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Extreme weather events cause significant crop yield losses at the farm level in German agriculture

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ABSTRACT

Extreme weather events frequently cause severe crop yield losses, affecting food security and farmers' incomes. In this paper, we aim to provide a holistic assessment of these impacts across various extreme weather events and multiple crops. More specifically, we estimate and compare the impact of frost, heat, drought and waterlogging on yields of winter wheat, winter barley, winter rapeseed and grain maize production in Germany. We analyse 423,815 farm-level yield observations between 1995 and 2019, and account for extreme weather conditions within critical phenological phases. Furthermore, we monetarize historical yield losses due to extreme weather events on a spatially disaggregated level. We find that drought is a main driver for farm-level grain yield and monetary losses in German agriculture. For instance, a single drought day can reduce winter wheat yields by up to 0.36%. It is estimated that during the period 1995–2019, summer drought led to yield losses in winter wheat, which, on average, caused annual revenues to sink by over 23 million Euro across Germany. We find that the impacts of extreme weather events vary considerably across space and time. For example, only the most important winter rapeseed production region in the North of Germany was prone to winter rapeseed yield losses due to heat during flowering. Moreover, waterlogging and frost are generally less relevant from an economic point of view, but can nevertheless cause crop- and regional-specific damage. Our analysis provides stakeholders with information for weather-related risk management and adaptation strategies.

1. Introduction

Extreme weather events like droughts, waterlogging due to heavy rain, heat waves and frosts frequently cause severe crop yield and income losses on a global scale (Lesk et al., 2016; Lobell et al., 2011; Powell & Reinhard, 2016; Schlenker & Roberts, 2009). This also applies to European agriculture (e.g. Beillouin et al., 2020) and, for example, the heat and droughts in 2003 and 2018 led to massive yield losses for several crops in various regions (BMEL, 2018; Ciais et al., 2005; Webber et al., 2020).

Quantifying the economic impacts of extreme weather events is a key factor when assessing famers' risk exposure and informing decisions in up- and downstream industries and public policies. This information also allows the agricultural sector to tailor adaptation strategies to cope with climate change (Global Commission on Adaptation, 2019; Olesen et al., 2011). There are numerous viable options including farm management practices such as e.g., diversification, crop/variety choice and input intensity, technological developments, breeding research and off-farm risk management like weather insurance (e.g. Bailey-Serres et al., 2019; Smit & Skinner, 2002; Yadav et al., 2011).

Farmers and agricultural advisory services need detailed information about the impacts of extreme weather events on crop production on the basis of which they can derive effective and regionally adapted risk management strategies. This information must allow specific inferences across crops, weather extremes and regions. In addition, governments require empirical insights and evidence when discussing and designing effective and efficient policies to support agricultural risk management (OECD, 2021). The monetary losses suffered by farmers due to extreme weather events must be quantified on a regional basis and then estimated for the whole country. This information is essential for policy-

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makers when deciding how to support the adaptation of agriculture to weather extremes and climate change.

In this paper, we use 423,815 farm-level crop yield observations from German agriculture for the period 1995–2019 to estimate the effects of extreme weather events such as drought, waterlogging due to excess rainfall, heat and frost on yield levels of winter wheat, winter barley, winter rapeseed and grain maize. We quantify the effects of these events on crop yields, explore their economic significance and scale up their estimated impact on yields to obtain an assessment of monetary losses at regional and national levels. This can help policy-makers to prioritize public support for adaptation measures and assess the (long-term) public costs of weather-risk related policy interventions like ad-hoc payments and the support of on– and off-farm risk management.

Previous research identified that extreme weather events cause severe crop yield losses (e.g., Lesk et al., 2016; Lobell et al., 2011; Powell & Reinhard, 2016; Schlenker & Roberts, 2009). These analyses usually focus on specific crops and the extreme weather events to which they are particularly susceptible (Albers et al., 2017; Lobell et al., 2013; Lüttger & Feike, 2018; Mäkinen et al., 2018; Tack et al., 2015). There are very few holistic assessments and comparisons of the effects of various extreme weather events on different crops (Schlenker & Roberts, 2009; Webber et al., 2018). However, a holistic assessment across differing weather extremes and crops is essential to inform agriculture and policy (e.g., Webber et al., 2020).

Earlier research also found that empirical approaches estimating yield/weather effects often face several data- and model-related challenges. For example, since weather extremes in one region are not automatically considered extreme in another, the definition of temperature and soil moisture thresholds is not straightforward and it is therefore important to describe threshold-decisions comprehensibly (e.g. Peterson et al., 2008; Zhang et al., 2011). Furthermore, since extreme weather events do not occur frequently and the timeframe of the available data is usually limited, yield effects could be over- or underestimated and, therefore, distort the risk assessment (Goodwin, 2015). In addition, the spatial and temporal aggregation of yield and weather data has important implications for the validity of the model (Auffhammer et al., 2013; Blanc & Schlenker, 2017; Conradt et al., 2016). Crop yield data at more aggregated levels (e.g., county-level) have different risk characteristics than at the farm level. In particular they exhibit a lower variance and less negative skewness of crop yields (e.g., Finger, 2012; Marra & Schurle, 1994). Different aggregation levels of yield data also result in differences in crop yield effects of weather extremes (D'Agostino & Schlenker, 2016), and thus may limit inference for the relevant level of individual farms. Furthermore, extreme weather events may be blurred or even vanish if e.g., monthly averages of rainfall or temperature are used. Besides, spatial and temporal aggregations interact due to the fact that crops need certain weather conditions during different phenological phases, which do not start and end simultaneously across a region or country.

This paper presents a holistic assessment of extreme weather impacts on crop production in Germany based on a rich dataset (N = 423,815) of farm-level yields, covered by 25 years of observations (1995–2019). We consider the most important weather risks in German and European crop production, i.e., drought, waterlogging due to excess rainfall, heat and frost (Barlow et al., 2015; Gömann et al., 2015; Heidecke et al., 2017; Peichl et al., 2019; Pullens et al., 2019; Trnka et al., 2014) and we focus on their impact on the most relevant crops, i.e., winter wheat, winter barley, winter rapeseed and grain maize (BMEL, 2019). Since Germany is the second largest cereal producer in Europe (2019, ca. 44.3 million tonnes, 6.5 bn. Euro ≈ 7.3 bn. USD currently; BMEL, 2020a), a close examination of its crop production provides insights into an economically highly relevant case study. In this analysis, we operationalize extreme weather events in our model using flexible time windows by tapping on rich crop phenology data (see also Bucheli et al, 2021; Dalhaus et al., 2018; Vroege & Finger, 2020). This allows to account for the large variation of potentially vulnerable phenological phases of the cash crops analysed over space and years. We provide several split sample analyses, e.g., splitting by regions and time periods, which allow to detect whether impacts of weather extremes have become more pronounced in recent years due to climate change. Finally, we provide an assessment of the economic relevance of the effects of extreme weather events on crop yields. In this way, our approach aids prioritization of efforts designed to cope with extreme weather events in agriculture, at both industrial and political levels.

We find that most of the extreme weather events analysed regularly cause yield losses across German crop production, whereby these effects are heterogeneous over space, time and crops. We show that extreme droughts represent the greatest and economically most relevant risk for German crop production. Winter wheat, winter barley and grain maize yields suffered noticeably from the impact of droughts, with a high spatial variation. For instance, summer drought during the phenological phases Fruit Formation & Ripening of winter wheat caused on average yearly revenue losses of 7.50 Euro/ha. Aggregated over the whole country, this implies that summer droughts caused, on average over the period 1995–2019, winter wheat yield losses amounting to over 23 million Euro per year, although variations over time and space were considerable. Spring droughts caused losses in winter barley yields amounting to a country-wide average of 3.37 Euro/ha per year. Especially Northern and Eastern Germany suffered from drought-related losses, e.g. in winter wheat and winter barley. Moreover, we find that waterlogging on winter wheat and winter barley, e.g., during Shooting & Flowering, had a significantly negative effect on yields of up to 1.50 Euro/ha across Germany. Waterlogging-related losses, however, occurred mainly in the South of Germany. We find that maize especially suffered from summer droughts, resulting in a country-wide average revenue loss of 7.64 Euro/ha per year. In the North of Germany, heat caused average yearly monetary losses in winter rapeseed yields amounting to approximately 21.18 Euro/ha.

The remainder of this paper is organized as follows. In section 2, we describe the econometric and economic framework of our analysis. In section 3, we present an overview of the data and describe how we operationalize those extreme weather events whose characteristics are potentially detrimental to the yields of the four crops analysed. Section 4 contains the results of the regression analyses and describes the economic relevance of the different weather events. Finally, we discuss our findings against the background of recent research and highlight caveats of our analyses.

2. Econometric and economic framework

We aim to identify the effects of extreme weather events on yield levels by using unbalanced farm-level panel data of crop yields. Our econometric approach accounts for farm-level and year fixed effects. Farm-level fixed effects account for invariant unobserved heterogeneity such as differences in environmental conditions and soil quality. The inclusion of year fixed effects captures all systemic shocks, which occur across all farms in a specific year and possibly affect crop yields (Dalhaus et al., 2020). For example, it accounts for changes in policies and market conditions that affect all farms across years and also captures the impact of technological change on crop yields.[1] Controlling for this year-fixed effect also implies that we 'only' recognize extreme weather effects as

[1] The effects of technological changes are non-linear in European crop production. Thus, after a long period of steady yield increases, a number of European agricultural sectors were faced by declining, or even stagnating, crop yields (e.g. Ray et al., 2012; Brisson et al., 2010; Finger, 2010). The inclusion of year-fixed effects is therefore more effective than linear trend estimates to capture yield developments over time.

deviating from the general state in a specific year. This means that effects of systemic events like droughts may be underestimated.[2]

We estimate various specifications of the following relationship:

$$Log(y_{jit}) = \beta_{wj} * WE_{wjit} + F_i + Y_t + \varepsilon_{jit} \quad (1)$$

where $Log(y_{jit})$ is the natural logarithm of crop yield j (dt/ha) of farm i in year t = 1995–2019. β_{wj} are weather- and crop-specific yield effects of the different extreme weather events to be estimated (see section 3 for details). WE_{wjit} represents the vector of different crop-specific extreme weather events. F_i denotes the farm-level fixed effect, Y_t is the year-fixed effect and ε_{jit} is an idiosyncratic error term. Extreme temperature parameters (black frost and heat) are expressed through degree days, which considers a sinusoidal temperature distribution during the day. To this end, we follow the approach of D'Agostino & Schlenker (2016) to estimate the daily sinusoidal temperature distribution based on the daily t_{max} and t_{min} temperatures and calculate degree days between or above certain temperature ranges. This, in turn, is based on Snyder (1985) and Schlenker & Roberts (2009) (see more details in the Supplementary Material section S4). Waterlogging and drought parameters are expressed as the number of days above (waterlogging) or under (drought) a critical soil moisture threshold. Since we assume that the error term is heteroskedastic, spatially correlated within each year, and temporally correlated on each farm during the observation period, we use heteroscedasticity robust standard errors clustered by year and farm (Cameron et al., 2011; Dalhaus et al., 2020).

We start estimating equation (1) for each crop separately and include all weather events as explanatory variables simultaneously. Next, we provide a number of robustness checks by estimating further variations of equation (1). Firstly, we estimate the yield effects for each crop and weather event separately. Secondly, we estimate the effects for all crops jointly, i.e., accounting for possible correlation of error terms across crops using a seemingly unrelated regression approach.[3] Thirdly, since observations indicate that extreme weather events are often regionally specific (e.g., Webber et al., 2020), we adopt split sample approaches and estimate equation (1) separately for four regions (see details below). To this end, we apply the definition of soil/climate regions in Germany advanced by Roßberg et al. (2007), which were aggregated to the four main production regions North, East, West and South by the Julius-Kuehn-Institute (JKI, 2009) (see Appendix A1 for details). Fourthly, we implement a sample split across time, i.e., 1995–2006 and 2007–2019. This allows us to investigate whether the relationship between crop yields and extreme events changed over time (e.g., Miller et al., 2021). Fifthly, we include an additional variable in equation (1) that provides information about weather conditions, which are beneficial for crop growth in the specific year and location of the farm. More specifically, we add the temperature range between 8 °C and 28 °C as an optimal growing temperature range (see section S9).[4] Sixthly, we implement a long-difference approach based on the cross-sectional observations of the time periods 1995–1999 and 2015–2019 to estimate the impact of extreme weather and to detect if agricultural adaptation to these severe conditions has taken place during our observation period.[5] This approach allows us to quantify farmers' behaviour in response to longer-term climate change as opposed to shorter-term adaptation by comparing the size of estimated coefficients of the long-difference and panel estimations (Dell et al., 2012; Burke & Emerick, 2016, Miller et al., 2021). Seventhly, we estimate the main specifications excluding organic farms from the sample, as their potential to adapt to extreme weather events may differ from non-organic farms (e.g. Scialabba & Müller-Lindenlauf, 2010). We then estimate the main specifications excluding farms which have irrigation systems, as irrigation could change estimation results of drought effects (see section S10).

We not only estimate the effects of extreme weather events on crop yields, expressed as relative yield losses in physical quantities (as described in Equation (1)), but also provide three assessments of the economic relevance of these effects across space and time. This allows industrial and political actors to prioritize their efforts towards coping with extreme weather events in agriculture. Based on an estimation of Equation (1) including all available information ($\beta_{wj,}$ $WE_{wjit,}$ F_i and Y_t), we quantify the estimated yield in each year when a relevant extreme event occurred. Subsequently, we estimate three different counterfactuals: Firstly, we estimate yield losses based on the hypothetical counterfactual assumption that a respective extreme weather event had not occurred in any year ($WE_{wjit} = 0$) in order to derive the hypothetical annual yields farmers would have achieved in the absence of the respective event. Secondly, we calculate the impacts on yields of a one-standard deviation increase in the frequency/severity of site- (i.e., municipality) and crop-specific extreme weather events. Thirdly, we estimate the site-specific reduction in yields associated with the marginal change of extreme weather events. Subsequently, we combine the estimated yield effects of the three approaches with average crop prices of 2016–2020 (AGMEMOD, 2021) to illustrate drops in revenues across space and time. Finally, revenue losses obtained using the hypothetical counterfactual approach ($WE_{wjit} = 0$) and a one-standard deviation increase are aggregated to the national level by considering total areas under cultivation.

Our analyses are conducted in SAS and R. The code is provided in the supplementary material.

3. Data and definition of extreme events

Our yield data is taken from the German Farm Accountancy Data Network[6] (see e.g., BMEL, 2020b). Farm-level crop yields for the years 1995 to 2019 are available for winter wheat, winter barley, winter rapeseed and grain maize. The sample is unbalanced, and comprises 423,815 observations.[7] See section S1 for an overview of the observations available per year, crop, region and average number of observations per farm. The coherent and consistent data collection in the German Farm Accountancy Data Network ensures that crop yield data is

[2] Yet, we find that the occurrence of extreme events is largely heterogeneous across Germany (see Supplementary Material sections S6 + S7 and also Webber et al., 2020).

[3] The highly unbalanced panel data set across equations only allows a seemingly unrelated regression estimation (SURE) on a very reduced set of observations. SURE of this reduced data set only resulted in small differences in parameter estimations.

[4] The temperature range between 8°C and 28°C was expressed in degree days and considered in the robustness check through linear and quadratic terms to account for nonlinear yield effects.

[5] Cross-sectional observations of the two time periods considered were derived by calculating the 5-year average farm-level yield and corresponding 5-year average extreme weather observations. Furthermore, fixed effects of the federal states in Germany (Bundesland) were included in the long-difference estimations to account for any unobserved federal state-level trends (see detailed working steps in Appendix A2).

[6] The German Farm Accountancy Network is the German source of the Farm Accountancy Data Network provided by the European Union. The advantages of the German Farm Accountancy Network are a larger sample as well as additional information about the municipality of each farm, which improves the matching of yield, weather and phenology data (see BMEL, 2020b).

[7] An accuracy check on the yield data was implemented by using a plausibility program provided by the Federal Ministry of Food and Agriculture (BMEL, 2020c).

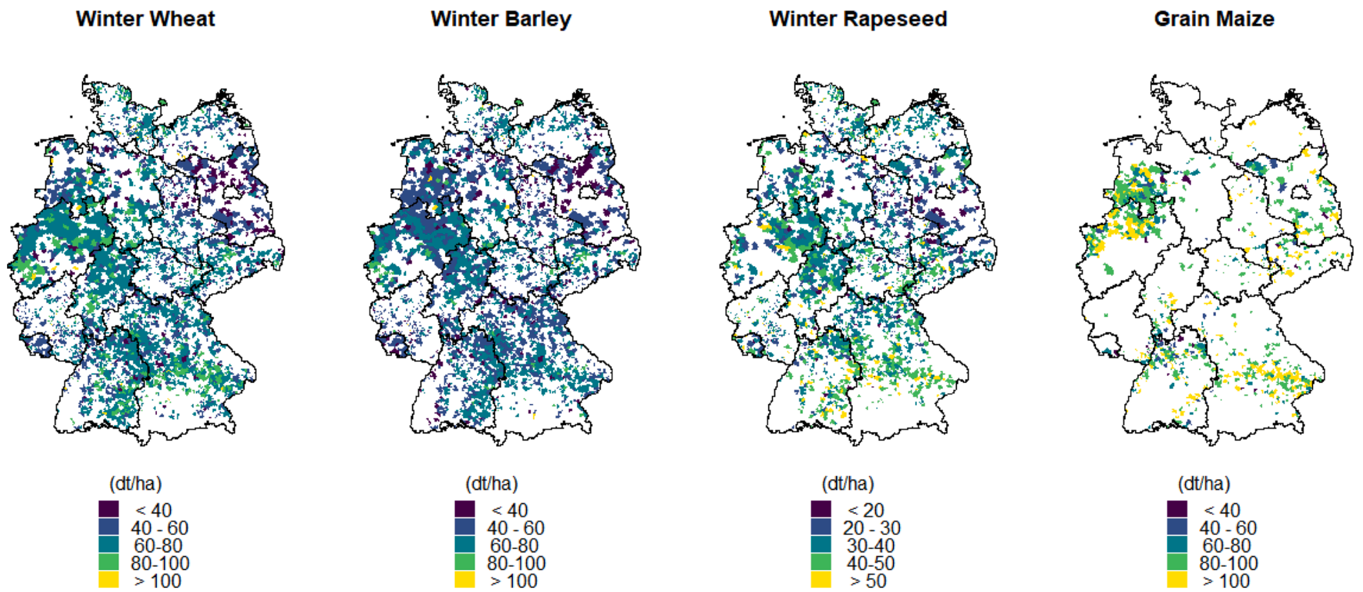

Fig. 1. Crop yields – spatial distribution of farm yield data in 2007 on the municipality level. Notes: (1) Own illustration based on e.g., BMEL (2020b). (2) dt/ha – decitonnes per hectare.

comparable across farms, crops and years.[8] Fig. 1 illustrates the yield data density of the four crops analysed in the dataset exemplarily for 2007 on the municipality level. In Fig. 1, if the crop analysed was cultivated by more than one farm in the same municipality, yield data were weighted by the farm area under cultivation.

Information about the municipal location of each farm allows us to match crop yield observations with spatially explicit information on weather data, crop-specific phenology data and crop-specific soil moisture data for the 0–60 cm layer (winter wheat and winter barley from one soil moisture dataset, winter rapeseed and grain maize).[9] We use interpolated weather, phenology and soil moisture data provided by the German Meteorological Service on a 1x1 km raster across Germany (see DWD, 2021, for details). The spatial resolution of our farm-specific yield data is, however, only available at the municipality level. Thus, we aggregate weather, phenology and soil moisture data to the municipality level.[10]

Site- and crop-specific phenology data are based on observations sent to the German Meteorological Service (DWD) by more than 1,000 reporters all over Germany. Some phenological phases are derived by adding a certain number of days to the observed data, based on e.g., averaged historical time-distances between two consecutive phenological phases. In exceptional cases, the phenological phase of a certain crop is derived from observation data of another crop's phenological phase, if their phenological phases showed a high correlation in the past (further information is provided in section S2).

Site- and crop-specific soil moisture data are obtained from the German Meteorological Service and are based on a statistical model. More specifically, the AMBAV model combines information of daily weather, evaporation and crop specific phenological phases to derive daily soil moisture information (see also Friesland & Löpmeier, 2007; Herbst et al., 2021; Löpmeier, 1983). We chose to express drought and waterlogging by means of the variable soil moisture accounting for site-, year- and crop-specific phenological phases across the country. This option offers considerable advantages compared to other approaches, e.g., using the total amount of precipitation over a period that is fixed over year, crop or space: Firstly, the AMBAV soil moisture model used here accounts for the daily water in-flows through precipitation and out-flows through the crop-specific evapotranspiration which depends on the phenological stage of the respective crop.[11] Secondly, the AMBAV model also considers regional variations in soil quality and type which influence regional water storage capacities. Therefore, the model recognizes that changes in soil moisture in response to (a lack of) precipitation depend on soil types. For example, soil moisture decreases faster in response to drought in regions with extremely sandy soils. Thirdly, if drought and waterlogging are expressed in terms of soil moisture rather than cumulative precipitation, water in- and outflows prior to a plant's critical growth phase can also be monitored. In fact, soil moisture reflects the reserves of water "stored" in the soil on which plants can draw during their growth (Bucheli et al., 2021; Vroege et al., 2021; Seneviratne et al. 2010).

3.1. *Definition and calculation of extreme weather events*

Several studies have identified frost, heat, drought and waterlogging as yield damaging events for the cash crops analysed (e.g., Barlow et al., 2015; Gömann et al., 2015; Heidecke et al., 2017; Mäkinen et al., 2018; Trnka et al., 2014; Peichl et al., 2019; Pullens et al., 2019). However, it is not easy to define these events precisely as what is regarded as an extreme weather incident in one region of the world is not automatically considered a threat elsewhere. Hence, we apply statistical approaches

[8] However, the comprehensive Farm Accountancy Data Network has limits in regard to the crop-specific assignment of farming measures on the farm-level. For instance, irrigation is defined as the annual total irrigated area per farm or fertilization as the annual amount of fertilization per farm. Hence, it is not possible to attribute irrigation and other farming practices correctly to the different crops cultivated on a farm. Overall, irrigation is of little importance in Germany; in the past, <5% of the utilized agricultural area was irrigated. Irrigation systems are mainly purchased by farms which cultivate high-value crops like potatoes or sugar beet and these fields are preferentially irrigated.

[9] Municipality codes are normed to the year 2007 due to changes of municipal borders during the observation period.

[10] No information is available regarding the exact location of the crop-specific plots on each farm in Germany due to private data protection regulations. Therefore, there is a natural variation of the weather and phenological variables across municipalities, which cannot be accounted for in our analyses since it is impossible to obtain information on crop-specific plot yields.

[11] For instance, winter wheat and grain maize "consume" different amounts of water on the same day of the year, also because of their temporally different phenological phases.

Table 1
Weather events with crop-specific time-windows and thresholds in °C for temperature and % of usable field capacity (fc) for soil moisture.

Weather Events [1]	Unit	Winter Wheat	Winter Barley	Winter Rapeseed	Grain Maize
Black Frost [2,3]	Degree Days	1st of January to Start of Shooting; ≤ – 12.8 °C; Snow-layer < 5 cm	1st of January to Start of Shooting; ≤ – 12.9 °C; Snow-layer < 5 cm	1st of January to Start of Stem Elongation; ≤ – 13.6 °C; Snow-layer < 5 cm	Not relevant for maize (sown in spring)
Spring Chill [2]	Degree Days	Not relevant	Not relevant	Stem Elongation & Flowering; ≤ −3.1 °C	Sowing & Emergence; ≤ 0.5 °C
Heat [4]	Degree Days	Flowering; ≥ 32.6° C	Flowering; ≥ 30.6 °C	Flowering; ≥ 29.3 °C	Stem Elongation & Flowering; ≥ 33.7 °C
Spring Drought [5]	Days	Shooting & Flowering; ≤ 14.4 % fc	Shooting & Flowering; ≤ 28.0 % fc	Stem Elongation & Flowering; ≤ 26.6 % fc	Emergence & Stem Elongation; ≤ 33.5 % fc
Summer Drought [5]	Days	Fruit Formation & Ripening; ≤ 7.8 % fc	Fruit Formation & Ripening; ≤ 7.9 % fc	Fruit Formation & Ripening; ≤ 21.7 % fc	Flowering & Fruit Formation; ≤ 8.7 % fc
Spring Waterlogging [6]	Days	Shooting & Flowering; ≥ 115.3 % fc	Shooting & Flowering; ≥ 116.4 % fc	Stem Elongation & Flowering; ≥ 115.5 % fc	Emergence & Stem Elongation; ≥ 118.7 % fc
Summer Waterlogging [6]	Days	Fruit Formation & Ripening; ≥ 111.6 % fc	Fruit Formation & Ripening; ≥ 108.8 % fc	Fruit Formation & Ripening; ≥ 111.5 % fc	Flowering & Fruit Formation; ≥ 112.7 % fc

Notes:
[1] In section S2, phenological phases are translated into averaged days of the year (DOY) across all years and municipalities to improve transparency. Furthermore, the spatial variation of the start dates of each time-window analysed is illustrated using the example of winter wheat in the year 2007.
[2] Averaged 1st municipality percentiles of daily t_{min}.
[3] Snow-layer estimated based on Trnka et al., 2010; see section S3.
[4] Averaged 99th municipality percentiles of daily t_{max}.
[5] Averaged 1st municipality percentiles of daily crop-specific soil moisture.
[6] Averaged 99th municipality percentiles of daily crop-specific soil moisture.

using percentiles of the frequency distribution to define thresholds for country-specific growing conditions (e.g., Peterson et al., 2008; Zhang et al., 2011; Seneviratne et al., 2021).

In Table 1, we define crop-specific thresholds for potentially extreme weather events during critical phenological phases. We refer to interviews with German cash crop experts conducted by Heidecke et al. (2017) to establish the critical phenological phases and the corresponding potentially yield damaging extreme weather events. Temperature thresholds were derived from the 1st percentiles (black frost, spring chill) of the daily t_{min}-values and 99th percentiles (heat) of the daily t_{max}-values during the critical phenological phases between 1995 and 2019 in each municipality and then averaged across all 12,502 municipalities. Soil moisture thresholds were derived from the 1st percentiles (drought days) and 99th percentiles (waterlogging days) of the daily soil moisture (expressed as % of the usable field capacity) during the critical phenological phases between 1995 and 2019 in each municipality and averaged across all 12,502 municipalities.

Subsequently, we approximate the intra-day temperature distribution as sinusoidal distribution by using daily maximum and minimum temperatures based on D'Agostino & Schlenker (2016).[12] Black frost, spring chill and heat are expressed in degree days as temperature sums below (black frost and spring chill) or above (heat) the derived thresholds (see section S4). Drought and waterlogging are expressed as the number of days when the soil moisture lies below or above the derived soil moisture threshold (see e.g. Bucheli et al., 2021; Vroege et al., 2021; Seneviratne et al. 2010). A comprehensive overview of the crop-specific weather events presented in Table 1 is provided in summary tables (section S5), time series plots (section S6) and graphical distributions across Germany (section S7).

4. Results

Results are divided into three parts. In the first part, we present the main estimation results on effects of weather extremes on crop yields based on the complete dataset. In the second part, we provide analyses for spatial and temporal sample splits and investigate regional differences in weather effects on yields. In addition, as part of a series of robustness checks, we analyse if weather effects on yields relate directly to the observation period and also discuss the results obtained from the long-difference approach. The third part presents the spatial distribution of the economic impacts of selected extreme weather events in relation to crop prices and historical incidences of these incidents. The estimated revenue losses are then aggregated to report overall average losses for Germany as a whole.

4.1. Key results

4.1.1. Drought regularly decrease yields of all crops

Fig. 2 shows the regression results of all crop-specific weather effects on yields from the joint (blue) and separate (red) estimations.[13] On average, one drought day during the phenological phases Shooting & Flowering reduced the winter wheat yield level by 0.36 % and one drought day during Fruit Formation & Ripening also led to the same loss (0.36 %). The winter barley yield level fell by 0.48 % due to a drought day during Shooting & Flowering. In the case of grain maize, a drought day during Emergence & Stem Elongation reduced the yield level by 0.52 % and during Flowering & Fruit Formation by 0.69 %. We find that drought also had a negative impact on rapeseed yield levels, but the effect is not unambiguously significant across specifications.

A day of waterlogging during Shooting & Flowering caused winter wheat yield levels to fall by 0.28 % and by 0.23 % during Fruit Formation & Ripening. One waterlogged day during Shooting & Flowering lowered winter barley yield levels by 0.40 % and by 0.24 % if waterlogging occurred during Fruit Formation & Ripening. However, the effects of waterlogging on winter rapeseed and grain maize yield levels were not statistically significant at the 1 % level.

In the estimations of the whole sample, the effects of black frost on the winter crops, the impacts of spring chill on winter rapeseed and grain maize, and the effects of heat on the yield levels of all the crops

[12] See also Snyder (1985) and Schlenker & Roberts (2009).

[13] Following interpretations refer to the joint estimation results (blue) and highlight the results with a 1% significance level.

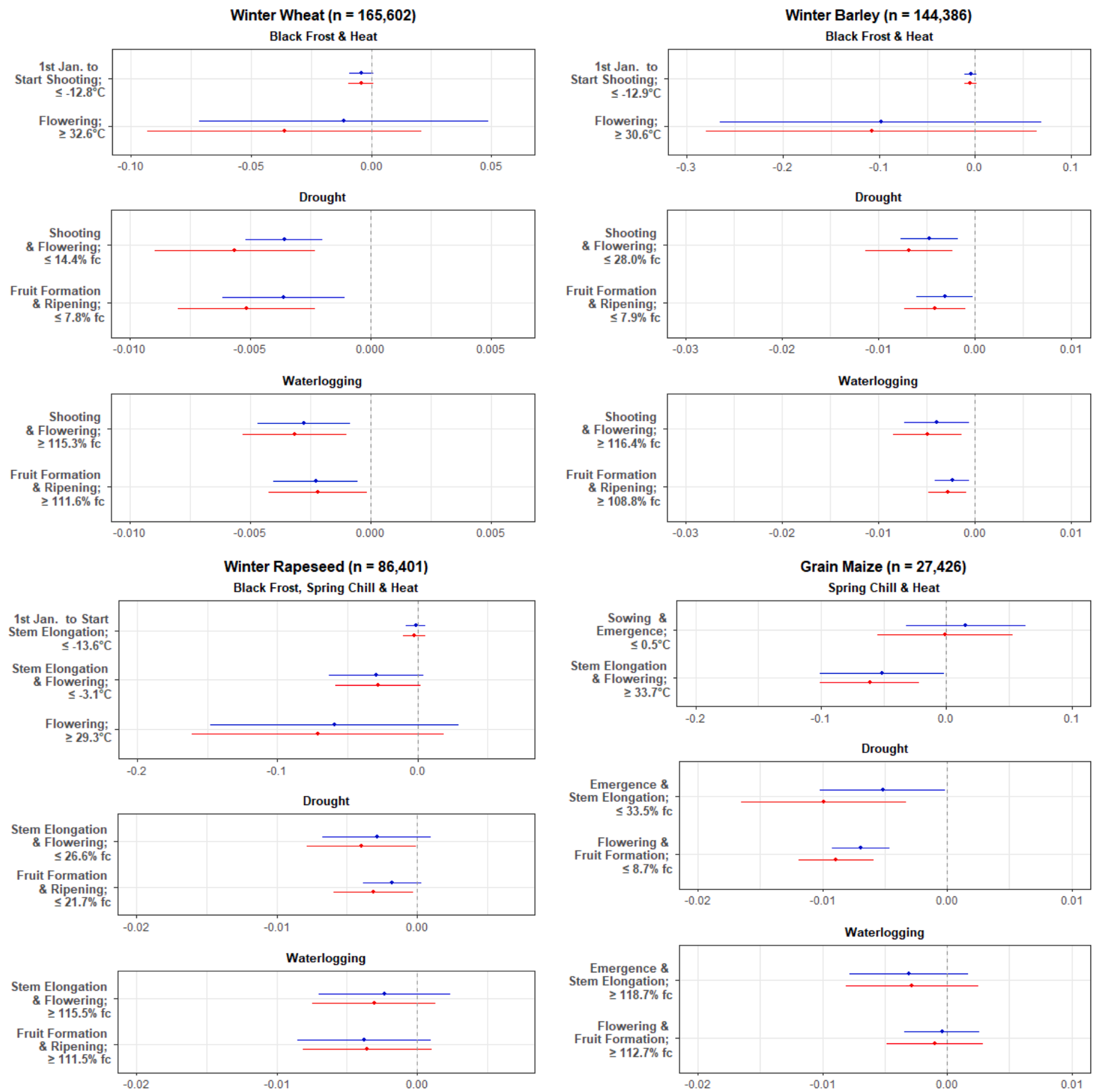

Fig. 2. Results of the joint estimations of crop-specific weather events on yields, i.e. all weather events (blue) and separate, individual extreme weather events only (red). Notes: (1) Due to the considerable differences in the sizes of the marginal effects, the illustrations present 99 % confidence intervals of the estimated coefficients and are subdivided into yield effects of degree days (black frost, spring chill and heat) and drought/waterlogging days. (2) fc = usable field capacity.

analysed were not statistically significant on a 1 % level.

4.2. Robustness checks

As robustness checks, spatial and temporal splittings are exemplarily illustrated in the main text for two selected weather events for each crop. The results of spatial and temporal splitting of the remaining weather events are illustrated in section S8. Furthermore, the results, including a temperature variable of the degree days between 8 °C and 28 °C as a positive growth variable (section S9), support the results of the joint estimations presented here. Therefore, controls carried out relating to favourable weather events do not modify the conclusions presented here regarding the effects of extreme weather events. Subsequently, we discuss the results of the long-difference approach (Appendix A2).[14]

4.2.1. Yield effects of extreme weather events vary considerably between regions and observation periods

4.2.1.1. Winter wheat. We find that drought damage in winter wheat production was most severe in Eastern Germany. More specifically, on average, one drought day during the phenological phases Shooting & Flowering reduced winter wheat levels in the East by 0.76 %, which is more than twice the average sample effect of 0.36 % (Fig. 3: 1.1). Temporal splitting reveals that the regional yield effects of a drought day during Shooting & Flowering in the North, East and West changed from insignificant in the period 1995–2006 (Fig. 3: 1.2) to significant on a 1 %

[14] Moreover, the subset of conventional farms only and of farms without irrigation systems support our main findings (section S10).

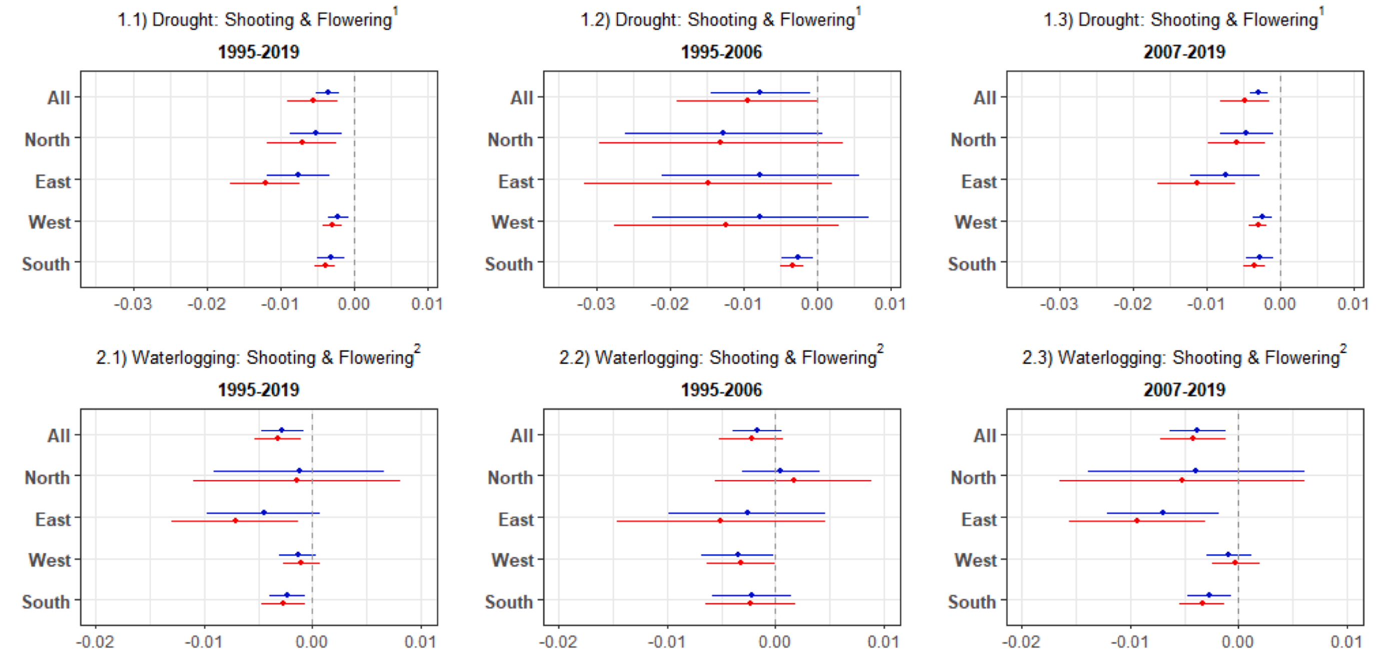

Fig. 3. Winter wheat - exemplary results of spatial and temporal splitting of the joint (blue) and separate (red) estimations. Notes: (1) Spatial sample splitting is based on the main production regions illustrated in Appendix A1. 'All' corresponds to all regions together. (2) Results are illustrated as 99 % confidence intervals. (3) Thresholds of the respective crop-specific weather events: [1]days with ≤ 14.4 % of usable field capacity (fc); [2]days with ≥ 115.3 % fc.

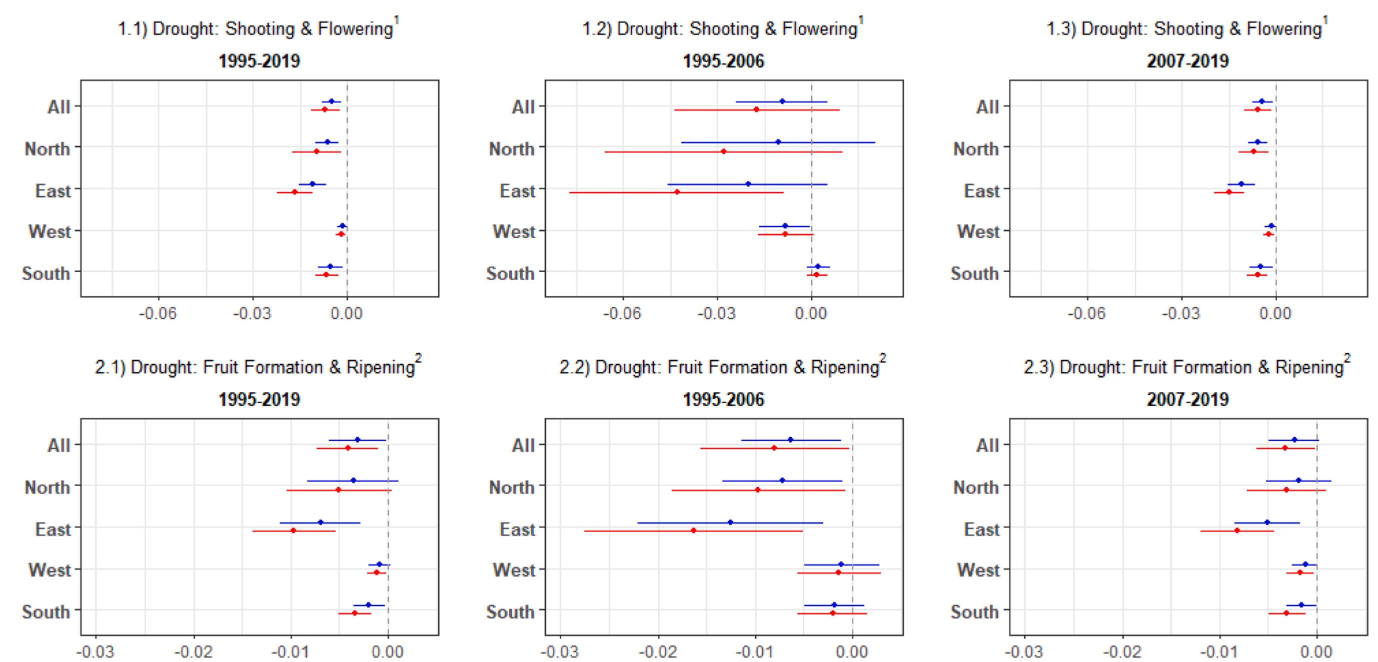

Fig. 4. Winter barley - exemplary results of spatial and temporal splitting of the joint (blue) and separate (red) estimations. Notes: (1) Spatial sample splitting is based on the main production regions illustrated in Appendix A1. 'All' corresponds to all regions together. (2) Results are illustrated as 99 % confidence intervals. (3) Thresholds of the respective crop-specific weather events: [1]days with ≤ 28.0 % of usable field capacity (fc); [2]days with ≤ 7.9 % fc.

level in the period 2007–2019 (Fig. 3: 1.3). Thus, the verifiability of drought related losses in winter wheat increased over time. The average effect of a waterlogged day during Shooting & Flowering was −0.28 % (Fig. 3: 2.1). Temporal splitting shows that the yield effect of a waterlogged day during 1995–2006 was only significant on a 1 % level in the Western region (Fig. 3: 2.2). Similar results can be observed for the remaining drought and waterlogging variables (see section S8: Figure S32). Furthermore, black frost only had significant effects on the winter wheat yield in the Northern and Western regions for the observation period 2007–2019. Although heat did not reduce winter wheat yields on a 1 % significance level in our analyses, the high standard errors in the Northern region during the observation period 2007–2019 suggest that there is nevertheless a risk of considerable yield losses (see section S8: Figure S32: 2.3).

4.2.1.2. Winter barley. One drought day during Shooting & Flowering in the East led on average to a 1.07 % decrease in winter barley yield level, which is larger than the effect in the North (-0.63 %) or South

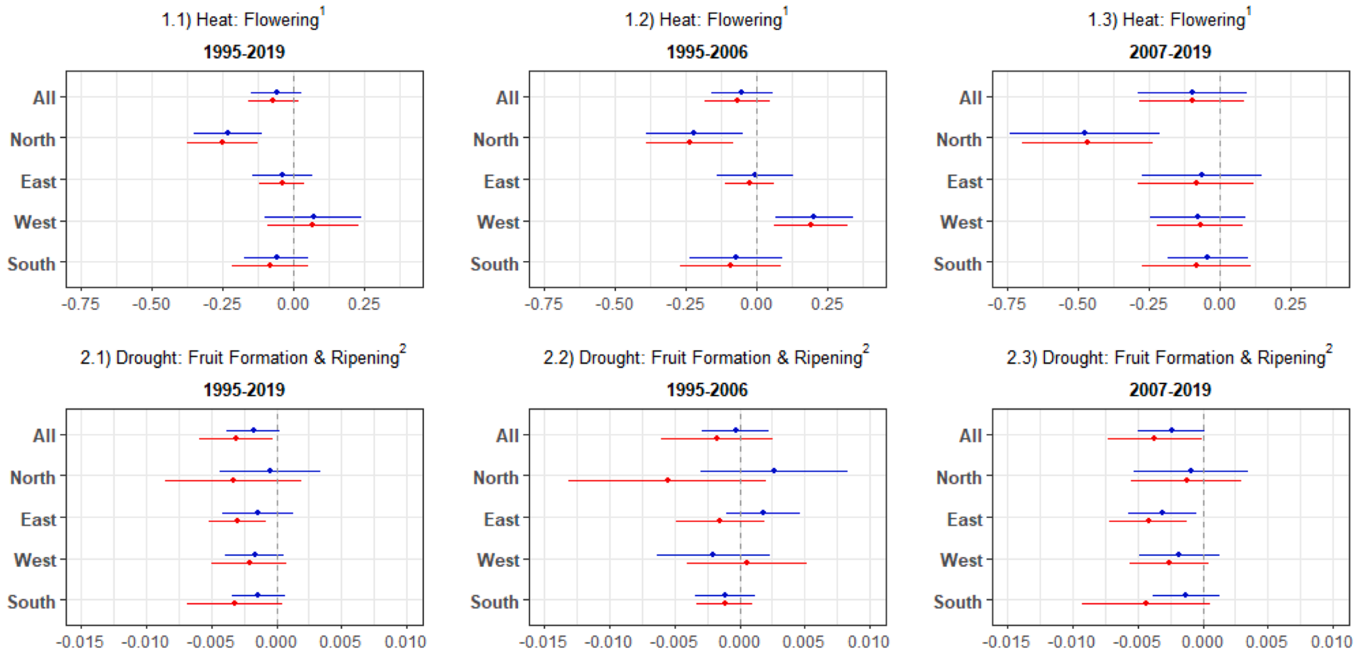

Fig. 5. Winter rapeseed - exemplary results of spatial and temporal splitting of the joint (blue) and separate (red) estimations. Notes: (1) Spatial sample splitting is based on the main production regions illustrated in Appendix A1. 'All' corresponds to all regions together. (2) Results are illustrated as 99 % confidence intervals. (3) Thresholds of the respective crop-specific weather events: [1]degree days ≥ 29.3 °C; [2]days with ≤ 21.7 % of usable field capacity.

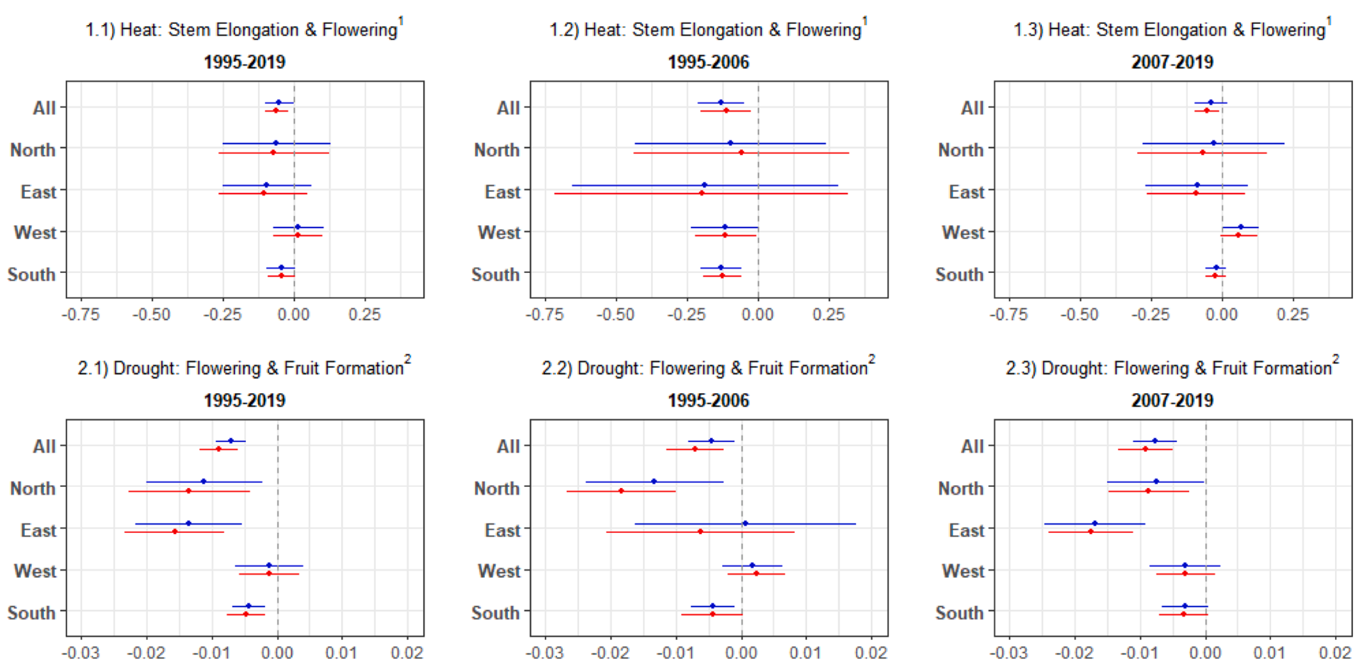

Fig. 6. Grain maize - exemplary results of spatial and temporal splitting of the joint (blue) and separate (red) estimations. Notes: (1) Spatial sample splitting is based on the main production regions illustrated in Appendix A1. 'All' corresponds to all regions together. (2) Results are illustrated as 99 % confidence intervals. (3) Thresholds of the respective crop-specific weather events: [1]degree days ≥ 33.7 °C; [2] days with ≤ 8.7 % of usable field capacity.

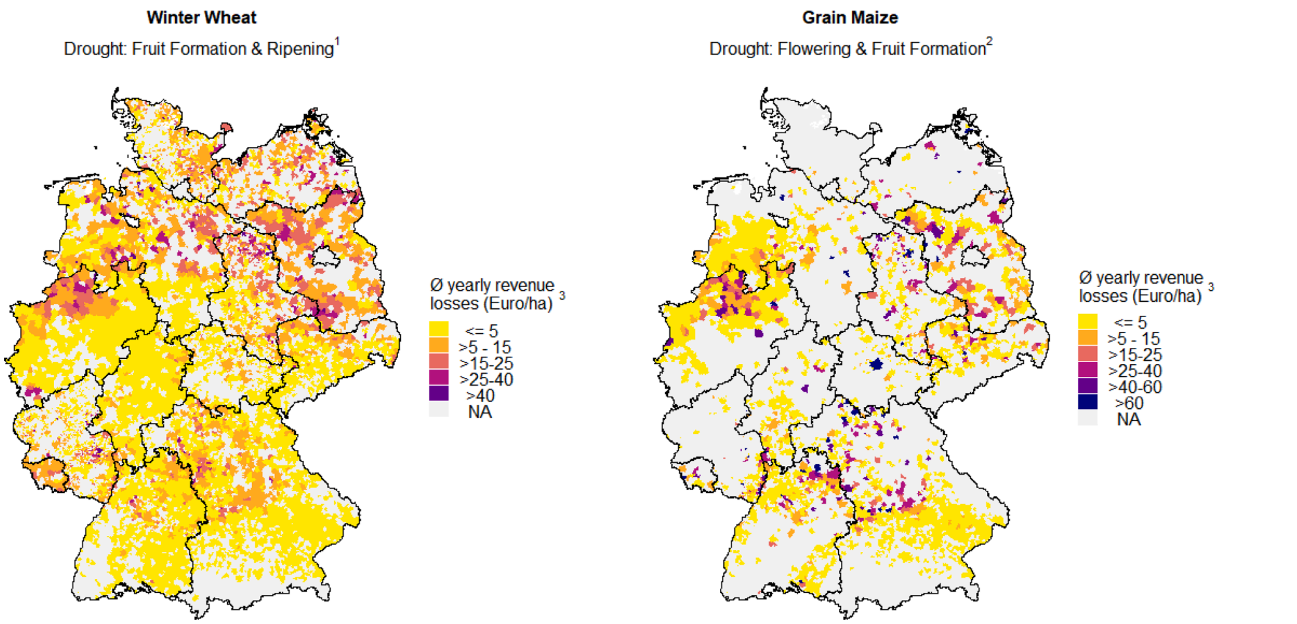

Fig. 7. Summer drought - estimated average yearly revenue losses in Euro/ha for winter wheat and grain maize based on the hypothetical counterfactual. Notes: (1) The illustration provides a municipality level overview across Germany and is weighted by the cultivated farm area if the crop is grown by more than one farm in the same municipality. (2) Thresholds of the respective crop-specific drought events: [1]days with $\leq$ 7.8 % of usable field capacity (fc); [2]days with $\leq$ 8.7 % fc. (3) Average product prices 2016–2020 based on AGMEMOD (2021): [3] winter wheat = 15.39 Euro/dt; grain maize = 16.04 Euro/dt.

(-0.51 %) (see Fig. 4: 1.1). Regional effects during 1995–2006 showed comparatively high variations for both drought variables (Fig. 4: 1.2 and 2.2). Moreover, a drought day during Fruit Formation & Ripening reduced the winter barley yield level on average by 0.70 % in the East and by 0.19 % in the South (Fig. 4: 2.1). The results of temporal and spatial splitting for the remaining weather events are illustrated in section S8 (Figure S33). The comprehensive analyses show that sub-sampling can generate highly significant results. For instance, although black frost shows no significantly negative effect on yield over the whole sample, between 2007 and 2019, one degree day of black frost reduced the winter barley yield level by 1.45 % in the Western region.

4.2.1.3. Winter rapeseed. In the North, a degree day of heat lowered winter rapeseed levels by an average of 20.59 % (see Fig. 5: 1.1) in the observation period 1995–2019, by 19.89 % between 1995 and 2006 and by 37.89 % during the period 2007–2019. The 95 %-percentile of all heat observations during flowering of winter rapeseed in our sample was 0.54 degree days (99 %-percentile = 1.21 degree days). A drought day during Fruit Formation & Ripening caused the yield level to fall by 0.31 % in the East during the observation period 2007–2019 (Fig. 5: 2.3). Regional sample splitting in section S8 shows that a degree day of black frost reduced winter rapeseed yield levels in the North by 1.94 % and in West by 2.22 % (Figure S34: 1.1). The effects of spring chill, drought during Stem Elongation & Flowering and waterlogging (Figure S34) are mainly insignificant on a 1 % level.

4.2.1.4. Grain maize. The observation period 1995–2006 (Fig. 6: 1.2: All) shows that the grain maize yield level dropped by an average of 12.17 % due to one degree day of heat during Stem Elongation & Flowering. Furthermore, a drought day during Flowering & Fruit Formation caused the grain maize yield level in the Eastern region to fall by 1.35 % during 1995–2019, which is approximately twice the sample effect of 0.69 % (Fig. 6: 2.1). Spring chill (Figure S35: 1.1 – 1.3) and waterlogging (Figure S35: 3.1 – 4.3) did not cause yield effects on a 1 % significance level with the exception of a waterlogged day during Emergence & Stem Elongation in the subsample 1995–2006 in the South (-0.94 %).

4.2.2. The long-difference approach reveals an increase of spring drought susceptibility of winter wheat and winter barley

In the case of the long-difference approach, we estimated the impact of extreme weather based on the cross-sectional observations of the time periods 1995–1999 and 2015–2019.[15] Subsequently, we compared the results of the long-difference and panel model. In addition, we checked for sample effects of our unbalanced panel by re-estimating the panel model with the reduced farm sample used in the long-difference model (see Appendix A2: (3) Limited Panel). Long-run adaptation is indicated if the coefficient of a crop-specific weather event in the long-difference specification is smaller than in the panel model (Burke & Emerick, 2016).

Winter wheat exhibits a slight decrease in susceptibility to summer drought, while winter barley shows considerably higher negative yield effects due to spring drought and summer waterlogging in the long-difference approach than in the panel estimation. In contrast, summer drought did not generate any negative yield effects on winter barley in the long-difference approach, which could be a sign that winter barley producers are engaged in long-term adaptation to summer droughts (e.g., via adjustment of production systems and/or varieties used). Winter rapeseed and grain maize show evidence of higher susceptibility towards heat in the long-difference approach than in the panel estimations. This could indicate that the winter rapeseed and grain maize varieties cultivated in recent years have become more susceptible to extreme heat.

4.3. Economic relevance of extreme weather events

The regression results in Figs. 2-6 reveal the relative impact of weather events on yields. However, this does not allow to fully assess the potential economic consequences of the weather events for farmers.

[15] Cross-sectional observations of the two relevant time periods were derived by calculating the 5-year average farm-level yield and corresponding 5-year average extreme weather observations (see detailed working steps in Appendix A2).

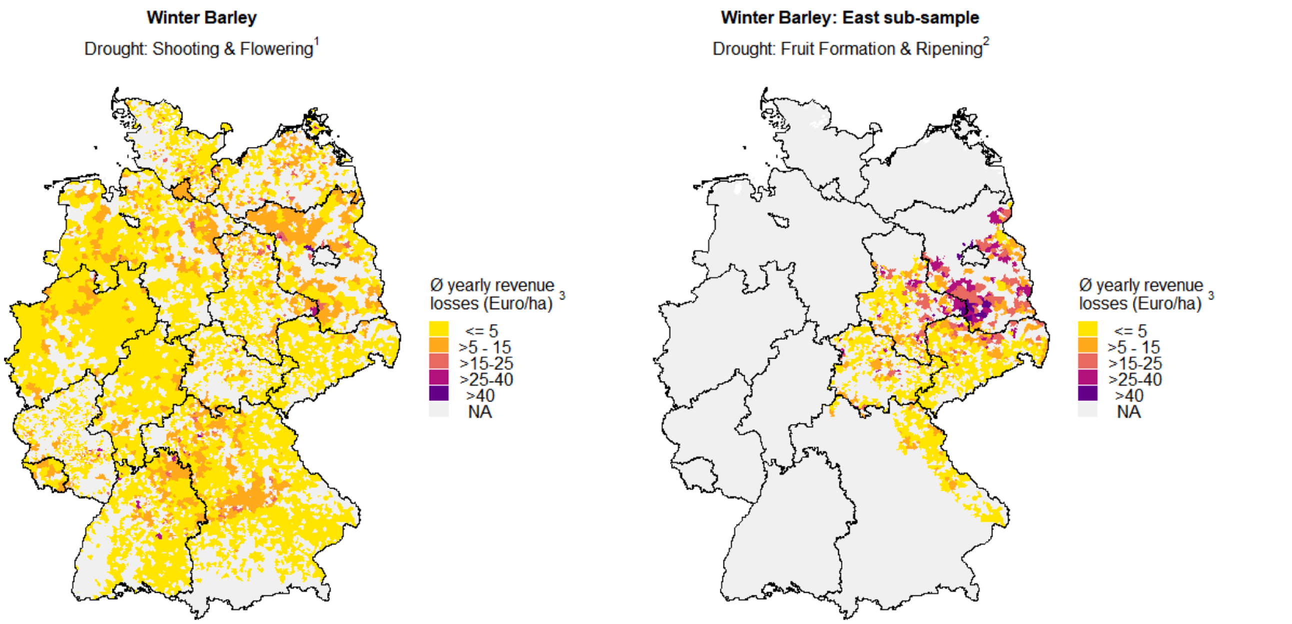

Fig. 8. Country-wide spring drought (left) and summer drought in the East (right) - estimated average yearly revenue losses in Euro/ha for winter barley based on the hypothetical counterfactual. Notes: (1) Estimated revenue losses due to summer drought only refer to the Eastern sub-sample based on Appendix A1 and the coefficient for the effects of summer drought on yield is based on Fig. 4: 2.1: East: Blue. (2) The illustration provides a municipality level overview across Germany and is weighted by the cultivated farm area if the crop is grown by more than one farm in the same municipality. (3) Thresholds of the respective crop-specific drought events: [1]days with ≤ 28.0 % of usable field capacity (fc); [2]days with ≤ 7.9 % fc. (4) Average product price 2016–2020 based on AGMEMOD (2021): [3] winter barley = 14.05 Euro/dt.

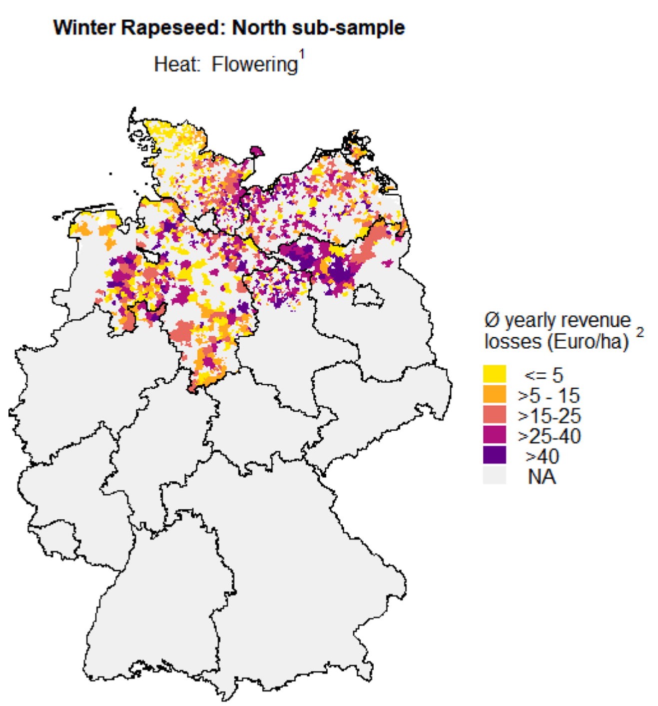

Fig. 9. Heat and winter rapeseed - estimated average yearly revenue losses in Euro/ha for Northern Germany based on the hypothetical counterfactual. Notes: (1) Estimated revenue losses only refer to the Northern sub-sample based on Appendix A1 and the coefficient for the effect of heat on yield is based on Fig. 5: 1.1: North: Blue. (2) The illustration provides a municipality level overview across Germany and is weighted by the cultivated farm area if the crop is grown by more than one farm in the same municipality. (3) Threshold: [1]degree days with ≥ 29.3 °C. (4) Average product price 2016–2020 based on AGMEMOD (2021): [2] winter rapeseed = 36.78 Euro/dt.

Therefore, we monetarize historical yield losses by combining our estimation results with the historical incidences of weather events, crop prices and information about the locations at which the crops are produced. We present results of three approaches to provide a comprehensive analysis of the economic relevance of the different extreme weather events. This allows us to illustrate the spatial distribution of the economic significance through the “Average yearly losses in revenues in Euro/ha” on a municipality level.[16]

4.3.1. *Estimated revenue losses are heterogeneous across Germany*

The estimated revenue losses are collated with respect to the hypothetical situation in which the respective pre-defined extreme weather event did not occur during the whole observation period 1995–2019. This hypothetical counterfactual helps farmers in their risk management decisions and serves as basis for policy-makers during debates on political support for these measures.[17] Figs. 7-9 illustrate the estimated average revenue losses based on the hypothetical counterfactual ($WE_{wjit} = 0$). The selection is based on statistically significant sample effects in Fig. 2. In the case of winter barley (Fig. 5: 2.1 – 2.3 summer drought in the East) and winter rapeseed (Fig. 6: 1.1 – 1.3 heat during flowering in the North), effects were not statistically significant at the national level, and we analysed the economic relevance based on robust sub-sample results.

Our sample shows that drought days during summer (Fruit Formation & Ripening) caused an estimated average annual fall in revenues from winter wheat of approximately 7.50 Euro/ha across the whole of Germany (based on Fig. 7: Winter Wheat). Given that the total area under winter wheat is relatively constant at approximately 3.1 million hectares (see BMEL, 2007a; BMEL, 2020a), this means that average

[16] If there are two farms in the same municipality, average yearly losses are weighted by the cultivated area of each farm.

[17] As previously described, the hypothetical counterfactual does not reflect reality, since realistic counterfactuals of the extreme weather events described are unequal to zero. Therefore, we complement this approach by estimating both the effects of a variation by one intra-municipality standard deviation and the effects of marginal changes in weather extremes.

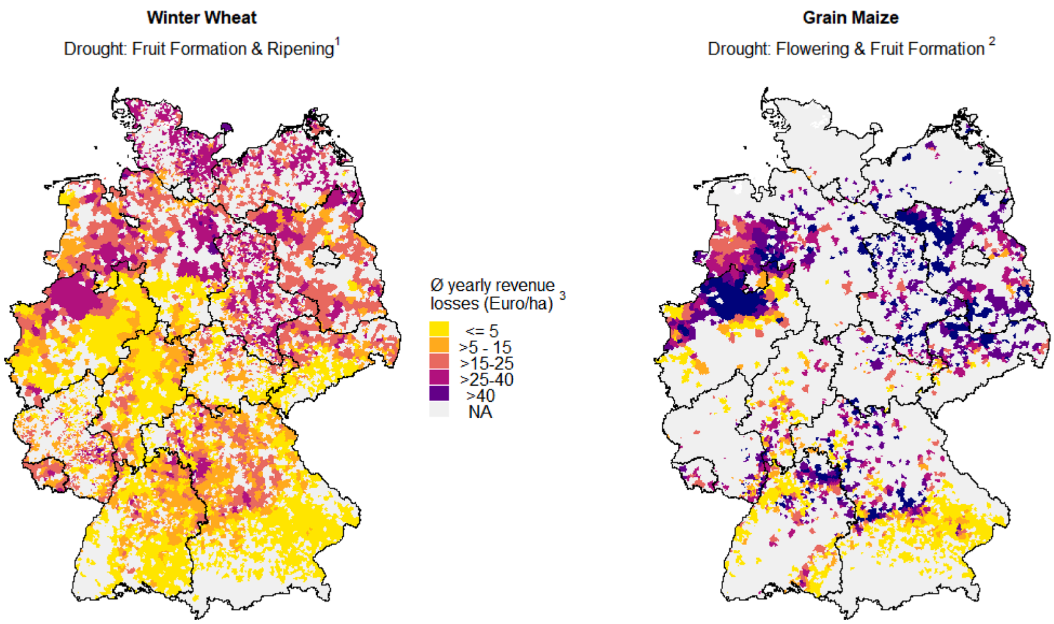

Fig. 10. Summer drought - estimated revenue losses for winter wheat and grain maize in Euro/ha due to one intra-municipality standard deviation increase based on the balanced weather-data panel (annual municipality weather observations 1995–2019). Notes: (1) The illustration provides a municipality level overview across Germany and is weighted by the cultivated farm area if the crop is grown by more than one farm in the same municipality. (2) Thresholds of the respective crop-specific drought events: [1]days with $\leq$ 7.8 % of usable field capacity (fc); [2]days with $\leq$ 8.7 % fc. (3) Average product prices 2016–2020 based on AGMEMOD (2021): [3] winter wheat = 15.39 Euro/dt; grain maize = 16.04 Euro/dt.

yearly revenues fell by 23.2 million Euro due to winter wheat losses arising from summer drought. In contrast, average country-wide revenue losses from winter wheat due to waterlogging during Shooting & Flowering amounted to 1.50 Euro/ha and, on the overall national level, to approximately 4.6 million Euro per year (section S11: Figure S44). Furthermore, there are regional differences in revenue losses from winter wheat. For instance, in the North and East of Germany, drought can cause average yearly losses of over 25 Euro/ha for winter wheat while in the South waterlogging can lead to similar losses.

Drought led to a fall in revenues in all the major German grain maize production regions. Summer drought days (Flowering & Fruit Formation) caused average country-wide yearly revenue losses amounting to 7.64 Euro/ha for this crop (based on Fig. 7: Grain Maize). Since approximately 0.4 million hectares are under grain maize (see BMEL, 2007a; BMEL, 2020a), this implies that summer drought leads to average annual revenue losses of up to 3.1 million Euro.

Between 1995 and 2019, spring drought caused average yearly revenue losses for winter barley of 3.37 Euro/ha across Germany (based on Fig. 8: Winter Barley - left). Given that the area under winter barley is relatively constant in Germany at roughly 1.2 million hectares (see BMEL, 2007a; BMEL, 2020a), this implies overall average spring drought related revenue losses for winter barley of up to 4.0 million Euro per year. In the Eastern sub-sample, summer drought led to a yearly average fall in revenues of 7.96 Euro/ha (based on Fig. 8: Winter Barley - right). Since the area used here for the cultivation of winter barley is relatively constant at 0.3 million hectares (see BMEL, 2019), this indicates that the summer drought related revenue losses for this crop amount on average to over 2.3 million Euro per year. Waterlogging during e.g., Shooting & Flowering of winter barley caused revenues to fall by an average of 1.54 Euro per hectare across Germany. However, this may be considerably higher in the South of Germany (section S11: Figure S45).

In the case of winter rapeseed, we do not find any country-wide robust yield effects due to the weather events analysed. However, regional sub-sampling reveals that winter rapeseed yield levels in Northern Germany are negatively affected by heat during flowering (Fig. 5: 1.1 – 1.3). The Northern sub-sample (see Appendix A1) in our analyses encompasses the most important production region accounting for over one-third of Germany's overall winter rapeseed production (BMEL, 2007b; BMEL, 2020a). This led us to analyse the economic relevance of heat for the Northern production area which revealed that heat during flowering caused estimated average yearly revenue losses amounting to approximately 21.18 Euro/ha for this sub-region (based on Fig. 9). Given that the production area under winter rapeseed is relatively constant at 0.4 million hectares in the Northern sub-sample (BMEL, 2007b; BMEL, 2020a: overall production area in the federal states Mecklenburg-Western Pomerania, Schleswig-Holstein and Lower-Saxony), this resulted in average yearly revenue losses of over 8.4 million Euro for the region.

The economic relevance of the estimated losses resulting from these extreme weather events is highlighted when the fall in revenues is viewed in relation to the expected gross margins, which are currently estimated to be, on average, approximately 462 Euro/ha for winter wheat, 451 Euro/ha for winter barley, 468 Euro/ha for winter rapeseed and 690 Euro/ha for grain maize (KTBL, 2021). This implies, for instance, that summer drought related revenue losses narrow the expected gross margins by an average of 1.1 % for grain maize and 1.6 % for winter wheat. In the hardest hit municipalities ($\geq$95 % percentile fall in revenues), summer drought cut expected gross margins for grain maize by over 4.2 % (=loss of 29.05 Euro/ha for grain maize) and for winter wheat by over 4.1 % (=losses of 19.24 Euro/ha for winter wheat).

4.3.2. The standard deviation approach considers historical variations of regional extreme weather observations

We now consider the spatial variation of estimated revenue losses by describing the monetary effects of the increase of one intra-municipality standard deviation based on the balanced weather panel (see sections S7 and S11). We find that some regions would be more strongly affected by such one-standard deviation increase in the frequency/severity of extreme weather events than it was indicated by previously reported

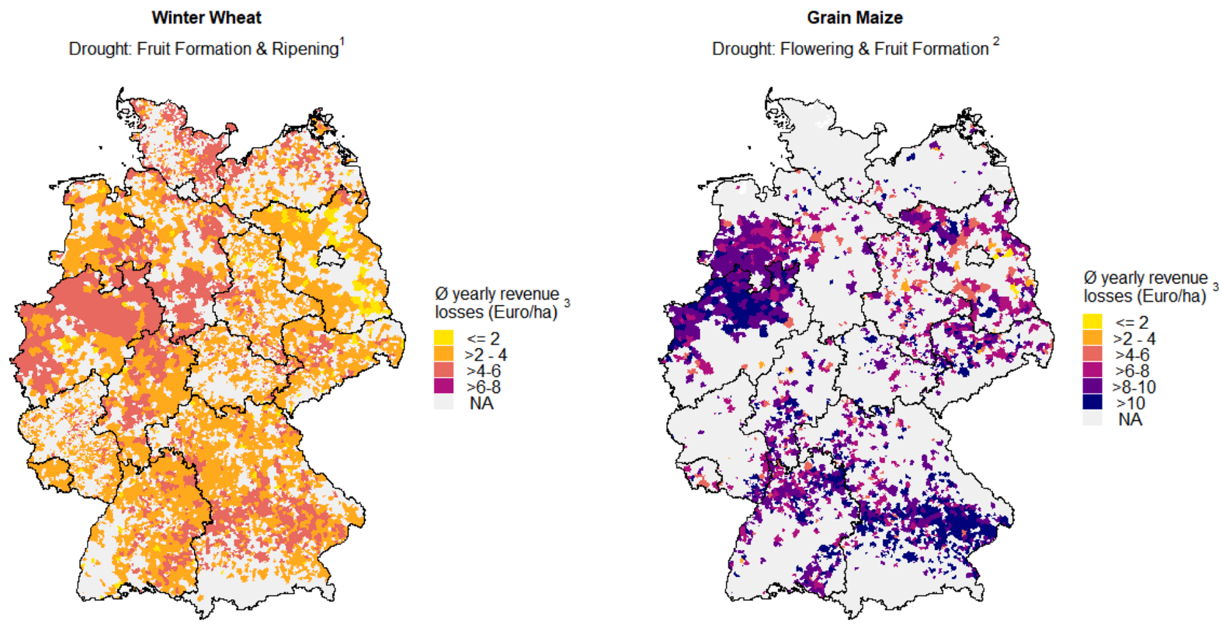

Fig. 11. Summer Drought - estimated marginal revenue losses in Euro/ha for winter wheat and grain maize in Euro/ha of one additional summer drought day. Notes: (1) The illustration provides a municipality level overview across Germany and is weighted by the cultivated farm area if the crop is grown by more than one farm in the same municipality. (2) Thresholds of the respective crop-specific drought events: [1]days with $\leq$ 7.8 % of usable field capacity (fc); [2]days with $\leq$ 8.7 % fc. (3) Average product prices 2016–2020 based on AGMEMOD (2021): [3] winter wheat = 15.39 Euro/dt; grain maize = 16.04 Euro/dt.

average effects on revenues obtained using the hypothetical counterfactual approach.

For instance, the average effect of summer drought on winter wheat in the North Sea regions is not severe (see Fig. 7, left). However, since variations are extremely pronounced in these maritime regions, an increase of one standard deviation in the drought indicator would lead to far higher losses (Fig. 10, left). In economic terms, this means that an intra-municipality-one-standard deviation increase for summer drought would trigger an average fall in revenues for winter wheat amounting to 17.10 Euro/ha across Germany, which represents overall country-wide losses of 53 million Euro on average per year. A comparison of Fig. 7 (right) and Fig. 10 (right) reveals that summer drought has a similar impact on grain maize in Eastern Germany. In the case of grain maize, an intra-municipality standard deviation increase of summer drought would cause an average drop in revenues across Germany of 38.46 Euro/ha, representing an overall country-wide loss of 15.4 million Euro.

Moreover, the impact of an increase of one-standard deviation for spring drought on winter barley had noticeable monetary consequences in the north-western and central-southern regions of Germany (see Figure S47, upper-left). On average, the impact of a one-standard deviation increase of spring drought on winter barley would, for instance, lead to revenue losses of 8.64 Euro/ha (10.4 million Euro across Germany as a whole). In the cases of winter wheat and winter barley, the monetary consequences of a one-standard deviation increase in waterlogging are felt hardest in the South of Germany (see Figures S46 and S47).

4.3.3. *Estimates of the marginal effects of crop-specific extreme weather events giving consideration to regional yield potentials*

Finally, we present exemplary estimations of revenue losses due to the impact of marginal changes in a summer drought day on winter wheat and grain maize. This allows us to consider regional yield levels and provides additional information regarding the average daily crop-specific damage potential of drought. This can be extremely useful, both for policy-makers when formulating ongoing forecasts of nationwide (drought induced) revenue losses and for farmers, as it can help them to adapt their input decisions during a current growing season. In Fig. 11, we observe that the regions in Western and South-Eastern Germany generally experience the highest revenue losses per summer drought day (>4–6 Euro/ha/day for winter wheat; >10 Euro/ha/day for grain maize).

5. Discussion

In our analyses, we included year-fixed effects to account for systemic shocks occurring across all farms in a specific year with possible yield effects and to account for non-linear technological change effects. Hence, we 'only' recovered extreme weather effects as deviations from a general state in a specific year, whereby this can lead to the underestimation of systemic events, such as droughts. However, although higher annual average drought days were observed across Germany in some years (e.g., in 2018 and 2019, see section S6), the spatial variation in drought intensity was still high and did not result in the drought effects being completely 'cancelled' by the year fixed effects (see also Webber et al., 2020). In fact, we observed an increase of spatial variation of drought in 2018 and 2019, which even led to a clearer identification of drought effects in our main specification and temporal sub-samples (see e.g. Fig. 3: 1.2 & 1.3; Fig. 4: 1.2 & 1.3). Furthermore, given the limited time-frame in our analyses, the results of temporal split sample estimations should be interpreted with a degree of caution. In addition, we implemented the long-difference approach to detect if any agricultural adaptation measures had been adopted during the observation period to meet the extreme weather events analysed (see Dell et al., 2012; Burke & Emerick, 2016; Miller et al. 2021).

We demonstrate that drought is a weather event which caused yield losses across winter wheat, winter barley and grain maize. The impact of drought became significantly more pronounced during the sub-period 2007–2019, which rather suggests a potential increase in vulnerability to the effect of drought. This assumption is supported by findings of Webber et al. (2020), whose country-wide analysis of the observation period 1998–2018 showed that four of the five biggest yield failures of the crops they analysed occurred after 2007. In the cases of winter wheat and winter barley, the long-difference approach (see Appendix A2) also reveals that the spring drought susceptibility of both crops has increased, suggesting that the varieties of these two crops recently favoured for cultivation could have become more vulnerable to spring drought.

The analyses of waterlogging underline that the investigation of regional crop- and weather-specific vulnerabilities benefits from combining estimated marginal effects with the information of observed incidences of extreme weather events. For instance, our results revealed that waterlogging caused particularly severe yield and monetary losses in winter wheat and winter barley in the South of Germany (see Figures S44 and S45).

The effects of heat on the yield levels of the crops analysed in our sample were not statistically significant at the national level (Fig. 2). However, sub-sampling of winter rapeseed revealed statistically significant heat effects indicating that unobserved regional conditions may influence the impact of heat on yields. Further research should be carried out in Central Europe to detect if the high standard deviation of yield effects of heat is due to non-linear yield effects (see Schlenker & Roberts, 2009), the interaction between heat and soil moisture (see Haqiqi et al. 2021) and/or other hitherto unobserved factors. The role of heat as a risk factor for yield losses needs to be better understood, especially in the context of rising temperatures due to climate change.

None of the cash crops in our analyses showed any robust yield effects due to black frost (in contrast to e.g. Fuller et al.,2007). The yield effects of black frost on winter crop yields are lower if these are hardened (i.e., have undergone cold temperatures in the period preceding the black frost; Mäkinen et al., 2018). However, this is not accounted for in the black frost temperature thresholds used in our analyses. Another potential explanation is that as there were no observations available for this variable, we used the estimation approach for the snow-layer (based on Trnka et al., 2010), which is not fully adapted to the natural conditions in Germany. Furthermore, since the German Farm Accountancy Data Network only considers the area actually harvested for each crop, the impact of weather extremes which result in complete crop failure can be blurred. In Germany, this applies mainly to severe black frost events, when farmers can limit economic losses by replanting the field with a summer crop. In addition, since farmers may decide that harvesting a field after a drought, severe waterlogging or heat events is not worthwhile, yield losses may be under-estimated as only the area actually harvested is recorded (e.g. Cui, 2020). While extreme yield failures of this magnitude are unusual in Germany, this potential data limitation must be borne in mind when interpreting the estimation results.

As a second step, we adopt three approaches to obtain an assessment of the economic relevance of the weather events by combining yield effects with crop prices and historical incidences of these events. Our analyses show that estimated revenue losses vary considerably across Germany in terms of annual averages (hypothetical counterfactual approach), variation (standard deviation approach) and marginal effects. Ideally, this information could flow into regional-specific risk management measures and policy actions. We are aware that the simplified estimation of the economic relevance relying on the average prices in 2016–2020 (AGEMOD, 2021) does not account for any (longer-term) price increases due to a potentially reduced supply. However, since Germany is a comparatively small producer and well-integrated in the world market, the 'natural hedge' at the farm level is relatively small for the crops analysed. Furthermore, the weather effect on an aggregated yield level e.g., the average yield of a federal state or Germany as a whole, is smaller than the yield effect of an extreme weather event at the farm level (see Finger, 2012), which further reduces the 'natural hedge' at the farm level. In addition, we did not consider any additional costs related to the weather events analysed, e.g., irrigation during a drought or planting a summer crop after a severe black frost, since the German Farm Accountancy Data Network only provides overall and not crop-specific costs of implementing these measures on the farm-level.

6. Conclusion and policy implications

In this paper, we compared the estimated yield effects of various extreme weather events during different critical phenological phases for winter wheat, winter barley, winter rapeseed and grain maize production in Germany. Based on these estimated effects, we calculated farmers' revenue losses associated with these extreme weather events. We find that drought caused the highest yearly yield and revenue losses across winter wheat, winter barley and grain maize, with a high regional variation of impact severity. In some regions, we observed a statistically significant rapeseed yield shortfall due to heat.

Our analyses revealed the high economic relevance of extreme weather events in German crop production. Our findings underline how vital it is to support farmers in their efforts to cope with, and adapt to, the challenges of these extreme events, especially given that they are likely to become more frequent due to climate change. This means that policy-makers should support the overall adaptation process and encourage robust production practices, especially in the vulnerable regions across Germany, and should avoid policies which hinder climate change adaptation.

We also find a high variation in weather effects on yields across regions and crops. Thus, our results highlight the fact that farmers must adopt site- and crop-specific risk management practices to meet the differences in their exposure to a range of extreme weather events. For instance, the North and East of Germany was more prone to drought-related losses in winter grains whilst waterlogging caused above average losses of winter grains in the South. In addition, the most important winter rapeseed production region, located in the North of Germany, was vulnerable to yield losses due to heat during flowering. Our results provide agricultural policy-makers with an additional source of information regarding the weather-vulnerable regions. This means that risk management and adaptation measures can be tailored regionally and explicitly, through e.g., irrigation, breeding, crop rotations or soil management, which in turn may enhance the cost-effectiveness of policy interventions. Farmers should be provided with spatially disaggregated information about their risk exposure and vulnerability to extreme weather events during different phenological phases of various crops so that they can develop regional- and crop-specific risk management and adaptation strategies. Policy-makers can support this development by making the relevant data publicly available (Bucheli et al., 2021).

Moreover, our results provide policy-makers with empirical insights which allow them to prioritize public support for adaptation measures and assess the (long-term) public costs of weather-risk related policy interventions. These comprise ad-hoc payments and the support of on– and off-farm risk management (e.g., use of irrigation, breeding and use of new varieties, crop insurance). For instance, our regional estimations of drops in revenues based on the hypothetical counterfactual offer an indication of crop- and weather-specific revenue losses and thus the compensation claims to be expected by insurance companies. Finally, our results on the revenue losses due to marginal changes in weather extremes can inform early warning systems regarding regional production shortages, or support farmers during ongoing production decisions like irrigation or fertilization.

Further research should investigate the potential of risk management measures, such as diversification, crop choice, irrigation or insurances to cope with the regional effects of extreme weather events on yields and income. Moreover, our results indicate that the susceptibility of yields to extreme weather events has persisted or even increased in the recent past. This underlines that climate change aggravates the risks faced by crop production under these extreme weather conditions (e.g., Ortiz-Bobea et al., 2021). More specifically, the frequency, severity and spatial extent of these events is expected to increase in several parts of the world, including Europe (Grillakis, 2019; Porter et al., 2014; Seneviratne et al., 2021; Trnka et al., 2014; Webber et al., 2018). Therefore, further research should investigate the ongoing impact of climate change on local exposure to extreme weather events, both in frequency and intensity, the resulting economic implications and adaptation potential. Moreover, future research could improve the estimation of extreme weather effects by exploiting satellite-based information to allow cropland weather information, farm level yields and other cropping practices to be aligned more precisely. In addition, further research should investigate the role of non-linear yield effects of weather extremes and interactions between the respective weather events in the context of compound extreme weather events.

CRediT authorship contribution statement

Jonas Schmitt: Conceptualization, Methodology, Visualization, Software, Writing – review & editing. **Frank Offermann:** Conceptualization, Methodology, Visualization, Software, Writing – review & editing. **Mareike Söder:** Conceptualization, Methodology, Visualization, Software, Writing – review & editing. **Cathleen Frühauf:** Data curation, Writing – review & editing. **Robert Finger:** Conceptualization, Methodology, Visualization, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A1. Spatial sample splitting

Spatial-Splitting is based on the definition of soil-climate regions in Germany by Roβberg et al. (2007) and the aggregation of these soil-climate regions to the four main production regions North, East, West and South as illustrated in Fig. A1 derived from the Julius-Kuehn-Institute (JKI, 2009). Roβberg et al. (2007) used information regarding temperature, precipitation and soil quality on a county level for the clustering of soil-climate regions and the authors finally implemented further aggregations to 22 soil climate regions across Germany based on regional expert knowledge. The JKI further aggregated these regions into the four main production regions during several analyses regarding e.g. plant protection analyses and comparisons across Germany (JKI, 2009).

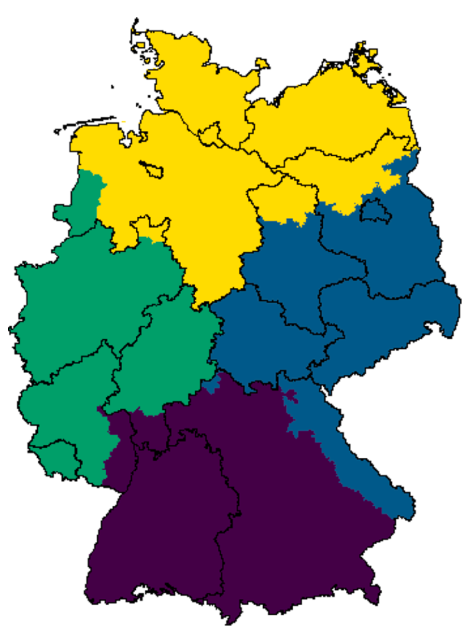

Fig. A1. Classification of main arable production regions in Germany. Note: based on JKI (2009).

Appendix A2. Long-difference estimations

We follow Burke & Emerick (2016) by implementing the following steps:

Step 1: we calculate the 5-year average farm-level yield and corresponding 5-year average weather observations for the two time periods 1995–1999 (Y_{ji95} and WE_{wji95}) and 2015–2019 (Y_{ji15} and WE_{wji15}) and merge both datasets. Hence, we receive only the farm observations, for which we have yield observations in both time periods.

Step 2: We adjust the long-difference specification of Burke & Emerick (2016) to the log-lin case of our main specification by considering for the dependent average farm-level yields:

$$\log(Y_{ji15}) - \log(Y_{ji95}) = \log(Y_{ji15}/Y_{ji95})$$

Further, we calculate the difference of the 5-year average weather observations between the two time periods:

$$WE_{wji15} - WE_{wji95} = \Delta WE_{wji}$$

Step 3: We additionally include a federal state ("Bundesland") fixed effect (α_{fs}), which controls for any unobserved federal state-level trends. Therefore, we eliminate any concerns regarding time-trending unobservables at the federal state level and the identification of effects comes only from the within-federal-state variation:

$$\log(Y_{ji15}/Y_{ji95}) = \sum \beta_{wj} {}^{*} \Delta WE_{wji} + \alpha_{fs} + \Delta\varepsilon_{ji}$$

Step 4: We additionally estimate the main specifications (see Tables A1-A4: (4) Whole Panel) with the sub-sample of farms, for which we have yield observations in both time periods for the long-difference approach ((see Tables A1-A4: (3) Limited Panel) to compare coefficients between the panel and long-difference estimations.

Step 5: We interpret more positive long-difference coefficients compared to panel coefficients as an evidence of adaptation. In the case of a more positive long-difference coefficient, farmers could better adapt to long run changes in climate compared to short-run weather changes.

Table A1
Winter wheat – comparison of results of the long-difference estimations with the panel estimation (main specification – see Fig. 2 (blue)).

Method:	(1) Long diff	(2) Long diff	(3) Limited Panel	(4) Whole Panel
Black Frost	−0.0106*(0.0054)	−0.0048(0.0065)	−0.0029(0.0022)	−0.0041*(0.0019)
Heat	0.2073(0.2397)	−0.0792(0.2472)	−0.0129(0.0275)	−0.011(0.0233)
Spring Drought	−0.0053**(0.0017)	−0.0047**(0.0018)	−0.0037***(0.0007)	−0.0036***(0.0006)
Summer Drought	−0.0028**(0.0011)	−0.0033**(0.0011)	−0.0035**(0.0011)	−0.0036**(0.0009)
Spring Waterlogging	−0.0041*(0.0016)	−0.0044**(0.0016)	−0.0036***(0.0009)	−0.0028***(0.0007)
Summer Waterlogging	−0.0114***(0.0019)	−0.0092***(0.0019)	−0.0031**(0.0009)	−0.0023**(0.0007)
Fixed-Effects:	None	Federal state	Farm & Year	Farm & Year
S.E.: Clustered	–	–	by: farm & year	by: farm & year
Observations	2,694	2,694	57,499	165,602

Notes:
(1) ***, **, * and. indicate statistical significance at the 0.001, 0.01, 0.05 and 0.10 level.
(2) Long-difference (Long diff) estimated with the two time periods 1995–1999 and 2015–2019.

Table A2
Winter barley – comparison of results of the long-difference estimations with the panel estimation (main specification – see Fig. 2 (blue)).

Method:	(1) Long diff	(2) Long diff	(3) Limited Panel	(4) Whole Panel
Black Frost	−0.0167**(0.0064)	−0.0139.(0.0076)	−0.0045(0.0027)	−0.0044.(0.0024)
Heat	−0.2797(0.0901)	−0.2334*(0.0921)	−0.0872(0.0904)	−0.0979(0.0649)
Spring Drought	−0.0137***(0.0030)	−0.0151***(0.0032)	−0.0050***(0.0013)	−0.0048***(0.0012)
Summer Drought	−0.0007(0.0012)	−0.0004(0.0013)	−0.0035**(0.0011)	−0.0031*(0.0011)
Spring Waterlogging	−0.0029(0.0028)	−0.0021(0.0029)	−0.0042**(0.0015)	−0.0039**(0.0013)
Summer Waterlogging	−0.0089***(0.0015)	−0.0075***(0.0016)	−0.0031***(0.0008)	−0.0024**(0.0007)
Fixed-Effects:	None	Federal state	Farm & Year	Farm & Year
S.E.: Clustered	–	–	by: farm & year	by: farm & year
Observations	2,363	2,363	48,932	144,386

Notes:
(1) ***, **, * and. indicate statistical significance at the 0.001, 0.01, 0.05 and 0.10 level.
(2) Long-difference (Long diff) estimated with the two time periods 1995–1999 and 2015–2019.

Table A3
Winter rapeseed – comparison of results of the long-difference estimations with the panel estimation (main specification – see Fig. 2 (blue)).

Method:	(1) Long diff	(2) Long diff	(3) Limited Panel	(4) Whole Panel
Black Frost	0.0030 (0.0129)	−0.0496*** (0.0143)	−0.0022 (0.0029)	−0.0012 (0.0027)
Spring Chill	−0.0064 (0.0305)	0.0699* (0.0353)	−0.0323* (0.0141)	−0.0297* (0.0130)
Heat	−0.1367* (0.0597)	−0.1584** (0.0612)	−0.0837. (0.0450)	−0.0594. (0.0344)
Spring Drought	0.0037 (0.0024)	0.0029 (0.0024)	−0.0022 (0.0019)	−0.0029. (0.0015)
Summer Drought	0.0018 (0.0018)	0.0002 (0.0019)	−0.0017. (0.0009)	−0.0018* (0.0008)
Spring Waterlogging	−0.0004 (0.0045)	0.0034 (0.0045)	−0.0030 (0.0029)	−0.0023 (0.0018)
Summer Waterlogging	−0.0058 (0.0031)	−0.0050 (0.0034)	−0.0034 (0.0023)	−0.0038 (0.0018)
Fixed-Effects:	None	Federal state	Farm & Year	Farm & Year
S.E.: Clustered	–	–	by: farm & year	by: farm & year
Observations	1,274	1,274	25,791	86,401

Notes:
(1) ***, **, * and. indicate statistical significance at the 0.001, 0.01, 0.05 and 0.10 level.
(2) Long-difference (Long diff) estimated with the two time periods 1995–1999 and 2015–2019.

Table A4
Grain maize – comparison of results of the long-difference estimations with the panel estimation (main specification – see Fig. 2 (blue)).

Method:	(1) Long diff	(2) Long diff	(3) Limited Panel	(4) Whole Panel
Spring Chill	0.0168 (0.0566)	0.0094 (0.0709)	−0.0030 (0.0178)	0.0154 (0.0185)
Heat	−0.0881*** (0.0259)	−0.1003** (0.0322)	−0.0442** (0.0153)	−0.0509* (0.0192)
Spring Drought	−0.0039 (0.0071)	−0.0035 (0.0073)	−0.0048 (0.0031)	−0.0052* (0.0019)
Summer Drought	−0.0121* (0.0048)	−0.0127* (0.0051)	−0.0046* (0.0018)	−0.0069*** (0.0009)
Spring Waterlogging	−0.0054 (0.0079)	−0.0054 (0.0079)	−0.0021 (0.0025)	−0.0030 (0.0018)
Summer Waterlogging	0.0095 (0.0141)	0.0077 (0.0143)	0.0003 (0.0019)	−0.0004 (0.0012)
Fixed-Effects:	None	Federal state	Farm & Year	Farm & Year
S.E.: Clustered	–	–	by: farm & year	by: farm & year
Observations	358	358	5,800	27,426

Notes:
(1) ***, **, * and. indicate statistical significance at the 0.001, 0.01, 0.05 and 0.10 level.
(2) Long-difference (Long diff) estimated with the two time periods 1995–1999 and 2015–2019.

Appendix B. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.foodpol.2022.102359.

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