https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

Measuring extremes-driven direct biophysical impacts in agricultural drought damages

Mansi Nagpal[1], Jasmin Heilemann[1], Luis Samaniego[2,3], Bernd Klauer[1], Erik Gawel[1,4], and Christian Klassert[1]

[1] Department of Economics, Helmholtz Centre for Environmental Research–UFZ, 04318 Leipzig, Germany
[2] Department of Computational Hydrosystems (CHS), Helmholtz Center for Environmental Research – UFZ, 04318 Leipzig, Germany
[3] University of Potsdam, Institute of Environmental Science and Geography, Potsdam, Germany
[4] University of Leipzig, Faculty of Economics and Business Management, 04109 Leipzig, Germany

Correspondence to: Mansi Nagpal (mansi.nagpal@ufz.de)

Abstract

Assessing the economic implications of droughts has become increasingly important due to their substantial impacts on agriculture. Existing empirical analyses for drought damages are often conducted on a national scale without spatially distributed data, which might bias estimates. Furthermore, the cumulative effects of multiple weather extremes, such as heat or preceded frost co-occurring with drought, are often overlooked. Measuring the direct biophysical impacts of such extremes on agriculture is essential for more precise risk assessment. This study presents a comprehensive economic impact assessment framework to measure the cumulative damages of droughts and other hydro-meteorological extremes on agriculture, focusing on eight major field crops in Germany. By utilizing a statistical yield model, we isolate the effects of multiple extremes on crop yields from other influencing factors (such as pests & diseases, farm management) and analyze their contribution to farm revenue losses during droughts at the district level from 2016-2022. Our findings indicate that the average annual direct biophysical damage caused by extremes under drought conditions during this period amounts to € 781 million across Germany. The study also reveals that biophysical impacts of extremes alone account for 60% of reported revenue damages during widespread drought years. For maize, direct biophysical damage explains up to 97% (2018) of revenue losses. Additionally, comparison of national-level damage estimates using aggregated and spatially disaggregated data shows that the aggregated data matches overall results, but diverges for maize and wheat, highlighting the importance of spatially distributed damage assessment. In this paper, we provide detailed estimates of extremes-driven direct biophysical damages at the district level, offering a high-resolution understanding of the spatial and temporal variability of these impacts. Assessing the extent of revenue losses resulting from these extremes alone can provide valuable insights for the development of effective drought mitigation programs and guide policy planning at local and national levels to enhance the resilience of the agricultural sector against future climate extremes.

Keywords: Drought impacts, economic impacts, climate change adaptation, extreme events, Germany

1 Introduction

Recent decades have seen a significant change in global temperature and precipitation patterns (Daramola & Xu, 2022). As climate change progresses, extreme events such as droughts and heat waves are expected to increase (Samaniego et al., 2018). The impacts of such hydro-meteorological extreme events on water resources and agriculture, which are strongly linked to global food security, are already being felt (Shukla et al., 2019). Quantifying the costs of these impacts and understanding their drivers is a prerequisite for assessing vulnerabilities and designing adaptation measures to increase the resilience of the agricultural sector (Rose, 2004).

A variety of factors including war (Appau et al., 2021), disease and pests (Savary et al., 2019), and extreme weather (Lesk et al., 2016) affect crop yields. Of these factors, climate variability has particularly pronounced impacts on yield variations. In major

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

agricultural production regions globally, over 60% of yield variability can be explained by climate variability (Ray et al., 2015). Drought, in particular, is one of the most severe climate-related hazards, significantly reducing crop yields and incurring high crop production losses. For instance, it is estimated that the average crop production impact of droughts (and heatwaves) has tripled from 1964 to 2015 across the European Union (Brás et al., 2021). Given the profound impact of droughts on agriculture, it is crucial to understand the economic consequences and the extent of damage caused by such extremes. However, the complexity of drought occurrences—characterized by their slow development, spatial and temporal accumulation, and significant variability in severity and intensity—makes research on their economic impacts challenging (Eckhardt et al., 2019).

Droughts are periods of significantly reduced moisture levels in the Earth system (Wilhite & Glantz, 1985), leading to restrictions in water availability and causing detrimental impacts on various environmental systems and economic sectors. Generally, there are four classifications of droughts: meteorological droughts (precipitation deficit), agricultural droughts (soil moisture deficit), hydrological droughts (abnormal streamflow, groundwater, reservoir, or lake deficits), and socioeconomic droughts (abnormal deficit due to imbalance between supply and demand) (Wilhite & Glantz, 1985).

The impacts of droughts extend to agriculture, livestock, forestry, energy, and industries, and even threaten human safety (de Brito et al., 2020). Due to its sensitivity to weather variability and soil moisture, the agricultural sector is often the first sector to be affected by drought (Ding et al., 2011; Wilhite, 2000). Agricultural droughts are soil moisture droughts that occur when crop water requirements are not met during the growing season due to a reduced water supply in the soil, mainly caused by decreased precipitation or/and increased temperatures (Liu et al., 2016; Rakovec et al., 2022). This lack of moisture affects crop growth and yields, posing a significant threat to harvests. These impacts can lead to a substantial decline in crop revenues and/or an increase in production costs, ultimately reducing farm profits, affecting farmers' livelihoods and economic stability within the sector, and threatening food security (FAO, 2023; Ziolkowska, 2016).

The impact of drought on agricultural production is not solely determined by the severity of the drought itself, but also by exposure to different weather extremes throughout the growing season (Haqiqi et al., 2021; Peichl et al., 2018; Schmitt et al., 2022). Most research on measuring the economic impacts of extreme events like droughts has been confined to assessing the impacts of specific weather extremes, despite growing evidence that such events are frequently driven by multiple interrelated climate drivers that can occur concurrently or successively within the same geographic area (AghaKouchak et al., 2014; Deng et al., 2024; Rakovec et al., 2022; Zscheischler et al., 2018, 2020). Failing to account for such concurrently or successively occurring extremes is likely to oversimplify the process leading to damages, underestimates the cumulative effects of weather extremes on crops, and may result in an incomplete risk perception and inaccurate damage estimates (Meyer et al., 2013).

In this study, we address this bias by economically measuring the concurrent or successive damages of various weather extremes together with droughts in agriculture (hereafter referred to as *extremes-driven damages*). To this end, we utilize a statistical yield model that isolates the impacts of multiple extremes on crop yields from other influencing factors, for eight major field crops in Germany. We then estimate the direct contribution of these extreme hydro-meteorological drivers to farm revenue losses through yield reductions during droughts (hereafter called *direct biophysical impacts*) and analyze the extent to which these extremes contribute to yield anomalies. Such an assessment can be useful in identifying the relative contribution of these factors across different regions and crops, which can guide more targeted drought adaptation and enable better decision-making.

Against this background, we first present a conceptual framework that outlines the biophysical and economic processes through which hydro-meteorological extremes associated with droughts impact revenues for rainfed and irrigated agriculture. Within this framework, we also emphasize the importance of standardizing the definition of counterfactual conditions for empirical drought impact assessments. Next, we present the empirical analysis where we measure extremes-driven direct biophysical damages during droughts at the district level for rainfed agriculture in Germany from 2016-2022. These estimates are derived from a the

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

methodology used to measure the impacts of the 2018 and 2019 droughts in Germany (Trenczek et al., 2022). We have enhanced this methodology for our current assessment.

Additionally, we demonstrate the utility of high-resolution damage assessment by comparing damages at the national level derived using both national-level and regional-level data. Existing research on measuring the economic impacts of droughts on agriculture often focuses on national-level damage assessments without considering spatially distributed data and typically examines specific drought events (COPA-COGECA, 2003; Trenczek et al., 2022). This approach can lead to biased estimates, as droughts can vary greatly across different locations and times (Jaeger et al., 2013; Samaniego et al., 2013), suggesting the need for consistent, high-resolution impact assessments (Meyer et al., 2013). Our analysis reveals that high-resolution damage assessment using regional-level data provide a more accurate quantification of crop-specific damages, which might not be captured by assessments using national-level data.

This study offers detailed, high-resolution estimates of extremes-driven direct biophysical damages at the district level, offering insights into the spatial and temporal variability of these impacts. By accounting for concurrent or successive weather extremes alongside droughts, our research provides a more accurate assessment of revenue losses during droughts. These findings can inform the development of effective drought mitigation programs and guide policy planning at local and national levels to enhance the resilience of the agricultural sector against future climate extremes.

2 Framework for assessing direct biophysical drought damages

In the conceptual framework below, we present two key components required to measure the damages of droughts. The first component describes the casual pathways by which droughts and related extreme events impact revenues in the year the drought occurred. The second component presents the benchmark against which the revenue impacts can be compared.

2.1 Contextualization

To conduct our assessment, we develop a systematic economic impact assessment framework for evaluating the direct biophysical effects of weather extremes during droughts on agriculture. In doing so, it is important to understand all the causal pathways by which extreme events can impact yields, and, in turn impact revenues. Our framework builds upon the damage function proposed by Diaz & Moore, (2017), which relates climate variables to the economic outcome of interest. In our conceptual framework, presented in **Figure1**, we integrate the biophysical impacts of concurrently or successively occurring weather-extremes (rather than changes in mean temperature, precipitation, etc. as done in context of climate change) on crop yields with response in economic variables over time. We also show how these impacts are linked with the other drivers of yields affecting the agricultural output that we isolate in this assessment. Specifically, extremes-driven direct biophysical damages are defined as the residual changes in farmers' revenue resulting from the direct biophysical effects of these extremes on crop yields, while accounting for adaptation costs and changes in economic variables (i.e. economic margin responses).

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

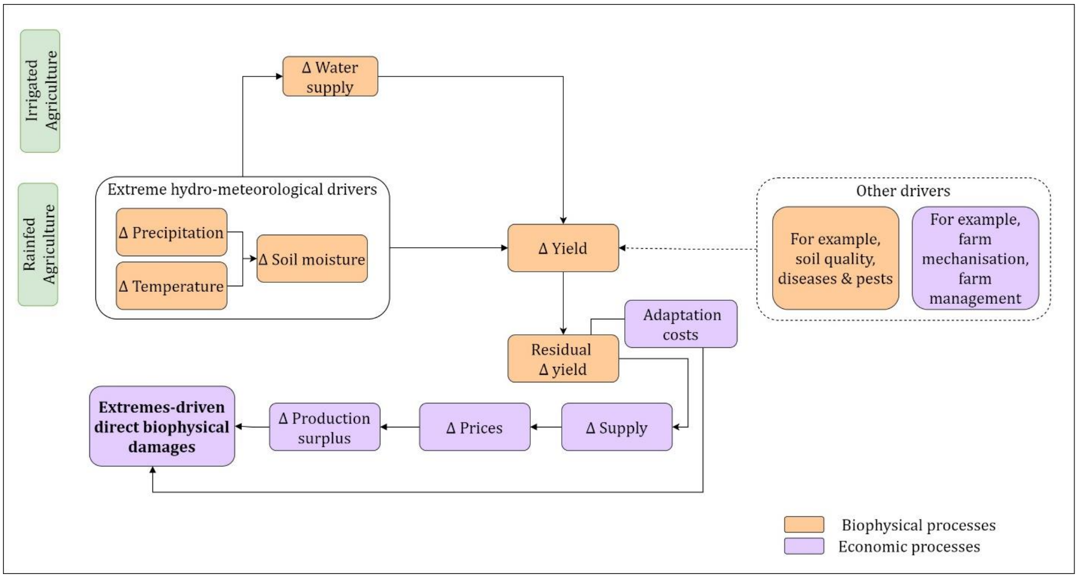

Figure 1 Schematic illustration of the series of biophysical (orange) and economic (purple) processes involved in measuring the impacts of hydro-meteorological extremes during droughts, over a single cycle of agricultural production. Drought affects crop yields through reduced soil moisture and other hydro-meteorological extremes, such as heat. Farmers may adopt short-term risk mitigation strategies, which incur additional adaptation costs. The net effect of these adaptations and biophysical impacts determines the residual change in yield, ultimately leading to a series of economic processes including changes in supply and prices, and ultimately revenue. Extremes-driven damages are defined as the sum of residual changes in farmers' revenue and adaptation costs.

As previously described, agricultural droughts occur when soil moisture levels are insufficient to meet crop water requirements during the growing season. Therefore, soil moisture (anomalies) are a more accurate predictor of biophysical impacts than precipitation or temperature (Bachmair et al., 2016). The importance of soil moisture in informing agricultural damage assessment is increasingly recognized (Haqiqi et al., 2021; Peichl et al., 2018). Moreover, other weather extremes, such as heat, can exacerbate damage to summer-grown crops like maize during droughts (AghaKouchak et al., 2014; Haqiqi et al., 2021). Similarly, for winter-grown crops like wheat, in addition to drought, excessive wet conditions during the growing season can lead to substantial damage to crop yields and harvests (Ben-Ari et al., 2018; Zampieri et al., 2017). There is growing evidence that multiple extremes explain a significant proportion of crop yield variability (Schmitt et al., 2022; E. Vogel et al., 2019; Webber et al., 2020). Thus, under evolving climate conditions, it is crucial to assess the direct biophysical impacts of droughts in conjunction with various hydro-meteorological extremes within a season and is central to our framework.

The agriculture sector is dependent on weather conditions as a critical factor of production. Each season, farmers anticipate a certain yield based on prevailing and expected weather conditions along with expected prices of agricultural output. However, when a weather extreme like drought occurs, resulting from a lack of precipitation or high temperatures, a decrease in soil moisture content follows, directly impeding crop growth and ultimately reducing crop yields. The biophysical impacts of droughts on crop yields can be exacerbated by the occurrence of other weather extremes, which are usually referred to as the direct impacts on agriculture (Meyer et al., 2013). The net impact of such an event is thus the reduction in crop yields that are lower than the anticipated yields of the farmer. The impact of declining soil moisture because of drought is more pronounced in rainfed agriculture, where crop yields can be significantly affected in the short term (Kurukulasuriya et al., 2006). Conversely, irrigation helps buffer the impact of low soil moisture on crop yields. However, if the drought persists and leads to acute water shortage and competition

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

for water use by other users as depicted in **Figure 1**, it can still cause considerable damage to irrigated agriculture during droughts (Smith & Edwards, 2021).

Depending on when droughts occur, farmers may implement various short-term risk mitigation strategies, such as adjusting their inputs or employing supplemental irrigation, to lessen the impact of the drought. These strategies, however, come with associated costs that need to be considered when estimating drought damages and are referred to as adaptation costs in our framework. The net effect of mitigation strategy (if implemented), combined with the biophysical impact on crop yield, results in the residual change in yield, as shown in **Figure 1**.

By the end of the agricultural production cycle, the direct damage to crop yields by drought and other weather extremes sets in motion a series of economic processes (**Figure 1**). The biophysical impact on crop yields results in a decrease in harvest that leads to negative supply shocks which can raise the prices of agricultural products. These price increases are known as indirect impacts of droughts and must be considered in economic impact assessments (Ding et al., 2011; Rose, 2004). In some cases, farmers may benefit from higher prices if the percentage increase in price exceeds the decrease in supply. This is particularly profitable for farmers operating outside the drought-affected area or farmers using irrigation. However, such impacts are difficult to measure using only national data and may require more detailed spatial assessments at the regional level. Moreover, given that droughts are unevenly distributed over regions, it is important to incorporate sufficiently detailed spatial disaggregation to assess the economic impacts on a national scale.

It is important to note that typically, all these impacts have an effect in a single production cycle. However, long-term impacts may also occur, including adjustments like behavioral changes in farmers that result in land use change (Biazin & Sterk, 2013; Henchiri et al., 2020). These long-term adjustments, while significant, are not measured or accounted for in this analysis.

2.2 Counterfactual Conditions

Measurement of damages requires comparing actual conditions (hazard impact) with counterfactual conditions (i.e. what would have happened in the absence of hazard). However, assessing the true counterfactual conditions is often challenging. As a result, there is a common practice in drought impact assessments in agriculture to compare agricultural production in drought years with that of recent non-drought years, which serve as a proxy for the counterfactual conditions. There is, however, a lack of consensus on the length of non-drought years, with some analyses using single-year (COPA-COGECA, 2003), three-year(Musolino et al., 2018), five-year(Trenczek et al., 2022), or six-year(Conradt et al., 2023) periods.

The selection of length of these previous non-drought years is particularly important for impact assessment as this determines the extent of the impact of the hazard. If the previous year(s) were exceptionally good or bad, they could bias the non-drought proxy and the resulting estimates. This is particularly challenging in the context of climate change, where the incidence of frequent or consecutive droughts (and other extremes) is on the rise (Fischer et al., 2021). Additionally, if the length of previous non-drought years is too long, it could take into account the technology effect on production, which is not desirable. Determining the optimal length of non-drought years to use as counterfactual conditions requires further research and is not addressed in this paper.

Another critical factor in defining counterfactual conditions is determining which years qualifies as a drought year. This becomes even more complicated due to the numerous factors influencing crop yields, such as soil quality, input materials, mechanization, and farm management practices, which can mask biophysical drought effects. Establishing indicators for drought declaration in the agricultural sector could prove useful in this regard. This would help consistently categorize a year and a region as drought or non-drought, ensuring accurate assessment of damages, even for small-scale drought events, and avoiding focusing solely on widespread droughts.

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

3 Methodology

The comprehensive framework presented in Sect. 2 illustrates the various biophysical and economic processes through which hydro-meteorological extremes associated with droughts result in damages in both rainfed and irrigated agriculture. The empirical analysis that follows focuses on the direct biophysical impacts of these extremes and their role in farm revenues losses, excluding any indirect impacts beyond the immediate consequences of biophysically induced yield losses or the adaptation costs incurred by the farmers during droughts. Additionally, we assess the utility of high-resolution damage assessment, given that numerous studies suggest the need for such detailed assessment.

The empirical analysis is conducted in Germany, where the agricultural sector plays a significant role, with half of its land area dedicated to agricultural use (BMEL, 2022). The analysis is performed at the district level in Germany from 2016-2022, focusing on eight key field crops: winter wheat, winter barley, rapeseed, maize, spring barley, spring oats, sugar beets, and potatoes. Together, these crops account for 75% of Germany's agricultural area (Statistisches Bundesamt (Destatis), 2022a). Given that German agriculture is predominantly rainfed, with less than 10% of the area equipped with irrigation (McNamara et al., 2024), our assessment primarily reflects impacts on rainfed agriculture.

3.1 Damage Measurement

The damage D in agricultural revenues during a drought year t is quantified as the sum of difference between the expected revenue under counterfactual conditions and the actual revenue for each crop c across eight crops. This can be expressed as:

$$D_t = \sum_{c=1}^{8} \left(\bar{R}_{expected,c,t} - R_{actual,c,t}\right) \quad (1)$$

where $\bar{R}_{expected,c,t}$ is the expected revenue for crop c, and $R_{actual,c,t}$ is the actual revenue for crop c during the year t.

In this analysis, we define the counterfactual conditions as the average conditions in the preceding five non-drought years. We determine drought years based on the soil moisture. In order to do so, we use the Soil Moisture Index (SMI) metric, as explained in Sect. 3.3, and exclude any drought years in the average estimation. This approach allows us to calculate revenue deviations using only normal year yield data without bias from multiple recent drought occurrences. Thus, the expected revenue is estimated using the average yield over the preceding five non-drought years i and the price in the drought year t, and actual revenue $R_{actual,c}$ is the revenue in the drought year. Therefore, for the present analysis, equation (1) can be rewritten as

$$D_t = \sum_{c=1}^{8} \left[\left(\frac{1}{5} \sum_{i=1}^{5} Y_{i,c} \right) \cdot P_{t,c} - Y_{t,c} \cdot P_{t,c} \right] \quad (2)$$

where, $Y_{i,c}$ denotes the average crop yield for crop c over the preceding five non-drought year i (i.e., from year t−1 to t−5). $Y_{t,c}$ is the crop yield for crop c in the drought year t, respectively, and $P_{t,c}$ is the price of crop c in the drought year t.

To isolate the direct biophysical impacts of extreme hydro-meteorological drivers on crop yields from other influencing factors, we define the crop yield Y_c for crop c as a function of crop specific extreme-weather events (EWE), derived from data on precipitation (PR), temperature (T) and SMI:

$$Y_c = f_c(EWE_c) \ = \ f_c\left(g_c(PR_c, T_c, SMI_c)\right) \quad (3)$$

These crop yields are simulated using a statistical crop yield model, which is described in the following section.

3.2 Statistical crop yield model

We apply a statistical crop yield model to isolate the impact of droughts on crop yields developed by Heilemann et al. (2024). The model predicts changes in crop yields based on different hydro-meteorological extremes, including drought. The statistical model is based on the Least Absolute Shrinkage and Selection Operator (LASSO) approach. It is a method for selecting relevant features via penalized multiple linear regression to avoid multicollinearity and obtain a higher predictive performance (Tibshirani, 1996). The statistical relationship between district-level crop yields and hydro-meteorological extreme variables was formulated using the following equation

$$Y = \sum_{j=1}^{p} \beta_j X_{ij} + \epsilon \tag{4}$$

Where Y is the yield anomaly of a crop, X_{ij} represents the vector of different crop-specific extreme weather events during sensitive growth phases in different months/seasons (explained below) and $\beta_1, \dots, \beta_p$ represent the model coefficients to be estimated. Each field crop used for the analysis is modeled separately.

By including the penalty parameter λ, the LASSO coefficients $\hat{\beta}_\lambda^L$ minimize the residual sum of squares of the regression models (James et al., 2013):

$$\sum_{i=1}^{n}\left(y_i - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}|\beta_j| \tag{5}$$

The model employs a 10-fold cross-validation to determine two key values of λ: λ_{min}, which minimizes the mean squared error (MSE) of the model, and λ_{1SE}, which is defined as λ_{min} plus the standard error of λ that results in the minimum loss. Following the approach outlined by (J. Vogel et al., 2021), the stronger penalty term λ_{1SE} is selected as a target, leading to the elimination of a greater number of variables compared to λ_{min}.

While we want to assess the impact of droughts on agriculture, other extreme weather events can co-occur and interact with drought, as described in Sect. 2. The statistical crop yield model employed accounts for this by taking 9 different extreme weather events into consideration (Table 1), which pose significant threats to crops in Germany, such as frost, heat, heavy rain, rain during harvest, precipitation scarcity, drought, and waterlogging. By focusing on extreme events rather than mean temperature changes, the statistical yield model can more accurately capture the effects of extreme weather events (Webber et al., 2020), making them better suited for assessing the impact of such events (Newman & Noy, 2023). In Sect. 3.3, we describe how we delineate a drought occurrence and then estimate the compound effect of multiple weather extremes during the drought.

The timing of these events is crucial in determining crop damage. Therefore, the indicators for frost, heat, heavy rain, rain during harvest, and precipitation scarcity are included in the model as monthly features assessed during the relevant months of the growing season using crop-specific thresholds (Gömann et al., 2015). The indicators of drought and waterlogging are determined using the seasonal SMI value calculated from the monthly SMI value for the topsoil (25 cm soil depth), tailored to the growing period of each crop. To this end, the monthly drought and waterlogging intensity as the difference between a SMI below 0.2 for drought, or above 0.8 for waterlogging is calculated. The model uses the seasonal drought and waterlogging intensity as the average of the monthly intensities.

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

Table 1Thresholds for extreme weather events from Heilemann et al. (2024)

	Thresholds for extreme weather events	**Time horizon of feature variable**	**Variable name**
Black frost	Tmin < -25 / -20 / - 10 / - 5 °C	monthly	BF
Late frost	Tmin < 0 °C	monthly	LF
Alternating frost	Tmin > -3 °C & Tmax > 3 °C	monthly	AF
Heat	Tmax > 28 / 30 °C	monthly	Heat
Heavy rain	P > 20 mm/d	monthly	HR
Rain during harvest	P > 5 mm/d	monthly	RdH
Precipitation scarcity	P = 0 mm/d	monthly	PS
Drought	SMI < 0.2	seasonal	Dr
Waterlogging	SMI > 0.8	seasonal	Wl

3.3 Drought categorization

To identify districts experiencing agricultural drought, we categorize the occurrence of drought in each district and year using the SMI (Samaniego et al., 2013) estimated from monthly soil moisture derived from the mesoscale Hydrological Model (mHM) (Samaniego et al., 2010). The SMI_k represents the monthly soil water quantile at a grid cell at time k, relative to the range of historical observations. A given cell is considered experiencing a soil moisture drought when $SMI_k < \tau$. The threshold τ denotes that the cell is experiencing a soil moisture deficit occurring less than $\tau \times 100\%$ of the time. For our analysis, τ was set as 0.2 indicating moderate drought conditions that may pose potential harm to crops and pastures (Zink et al., 2016). To consider the seasonal variations in water-supply-related impacts, we focus on the SMI during the active vegetative period from April to October. While recent studies have shown varying relationships between monthly SMI and crop yields (Peichl et al., 2021, 2021), we chose to utilize the average SMI during the active vegetative period to establish a neutral classification of drought impacting different crops.

Using monthly SMI data, at a resolution of 4km x 4km and covering the Germany entirely, the monthly average area under drought conditions was estimated (Nagpal et al., 2024). To classify the occurrence of drought at a district level, it was considered that at least 20% area of each district must have an SMI<0.2 per month, and this condition should persist for at least three months during the active vegetative period i.e., the months of April to October in a given year (Belleza et al., 2023).

3.4 Data

3.4.1 Yield model inputs

Here, we provide a concise overview of the data used in the yield model used to analyze the direct biophysical impact during drought on agriculture. Crop yields are simulated at the district level in Germany for eight field crops: winter wheat, winter barley, rapeseed, maize, spring barley, spring oats, sugar beets, and potatoes, using the LASSO model. Detailed information on the input data used for yield estimation can be found in (Heilemann et al., 2024).

The annual yield data, used to simulate the yields, is sourced from the Federal Statistical Office of Germany available for the district level from 1999-2022 (Statistisches Bundesamt (Destatis), 2022b). Meteorological data encompassing minimum and maximum daily temperature and daily precipitation is obtained from the German Weather Service (DWD) through a network of

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

stations (*Deutscher Wetterdienst*, 2024). Additionally, the monthly SMI for Germany is derived from mHM (Samaniego et al., 2010, 2013).

3.4.2 Damage assessment

For the economic assessment of biophysically induced damages of extremes under droughts, we use data on crop acreage at the district level for the years 2016-2022. The data for cultivation on the arable land by crop (in ha) at the district level is collected periodically by the statistical office in Germany and is not available for all years. Consequently, we use official statistical data for the years 2016 and 2020 (Statistisches Bundesamt (Destatis), 2020). For the remaining years, we rely on spatially explicit, remote-sensing-based crop maps with 10 m resolution for Germany (Blickensdörfer et al., 2022). The area under the eight crops analyzed in this study is extracted from the high-resolution crop map data at the district level using QGIS and R.

Yearly producer prices (€/dt) for crops in Germany are accessible from the European Statistical Office, except for sugar beets and maize (EUROSTAT, 2022). To achieve spatially-differentiated prices at a higher resolution, we scale this data using prices provided by the *Kuratorium für Technik und Bauwesen in der Landwirtschaft* (KTBL) calculator on the standard gross margin (KTBL, 2023b). For further details, please refer to Nagpal et al. (2024). For sugar beets, prices from KTBL at the country level are used, which were homogeneous until 2017 due to production limits imposed by the European Union and price guarantees provided to producers (Wimmer & Sauer, 2020). Since silage maize in Germany is not directly marketed but is used for fodder or biogas production (*FNR*, 2023), prices for silage maize are estimated by accounting for both these uses separately as described in Nagpal et al. (2024).

4 Results

4.1 Relevance of spatially disaggregated damage assessment

To show the utility of spatially disaggregated damage assessment and to understand the potential biases in using national-level data, we apply the methodology outlined in (Trenczek et al., 2022) using both national-level and regional-level reported crop yields, prices and land use data for Germany. The referenced report calculated damage estimates for 2018 and 2019 based on national-level reported data by determining the difference between expected and actual revenue. Expected revenue was derived from the average crop yields of the five year period of 2013-2017, combined with the prices and cultivated area from the assessment year.

While the report provided crop-wise damages specifically for winter wheat and silage maize and aggregate the damages for all other crops into a single category, our analysis extends this methodology to estimate the damages for six additional crops: winter barley, rapeseed, spring barley, spring oats, sugar beets, and potatoes. We conduct our assessment at both the national level, using aggregated reported national data, and at the district level, by calculating damages using reported yields from each district and summing these to obtain a national total. This approach allows us to compare the extent of differences in damage estimates between national-level and regional-level data sources, providing insights into the potential biases that may arise from relying solely on national-level data.

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

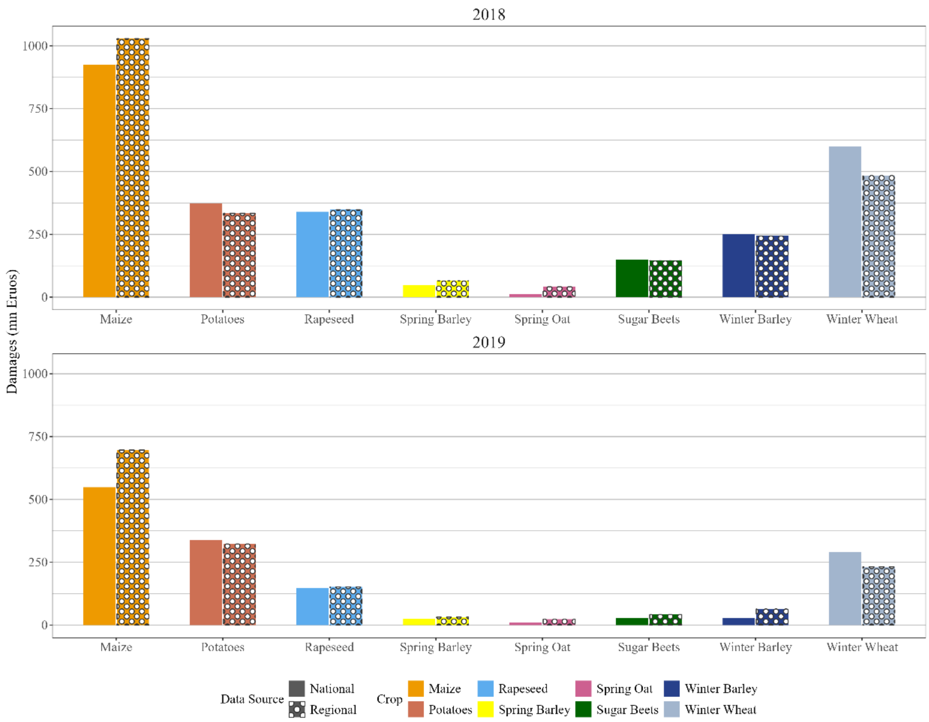

Figure 2 Authors' crop-wise damage assessment based on the methodology outlined in (Trenczek et al., 2022) for the years 2018 and 2019 with both national-level and regional-level reported yield data for Germany.

In our analysis, we found moderate difference between the total damages derived from national-level data and regional-level data. For 2018, the aggregated damages across all crops based on both national-level data and regional-level data are estimated at approximately €2.6 billion. For 2019, the aggregated damages across all crops based on national-level data (€1.4 billion) are slightly lower than those based on regional-level data (1.6 billion). However, there are notable differences in the damages across two major crops grown across Germany- maize and winter wheat (**Figure 2**). In both 2018 and 2019, the spatially distributed damages on winter wheat are lower than those based on aggregated national data, while they are significantly higher for maize. These results demonstrate that the use of spatially disaggregated data provides a more accurate quantification of crop-wise damages, which might not be captured by national-level assessments.

4.2 Spatiotemporal analysis of direct biophysical damages

Using the yields simulated by the statistical yield model (equation 4), we evaluate the extremes-driven direct biophysical damages during droughts at the district-level in Germany from 2016 to 2022. This evaluation is done by comparing the actual revenue during a drought year with the expected revenue of non-drought years (equation 2). The revenues are estimated using simulated yields that isolate the direct biophysical impacts of extremes on crop yields from other influencing factors. The top row of panels in **Figure 3** shows the spatial distribution of these estimated extremes-driven biophysical damages during droughts from 2016-2022. Our analysis reveals that the average annual direct biophysical damage across Germany, weighted by the proportion of agricultural area affected by drought (supplementary results 1), is estimated to be 781 million euros. The highest direct biophysical damage occurred in the years 2018 and 2022, with revenue losses estimated at €1.7 billion and €918 million, respectively. In northern Germany, a particularly notable decrease in revenues is observed, likely due to the substantial yield losses in these regions (**Supplementary Figure S3**).

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

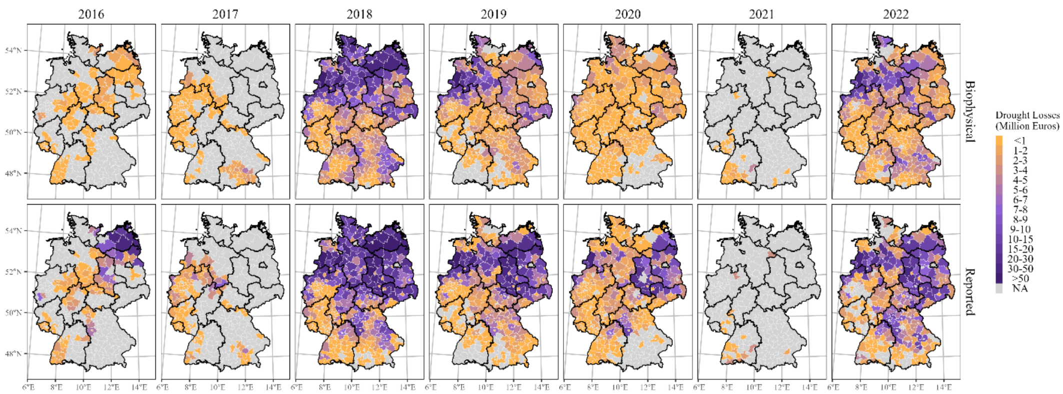

Figure 3 Spatial distribution of the estimated total revenue losses during droughts in German district-level administrative units based on (top panels) yields simulated using statistical crop yield model that isolates the effect of hydro-meteorological extremes on yields and (bottom panels) reported yields reported in official statistics. The different colors indicate the total revenue losses (million Euros) in the districts.

To further understand the relevance of impacts of extreme weather on agriculture during droughts, we compare the estimated extremes-driven direct biophysical damages (using simulated yields) with the damages calculated from the yields reported in official statistics (hereafter called *reported* damages). This comparison helps understand the extent of direct damage specifically caused by extreme hydro-meteorological drivers on agriculture during droughts. The reported damages are presented in the bottom row of panels in **Figure 3**.

According to our analysis, the extremes-driven direct biophysical damages account for an average of 45% of reported revenue losses during droughts between 2016 and 2022. In years with widespread droughts (2018, 2019, and 2022), the extremes-driven direct biophysical damages represent an average of 60% of reported revenue damages (64%, 52%, and 65% respectively). These results demonstrate that the direct biophysical impacts of extremes constitute a considerable contribution to the overall revenue losses experienced by farmers during the period of widespread droughts in Germany.

4.3 Crop-wise analysis of direct biophysical damages

We present the aggregated crop-wise damages during droughts for four years with the highest revenue losses in Germany (2018, 2019, 2020, and 2022) in **Figure 4**. Our analysis reveals that silage maize suffered the most notable extremes-driven damage due to droughts, followed by potatoes and winter wheat. When comparing these extremes-driven damages with reported damages, we note a similar trend for maize and potatoes; however, reported losses for winter wheat are considerably higher than their extremes-driven losses. Specifically, the impacts of extreme hydro-meteorological drivers on wheat crops are found to be 62% lower than the reported drought impacts. The situation is somewhat similar for other winter crops like winter barley and rapeseed. These findings indicate that drought-prone summer-grown maize and potatoes incur greater extremes-driven damage compared to winter-grown wheat and barley. For maize, the direct biophysical impacts explain upto 97% (2018) of revenue losses and for winter wheat, upto 32% (2019). For the year 2020, the extremes-driven damage of drought is significantly lower in comparison to the reported damages. This could be attributed to the fact that the dry conditions in 2020 were primarily limited to the spring season (van der Wiel et al., 2023) and, therefore, had limited impact on crop yields (**Supplementary Figure S2**).

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

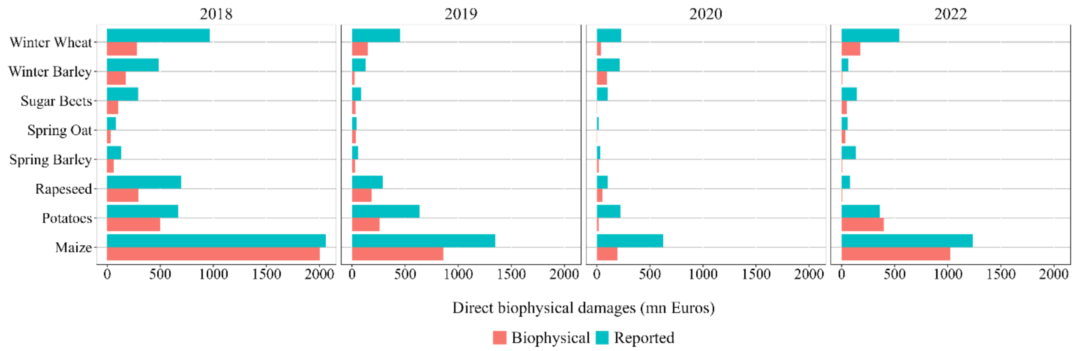

Figure 4 Crop-wise estimates of revenue loss in the four years with the largest aggregate losses during droughts across Germany based on yields simulated using the statistical yield model that isolates the impact of hydro-meteorological extremes on yields (orange bars) and yields reported in regional statistics (blue bars)

The spatial distribution of extremes-driven direct damages by crop for the four years with the highest revenue losses is depicted in **Figure 5**. The drought resulted in widespread revenue loss for almost all crops in Germany in 2018, 2019, and 2022 with some exceptions (like rapeseed in 2019 and 2022, spring barley and spring oats in 2022). Notably, potatoes experienced the highest revenue losses per ha amongst all crops across almost all districts in Germany given their high economic value (high yields per ha and high prices per ha). Drought-prone maize suffered significantly higher losses in the major production regions of the north (Lower Saxony and the surrounding districts) compared to the south (districts in Bavaria and Baden-Württemberg). In contrast, despite being the most widely cultivated crop across Germany, winter wheat showed much lower revenue losses than maize. In 2020, spring barley incurred more widespread crop losses than any other crop. Interestingly, in 2019, 2020, and 2022, only limited losses were observed for sugar beets in Mecklenburg-Vorpommern and the bordering districts of Lower Saxony and Saxony-Anhalt, despite a considerable share of area in these regions dedicated to growing this crop.

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

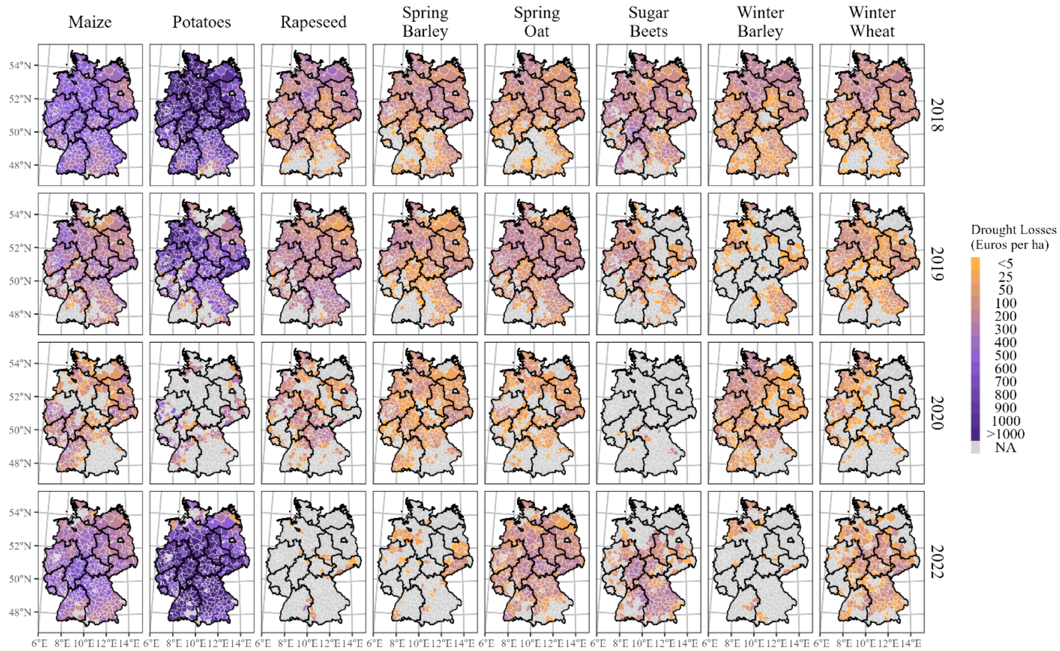

Figure 5 Spatial distribution of direct biophysical crop specific damages during droughts in German district-level administrative units in the four years with the highest revenue losses. The different colors indicate different levels of revenue losses (in Euros per ha) in the districts.

4.4 Contribution of droughts and various hydro-meteorological extremes to biophysical damages

Next, we examine to which degree droughts and other hydro-meteorological extreme events contributed to fluctuations in yields during 2016-2022, in order to understand the relative importance of their impacts on agriculture. This is done by calculating the feature contributions to the predicted yield change using the coefficients estimated with the LASSO models at the optimal penalty parameter λ_{1SE} (Heilemann et al., 2024). **Figure 6** displays the average contribution of various hydro-meteorological extremes to yield anomalies across Germany, which vary by crop and year. Contrary to intuition, some extremes also have positive effects on yield anomalies, although this is dependent upon the season/month of occurrence and the intensity of extremes, and the specific crop affected (Heilemann et al., 2024; Schmitt et al., 2022).

In 2016, 2017, and 2021, positive yield effects from weather extremes outweighed the negative impacts on crop yields. Despite limited drought-affected areas in Germany (**Supplementary Figure S1**), the negative impacts of droughts are evident in various crops during these years. Except 2020, the years with widespread droughts in Germany (2018, 2019, and 2022) saw droughts and heat contributing to negative yield anomalies for almost all crops. While there are some exceptions (sugar beets in 2018, and spring oats in 2019), droughts generally cause more severe impacts than heat. In 2019, the effect of drought, and heat was coupled with precipitation scarcity during spring (meteorological drought) which led to notable negative yield anomalies in spring oats and, to some extent, in spring barley and winter wheats. In contrast, negative yield anomalies in 2020 were largely driven by meteorological drought during spring instead of soil moisture drought. Meteorological droughts during spring commonly threaten agricultural productivity, as sufficient rainfall in spring is critical for distributing fertilizers throughout the soil (Gömann et al., 2015). These results show the complex interplay of weather extremes and their varying combinations, which determine the extent of yield losses in different years.

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

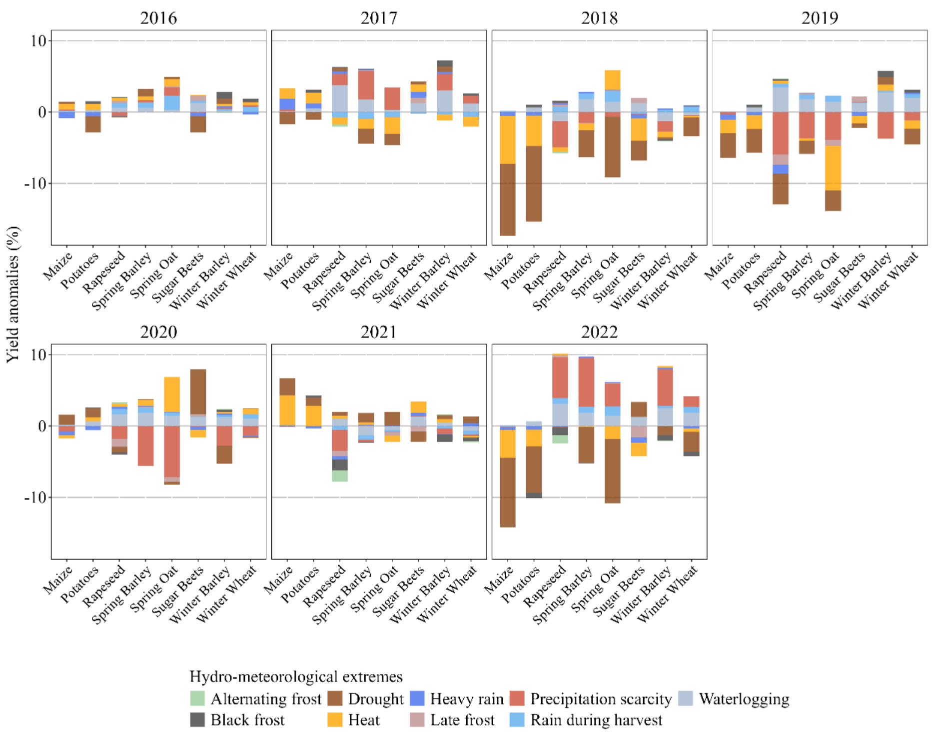

Figure 6 Contribution factors of hydro-meteorologically extremes to yield anomalies across different crops computed from the LASSO regression model.

5 Discussion

For our analysis of direct biophysical damages of extremes during droughts, we aggregate the impacts of eight field crops in Germany. The economic impacts of droughts were estimated by comparing the revenue generated during the drought year with that of the preceding five non-drought years across all districts in Germany. Recent research by Di Marcoberardino & Cucculelli (2024) has highlighted the significant impact of extreme events like droughts and heatwaves on the local economies across Europe, underscoring their localized nature. Providing a spatially distributed assessment is especially important for enhancing risk management, as it can help communicate risk to stakeholders and inform targeted policies and support programs (Brás et al., 2021; Rose, 2004). Our analysis comparing regional-level and national-level data for estimating drought damages reveals that using spatially disaggregated information yields more accurate assessments of revenue losses by crop, which may not be reflected in national-level assessments.

Our findings reveal that the average direct biophysical damage driven by extremes during droughts from 2016 to 2022 was €781 million per year across Germany. The years 2018 and 2022 experienced the highest losses, estimated at €1.7 billion and €1 billion respectively. The spatial distribution of the total impacts we found for 2018 is consistent with previous research. The sector-wise analysis of the impacts of droughts for 2018, conducted by de Brito et al., (2020) showed that agriculture in eastern Germany had the highest impacts. Conradt et al. (2023) found that the German part of the Elbe River basin in northern Germany suffered the highest yield losses in 2018. During years of widespread droughts, the revenue losses were greater in northern Germany compared to southern Germany. In southern Germany, there is some evidence that drought stress has little impact on crop yields (Lüttger &

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

Feike, 2018). Our analysis of the spatial distribution of annual average yield loss for all crops during droughts across Germany also found similar patterns (supplementary figure S3).

The comparison of the extremes-driven direct biophysical losses with reported losses shows that in years of widespread drought, biophysical factors like hydro-meteorological extremes explain 60% of the economic losses in Germany. These losses are largely driven by varying combinations of droughts, heat, and precipitation scarcity. This is consistent with emerging research on the joint impacts of extreme events on crop yields, which has identified drought and heat as the most relevant concurrent extremes in Europe, both in the current and future climate (Brás et al., 2021; Orth et al., 2022; von Buttlar et al., 2018; Webber et al., 2018). The contribution of this study lies in quantifying the extent to which economic damages are directly driven by the biophysical yield impacts of these drivers. While several weather extremes driving damages during droughts have been assessed and included, this assessment cannot be considered comprehensive. Important factors such as the impacts of pests and diseases (Khodaverdi et al., 2016; Meisner & de Boer, 2018), soil water retention capacity (Blanchy et al., 2023), as well as farm management practices (Soares et al., 2023) are not included in these damage estimates.

The crop-wise examination of revenue losses during drought in Germany revealed that summer crops like maize suffered the highest aggregate losses, followed by potatoes. The maize crop is particularly vulnerable to droughts, as highlighted by previous studies (Schmitt et al., 2022; Webber et al., 2020) and this vulnerability was evident in the high revenue losses we observed in almost all years. According to our analysis, up to 97.4% (2018) of maize's revenue loss can be explained by the direct biophysical impacts. These results are consistent with findings of Reinermann et al. (2019) who analyzed drought impacts using satellite-based vegetation indices. Interestingly, potatoes, which are typically considered a high-value cash crop grown under irrigation, suffered the highest losses in Lower Saxony, a region with extensive irrigation infrastructure. This could be because the potato yield losses during droughts are mostly due to increased temperatures, rather than a reduction in precipitation which could be mitigated through irrigation only upto a certain degree (Egerer et al., 2023).

6 Conclusion

This study presents a conceptual framework to facilitate the understanding and estimation of economic impacts of hydro-meteorological extremes associated with droughts in agriculture. Using the framework, we measured spatially distributed, direct biophysical damages on farmers' revenue at the district level in Germany during droughts. Our damage estimates bridge gaps related to consistent economic impact assessment that can be used for the assessment of the costs of climate change (Frame et al., 2020). Farmers' decision-making in the context of drought would also benefit from such analysis, especially if these assessments are extended and linked with drought monitoring and early warning systems (Muller et al., 2024). Additionally, we show the utility of spatially distributed data for accurate crop-specific damage assessments.

Our analysis revealed an average annual revenue loss due to biophysical impacts of extremes of €781 million across Germany during drought, accounting for 45% of reported revenue losses. In years with widespread droughts (2018, 2019, and 2022), the extreme-driven damages represent an average of 60% of reported revenue loss, highlighting the dominant role of hydro-meteorological extremes in driving the revenue losses experienced by farmers. By isolating the impacts of hydro-metrological extremes from other drivers of farm revenue losses in droughts, the findings emphasize the critical need to adapt to such extremes not only in the present-day climate but also in the future, where such extremes are expected to become more frequent and intense. Our results underscore the role of hydro-metrological extremes in revenue losses during droughts in Germany. Specifically, for drought-prone, summer-grown crops like maize, the hydro-meteorological extremes, such as reduced soil moisture, can explain upto 97% of the reported losses in 2018. In contrast, for the winter-grown crops like wheat, the contribution of hydro-meteorological extremes is less pronounced, explaining upto 32% of the reported losses in 2019. These results can guide more targeted adaptation during droughts, focusing on specific crop types. For example, insuring summer-grown crops against simultaneous or successive extremes, such as drought and heat, or enhancing breeding effectiveness.

While our estimates are robust, there are areas for improvement. Notably, our analysis is focused on short-term impacts and does not include adaptation costs or indirect impacts beyond or indirect impacts beyond the immediate consequences of biophysically induced yield losses. Additionally, the estimation of revenue losses might be underestimated due to the limitation of statistical yield model in simulating extreme crop yields. Despite these limitations, our analysis provides valuable insights into the far-reaching economic consequences of droughts in the agricultural sector. These insights should be of significant interest to decision-makers, guiding the development of effective strategies for mitigating the effects of droughts and implementing measures to build resilience in affected regions.

Author contribution

MN, BK, EG, and CK conceptualized the study; MN, JH, and CK developed the methodology; MN and JH curated the data and developed the software; MN conducted the formal analysis, visualization and prepared the original draft of the manuscript. JH, LS, BK, EG, and CK reviewed and edited the manuscript. BK, EG, and CK supervised the research.

Declaration of competing interests

The authors do not have any competing interests.

Acknowledgements

We would like to thank Edward Digman for proofreading this article. The authors acknowledge the assistance of ChatGPT in enhancing the language quality. Following the use of this tool, the authors have carefully reviewed and edited the content as necessary, and they assume full accountability for the publication's content.

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

References

AghaKouchak, A., Cheng, L., Mazdiyasni, O., & Farahmand, A. (2014). Global warming and changes in risk of concurrent climate extremes: Insights from the 2014 California drought. *Geophysical Research Letters*, *41*(24), 8847–8852. https://doi.org/10.1002/2014GL062308

Appau, S., Awaworyi Churchill, S., Smyth, R., & Trinh, T.-A. (2021). The long-term impact of the Vietnam War on agricultural productivity. *World Development*, *146*, 105613. https://doi.org/10.1016/j.worlddev.2021.105613

Bachmair, S., Svensson, C., Hannaford, J., Barker, L. J., & Stahl, K. (2016). A quantitative analysis to objectively appraise drought indicators and model drought impacts. *Hydrology and Earth System Sciences*, *20*(7), 2589–2609. https://doi.org/10.5194/hess-20-2589-2016

Belleza, G. A. C., Bierkens, M. F. P., & Vliet, M. T. H. van. (2023). Sectoral water use responses to droughts and heatwaves: Analyses from local to global scales for 1990–2019. *Environmental Research Letters*, *18*(10), 104008. https://doi.org/10.1088/1748-9326/acf82e

Ben-Ari, T., Boé, J., Ciais, P., Lecerf, R., Van der Velde, M., & Makowski, D. (2018). Causes and implications of the unforeseen 2016 extreme yield loss in the breadbasket of France. *Nature Communications*, *9*(1), 1627. https://doi.org/10.1038/s41467-018-04087-x

Biazin, B., & Sterk, G. (2013). Drought vulnerability drives land-use and land cover changes in the Rift Valley dry lands of Ethiopia. *Agriculture, Ecosystems & Environment*, *164*, 100–113. https://doi.org/10.1016/j.agee.2012.09.012

Blanchy, G., Bragato, G., Di Bene, C., Jarvis, N., Larsbo, M., Meurer, K., & Garré, S. (2023). Soil and crop management practices and the water regulation functions of soils: A qualitative synthesis of meta-analyses relevant to European agriculture. *SOIL*, *9*(1), 1–20. https://doi.org/10.5194/soil-9-1-2023

Blickensdörfer, L., Schwieder, M., Pflugmacher, D., Nendel, C., Erasmi, S., & Hostert, P. (2022). Mapping of crop types and crop sequences with combined time series of Sentinel-1, Sentinel-2 and Landsat 8 data for Germany. *Remote Sensing of Environment*, *269*, 112831. https://doi.org/10.1016/j.rse.2021.112831

BMEL. (2022). *Daten und Fakten Land-, Forst- und Ernährungswirtschaft mit Fischerei und Wein- und Gartenbau*. Bundesministerium für Ernährung und Landwirtschaft (BMEL). https://www.bmel.de/SharedDocs/Downloads/DE/Broschueren/daten-fakten-2022.pdf?__blob=publicationFile&v=5

Brás, T. A., Seixas, J., Carvalhais, N., & Jägermeyr, J. (2021). Severity of drought and heatwave crop losses tripled over the last five decades in Europe. *Environmental Research Letters*, *16*(6), 065012. https://doi.org/10.1088/1748-9326/abf004

Conradt, T., Engelhardt, H., Menz, C., Vicente-Serrano, S. M., Farizo, B. A., Peña-Angulo, D., Domínguez-Castro, F., Eklundh, L., Jin, H., Boincean, B., Murphy, C., & López-Moreno, J. I. (2023). Cross-sectoral impacts of the 2018–2019 Central European drought and climate resilience in the German part of the Elbe River basin. *Regional Environmental Change*, *23*(1), 32. https://doi.org/10.1007/s10113-023-02032-3

COPA-COGECA. (2003). *Assessment of the impact of the heat wave and drought of the summer 2003 on agriculture and forestry Technical Report* [Technical]. Committee of Agricultural Organisations in the European Union.

Daramola, M. T., & Xu, M. (2022). Recent changes in global dryland temperature and precipitation. *International Journal of Climatology*, *42*(2), 1267–1282. https://doi.org/10.1002/joc.7301

de Brito, M. M., Kuhlicke, C., & Marx, A. (2020). Near-real-time drought impact assessment: A text mining approach on the 2018/19 drought in Germany. *Environmental Research Letters*, *15*(10), 1040a9. https://doi.org/10.1088/1748-9326/aba4ca

Deng, S., Zhao, D., Chen, Z., Liu, L., Zhu, Y., Wang, K., Gao, X., Wu, H., & Zheng, D. (2024). Global Distribution and Projected Variations of Compound Drought-Extreme Precipitation Events. *Earth's Future*, *12*(7), e2024EF004809. https://doi.org/10.1029/2024EF004809

Deutscher Wetterdienst. (2024). Climate Data Center. https://www.dwd.de/EN/climate_environment/cdc/cdc_node_en.html

Di Marcoberardino, D., & Cucculelli, M. (2024). "Natural" disasters and regional governance: Evidence from European NUTS-3 regions. *Papers in Regional Science*, *103*(1), 100003. https://doi.org/10.1016/j.pirs.2024.100003

Diaz, D., & Moore, F. (2017). Quantifying the economic risks of climate change. *Nature Climate Change*, *7*(11), Article 11. https://doi.org/10.1038/nclimate3411

Ding, Y., Hayes, M. J., & Widhalm, M. (2011). Measuring economic impacts of drought: A review and discussion. *Disaster Prevention and Management: An International Journal*, *20*(4), 434–446. https://doi.org/10.1108/09653561111161752

Eckhardt, D., Leiras, A., & Thomé, A. M. T. (2019). Systematic literature review of methodologies for assessing the costs of disasters. *International Journal of Disaster Risk Reduction*, *33*, 398–416. https://doi.org/10.1016/j.ijdrr.2018.10.010

Egerer, S., Puente, A. F., Peichl, M., Rakovec, O., Samaniego, L., & Schneider, U. A. (2023). Limited potential of irrigation to prevent potato yield losses in Germany under climate change. *Agricultural Systems*, *207*, 103633. https://doi.org/10.1016/j.agsy.2023.103633

EUROSTAT. (2022). *Agriculture-Database. Selling prices of crop products (absolute prices)—Annual price (from 2000 onwards)* [Dataset]. https://ec.europa.eu/eurostat/databrowser/view/apri_ap_crpouta/default/table?lang=en

FAO. (2023). *The impact of disasters on agriculture and food security 2023*. https://doi.org/10.4060/cc7900en

Fischer, E. M., Sippel, S., & Knutti, R. (2021). Increasing probability of record-shattering climate extremes. *Nature Climate Change*, *11*(8), 689–695. https://doi.org/10.1038/s41558-021-01092-9

FNR. (2023). Mais. https://pflanzen.fnr.de/energiepflanzen/pflanzen/mais

Frame, D. J., Rosier, S. M., Noy, I., Harrington, L. J., Carey-Smith, T., Sparrow, S. N., Stone, D. A., & Dean, S. M. (2020). Climate change attribution and the economic costs of extreme weather events: A study on damages from extreme rainfall and drought. *Climatic Change*, *162*(2), 781–797. https://doi.org/10.1007/s10584-020-02729-y

Gömann, H., Bender, A., Bolte, A., Dirksmeyer, W., Englert, H., Feil, J.-H., Frühauf, C., Hauschild, M., Krengel, S., Lilienthal, H., Löpmeier, F.-J., Müller, J., Mußhof, O., Natkhin, M., Offermann, F., Seidel, P., Schmidt, M., Seintsch, B., Steidl, J., … Zimmer, Y. (2015). *Agrarrelevante Extremwetterlagen und Möglichkeiten von Risikomanagementsystemen: Studie im Auftrag des Bundesministeriums für Ernährung und Landwirtschaft (BMEL)*. Johann Heinrich von Thünen-Institut. https://doi.org/10.3220/REP1434012425000

Haqiqi, I., Grogan, D. S., Hertel, T. W., & Schlenker, W. (2021). Quantifying the impacts of compound extremes on agriculture. *Hydrology and Earth System Sciences*, *25*(2), 551–564. https://doi.org/10.5194/hess-25-551-2021

Heilemann, J., Klassert, C., Samaniego, L., Thober, S., Marx, A., Boeing, F., Klauer, B., & Gawel, E. (2024). *Projecting Impacts of Extreme Weather Events on Crop Yields Using Lasso Regression* (SSRN Scholarly Paper 4893832). https://doi.org/10.2139/ssrn.4893832

Henchiri, M., Liu, Q., Essifi, B., Javed, T., Zhang, S., Bai, Y., & Zhang, J. (2020). Spatio-Temporal Patterns of Drought and Impact on Vegetation in North and West Africa Based on Multi-Satellite Data. *Remote Sensing*, *12*(23), Article 23. https://doi.org/10.3390/rs12233869

Jaeger, W. K., Plantinga, A. J., Chang, H., Dello, K., Grant, G., Hulse, D., McDonnell, J. J., Lancaster, S., Moradkhani, H., Morzillo, A. T., Mote, P., Nolin, A., Santelmann, M., & Wu, J. (2013). Toward a formal definition of water scarcity in natural-human systems. *Water Resources Research*, *49*(7), 4506–4517. https://doi.org/10.1002/wrcr.20249

Khodaverdi, H., Fowles, T., Bick, E., & Nansen, C. (2016). Does Drought Increase the Risk of Insects Developing Behavioral Resistance to Systemic Insecticides? *Journal of Economic Entomology*, *109*(5), 2027–2031. https://doi.org/10.1093/jee/tow188

Kurukulasuriya, P., Mendelsohn, R., Hassan, R., Benhin, J., Deressa, T., Diop, M., Eid, H. M., Fosu, K. Y., Gbetibouo, G., Jain, S., Mahamadou, A., Mano, R., Kabubo-Mariara, J., El-Marsafawy, S., Molua, E., Ouda, S., Ouedraogo, M., Séne, I., Maddison, D., … Dinar, A. (2006). Will African Agriculture Survive Climate Change? *The World Bank Economic Review*, *20*(3), 367–388. https://doi.org/10.1093/wber/lhl004

Lesk, C., Rowhani, P., & Ramankutty, N. (2016). Influence of extreme weather disasters on global crop production. *Nature*, *529*(7584), Article 7584. https://doi.org/10.1038/nature16467

Liu, X., Zhu, X., Pan, Y., Li, S., Liu, Y., & Ma, Y. (2016). Agricultural drought monitoring: Progress, challenges, and prospects. *Journal of Geographical Sciences*, *26*(6), 750–767. https://doi.org/10.1007/s11442-016-1297-9

Lüttger, A. B., & Feike, T. (2018). Development of heat and drought related extreme weather events and their effect on winter wheat yields in Germany. *Theoretical and Applied Climatology*, *132*(1), 15–29. https://doi.org/10.1007/s00704-017-2076-y

McNamara, I., Flörke, M., Uschan, T., Baez-Villanueva, O. M., & Herrmann, F. (2024). Estimates of irrigation requirements throughout Germany under varying climatic conditions. *Agricultural Water Management*, *291*, 108641. https://doi.org/10.1016/j.agwat.2023.108641

Meisner, A., & de Boer, W. (2018). Strategies to Maintain Natural Biocontrol of Soil-Borne Crop Diseases During Severe Drought and Rainfall Events. *Frontiers in Microbiology*, *9*. https://doi.org/10.3389/fmicb.2018.02279

Meyer, V., Becker, N., Markantonis, V., Schwarze, R., van den Bergh, J. C. J. M., Bouwer, L. M., Bubeck, P., Ciavola, P., Genovese, E., Green, C., Hallegatte, S., Kreibich, H., Lequeux, Q., Logar, I., Papyrakis, E., Pfurtscheller, C., Poussin, J., Przyluski, V., Thieken, A. H., & Viavattene, C. (2013). Review article: Assessing the costs of natural hazards – state of the art and knowledge gaps. *Natural Hazards and Earth System Sciences*, *13*(5), 1351–1373. https://doi.org/10.5194/nhess-13-1351-2013

Muller, L. C. F. E., Schaafsma, M., Mazzoleni, M., & Van Loon, A. F. (2024). Responding to climate services in the context of drought: A systematic review. *Climate Services*, *35*, 100493. https://doi.org/10.1016/j.cliser.2024.100493

Musolino, D. A., Massarutto, A., & de Carli, A. (2018). Does drought always cause economic losses in agriculture? An empirical investigation on the distributive effects of drought events in some areas of Southern Europe. *Science of The Total Environment*, *633*, 1560–1570. https://doi.org/10.1016/j.scitotenv.2018.02.308

Nagpal, M., Klassert, C., Heilemann, J., Klauer, B., & Gawel, E. (2024). *Measuring Crop Acreage Adaptation to Changing Yields and Prices: An Empirical Analysis for Agriculture in Germany* (SSRN Scholarly Paper 4728661). https://doi.org/10.2139/ssrn.4728661

Newman, R., & Noy, I. (2023). The global costs of extreme weather that are attributable to climate change. *Nature Communications*, *14*(1), Article 1. https://doi.org/10.1038/s41467-023-41888-1

Orth, R., O, S., Zscheischler, J., Mahecha, M. D., & Reichstein, M. (2022). Contrasting biophysical and societal impacts of hydro-meteorological extremes. *Environmental Research Letters*, *17*(1), 014044. https://doi.org/10.1088/1748-9326/ac4139

Peichl, M., Thober, S., Meyer, V., & Samaniego, L. (2018). The effect of soil moisture anomalies on maize yield in Germany. *Natural Hazards and Earth System Sciences*, *18*(3), 889–906. https://doi.org/10.5194/nhess-18-889-2018

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

Peichl, M., Thober, S., Samaniego, L., Hansjürgens, B., & Marx, A. (2021). Machine learning methods to assess the effects of a non-linear damage spectrum taking into account soil moisture on winter wheat yields in Germany. *Hydrology and Earth System Sciences Discussions*, 1–28. https://doi.org/10.5194/hess-2021-9

Rakovec, O., Samaniego, L., Hari, V., Markonis, Y., Moravec, V., Thober, S., Hanel, M., & Kumar, R. (2022). The 2018–2020 Multi-Year Drought Sets a New Benchmark in Europe. *Earth's Future*, *10*(3). https://doi.org/10.1029/2021EF002394

Ray, D. K., Gerber, J. S., MacDonald, G. K., & West, P. C. (2015). Climate variation explains a third of global crop yield variability. *Nature Communications*, *6*(1), 5989. https://doi.org/10.1038/ncomms6989

Reinermann, S., Gessner, U., Asam, S., Kuenzer, C., & Dech, S. (2019). The Effect of Droughts on Vegetation Condition in Germany: An Analysis Based on Two Decades of Satellite Earth Observation Time Series and Crop Yield Statistics. *Remote Sensing*, *11*(15), 1783. https://doi.org/10.3390/rs11151783

Rose, A. (2004). Economic Principles, Issues, and Research Priorities in Hazard Loss Estimation. In Y. Okuyama & S. E. Chang (Eds.), *Modeling Spatial and Economic Impacts of Disasters* (pp. 13–36). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-24787-6_2

Samaniego, L., Kumar, R., & Attinger, S. (2010). Multiscale parameter regionalization of a grid-based hydrologic model at the mesoscale. *Water Resources Research*, *46*(5). https://doi.org/10.1029/2008WR007327

Samaniego, L., Kumar, R., & Zink, M. (2013). Implications of Parameter Uncertainty on Soil Moisture Drought Analysis in Germany. *Journal of Hydrometeorology*, *14*(1), 47–68. https://doi.org/10.1175/JHM-D-12-075.1

Samaniego, L., Thober, S., Kumar, R., Wanders, N., Rakovec, O., Pan, M., Zink, M., Sheffield, J., Wood, E. F., & Marx, A. (2018). Anthropogenic warming exacerbates European soil moisture droughts. *Nature Climate Change*, *8*(5), Article 5. https://doi.org/10.1038/s41558-018-0138-5

Savary, S., Willocquet, L., Pethybridge, S. J., Esker, P., McRoberts, N., & Nelson, A. (2019). The global burden of pathogens and pests on major food crops. *Nature Ecology & Evolution*, *3*(3), 430–439. https://doi.org/10.1038/s41559-018-0793-y

Schmitt, J., Offermann, F., Söder, M., Frühauf, C., & Finger, R. (2022). Extreme weather events cause significant crop yield losses at the farm level in German agriculture. *Food Policy*, *112*, 102359. https://doi.org/10.1016/j.foodpol.2022.102359

Shukla, P. R., Skeg, J., Buendia, E. C., Masson-Delmotte, V., Pörtner, H.-O., Roberts, D. C., Zhai, P., Slade, R., Connors, S., van Diemen, S., Ferrat, M., Haughey, S., Luz, Neogi, S., Pathak, M., Petzold, J., Portugal Pereira, J., Vyas, P., Huntley, H., … Malley, J. (2019). *Climate Change and Land: An IPCC special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems.*

Smith, S. M., & Edwards, E. C. (2021). Water storage and agricultural resilience to drought: Historical evidence of the capacity and institutional limits in the United States. *Environmental Research Letters*, *16*(12), 124020. https://doi.org/10.1088/1748-9326/ac358a

Soares, P. R., Harrison, M. T., Kalantari, Z., Zhao, W., & Ferreira, C. S. S. (2023). Drought effects on soil organic carbon under different agricultural systems. *Environmental Research Communications*, *5*(11), 112001. https://doi.org/10.1088/2515-7620/ad04f5

Statistisches Bundesamt (Destatis). (2020). *Regionaldatenbank Deutschland. 41141-02-02-4: Anbau auf dem Ackerland in landwirtschaftlichen Betrieben nach Fruchtarten. 2010-2020* [Dataset]. https://www.regionalstatistik.de/genesis/online?operation=table&code=41141-02-02-4&bypass=true&levelindex=1&levelid=1677842176178#abreadcrumb

Statistisches Bundesamt (Destatis). (2022a). *Fachserie 3, R 3.1.2, Bodennutzung der Betriebe (Landwirtschaftlich genutzte Flächen),*. Statistisches Bundesamt (Destatis). https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Landwirtschaft-Forstwirtschaft-Fischerei/Publikationen/Bodennutzung/landwirtschaftliche-nutzflaeche-2030312227004.pdf?__blob=publicationFile

Statistisches Bundesamt (Destatis). (2022b). *Regionaldatenbank Deutschland. 41241-01-03-4: Erträge ausgewählter Feldfrüchte—Jahressumme. 1999-2022* [Dataset]. https://www.regionalstatistik.de/genesis/online?operation=table&code=41241-01-03-4&bypass=true&levelindex=1&levelid=1677842497003#abreadcrumb

Tibshirani, R. (1996). Regression Shrinkage and Selection via the Lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, *58*(1), 267–288.

Trenczek, J., Lühr, O., Eiserbeck, L., Sandhövel, M., & Ibens, D. (2022). *Schäden der Dürre-und Hitzeextreme 2018 und 2019-eine ex-post-Analyse* [Studie im Auftrag des Bundesministeriums für Wirtschaft und Klimaschutz]. Prognos AG.

van der Wiel, K., Batelaan, T. J., & Wanders, N. (2023). Large increases of multi-year droughts in north-western Europe in a warmer climate. *Climate Dynamics*, *60*(5), 1781–1800. https://doi.org/10.1007/s00382-022-06373-3

Vogel, E., Donat, M. G., Alexander, L. V., Meinshausen, M., Ray, D. K., Karoly, D., Meinshausen, N., & Frieler, K. (2019). The effects of climate extremes on global agricultural yields. *Environmental Research Letters*, *14*(5), 054010. https://doi.org/10.1088/1748-9326/ab154b

Vogel, J., Rivoire, P., Deidda, C., Rahimi, L., Sauter, C. A., Tschumi, E., van der Wiel, K., Zhang, T., & Zscheischler, J. (2021). Identifying meteorological drivers of extreme impacts: An application to simulated crop yields. *Earth System Dynamics*, *12*(1), 151–172. https://doi.org/10.5194/esd-12-151-2021

von Buttlar, J., Zscheischler, J., Rammig, A., Sippel, S., Reichstein, M., Knohl, A., Jung, M., Menzer, O., Arain, M. A., Buchmann, N., Cescatti, A., Gianelle, D., Kiely, G., Law, B. E., Magliulo, V., Margolis, H., McCaughey, H., Merbold, L.,

https://doi.org/10.5194/egusphere-2024-2585
Preprint. Discussion started: 29 August 2024

Migliavacca, M., … Mahecha, M. D. (2018). Impacts of droughts and extreme-temperature events on gross primary production and ecosystem respiration: A systematic assessment across ecosystems and climate zones. *Biogeosciences*, *15*(5), 1293–1318. https://doi.org/10.5194/bg-15-1293-2018

Webber, H., Ewert, F., Olesen, J. E., Müller, C., Fronzek, S., Ruane, A. C., Bourgault, M., Martre, P., Ababaei, B., Bindi, M., Ferrise, R., Finger, R., Fodor, N., Gabaldón-Leal, C., Gaiser, T., Jabloun, M., Kersebaum, K.-C., Lizaso, J. I., Lorite, I. J., … Wallach, D. (2018). Diverging importance of drought stress for maize and winter wheat in Europe. *Nature Communications*, *9*(1), 4249. https://doi.org/10.1038/s41467-018-06525-2

Webber, H., Lischeid, G., Sommer, M., Finger, R., Nendel, C., Gaiser, T., & Ewert, F. (2020). No perfect storm for crop yield failure in Germany. *Environmental Research Letters*, *15*(10), 104012. https://doi.org/10.1088/1748-9326/aba2a4

Wilhite, D. A. (2000). Drought as a Natural Hazard: Concepts and Definitions. In *Drought: A Global Assessment*.

Wilhite, D. A., & Glantz, M. H. (1985). Understanding: The Drought Phenomenon: The Role of Definitions. *Water International*, *10*(3), 111–120. https://doi.org/10.1080/02508068508686328

Wimmer, S., & Sauer, J. (2020). Profitability Development and Resource Reallocation: The Case of Sugar Beet Farming in Germany. *Journal of Agricultural Economics*, *71*(3), 816–837. https://doi.org/10.1111/1477-9552.12373

Zampieri, M., Ceglar, A., Dentener, F., & Toreti, A. (2017). Wheat yield loss attributable to heat waves, drought and water excess at the global, national and subnational scales. *Environmental Research Letters*, *12*(6), 064008. https://doi.org/10.1088/1748-9326/aa723b

Zink, M., Samaniego, L., Kumar, R., Thober, S., Mai, J., Schäfer, D., & Marx, A. (2016). The German drought monitor. *Environmental Research Letters*, *11*(7), 074002. https://doi.org/10.1088/1748-9326/11/7/074002

Ziolkowska, J. R. (2016). Socio-Economic Implications of Drought in the Agricultural Sector and the State Economy. *Economies*, *4*(3), Article 3. https://doi.org/10.3390/economies4030019

Zscheischler, J., Martius, O., Westra, S., Bevacqua, E., Raymond, C., Horton, R. M., van den Hurk, B., AghaKouchak, A., Jézéquel, A., Mahecha, M. D., Maraun, D., Ramos, A. M., Ridder, N. N., Thiery, W., & Vignotto, E. (2020). A typology of compound weather and climate events. *Nature Reviews Earth & Environment*, *1*(7), 333–347. https://doi.org/10.1038/s43017-020-0060-z

Zscheischler, J., Westra, S., Hurk, B. J. J. M. V. D., Seneviratne, S. I., Ward, P. J., Pitman, A., Aghakouchak, A., Bresch, D. N., Leonard, M., Wahl, T., & Zhang, X. (2018). Future climate risk from compound events. *Nature Climate Change*, *8*(6), Article 6. https://doi.org/10.1038/s41558-018-0156-3