crops, and the brown dotted vertical line denotes the start of our hazard analysis with SAFRAN climate data. In (b), the black horizontal dotted line indicates the threshold for defining an observed yield percentage as "loss" compared to trend-expected yields. In both panels, the points for individual crops are slightly staggered along the x axis to avoid overlaps within a decade.

3.2 Weather is involved in the majority of yield loss events

The performance (AUC) of the two machine learning methods to separate losses from non-losses is shown in Table 4. For spring barley, maize, spring oats, potatoes and sunflower, Random Forests (RF) produced more accurate out-of-sample estimates than Lasso. Thus, important variables were selected based on RF in these cases. For the other six crops the Lasso-based variable selection was chosen. RF in-sample performance is consistently equal to one, suggesting a perfect model fit. Yet the substantially lower OOS performance shows that this pattern may be due to overfitting. An ancillaryestimate for maize, where the Lasso model was trained on all years except 1976 and 2003 (where substantial weather-induced yield losses occurred), produced no substantial difference in model performance (AUC = 0.79, AUC-OOS = 0.73) compared to Lasso with all years, and the selected variables were the same, except for D^{30}_{9} which was additionally selected in the model without 1976 and 2003.

For all crops, the most influential variables were related to temperature and precipitation (SI Figure 5). Radiation-related variables were less frequently selected, mostly in the form of ETP. Temperature extremes (high or low) were found important in almost all crops for determining whether yield losses occur. Specifically, the variables most often selected were D^{30}_{6} (all 11 crop types), D^{Pr}_{5} (10 crops), T^{m}_{6} (9 crops), D^{Pr}_{7} (7 crops), Pr_5, Pr_7, D^{30}_{5}, D^{30}_{7}, T^{m}_{5} and T^{m}_{9} (for 6 crops each). Other variables were selected for five or fewer crops. Interaction variables between temperature and precipitation (tested across all months) were never selected. Bootstrapped variable selection results are portrayed in SI Figure 6, mostly showing good correspondence to those variables selected with the full data set.

Table 4: Method performance (Area Under the Curve, AUC) for simulating yield losses. Full: full data used in estimation, OOS: out-of-sample with each year omitted in turn. The chosen method for selecting important variables is indicated in the last column.

Crop	LASSO		Random Forest		Chosen method
	Full	OOS	Full	OOS	
Barley, spring	0.67	0.50	1.00	0.57	Random Forest
Maize	0.80	0.72	1.00	0.76	Random Forest
Oats, spring	0.67	0.52	1.00	0.65	Random Forest
Oats, winter	0.73	0.60	1.00	0.60	Lasso
Potatoes	0.65	0.60	1.00	0.63	Random Forest
Rapeseed, spring	0.72	0.58	1.00	0.57	Lasso
Rapeseed, winter	0.74	0.60	1.00	0.58	Lasso
Sugar beet	0.80	0.69	1.00	0.68	Lasso
Sunflower	0.81	0.72	1.00	0.74	Random Forest
Wheat, spring	0.72	0.66	1.00	0.64	Lasso
Wheat, winter	0.81	0.71	1.00	0.64	Lasso

3.3 Weather hazards are often related to low precipitation and high temperature

Hazards defined from the selected yield-influencing weather variables form a unique set for each crop, but with some overlaps (Table 5 for maize and winter wheat; SI Table 1 for other crops). Across crops, the most frequent hazards are related to the number of days above 30°C in June (11 times, i.e. all crops) or July (5 times), high mean temperature in June (9 times), number of rainy days > 0.1 mm or absolute precipitation in May (4 and 6 times) and high mean temperature in April (4 times). Other hazards were selected three or fewer times.

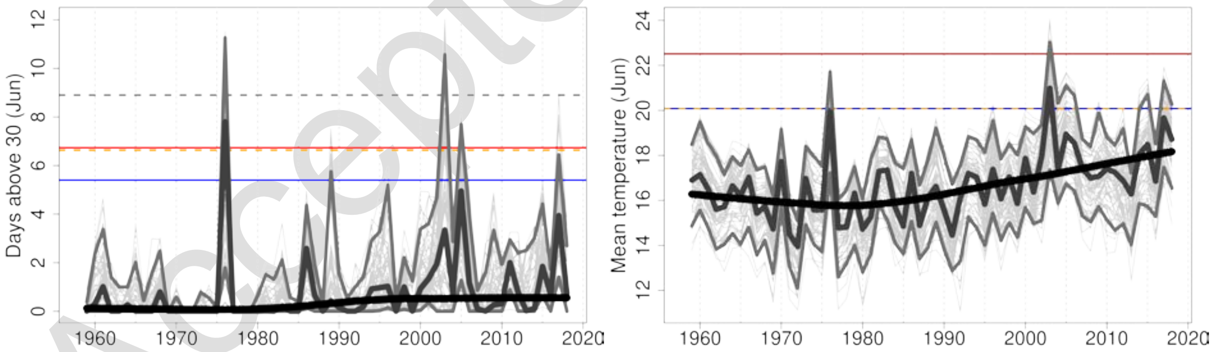
In a comparative estimate for maize, the sets of hazards derived independently for the two time periods 1959-1988 and 1989-2018 (instead of the full time frame as above) were not identical: 20 hazards were identified for the first period, but only 11 hazards for the second. Before 1989, low and high precipitation in May increased the odds of yield loss, but after 1989 only excess May precipitation showed detrimental effect on yields. Low July precipitation remained problematic in both periods, with similar thresholds. Low precipitation levels in June or August were identified as yield-reducing only before 1989. Both high and low mean temperatures in June had negative effects before 1989, but only high temperatures remained hazardous afterwards, indicating that cold-related yield losses were reduced. Hazards related to September mean temperatures were only selected before 1989. For D^{30}_6, D^{30}_7 and D^{30}_8, the critical thresholds increased after 1989. Low evapotranspiration in May or high levels in July and August remained equally noxious over time, with similar thresholds.

Table 5: Yield-reducing hazards for maize and winter wheat; hazards for the other nine crops are provided in SI Table 1

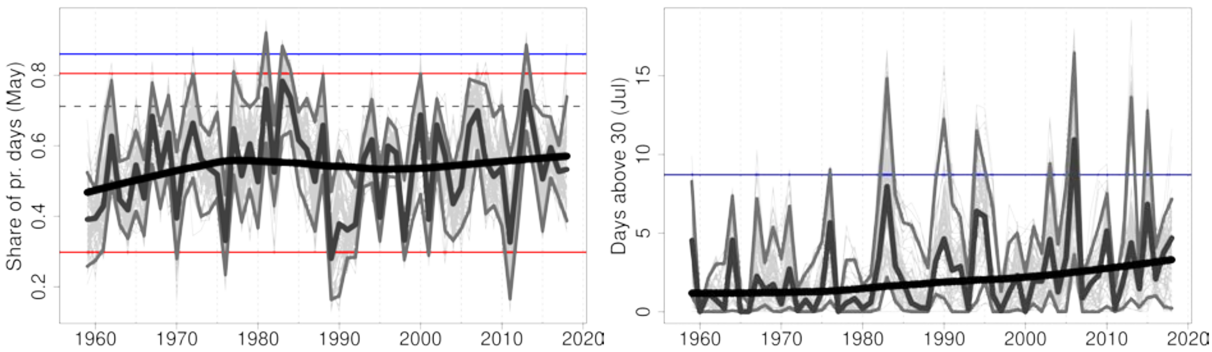
Weather variable	Maize	Winter wheat
Days above 30°C	$D^{30}_6 > 5.4$; $D^{30}_7 > 8.7$; $D^{30}_8 > 14.2$	$D^{30}_6 > 6.6$
Days between 0 and 10°C	$D^{0..10}_{10} > 15.4$	$D^{0..10}_1 < 11.2$
ETP	$ETP_5 < 1.9$; $ETP_7 > 4.8$; $ETP_8 > 4.2$	$ETP_{10} < 0.6$; $ETP_2 < 0.4$; $ETP_3 < 0.8$
Precipitation	$Pr_5 > 6.2$; $Pr_7 < 0.9$; $Pr_8 < 0.6$	$Pr_{11} > 7.8$; $Pr_2 > 7.0$
Days with precipitation	$D^{Pr}_5 > 0.9$; $D^{Pr}_6 < 0.2$; $D^{Pr}_7 < 0.3$; $D^{Pr}_8 < 0.3$	$D^{Pr}_{10} < 0.2$; $D^{Pr}_3 < 0.2$
Radiation		$R_{11} < 28$; $R_4 < 118$; $R_6 < 147$; $R_6 > 292$
Mean temperature	$T^m_6 > 20.1$; $T^m_9 > 19.0$	$T^m_{10} < 6.7$; $T^m_4 > 12.2$; $T^m_6 > 20$

3.4 The exposure to weather hazards has changed over time

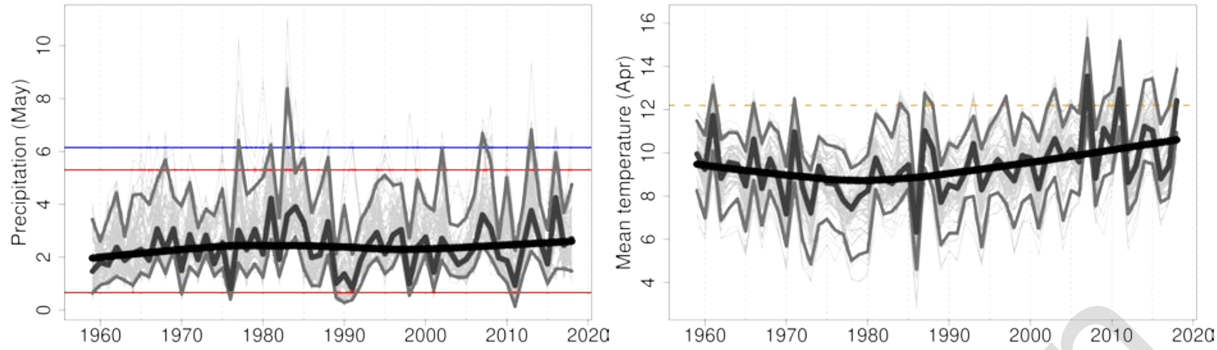
The climate during the growing season has changed between 1959 and 2018 for many yield-influencing variables (Figure 4, SI Figure 7). Trends towards higher temperatures are particularly apparent: there are more heat days above 30°C in June and July, and mean temperatures in all months have increased (Figure 4 for April and June). Accordingly, hazardous upper temperature thresholds were more often exceeded in recent decades than in the beginning of our study period, while low-temperature hazards occurred less frequently. Shifts in atmospheric evaporative demand, precipitation or solar radiation cannot be detected for all months. Still, hazardous conditions due to high radiation in June – tantamount to low cloudiness or precipitation – have become more frequent for several crops. Some evidence for optimal growth envelopes was identified: an example is radiation in June for winter wheat, where both too low and too high values were found to reduce yields (Table 5; Figure 5b). The years 1976, 2003, 2005 and 2017 were saliently hot in June and 1976 additionally dry in May, with associated hefty yield losses in many crops. Compound hazards, defined as two hazards during the same season, have changed in frequency but not with a clear pattern (SI Figure 11). Overall, the exposure to yield-reducing hazards has changed over time along with trends in climate. Exposure to hazardous high temperatures has increased during the recent period, while exposure to cold-related hazards has decreased. Exposure to hazards related to radiation or precipitation shows no clear trend.



(a) Days above 30°C in June (b) Mean temperature in June



(c) Rainy days (fraction) in May (d) Days above 30°C in July



(e) Precipitation in May (f) Mean temperature in April

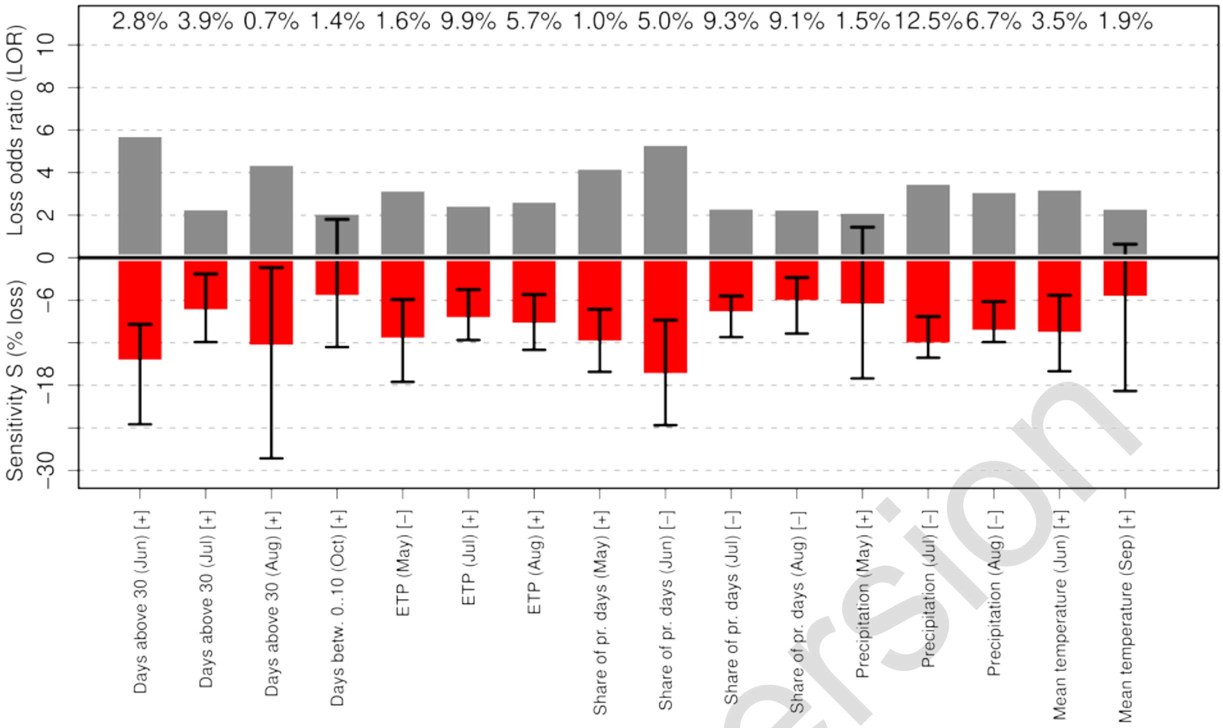
Figure 4: Trends in yield-related weather variables and associated hazard thresholds for different crops. Here, only the four major-area crops and six most frequent hazards are shown; all crops and further hazards are provided in SI Figure 7. For each panel, light grey lines denote the trajectories for individual departments. Darker shades of grey indicate the 5%, 50% and 95% quantiles. The solid bold black line is the smoothed trend in annual medians across departments. Coloured horizontal lines indicate hazardous thresholds for single crops, if defined (legend at the bottom). Whether hazards occur for too high or too low values can visually be deduced from the line position – if at the lower margin of observed values, a hazard is related to too low values, and vice versa. For some crops there are two thresholds (lower and upper margin) for the same variable, indicating that an optimal climate envelope is required for growth; an example is May precipitation for spring barley.

3.5 Yields are sensitive to climatic hazards

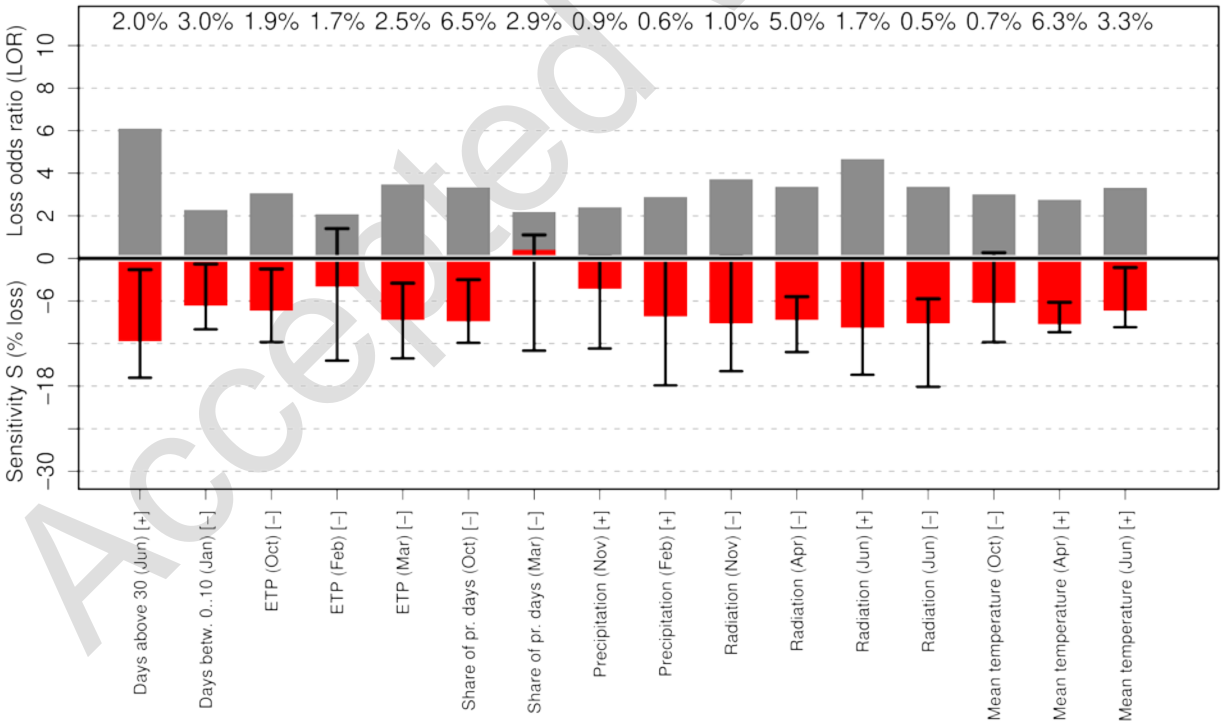
Weather-related hazards reduced crop yields by up to more than 25% (Figure 5; SI Figure 8). Yet, despite substantial average yield reductions, the occurrence of a hazard does not always induce a severe loss, as the bootstrapped uncertainty bars (Figure 5) and the existence of non-losses even under hazard occurrence in our data base show. For example, too few precipitation days in March increase the risk for loss (loss odds ratio > 2), but on average they are not harmful to winter wheat (Figure 5b). Uncertainty of losses is higher for those hazards that occur less frequently; for example, a clear loss signal cannot be detected for high precipitation in November for winter wheat.

For maize, the strongest yield losses are observed for a high number of hot days above 30°C in June or August and lack of precipitation between May and July. Particularly June to August are decisive for maize growth, with most hazards occurring in these months. The divergent impacts of hazards on maize over time are illustrated in Figure 6 (an analogous plot for winter wheat is in SI Figure 9). Hazards due to hot days in June occur more frequently after 1989 but have less severe impacts. For maize, cold days-hazard $D^{0..10}_{10}$ has become much less frequent after 1989, and even turned into a positive effect for yields then. For winter wheat, the strongest yield reductions are caused by many hot days or high average temperature in June, and hot conditions in April. Hazards for winter wheat have also changed in frequency and impacts over time (SI Figure 9 plus explanations there). For other crops, strong losses are frequently observed for hot days in June or non-optimal precipitation in May (Figure S7).

Compound hazards may prove particularly detrimental for yields. This is obvious for several combinations of hazards (SI Figure 10). For maize, the joint occurrence of a hot and dry June leads, on average, to yield losses of 25% and has occurred in 1.3% of the department-year combinations in our database. Spring rape yields can go down by 56% if plants suffer from limited rainfall in June and hot conditions in July. For winter wheat, high irradiation and hot conditions in June reduced yields by 15% on average and occurred in 0.9% of cases. Similar detrimental compound effects can be identified for all crops (SI Figure 10).



(a) Maize



(b) Winter wheat

Figure 5: Loss odds ratios (LOR, equation 3) under hazards for (a) maize and (b) winter wheat along with their impacts on crop yields (sensitivity S, equation 6) estimated over the full time frame (1959-2018). For both crops, the upper half shows the loss odds ratios, i.e. the ratio of chances to observe a loss (at least 10% below expectation) in comparison to average conditions. A LOR of 2, for example, indicates a doubled chance that losses occur compared to the base case.

The bottom half shows the sensitivity of yields to hazards (observed yield loss in % when the hazard occurs). Black lines indicate uncertainty ranges based on bootstrapping (whiskers extend to 5% and 95% percentiles of 500 values). The direction of the hazard, too low or too high, is indicated with a [-] or [+] symbol, respectively. Weather variables can occur twice, e.g. radiation in June for winter wheat – only an optimal envelope of radiation does not induce yield losses. Numbers on top indicate the frequency a hazard occurs in the database (exposure E_{H^w}, equation 5). Plots for the other nine crops are provided in SI Figure 8. Impacts of compound hazards are shown in SI Figure 10.

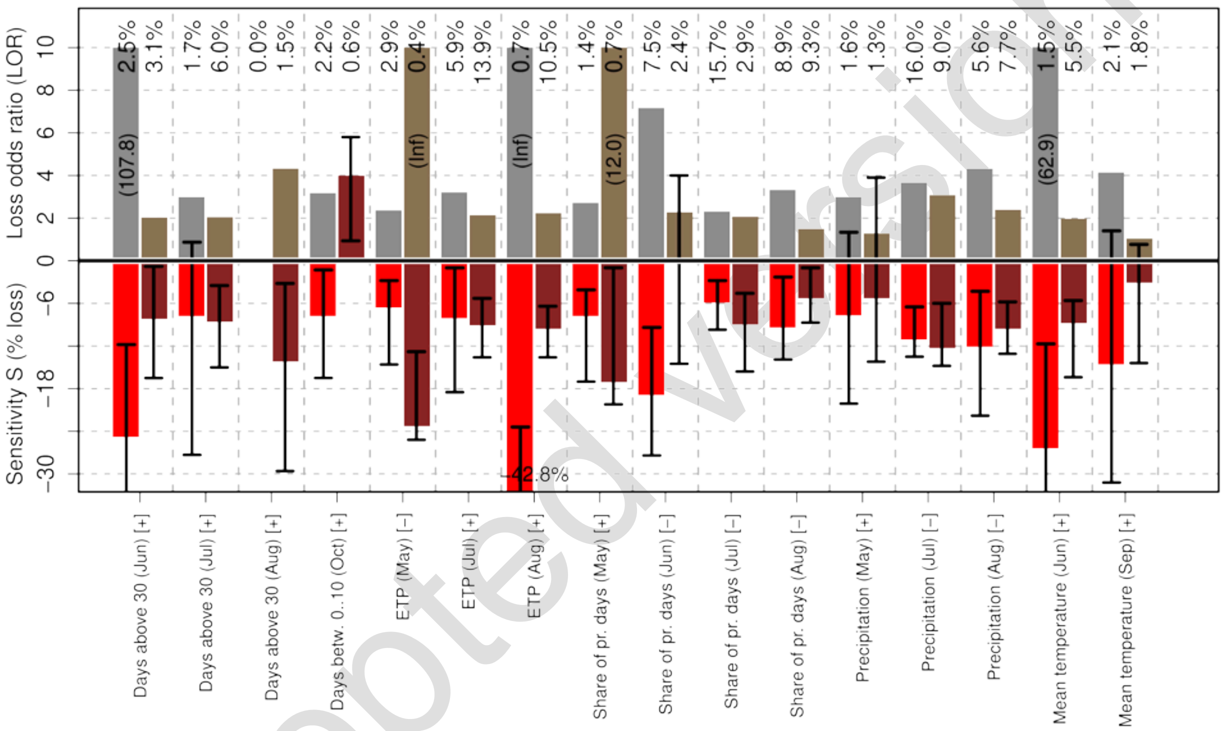


Figure 6: Loss odds ratios and sensitivity of maize yields to weather hazards, similar to Figure 5a, but here split into two time frames: 1959-1988 (left bars for each hazard; grey & red) and 1989-2018 (right bars; bronze & brown). Some bars extend beyond the margins and were clipped for display reasons; the numbers are given in the bars ("Inf" means infinity, i.e. there are no non-loss cases). Other elements are analogous to Figure 5.

3.6 Crop vulnerability to weather hazards has not increased since 1959

Exposure-weighted average loss – the vulnerability – of French crops to weather hazards in an average year has decreased for six crops and remained similar for the other five between 1959-1988 and 1989-2018 (Figure 7). For maize and winter rape, impacts stayed virtually constant with only a non-significant decrease. For winter oats, sunflower and winter wheat, the average impacts of hazards decreased slightly but remained similar in magnitude. For spring barley, oats, rape and wheat, potatoes and sugarbeet, vulnerability decreased significantly by 50% or more – in particular for potatoes and spring rape. This decrease is partly due to fewer hazards, often related to cold temperatures, and partly due to mitigated impacts.

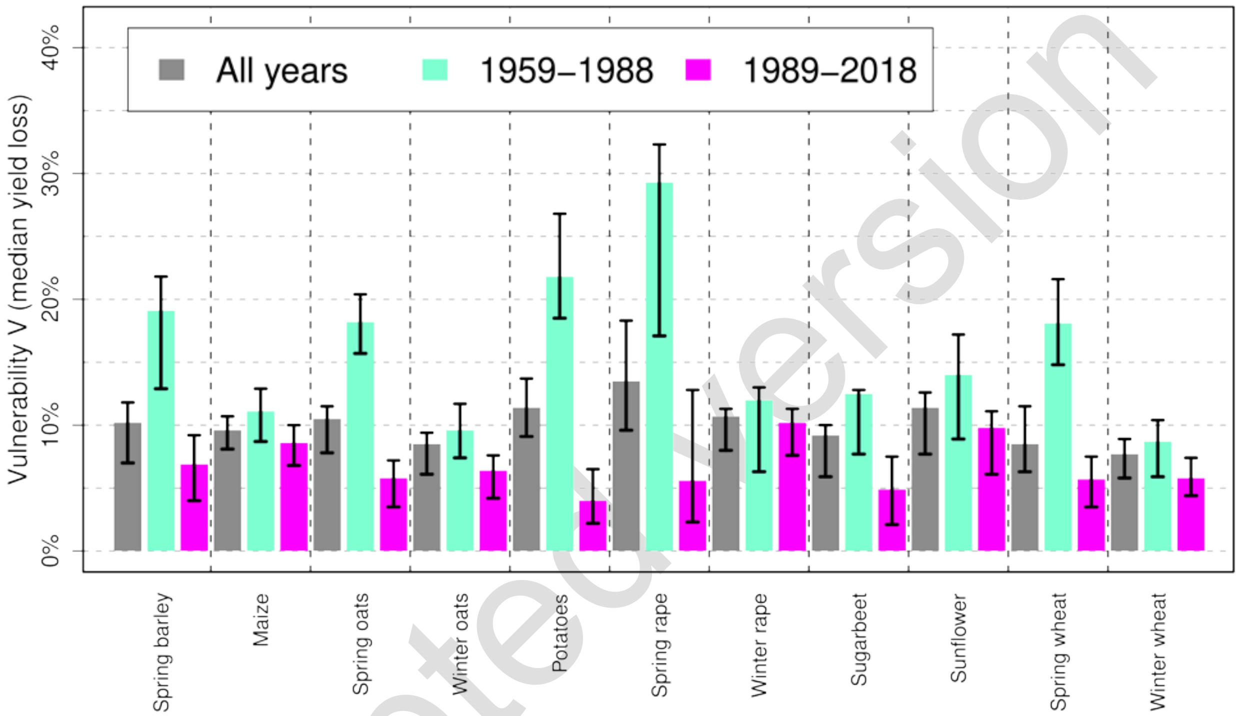


Figure 7: Vulnerability (exposure-weighted yield loss in % of expected yield, V from eq. 7) of weather hazards on crop production in an average year for three time frames: 1959-2018, 1959-1988 and 1989-2018. Black lines denote the 5% and 95% percentile range of 500 bootstrapped estimates.

4. Discussion

We have presented an approach to estimate weather influences on observed crop losses in France, based on a vulnerability index combining exposure and yield sensitivity to weather-related hazards. Weather emerges as a major cause of yield loss for the eleven staple crops studied. We found that the vulnerability to weather hazards has decreased for six crops (spring barley, oats, rapeseed and wheat, as well as potatoes and sugarbeet) since 1959 and remained stable for winter oats, winter rapeseed and sunflower as well as the two major crops maize and winter wheat. This declining or stable vulnerability is observed despite an increase of crop exposure to some hazards, in particular high temperatures. Compound hazards can have particularly damaging effects on crops and require the attention of farmers and crop breeders.

4.1 Input data

The outlier filtering of the department-level crop yield data may mask some true extremes in particular at the lower end. With the current data set we see, however, no possibility to dissect a possible confounding of reporting errors with truly unusual values. The 1940's serves as an egregious example: this decade was likely the driest in the 20th century (Bonnet et al., 2017; Bonnet et al., 2020; Hanel et al., 2018; Sanson and Pardé, 1950) which reduced crop yields, but may also have suffered from deteriorating agricultural practices to combat these droughts, or less accurate harvest reporting during and after World War 2 (Figure 3). The study of weather influences on yields only starts in 1959, though, so is not affected by this issue. Farm-specific management decisions or extreme losses are usually not visible at the department level, despite local economic relevance, but may balance out at the aggregated spatial and temporal scale considered here. There is no distinction between rainfed and irrigated agriculture, although increased water availability could drastically alter plant responses to heat or drought (Schauberger et al., 2017). Irrigation in France has increased, but is still rather marginal for most crops except maize (maize: around 40%, wheat: 2.5% in 2010) and long-term data is not available on department level (Gammans et al., 2017; Hawkins et al., 2013), such that we decided to neglect irrigation fractions. For future yield prospects, irrigation may play a larger role (Trnka et al., 2019). Growing seasons were assumed as fixed over the 60-year time frame and all considered departments, based on a data set around the year 2000 (Portmann et al., 2010). Both assumptions do not reflect variations of planting and harvesting dates at local level. But as we consider seasons on monthly time scale, and farmer response to shifting seasons seems slower than the observed changes (Menzel et al., 2006), there is sufficient flexibility to subsume individual variations. Finally, the omission of a tenth of departments per crop (those with the smallest cultivation areas) was performed to avoid spurious effects from marginal lands. This is not assumed as problematic, since, first, total omitted areas are small (less than 2%) and, second, previous analyses (Schauberger et al., 2018) showed no sensitivity to such omission.

The SAFRAN weather data provided by Meteo France are the best available long-term reanalysis data set for France on high resolution (originally 8 km and with daily values) (Quintana-Seguí et al., 2008; Vidal et al., 2010). Like many weather datasets, SAFRAN may suffer from artificial low-frequency temporal variations since input station data are generally not homogenized. Temperature and precipitation trends over France in SAFRAN are nonetheless acceptable (Vidal et al., 2010). SAFRAN uses a large amount of precipitation and temperature stations to properly represent regional climate variations, which makes this dataset suitable for analysing processes at the department level. The quality of the variables may vary, though: in particular, lower confidence can be given to solar radiation (and consequently ETP that ingests solar radiation) as it is based on a radiative transfer scheme. There is a climate gradient in France, from North to South, such that response equations derived for the whole country may be inadequate. We accounted for this by considering only those departments in the same Köppen-Geiger climate zone (*Cfb*), but encourage further work on higher resolution.

4.2 Yield losses

The frequency of yield losses has changed since 1900 with lowest loss frequencies observed around 1990. But there was a slight increase of loss propensities in the three recent decades for most crops. The latter could be a consequence of physiological yield limits being reached (leading to more pronounced negative than positive amplitudes), no further improvement of management to avoid losses, more adverse weather conditions or a combination of these factors. As discussed in Schauberger et al. (2018), the reaching of a physiological yield limit is unlikely for the crops considered here. Changes in management are difficult to assess since the required high-resolution and large-scale, long-term data are not available – but we deem it unlikely that loss aversion techniques have deteriorated rather than improved in the last 30 years. A related point is that the attained percentage of yields within loss events (Figure 3b) has increased, indicating that although losses have recently increased in frequency, they remained stable in average severity. Therefore, the remaining option is changes in climatic growing conditions. If crop-specific, optimal climatic envelopes for temperature or precipitation (Barnabas et al., 2008; Porter and Gawith, 1999) are exceeded , the odds for losses may increase. Tigchelaar et al. (2018) point to a higher yield variation in warmer climates, even if climate variation itself has not changed. Moreover, yield losses do not need to be as extreme as in 1976, 2003 or 2016 to cause economic turmoil. Our analysis aims to shed light on the causes for such sub-extreme losses, too.

For selecting yield-related weather variables, yield loss was expressed as a dichotomous variable similarly to previous studies (Ben-Ari et al., 2018; Mathieu and Aires, 2018), with a critical threshold of 10% below expected yields. The aptitude of a unique threshold for all crops is debatable, though, as this assumes that all losses have the same costs. But this could be inappropriate as for a farmer a 5% loss in winter wheat may be costlier than a 20% loss in spring rape. We limit the influence of our assumption by later inspecting continuous percentages of yield loss under hazards, using the fixed-percentage definition only for identifying hazards.

Across crops in the same departments, loss events are only partly co-occurring (SI Figure 3a), indicating that, on department scale, losses in one crop can be compensated by normal or above-normal harvests in others. Only few events affected large regions (SI Figure 3b), indicating a current robustness of the crop distribution across France.

4.3 Variable selection and model quality

Lasso regression and Random Forest are widely applied modelling strategies also in agronomy. We used the method with the better out-of-sample fit per crop to identify the variables with the strongest impacts on yields, but not to compute the exposure and yield sensitivity. With this approach, our main conclusions do not depend on model assumptions. We considered the temporal and spatial correlation of yield losses (SI Figures 3, 4) which could affect model predictions by altering confidence intervals, to be unproblematic for variable selection since our approach is descriptive, not predictive and does not rely on coefficient values. Moreover, a bootstrapped variable selection with reduced spatial correlation shows similar results as with the full data set (SI Text 4, SI Figure 6), indicating robustness of the selection process.

We use the Area Under the Curve (AUC) as criterion for model selection, a standard measure for dichotomous target variables (Makowski et al., 2009). The high AUC values (> 0.7 can be considered as acceptable (Guimaraes Nobre et al., 2019)) for all crops and out-of-sample AUC values >= 0.6 for nine crops indicate that weather played a major role in yield losses. The additional consideration of out-of-sample performance is relevant, as the discrepancy to in-sample performance in particular for Random Forests shows. Notably, non-parametric models like Random Forests are not necessarily outperforming more constrained, linear approaches like Lasso (Das et al., 2018). The Lasso model was able to capture climatic drivers of yield losses even when severe loss events were omitted from the training database, indicating a reasonable model fit (tested for maize).

More temperature-based than precipitation-based variables were selected (SI Figure 5), which could be due to a higher relevance of temperature, more accurate representation of temperature (compared to precipitation) when aggregated to department scale or a bias in the initial set of variables with four temperature, but only two precipitation variables. Interactions between temperature and precipitation were not selected by the models, in contrast to Ben-Ari et al. (2018), where the occurrence probability of extreme loss was linearly modelled for winter wheat in Northern and Central France. The ensuing analysis of compound hazards, though, underlines the relevance of noxious interactions (SI Figure 10).

4.4 Hazard definition

We defined hazards to crop growth as those value ranges of weather variables where reported crop yield losses on department level are substantially more frequent. We used a threshold of two for odds ratios, indicating a doubled chance of observing losses, instead of a suggested odds ratio of at least 3.2 (Kass and Raftery, 1995) for 'substantial evidence'. We chose the more inclusive threshold for two reasons: first, to consider a larger number of observed hazards and, second, since we inspect the actual impacts of hazards in a separate step, allowing them to adjust to observational data. The consistently negative impact of hazards on crop yields (with few exceptions mostly for rarely observed hazards, SI Figure 8) indicates that hazards are reasonably defined. Yet, the non-parametric definition may suffer from three drawbacks. First, odds may be sensitive to the size of the segments used (Figure 2), though we assume 50 segments to be sufficiently flexible. Second, when studying single hazards, unconsidered interactive effects of simultaneous hazards may underestimate impacts. We argue that these compound impacts are contained in the single-hazard impacts (Figure 5) as implicit sub-cases for either hazard and are also explicitly addressed (SI Figure 10). Third, the building of hazards based on pre-selected variables may overlook some hazards based on non-selected variables, but we chose this two-step approach to estimate the overall contribution of weather to yield losses and to avoid spurious findings based on non-informative variables. The advantage of the non-parametric hazard definition is that subsequent analyses are not limited by model quality. A comparable two-step approach has been taken by Alipour et al. (2020) for estimating flood damage in the South Eastern US, identifying relevant variables first and then modelling impacts in a second step.

The identified hazards and associated thresholds changed when defined for different time frames instead of the full 60-year window (tested for maize). The results support the same interpretation as observed in Figure 6: while heat-related hazards have often become more prevalent, cold-related hazards diminished. To have a consistent framework over time, we therefore used only hazards defined with the full data set.

Several hazards are shared between crops (Table 5, Table S1), in particular the detrimental effect of too many heat days in June, where all plants undergo decisive development stages like anthesis or grain filling. The right amount and distribution of spring precipitation (March to May) is also decisive for all crops. Nonetheless, each crop portrays its idiosyncratic growth constraints and combination of hazards. This is advantageous for agricultural resilience when not all crops are equally affected by adverse weather conditions.

For few crops, in particular potatoes, maize, and winter oats, a significant temporal autocorrelation of the yield anomalies was found in some departments. This correlation was partly considered in our statistical analysis (by annual cross-validation in the variable selection and by bootstrapping), but the effects of some of the selected climate hazards may have been overestimated for these crops as the data in the cross-validation or bootstrapping were potentially not fully independent if autocorrelation occurred.

4.5 Trends in hazard exposure

The exposure of crops to weather hazards has changed since 1959. For all months in the growing season, mean temperatures and the number of days >30°C have increased, while cold days have decreased (Figure 6). The year 1976 stands out as uniquely hot and dry in June within its vicinity – but comparable levels of hot days have already been observed more often after 2000. For radiation, clear trends can only be identified for selected months: radiation has, for example, increased in April or August but not in June. There is no detectable trend for precipitation within our database. The scarcity of trends in radiation and precipitation may be due to the national averages considered here, as trends can be observed in some parts of France, particularly over the Mediterranean region (references below).

While more hot days in June are detrimental for all crops, there are other cases where weather trends may conjointly affect crops negatively and positively. An example is April weather for winter wheat: while both radiation and temperature increase, the first is beneficial and the latter detrimental (Table 5).

The apparent trends in weather occur in critical phases of plant growth, namely green-up (early spring for most crops), anthesis (late spring) or grain filling. Each of these steps in plant growth requires different crop-specific climatic envelopes, which may be crossed if precipitation patterns or temperatures change too strongly. In particular strong heat during anthesis or grain filling may severely depress yields (Barnabas et al., 2008).

Past temperature trends in France are incompatible with internal variability alone (Ribes et al., 2016), pointing to the role of external forcing (Terray and Boé, 2013). Greenhouse gases are likely not the only anthropogenic forcing to have impacted temperature trends in France, as decreasing aerosol concentrations after the late 1970s explain 23% of the surface warming over Europe from 1980 to 2012 (Nabat et al., 2014). Phase transitions of the Atlantic Multidecadal Variability (AMV) in the mid-nineties may have contributed to accelerate the warming over France during the last decades (O'Reilly et al., 2017; Qasmi et al., 2017).

Warming trends observed over France are expected to continue during the 21st century with unabated greenhouse gas emissions, causing warming up to 6°C in summer and 4°C in winter, compared to the early 20th century (Bador et al., 2017; Terray and Boé, 2013). As shown therein, observed trends in precipitation in France over the 20th century have been limited. The impact of anthropogenic forcing is projected to emerge progressively during the 21st century, with a strong decrease in summer (around -20%) and a moderate increase in winter precipitation with spatial or seasonal inhomogeneity. A large increase in surface solar radiation is projected in summer over western Europe including France (Boé, 2016; Gutiérrez et al., 2020). Combined with our identified hazards, these projected changes could severely threaten future agricultural production.

4.6 Sensitivity to hazards and crop vulnerability

French crops show a clear negative response to hazardous weather events. Naturally, this is a consequence of our definition of hazards – but nonetheless indicates major impacts of adverse growing conditions on crop productivity. The negative impacts identified here are in line with previous research. For cereals, Barnabas et al. (2008) highlighted the detrimental effects of heat and drought during anthesis or grain filling, which are represented by the D^{30}_6 and D^{30}_7 as well as Pr_5 and D^{Pr}_5 hazards. Ben-Ari et al. (2016) found that simple climatic indicators can be predictive for yield variation, and in particular this holds for temperature or radiation in April and spring precipitation. Ceglar et al. (2016) study French maize and winter wheat between 1989 and 2014, and we agree with their finding that summer weather is decisive for maize and radiation budgets for winter wheat. Ben-Ari et al. (2018) identified causes for the strong loss in winter wheat yields in 2016, stating that late autumn and June temperature as well as November and spring precipitation are decisive – which agrees with our hazards (except November precipitation), though we found more drivers of yield loss. Reasons for differences lie in method and spatial coverage with more departments here. Webber et al. (2018), using ensembles of crop models, found that maize and winter wheat in France suffered substantially from drought and heat combined, but less so from heat alone. We identified, however, heat in June as a major cause of losses also at normal precipitation levels – which agrees with Hawkins et al. (2013). Gouache et al. (2015) provided a forecasting scheme for winter wheat in Northern France and identified that excess temperature during grain filling or too much moisture in winter are detrimental. A negative effect of too much precipitation in summer proposed therein is not picked up by our hazards on the national scale, possibly due to the monthly time scale considered here. Gammans et al. (2017) corroborate the detrimental impact of high temperatures during summer or cold after planting for winter wheat. Season-scale water dearth or excess in selected departments were identified as detrimental for winter wheat and sunflower by Kapsambelis et al. (2019), which corresponds with our results (Pr_7 and Pr_8 hazards for sunflower). Sugarbeet yields are forecasted by Guimaraes Nobre et al. (2019), using climate modes like ENSO. They identified heat and water stress in June as major drivers, which we did as well – next to ETP in September.

Between 1959 and 2018, the yield sensitivity to single hazards has changed. Many – but not all – hazards became less impactful for crop yields, even when rising in frequency. Thus, the total vulnerability to climatic hazards has markedly decreased for several crops (Figure 7). This matches with a positive trend in crop yields (Schauberger et al., 2018): average yield increase between 1959-1988 and 1989-2018 across crops was 54% (even 74% for sugarbeet and 70% for maize). There were also fewer loss events in the latter period and a lower percentage of yield reductions in loss events (Figure 3). Beillouin et al. (2020) showed that the European area share with extremely negative yield anomalies did not increase since 1991, additionally substantiating a non-increase in vulnerability. Yet it should be noted that particularly for maize and winter wheat, two key crops in France, vulnerability was stable across time (maize) or declined only insignificantly (winter wheat). The positive trend towards more stability is probably due to adapted management decisions such as shifting sowing or harvesting dates, irrigation (particularly for spring crops), breeding efforts towards more heat or dryness tolerance, or over-compensating effects from other weather conditions as exemplified above with the opposite effect of April weather trends on winter wheat and also the occurrence of non-losses even in very hot Julys for spring wheat (Figure 2). Further reasons for an apparent decrease in vulnerability include more fertilizer use (Schauberger et al., 2018), increased use of pesticides or herbicides and a decrease of exposure to hazards that in the earlier period severely diminished crop yields. In particular compensation of single adverse weather events seems to play a major role, as the loss odds (number of losses vs. non-losses under a hazard) are in several cases around or smaller than 1, indicating that the occurrence of one hazard need not have strong impacts. Only for those hazards with odds ratios substantially larger than 2 (e.g. too many heat days in June for maize, spring rape or sugarbeet) compensation seems difficult. Hazard-balancing effects may be more frequent in recent climate since slightly warmer conditions in temperate climate zones may initially be beneficial for crop growth. Yet particularly detrimental effects of compound hazards may change frequency and impacts under a future climate. Between crops, compensation effects can occur as hazards do not affect all crops uniformly. The relative areas and agronomic importance of crops need to be considered then, as, for example, a 20% gain in spring oats may not be enough to compensate a 5% reduction in maize. There are several reasons for differences between the absolute values and dynamics in vulnerability of the individual crops, which in combination explain the divergent impacts: agronomic importance and thus farmers' investments or breeders' efforts diverge, freezing events after sowing (particularly damaging for spring crops, e.g. sugarbeet or spring wheat) have decreased, irrigation increases mainly for spring but not winter crops, different shares of organic vs. conventional areas, differential improvements in sowing conditions (soil temperature or moisture), a multitude of damaging hazards in the past that are less relevant in exposure or impacts recently (particularly for potatoes, spring oats and spring barley) or changes in pathogen or pest cycles and associated political regulations like pesticide bans. We consider these thoughts as hypotheses, due to lack of convincing evidential data, which merit further detailed investigation.

For the US, maize yield increases have been associated with a higher sensitivity to drought due to increased planting densities (Lobell et al., 2014), with evidence based on growth trend differences between yield quintiles. For France, we observe the opposite: recent yield increases are not associated with increased drought sensitivity, as the negative impacts of low-precipitation hazards in June and August on maize yields have decreased and for July they remained similar. Too many precipitation days in May, meanwhile, have become more detrimental over time – indicating that maize has become more drought but less logging tolerant. Our results are also contradicting other findings in the US (Ortiz-Bobea et al., 2018), where the authors claim increased climatic sensitivity of agricultural productivity in the Midwest since 1960. They suggest a higher susceptibility of crops as one reason. A similar econometric analysis of total factor productivity would be pertinent for France, to corroborate or contradict our results here.

A change in CO_2 concentration may decrease crop sensitivity towards heat or drought (Deryng et al., 2016; Long et al., 2006; Schauberger et al., 2017; Wang et al., 2012). We did not consider this effect in our historical analysis, although historical changes in CO_2 (1959-1988 average is 331 ppm, while for 1989-2018 it is 378 ppm; NOAA (2020)) could already have affected past crop responses to heat or drought. A further important factor shaping plant response to climatic hazards is soil physics, which is not explicitly considered in our approach – though it is possibly partly accounted for by indirect effects of climate on soil processes, since the hazards are agnostic about the underlying physiological reasons. Adequate soil moisture is a key prerequisite for plant growth and is also only indirectly considered here. Indicators like the SP(E)I (Vicente-Serrano et al., 2010) that account for lagged effects in plant available water could be a natural extension. Finally, our approach only considers weather hazards, but no biotic stressors like pests or diseases. We argue, as for soil factors, that biotic stressors are – at least partly – affected by weather and thus indirectly considered in our approach. Yet we encourage an in-depth study of these relationships to identify additional or weather-linked pressures on crop production from biotic stressors.

Our vulnerability definition follows the IPCC (Krishnamurthy et al., 2014) where exposure, sensitivity and adaptive capacity are considered as separate entities. This definition can be operationalized and has often been followed in the literature, mainly for tropical countries (Eggen et al., 2019; Kamali et al., 2018; Kerr et al., 2018; Mohmmed et al., 2018; Murthy et al., 2015; Parker et al., 2019; Sehgal and Dhakar, 2016; Shukla et al., 2018). Naylor et al. (2020) propose additional considerations of this vulnerability concept, framing it as dynamic process rather than static measure. An advantage of the single measure for vulnerability is the straight-forward comparison across time and crops. Disadvantages of this definition may include a partly overlap of exposure and sensitivity. An example are shifting growing seasons: while there is a trend towards earlier season onsets due to warmer springs, farmers can also adapt their season management by choosing sowing dates or cultivars. Both changes affect exposure and sensitivity simultaneously. Also, co-variances between exposure and sensitivity – e.g. non-linear strong increases of sensitivity with slight increases in exposure – are not considered here, although these occur in practice (Figure 2). Moreover, a single aggregate measure of vulnerability may conceal changes over time that could affect future expectations. We address this by inspecting exposure frequency and crop sensitivity for individual hazards.

Within our study we assumed adaptive capacity (AC) as constant over time and space. This may be justified by the use of similar practices and agroeconomic structures over France. Yet the assumption of constant AC may not be realistic for the future, since France is not uniformly impacted by climate change (see above) and agronomic structures like administrative capacity, water available for irrigation or access to improved seeds may change over time. Adaptation may change both exposure and sensitivity to climatic hazards, for example by shifting growing seasons, using more resistant crops or those with different maturity requirements, changing crop rotation, expanding irrigation, to name only some options. Therefore, we encourage a more thorough analysis of AC, possibly using one of the following measures as a proxy for AC: historical farmer-driven shifts in seasons, characteristics and speed in taking up new cultivars, changing rotation patterns, share of irrigated land, a shift towards different crops, a geographic (northward) shift of areas or increasing crop diversification. Social factors like increasing use of risk transfer mechanisms like insurances, more regular use of consultancy services or subsidies for e.g. irrigation can equally be indicative for AC. It should be noted that neither exposure nor sensitivity can fully be disentangled from AC since historical adaptation would implicitly be enmeshed in our long-term measures of E and S.

We did not perform an out-of-sample validation of our hazards concept with a fully independent dataset. Therefore, the models and estimated impacts should not be used to predict the impact of future weather hazard on crop yields. The objective of our analysis was not to develop a tool to predict future yield anomalies but rather to devise an approach for describing the impacts of weather hazards that occurred in the past and are relevant for major parts of France. Using the same data set for selecting important variables and estimating the impact of hazards may have led to an upward bias in sensitivities. We argue, though, that the model-based pre-screening of variables was helpful to focus on major hazards and that the observed hazards are too scarce to enable a robust splitting for these two tasks.

5. Conclusion and practical implications

We presented a two-step approach to identify major climatic hazards on French crop production, applying machine-learning models and non-parametric estimates of exposure and sensitivity to hazards. We found no evidence of increased crop vulnerability to climate hazards since 1959 – in line with strongly increasing absolute yields since this time. Yet our results suggest that adaptation strategies should be found to deal with increasingly occurring heat hazards, either by adapting crop management practices (increasing irrigation, preponed sowing dates, cultivar choice), breeding of more heat-tolerant cultivars, replacement of crop types by more heat-tolerant ones or relocation of growing areas to cooler regions. The particularly detrimental effects of compound hazards could be addressed by improved forecasting efforts, thus raising the stakes for preparing against further hazards if one was already observed during the current season. Single hazards could also be incorporated into agro-meteorological weather forecasts, allowing more lead time to prepare. Apart from farmers, insurance companies or political institutions might use hazard frequencies to adapt their financial or regional adaptation planning. The future vulnerability of crops could be studied by plugging weather indices, derived from climate projections, into our presented hazards (though this would require an amendment of our framework into a predictive one). The possible dampening effect of higher CO_2 concentrations will have to be considered then. Finally, on farm and aggregate scale, cross-crop compensation effects, for example between winter wheat, spring rape or sunflower that react to different hazards, could be used to redistribute growing areas or cultivate a more diverse set of crops with differently affected suitability under climate change.

Interestingly, cereal production in France was record high in 2019 (La France Agricole, 2020). But record yields or decreased dangers from weather hazards should not be taken as a safeguard for the future, as neither compensating beneficial climatic factors nor adaptation efforts may linearly be extrapolated under a stronger global warming (Tigchelaar et al., 2018). Moreover, vulnerability estimates based only on observed events may underestimate the true danger due to practical under-sampling of theoretical climate variability (Kent et al., 2017). The increasing absolute yield variation (Schauberger et al., 2018) and recent climate-induced losses as in 2003 or 2016 raise the question whether below the surface of increasing and apparently less sensitive crop yields a higher vulnerability has already started to shape.

Author contributions

BS, DM, PC and TB designed research. BS performed research and wrote the manuscript. JB provided the weather data on department level. All authors contributed to writing and result discussion.

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Data availability

The data on French agriculture are publicly available at http://agreste.agriculture.gouv.fr from 1989 on. Data before 1989 are available from the corresponding author on reasonable request. SAFRAN data are available upon request at https://mistrals.sedoo.fr/?editDatsId=47&datsId=47&project_name=HyMeX&q=SAFRAN (accessed on Dec 18, 2020).

Competing interests statement

The authors declare to have no competing interests.

Supplementary information

Supplementary information for this article is available online.

References

Alipour, A., Ahmadalipour, A., Abbaszadeh, P. and Moradkhani, H., 2020. Leveraging machine learning for predicting flash flood damage in the Southeast US. Environmental Research Letters, 15(2): 024011.

Bador, M. et al., 2017. Future summer mega-heatwave and record-breaking temperatures in a warmer France climate. Environmental Research Letters, 12(7): 074025.

Barnabas, B., Jager, K. and Feher, A., 2008. The effect of drought and heat stress on reproductive processes in cereals. Plant, cell & environment, 31(1): 11-38.

Beillouin, D., Schauberger, B., Bastos, A., Ciais, P. and Makowski, D., 2020. Impact of extreme weather conditions on the European crop production in 2018. Philosophical transactions of the Royal Society of London. Series B, Biological sciences.

Ben-Ari, T. et al., 2016. Indentifying indicators of extreme wheat and maize yield losses. Agricultural and Forest Meteorology: 130-140.

Ben-Ari, T. et al., 2018. Causes and implications of the unforeseen 2016 extreme yield loss in the breadbasket of France. Nature communications, 9(1): 1627.

Bhend, J. and Whetton, P., 2013. Consistency of simulated and observed regional changes in temperature, sea level pressure and precipitation. Climatic Change, 118(3): 799-810.

Boé, J., 2016. Modulation of the summer hydrological cycle evolution over western Europe by anthropogenic aerosols and soil-atmosphere interactions. Geophysical Research Letters, 43(14): 7678-7685.

Bonnet, R., Boé, J., Dayon, G. and Martin, E., 2017. Twentieth-Century Hydrometeorological Reconstructions to Study the Multidecadal Variations of the Water Cycle Over France. Water Resources Research, 53(10): 8366-8382.

Bonnet, R., Boé, J. and Habets, F., 2020. Influence of multidecadal variability on high and low flows: the case of the Seine basin. Hydrol. Earth Syst. Sci., 24(4): 1611-1631.

Breiman, L., 2001. Random Forests. Machine Learning, 45: 5-32.

Brisson, N. et al., 2010. Why are wheat yields stagnating in Europe A comprehensive data analysis for France. Field Crops Research, 119: 201-212.

Ceglar, A., Toreti, A., Lecerf, R., Van der Velde, M. and Dentener, F., 2016. Impact of meteorological drivers on regional inter-annual crop yield variability in France. Agricultural and Forest Meteorology, 216: 58-67.

Ciais, P. et al., 2005. Europe-wide reduction in primary productivity caused by the heat and drought in 2003. Nature, 437(7058): 529-33.

Copernicus, 2020. European temperatures: https://climate.copernicus.eu/european-temperature.

Das, B., Nair, B., Reddy, V.K. and Venkatesh, P., 2018. Evaluation of multiple linear, neural network and penalised regression models for prediction of rice yield based on weather parameters for west coast of India. International Journal of Biometeorology, 62(10): 1809-1822.

Deryng, D. et al., 2016. Regional disparities in the beneficial effects of rising CO2 concentrations on crop water productivity. Nature Climate Change, 6: 786-790.

Eggen, M. et al., 2019. Vulnerability of sorghum production to extreme, sub-seasonal weather under climate change. Environmental Research Letters, 14(4).

Field, C.B. et al., 2012. Managing the Risks of Extreme Events and Disasters to Advance Climate Change Adaptation.

Gammans, M., Mérel, P. and Ortiz-Bobea, A., 2017. Negative impacts of climate change on cereal yields: statistical evidence from France. Environmental Research Letters, 12(5).

Gouache, D., Bouchon, A.-S., Jouanneau, E. and Le Bris, X., 2015. Agrometeorological analysis and prediction of wheat yield at the departmental level in France. Agricultural and Forest Meteorology, 209-210: 1-10.

Guimaraes Nobre, G., Hunink, J.E., Baruth, B., Aerts, J. and Ward, P.J., 2019. Translating large-scale climate variability into crop production forecast in Europe. Sci Rep, 9(1): 1277.

Gutiérrez, C. et al., 2020. Future evolution of surface solar radiation and photovoltaic potential in Europe: investigating the role of aerosols. Environmental Research Letters, 15(3): 034035.

Hanel, M. et al., 2018. Revisiting the recent European droughts from a long-term perspective. Scientific Reports, 8(1): 9499.

Hawkins, E. et al., 2013. Increasing influence of heat stress on French maize yields from the 1960s to the 2030s. Global change biology, 19(3): 937-947.

Iizumi, T., Sakurai, G. and Yokozawa, M., 2014. Contributions of historical changes in sowing date and climate to U.S. maize yield trend: An evaluation using large-area crop modeling and data assimilation. Journal of Agricultural Meteorology, 70(2): 73-90.

Kamali, B., Abbaspour, K.C., Lehmann, A., Wehrli, B. and Yang, H., 2018. Spatial assessment of maize physical drought vulnerability in sub-Saharan Africa: Linking drought exposure with crop failure. Environmental Research Letters, 13(7).

Kapsambelis, D., Moncoulon, D. and Cordier, J., 2019. An Innovative Damage Model for Crop Insurance, Combining Two Hazards into a Single Climatic Index. Climate, 7(11).

Kass, R.E. and Raftery, A.E., 1995. Bayes Factors. Journal of the American Statistical Association, 90(430): 773-795.

Kent, C. et al., 2017. Using climate model simulations to assess the current climate risk to maize production. Environmental Research Letters, 12(5): 054012.

Kerr, A., Dialesandro, J., Steenwerth, K., Lopez-Brody, N. and Elias, E., 2018. Vulnerability of California specialty crops to projected mid-century temperature changes. Climatic Change, 148(3): 419-436.

Klein Tank, A.M.G. and Können, G.P., 2003. Trends in Indices of Daily Temperature and Precipitation Extremes in Europe, 1946–99. Journal of Climate, 16: 3665-80.

Krishnamurthy, P.K., Lewis, K. and Choularton, R.J., 2014. A methodological framework for rapidly assessing the impacts of climate risk on national-level food security through a vulnerability index. Global Environmental Change, 25: 121-132.

La France Agricole, 2020. http://www.lafranceagricole.fr/actualites/cereales-la-recolte-de-2019-sur-la-troisieme-marche-du-podium-1,10,1066779449.html.

Lobell, D.B. et al., 2014. Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest. Science, 344(6183): 516-9.

Long, S.P., Ainsworth, E.A., Leakey, A.D., Nosberger, J. and Ort, D.R., 2006. Food for thought: lower-than-expected crop yield stimulation with rising CO2 concentrations. Science, 312(5782): 1918-21.

Luo, Q., 2011. Temperature thresholds and crop production: a review. Climatic Change, 109(3-4): 583-598.

Makowski, D., Tichit, M., Guichard, L., Van Keulen, H. and Beaudoin, N., 2009. Measuring the accuracy of agro-environmental indicators. Journal of Environmental Management, 90: S139-S146.

Mathieu, J.A. and Aires, F., 2018. Using Neural Network Classifier Approach for Statistically Forecasting Extreme Corn Yield Losses in Eastern United States. Earth and Space Science, 5(10): 622-639.

Menzel, A., von Vopelius, J., Estrella, N., Schleip, C. and Dose, V., 2006. Farmers' annual activities are not tracking the speed of climate change. Climate Research, 32: 201-7.

Mohmmed, A. et al., 2018. Analysis of drought and vulnerability in the North Darfur region of Sudan. Land Degradation & Development, 29(12): 4424-4438.

Murthy, C.S., Laxman, B. and Sesha Sai, M.V.R., 2015. Geospatial analysis of agricultural drought vulnerability using a composite index based on exposure, sensitivity and adaptive capacity. International Journal of Disaster Risk Reduction, 12: 163-171.

Nabat, P., Somot, S., Mallet, M., Sanchez-Lorenzo, A. and Wild, M., 2014. Contribution of anthropogenic sulfate aerosols to the changing Euro-Mediterranean climate since 1980. Geophysical Research Letters, 41(15): 5605-5611.

Naylor, A., Ford, J., Pearce, T. and Van Alstine, J., 2020. Conceptualizing Climate Vulnerability in Complex Adaptive Systems. One Earth, 2(5): 444-454.

NOAA, 2020. CO2 concentrations: www.esrl.noaa.gov/gmd/ccgg/trends/.

O'Reilly, C.H., Woollings, T. and Zanna, L., 2017. The Dynamical Influence of the Atlantic Multidecadal Oscillation on Continental Climate. Journal of Climate, 30(18): 7213-7230.

Ortiz-Bobea, A., Knippenberg, E. and Chambers, R.G., 2018. Growing climatic sensitivity of U.S. agriculture linked to technological change and regional specialization. Science Advances, 4(12): eaat4343.

Parker, L., Bourgoin, C., Martinez-Valle, A. and Laderach, P., 2019. Vulnerability of the agricultural sector to climate change: The development of a pan-tropical Climate Risk Vulnerability Assessment to inform sub-national decision making. PLoS One, 14(3): e0213641.

Perronne, R., Makowski, D., Goffaux, R., Montalent, P. and Goldringer, I., 2017. Temporal evolution of varietal, spatial and genetic diversity of bread wheat between 1980 and 2006 strongly depends upon agricultural regions in France. Agriculture, Ecosystems & Environment, 236: 12-20.

Porter, J.R. and Gawith, M., 1999. Temperatures and the growth and development of wheat a review. European Journal of Agronomy, 10: 23-36.

Portmann, F.T., Siebert, S. and Döll, P., 2010. MIRCA2000-Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling. Global Biogeochemical Cycles, 24(1): GB1011.

Qasmi, S., Cassou, C. and Boé, J., 2017. Teleconnection Between Atlantic Multidecadal Variability and European Temperature: Diversity and Evaluation of the Coupled Model Intercomparison Project Phase 5 Models. Geophysical Research Letters, 44(21): 11,140-11,149.

Quintana-Seguí, P. et al., 2008. Analysis of Near-Surface Atmospheric Variables: Validation of the SAFRAN Analysis over France. Journal of Applied Meteorology and Climatology, 47(1): 92-107.

R Core Team, 2016. R: A Language and Environment for Statistical Computing. In: R.F.f.S. Computing (Editor). R Foundation for Statistical Computing.

Rahmstorf, S. and Coumou, D., 2011. Increase of extreme events in a warming world. Proceedings of the National Academy of Sciences of the United States of America, 108(44): 17905-9.

Ribes, A., Corre, L., Gibelin, A.-L. and Dubuisson, B., 2016. Issues in estimating observed change at the local scale – a case study: the recent warming over France. International Journal of Climatology, 36(11): 3794-3806.

Samaniego, L. et al., 2018. Anthropogenic warming exacerbates European soil moisture droughts. Nature Climate Change, 8(5): 421-426.

Sanson, J. and Pardé, M., 1950. La sécheresse des années 1942-49 en France. Revue de Géographie Alpine, 38(2): 369-404.

Schauberger, B. et al., 2017. Consistent negative response of US crops to high temperatures in observations and crop models. Nature communications, 8: 1-9.

Schauberger, B. et al., 2018. Yield trends, variability and stagnation analysis of major crops in France over more than a century. Scientific Reports, 8(1): 16865.

Sehgal, V.K. and Dhakar, R., 2016. Geospatial approach for assessment of biophysical vulnerability to agricultural drought and its intra-seasonal variations. Environ Monit Assess, 188(3): 197.

Sheffield, J. and Wood, E.F., 2008. Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. Climate Dynamics, 31(1): 79-105.

Shukla, R., Sachdeva, K. and Joshi, P.K., 2018. Demystifying vulnerability assessment of agriculture communities in the Himalayas: a systematic review. Natural Hazards, 91(1): 409-429.

Stott, P., 2016. How climate change affects extreme weather events. Science, 352(6293): 1517-1518.

Terray, L. and Boé, J., 2013. Quantifying 21st-century France climate change and related uncertainties. Comptes Rendus Geoscience, 345(3): 136-149.

Tigchelaar, M., Battisti, D.S., Naylor, R.L. and Ray, D.K., 2018. Future warming increases probability of globally synchronized maize production shocks. Proceedings of the National Academy of Sciences of the United States of America, 115(26): 6644-6649.

Trnka, M. et al., 2019. Mitigation efforts will not fully alleviate the increase in water scarcity occurrence probability in wheat-producing areas. Science Advances, 5(9): eaau2406.

Trnka, M. et al., 2011. Agroclimatic conditions in Europe under climate change. Global change biology, 17(7): 2298-2318.

Vicente-Serrano, S.M., Beguería, S. and López-Moreno, J.I., 2010. A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. Journal of Climate, 23(7): 1696-1718.

Vidal, J.-P., Martin, E., Franchistéguy, L., Baillon, M. and Soubeyroux, J.-M., 2010. A 50-year high-resolution atmospheric reanalysis over France with the Safran system. International Journal of Climatology, 30(11): 1627-1644.

Wang, D., Heckathorn, S.A., Wang, X. and Philpott, S.M., 2012. A meta-analysis of plant physiological and growth responses to temperature and elevated CO2. Oecologia, 169(1): 1-13.

Webber, H. et al., 2018. Diverging importance of drought stress for maize and winter wheat in Europe. Nature communications, 9(1): 4249.