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Drought risk management in agriculture: A copula perspective on crop diversification

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Abstract

Drought events are a major cause of large crop yield losses with implications for food security and farmers' incomes. Growing multiple crops simultaneously during a cropping season is a well-known on-farm risk management strategy to cope with these drought risks. However, the effectiveness of this crop diversification under different severity levels of drought and how this effectiveness is influenced by the crop composition is unclear. This article provides new methodological and empirical insights to assess the effectiveness of such diversification, in particular to cope with extreme drought. We apply and evaluate nested Archimedean copulas and elliptical copulas to assess simultaneous farm-level yield losses of different cash crops in German agriculture (winter wheat, winter barley, winter rapeseed, sugar beet, and grain maize) under different drought severity levels ($N = 249{,}756$; regionally pooled farm-level crop-yield pairs, 1995–2019). We show that on-farm crop diversification contributes to cope with drought risks, but its effectiveness varies considerably across regions, crop pairs, and drought severity. Our results underline that cropping system diversification alone is often not sufficient to cope with drought risks, but that the right crop combinations are needed. For example, during a severe drought (one in 20 years event), 26.4% of farmers in eastern Germany suffered simultaneous yield losses of at least 20% in winter wheat and winter barley, while 19.1% of farmers in eastern Germany suffered simultaneous yield losses of at least 20% in winter wheat and sugar beet. Farmers should therefore be encouraged to grow crops with more diverse phenological requirements throughout the year.

KEYWORDS
agricultural risk management, copula, crop diversification, drought risk

JEL CLASSIFICATION
Q18, Q54

1 | INTRODUCTION

Extreme weather events regularly cause large yield losses affecting food security and farmers' incomes. Droughts in particular are of great and increasing importance. For example, drought events in 2003 and 2018 caused yield losses of more than 20% for a wide range of crops in many regions of Europe (Beillouin et al., 2020; Ciais et al., 2005; Schmitt et al., 2022; Webber et al., 2020). Furthermore, drought risk is becoming increasingly important due to climate change (Grillakis, 2019; Brás et al., 2021). Thus, drought risk increasingly threatens food production and the economic viability of farms, and also has major implications for industry and policy. A key strategy to cope with increasing drought risk is to diversify cropping patterns during a planting season. Not putting all the eggs in one basket and having diverse crop rotations can be a viable strategy to stabilize food production and farm incomes. However, the extent of the potential of crop diversification in the context of (extreme) drought shocks and the most promising crop combinations are not well understood. Yet, such information is needed to guide decisions made by farmers and policy makers.

In this article, we offer a new perspective to quantify the risk-reducing potential of crop diversification at the farm level by considering its potential to cope with (extreme) drought-related crop yield shocks. To this end, we use nested Archimedean copulas[1] as the main specification to explore the dependence structure between the yields of multiple crops and drought, and compare these results with estimates of elliptical copulas (Gaussian and Student-t). We use Archimedean copulas as the starting point for our analyses, as they are widely used in several real-world applications in the insurance and finance industry or in agricultural and meteorological contexts due to their simple form for analyses of higher dimensions and a variety of dependence structures (see e.g., Nelsen, 2006; Hofert & Mächler, 2011; Leng & Hall, 2019). In our approach, we nest Archimedean copulas to estimate trivariate joint dependencies to circumvent exchangeability, and we also compare the results with the exchangeable Archimedean copulas in three dimensions. The analysis of nested Archimedean copulas is implemented as a two-step procedure. More specifically, we first fit several bivariate Archimedean copulas to pooled farm-level crop yield observations (i.e., 249,756 pairs of relative crop yield deviations at the same farm and year, pooled together within predefined regions with similar soil-climate conditions) over the period 1995–2019 to investigate simultaneous crop yield losses (simultaneous deviations from the respective long-term farm-level yield means). We then extend this analysis to examine how different levels of drought severity modulate simultaneous crop yield shocks of multiple crop pairs.

Previous research has identified (nested) Archimedean copulas as a helpful method to analyze these multidimensional dependence structures of extreme weather and yield losses in a single model, as they can account for a variety of dependence structures in the extreme tails (Bokusheva et al., 2016; Goodwin & Hungerford, 2015; Okhrin et al., 2013; Ribeiro et al., 2019, 2020; Xu et al., 2010). Nested Archimedean copulas are able to express multidimensional dependence structures by implementing successive bivariate copula analyses as two-level (or multilevel) tree structures. Each of the nested Archimedean copulas for itself (Gumbel, Clayton, Frank, and Joe copulas) has a limited flexibility in analyzing tail dependencies due to its respective properties. However, the flexibility of the overall analyses is achieved by applying all of these nested Archimedean copulas to a dataset in order to cover and represent a variety of tail dependencies.

To date, copula analyses in the context of agricultural risk have predominantly considered yield data at aggregated spatial levels, such as county-level yields. The focus on high levels of aggregation (e.g., at level of states or counties) has been used to assess regional or national supply risks or probabilistic relationships between crop yield losses and weather anomalies (e.g., Gaupp et al., 2017; Madadgar et al., 2017; Du et al., 2018; Ribeiro et al., 2019, 2020). However, this analysis is not necessarily informative for farm-level risk management decisions or for policy makers aiming to achieve the goal of stable farm incomes (see e.g., Glauber et al., 2021). Yield data at higher spatial scales have different risk characteristics than at the individual farm level, such as lower variance and less negative skewness of crop yields (e.g., Finger, 2012; Marra & Schurle, 1994).[2] Therefore, the implications of these previous analyses for farm-level risk assessment and risk management decisions are limited. Furthermore, most previous weather-related copula studies focused on yield data of one or two crops, and these analyses were conducted for each crop individually. However, considering one or two crops and/or performing the copula analyses crop by crop does not realistically reflect real diversification mechanisms at farm level.

To contribute filling this gap, we analyze the risk-reducing potential of crop diversification at farm level. We quantify the interrelationship between yields of different arable crops and quantify how this natural hedge property changes in the presence of extreme drought. To this end, we use nested Archimedean copulas to examine

[1] Also known in the literature as "hierarchical Archimedean copulas."

[2] We observe similar differences between farm-level and county-level yield variation for the crops analyzed in this article (see Table S1).

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how farm-level yield losses of different crops are related to each other when drought events of different severity occur. More specifically, we model how different levels of drought severity modulate concurrent crop yield losses at farm level. We also analyze whether the effectiveness of farm-level crop diversification is influenced by regional soil/climate and cropping conditions. We use large-scale evidence from representative observed crop yield realizations from German farms (i.e., 249,756 pairs of farm-level crop yield observations), over a long period (1995–2019). We consider the most important arable crops: winter wheat, winter barley, winter rapeseed, sugar beet, and grain maize. Focusing on German crop production provides important information from an economically highly relevant case study, as Germany is the second largest cereal producer in the European Union (World Bank, 2023). We focus on drought because it has been identified as the most economically damaging weather risk in German agriculture. More specifically, most monetary losses in German agriculture are associated with crop water stress, and many crops were simultaneously affected by the severe drought events in 2018 across Germany and Europe through significant yield losses (see e.g., Beillouin et al., 2020; Webber et al., 2020; Schmitt et al., 2022).[3]

We find that crop diversification can allow to mitigate drought risk, but its effectiveness varies by crop pair and by regional growing conditions, and is often reduced when droughts are more intense. For example, in the case of a severe drought (i.e., a one in 20 years event), 26.4% of farms in eastern Germany suffer from simultaneous yield losses of ≤−20% in winter wheat and winter barley. In comparison, 19.1% of these farms experience simultaneous yield losses of ≤−20% in winter wheat and sugar beet in the case of severe drought. In western Germany, these risks are much lower, with 3.6% of farms suffering from simultaneous yield losses of ≤−20% in winter wheat and winter barley, and 1.6% of farms experiencing yield losses of ≤−20% for the combination of winter wheat and sugar beet.

Our findings can help farmers and extension services to adjust cropping programs and overall risk management to mitigate income losses due to drought.[4] In particular, it can help prioritize which crop combinations are best suited to reduce the overall impact of extreme drought. Furthermore, our results can guide improved policies, such as those related to crop insurance support and disaster payments to stabilize production and farm incomes (see e.g., Glauber et al., 2021).

The remainder of this article is structured as follows. In Section 2, we situate our analyses within the current literature on crop diversification and crop asynchrony. Section 3 describes the conceptual background. Section 4 presents the overall copula modeling workflow and robustness checks. Section 5 provides an overview of the data. In Section 6, we present the results of the descriptive data analyses, the copula estimations, the estimation of confidence intervals via parametric bootstrapping, and several robustness checks. In Section 7, we discuss our main findings. Finally, we draw conclusions for farmers' risk management, policy makers, and areas for further research.

2 | LITERATURE BACKGROUND ON CROP DIVERSIFICATION AND CROP ASYNCHRONY

The literature on crop diversification is diverse and includes perspectives on spatial arrangements or temporal sequences of different crops and varieties (see e.g., Chavas et al., 2022; Di Falco & Perrings, 2005; Smit & Skinner, 2002). Thus, crop diversification can meet multiple objectives related to, for example, biodiversity, risk reduction or soil conservation (see e.g., Lin, 2011; Mijatovic et al., 2013). However, the literature on how crop diversification contributes to production stability and risk reduction is limited (Beillouin et al., 2019). In particular, empirical results of quantitative and probabilistic analyses of simultaneous yield losses of different crops during a planting season due to extreme weather events are scarce (see e.g., Kornhuber et al., 2023). Previous studies have investigated diversification effects (e.g., due to plot rotation) on individual crop yields in drought situations (see e.g., Gaudin et al., 2015; Bowles et al., 2020), instead of analyzing the simultaneous yield effects of different crops due to drought.

From a risk management perspective, the main underlying mechanism of crop diversification is the portfolio effect (Markowitz, 1952, 2010), which describes that yield deviations of different crops (e.g., on the same farm) are not perfectly correlated (see e.g., Di Falco & Chavas, 2009; Barkley et al., 2010; Paut et al., 2019, 2020).[5] One of the

[3] The following analyses can easily be adapted to any type of (extreme) weather event. The focus on drought in this article does not mean that drought is the only threat to German farmers. However, it is the extreme weather event with the highest monetary impact on German agriculture (Schmitt et al., 2022).

[4] In our analyses, we exclude the price risk, because (German) farmers have the option to manage price risk through the availability of futures contracts (see e.g., Anastassiadis et al., 2014; Bucheli et al., 2022). Thus, (German) farmers have the possibility to control the price risk, but production risk remains as the main source of income volatility.

[5] The regional portfolio effect, which considers yield deviations of the same crop in different regions, is out of scope of this article, but has been discussed and analyzed through copulas in several studies (see e.g., Larsen et al., 2013; Goodwin, 2015; Gaupp et al., 2017; Chavas et al., 2022).

reason for this imperfect correlations is that suboptimal weather conditions for one crop may be less relevant or even beneficial for another crop. For example, winter wheat and sugar beet "consume" different amounts of water on the same day of the year due to temporally different phenological phases and different total crop-specific daily water requirements, leading to different daily drought susceptibility over the course of the year. However, it is not clear whether and how this mechanism may be modulated by the severity of an "external" risk factor. This is particularly relevant for systemic and long-lasting weather shocks such as droughts (Gupta et al., 2020; Kuwayama et al., 2019). More specifically, an extreme and prolonged drought may affect important growing phases of different crops during a planting season, even if these growing phases do not overlap or only partially overlap.

In addition, the concept of crop (a)synchrony describes that the crop combination is important in crop diversification as a risk management tool (Egli et al., 2020; Mehrabi & Ramankutty, 2019). It implies that different crops have temporally different growth patterns, phenological phases, and vulnerability to different risk factors throughout the year. Commonly used crop diversification indices, such as the Shannon index or Margalef index, do not take into account the above-mentioned characteristics of crop (a)synchrony, as they only consider the absolute number of crops, and cannot provide information on how the effectiveness of crop diversification changes when the severity of a risk factor, such as drought, varies. Therefore, we use copula analyses to shed light on the influence of crop composition and drought severity level on the effectiveness of crop diversification as a risk management instrument.

3 | CONCEPTUAL BACKGROUND

The nested Archimedean copula approach presented here serves as a method for analyzing non-linear dependency structures that is able to capture different types of tail dependencies. A copula is a function that links marginal distribution functions to form their joint distribution (Nelsen, 2003). Sklar's theorem (1959) decomposes a multivariate probability distribution into (1) its marginal distributions and (2) a copula describing the dependence structure between the margins. For the bivariate case, the joint distribution function of any continuous pair of random variables can be written as:

$$F_{X,Y}\ (x, y) = C_{X,Y}\ (u_X,\ u_Y) \tag{1}$$

where $u_X = F_X(x)$ and $u_Y = F_Y(y)$ are marginal probability distributions uniformly distributed in the interval [0,1] and $C_{X,Y}$ is the bivariate copula. Here, $C_{X,Y}$ describes the dependence structure between pairs of crops (i.e., the pooled farm level yield deviations within an agricultural production region of crop X from their corresponding long-term farm level means and the pooled farm level yield deviations within an agricultural production region of crop Y from their corresponding long-term farm level means). $C_{X,Y}$ is uniquely defined if $F_X(x)$ and $F_Y(y)$ are continuous (see also Durante & Sempi, 2016; Nelsen, 2006; Salvadori & De Michele, 2007).

To model the trivariate dependence, we subsequently consider the cumulative rainfall deviation CR ($u_{CR} = F_{CR}(cr)$). We non-parametrically transform the margins to uniform variables through their cumulative distribution functions. The trivariate distribution is expressed as:

$$F_{X,Y,CR}\ (x,\ y,\ cr) = C_{X,Y,CR}\ (u_X,\ u_Y,\ u_{CR}). \tag{2}$$

The nested Archimedean copulas used here consist of successive bivariate copulas which are implemented as a tree structure:

$$C\ (u_X,\ u_Y,\ u_{CR};\ \theta_{12}, \theta_1) = C_{X,Y,CR}\ \left(C_{X,Y}\left(u_X, u_Y;\ \theta_{12}\right), u_{CR}; \theta_1\right) \tag{3a}$$

$$C\ (u_X,\ u_Y,\ u_{CR};\ \theta_{13}, \theta_2) = C_{X,CR,Y}\ \left(C_{X,CR}\left(u_X, u_{CR};\ \theta_{13}\right), u_Y; \theta_2\right) \tag{3b}$$

$$C\ (u_X,\ u_Y,\ u_{CR};\ \theta_{23}, \theta_3) = C_{Y,CR,X}\ \left(C_{Y,CR}\left(u_Y, u_{CR};\ \theta_{23}\right), u_X; \theta_3\right) \tag{3c}$$

where θ_{12}, θ_{13}, and θ_{23} are the generators of the inner copula (either crop-crop Equation (3a) or crop-rainfall Equations (3b, 3c)) and θ_1, θ_2, and θ_3 are the generators of the outer copula joining the third margin (either rainfall Equation (3a) or second crop Equations (3b, 3c)). In our analysis, the structures of nested Archimedean copulas require the inner copula to correspond to the pair with the strongest dependence, that is, $\theta_{12} > \theta_1$. In the following methodological description, we refer exemplarily to the case of Equation (3a) with the strongest crop-crop dependence (see more details in Section 4.2), as it illustrates the predominant dependence structure of our analyses.

Using nested Archimedean copulas, we model the probabilities of yield losses of two different crops on a farm simultaneously conditional on different severity levels of drought, which are expressed through relative rainfall

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deviations at the municipality level (Equation 4):

$$F_{X,\,Y|CR}\ (x,\ y|CR\ \le\ cr) = P(X \le x,\ Y \le y \mid CR \le cr). \tag{4}$$

We pool the farm-level yield and corresponding cumulative rainfall data into sub-samples based on the four main production regions of Germany in order to account for regional characteristics such as soil/climate conditions or farm structures (see more details in Section 5).

We choose nested Archimedean copulas in our analyses, because they represent a good compromise between the complexity of analyzing trivariate dependence, but also allow an understandable interpretation of our research question, how drought modulates the dependence of yield losses of different crops. Following Okhrin et al. (2017), we implement here the estimation of nested Archimedean copulas, assuming that all generators in different hierarchy levels belong to the same family. Although nested Archimedean copulas do not allow for different dependence families in each hierarchy level, they do allow for different values of theta (from the same generator family).[6]

4 | EMPIRICAL IMPLEMENTATION

4.1 | Goodness-of-fit testing

We implement a comprehensive goodness-of-fit testing to decide which copula family best fits the underlying dependence structure of our data. We start by estimating the copula generators (Gumbel, Clayton, Frank, and Joe copulas) and the corresponding Akaike's Information Criterion (AIC) of all bivariate combinations (shown exemplarily for the East German subsamples in Tables S7–S10).

We then take the bivariate copula with the lowest AIC and strongest dependence (e.g., winter wheat and winter barley yield deviation) and estimate the nested trivariate copula(s) by adding the remaining variable (cumulative rainfall deviation) to the previously selected bivariate copula (see Tables S11–S14). Additionally, we estimate the trivariate copula with one parameter (Tables S11–S14: $C(u_1,u_2,u_3;\ \theta)$). The AIC of the nested trivariate copula (two parameters) and the trivariate copula with one parameter are compared. Finally, we implement an additional "graphical goodness-of-fit analysis".

Based on the selection process described above, the nested Clayton copula is selected for the analysis.[7] The results of the Frank copula are shown in the supplementary material for comparison (see Figures S10–S14), which represents a symmetric and non-increasing tail dependence.

4.2 | Implementation of nested Clayton copula

After the copula selection, we mathematically derive the probabilities of simultaneous yield losses at farm level based on Equation (5):

$$\text{Clayton copula:}\ \ C\,(u_X,\ u_Y;\ \theta) = \left(u_X{}^{-\theta} + u_Y{}^{-\theta} - 1\right)^{\frac{-1}{\theta}} \tag{5}$$

where u_X and u_Y are uniform in the interval [0,1] and theta θ is the respective coefficient of the bivariate Clayton copula (see Nelsen, 2006).[8] The trivariate extension of Equation (5) can be expressed in terms of a nested structure for a stronger crop–crop dependence via Equation (6):

$$\begin{aligned} &C\ (u_X,\ u_Y,\ u_{CR};\ \theta_{12},\theta_1) \\ &\quad = C_{X,Y,CR}\ \left(C_{X,Y}\,(u_X, u_Y;\ \theta_{12})\,, u_{CR}; \theta_1\right) \\ &\quad = \left(\left(\left(u_X^{-\theta_{12}} + u_Y{}^{-\theta_{12}} - 1\right)^{\frac{-1}{\theta_{12}}}\right)^{-\theta_1} + u_{CR}{}^{-\theta_1} - 1\right)^{\frac{-1}{\theta_1}} \end{aligned} \tag{6}$$

where θ_{12} is the parameter of the inner copula considering the pair with the strongest dependence and θ_1 is the parameter of the outer copula that joins the third margin.[9]

Subsequently, we calculate the probabilities of simultaneous yield losses conditional on different drought levels using Equation (7) (obtained on the basis of Equations 4–6) and estimate confidence intervals by repeated sampling (10,000 times) of the fitted model with the number of observations of each crop pair specific sample size (see

[6] For dimensions higher than three, vine copulas may provide an alternative, as they allow for more complex structures with other families (see, for example, Gaupp et al., 2017).

[7] Note that while the Clayton copula can represent (increasing) dependencies in the lower tail (suggesting increasing probabilities of joint crop yield losses), the Frank copula captures symmetric dependencies in a manner similar to the Gaussian copula (suggesting equal dependencies of negative and positive joint yield deviations of different crops). In contrast, the Gumbel copula represents an increasing dependence in the upper tail and no increasing dependence in the lower tail.

[8] Each copula-specific coefficient theta θ has a different relation to the Kendall's tau correlation. For instance, the relationship for the Clayton copula coefficient θ to Kendall's tau correlation is $\tau = \theta\ /\ (\theta{+}2)$.

[9] In the case of a stronger crop-rainfall dependence, Equation (6) is modified by switching the position of u_Y and u_{CR}.

Ribeiro et al., 2020).[10]

$$P(X \le x,\ Y \le y \mid CR \le cr) = \frac{P(X \le x \cap Y \le y \cap CR \le cr)}{P(CR \le cr)}$$

$$= \frac{\left(\left(\left(u_X{}^{-\theta_{12}} + u_Y{}^{-\theta_{12}} - 1\right)^{\frac{-1}{\theta_{12}}}\right)^{-\theta_1} + u_{CR}{}^{-\theta_1} - 1\right)^{\frac{-1}{\theta_1}}}{cumulative\ rainfall\ percentile\,(s)} \tag{7}$$

4.3 | Robustness checks

We perform six robustness checks. First, we compare the results of the Clayton copula estimates with the Gaussian and Student-t copulas, which represent the family of elliptical copulas. Second, we use different time windows for the definition of the drought variable (see Section 5 for more details). This allows us to see whether the results are stable across different periods of drought. Third, we exclude farms that have irrigation in order to eliminate any influence of irrigation on our results. Fourth, we aggregate the four production regions to the national sample. This shows how the results presented here are affected by a spatial extension of the analyses. Fifth, we implement a temporal subdivision of the German-wide samples into the timeframes 1995–2006 and 2007–2019 to analyze whether the dependence structures have changed considerably over time. Sixth, we exclude winter wheat to investigate the diversification effect of other crop combinations.

Our analyses were conducted in SAS and R and the code is available in the supplementary material (R Core Team, 2022).[11]

5 | DATA AND CASE STUDY

Our yield data come from the German Farm Accountancy Data Network (see e.g., BMEL, 2020).[12] We use farm level crop yields for the years 1995–2019 for winter wheat, winter barley, winter rapeseed, sugar beet, and grain maize. A key feature of our data is that we know the location of the farm, which allows for matching with local weather information.[13] Through coherent and consistent data collection, the German Farm Accountancy Data Network ensures that we can compare yields across farms, crops, and years. These crops were chosen because they are the most important cash crops in German agriculture and cover more than 50% of the total arable farm land (Statistisches Bundesamt, 2022).[14]

As a prerequisite, we only consider farms with at least 11 observations for each crop in the period considered in order to obtain meaningful yield averages at farm level.[15] Furthermore, we apply the analyses "only" to farms that were under conventional (non-organic) management during the observation period in order to achieve a high homogeneity of expected yields and yield trends across farms within a production region.[16] We use the outlier robust M-estimator to linearly detrend the historical yield data to account for technological progress (see Figure S1.1 and S1.2; Bucheli et al., 2021; Finger, 2013). In total, we analyze 249,756 pairs of crop yields at the farm level. We pool the farm-level data and corresponding cumulative rainfall information into regional subsamples that have similar soil/climate conditions and production systems in terms of farm structures such as plot size. To do this, we implement a spatial subdivision based on the four main production regions North, East, West, and South as defined by the Julius Kuehn Institute, which takes into account the soil-climate regions of Germany and expert knowledge for the regional aggregation (JKI, 2009) (see Figure A1). We further define crop failure as ≤−20% deviation from the long-term average yield at farm level, which is also the threshold for yield failure used for public support programs in the EU (European Union, 2021). To illustrate

[10] Uncertainties are derived by counting exceedances of thresholds based on repeated sampling (10,000 times) of the fitted model with sample size N equal to the number of crop-pair specific observations. From these samples (10,000 × N), we calculate standard deviations at each drought level. Using the crop-pair specific sample sizes' number of observations emphasizes that the uncertainties are also influenced by the sample size number.

[11] For the bivariate and trivariate copula modeling, we use the R packages "*copula*" (Kojadinovic & Yan, 2010), "*VineCopula*" (Nagler et al., 2020), and "*HAC*" (Okhrin & Ristig, 2014). The "HAC" package uses Maximum Likelihood to estimate the copula coefficients and determines the structure of the nested Archimedean copulas.

[12] The German Farm Accountancy Data Network contributes to the Farm Accountancy Data Network of the European Union. The data of the German Farm Accountancy Data Network are available according to the regulations of the German Ministry of Food and Agriculture (see section 10 of Supplementary Material).

[13] We note that the dataset does not contain information on the spatial structure of crop cultivation within a farm. Therefore, we cannot account for a spatial influence on the effectiveness of diversification. More specifically, the portfolio effect could be different depending on the spatial structure of crop cultivation, if the cultivation of crop A on plot X affects the drought susceptibility of crop B on neighboring plot Y, or if crop A and crop B are cultivated together on plot Z.

[14] The comprehensive Farm Accountancy Data Network has some limitations that are relevant to the analyses presented here. For example, irrigation at farm level is expressed as the total area irrigated per year and cannot be allocated to a specific crop. However, as <5% of the utilized agricultural area in Germany was irrigated in the past, irrigation is of rather minor importance.

[15] We consider the annual farm observations only if both crops are grown in a given year.

[16] The average observations at farm level in Germany for the crop pairs are: winter wheat & winter barley $n = 18.5$, winter wheat & winter barley $n = 17.8$, winter wheat & sugar beet $n = 18.4$ and winter wheat & grain maize $n = 16.8$.

TABLE 1 Summary statistics of the relative detrended yield deviations at farm level and relative cumulative rainfall deviations at municipality level.

	Observations	SD (%)	Min (%)	1st Quantile (%)	3rd Quantile (%)	Max (%)
Winter wheat yield		17.6	−100	−9.4	9.3	186.3
Winter barley yield	81,049	19.8	−100	−10.2	10.4	172.2
Cumulative rainfall April 1st to June 30th		25.0	−56.9	−17.6	13.4	147.8
Winter wheat yield		17.7	−98.8	−9.7	9.9	185.1
Winter rapeseed yield	51,411	24.8	−100	−14.4	15.5	169.3
Cumulative rainfall April 1st to June 30th		26.0	−55.6	−18.3	13.3	145.3
Winter wheat yield		17.4	−100	−9.7	9.7	120.6
Sugar beet yield	35,331	22.5	−100	−12.3	13.2	176.3
Cumulative rainfall April 1st to June 30th		25.4	−55.2	−17.4	12.3	145.3
Winter wheat yield		18.0	−91.3	−9.5	9.2	121.6
Grain maize yield	9,467	25.3	−100	−12.3	14.3	167.4
Cumulative rainfall April 1st to June 30th		23.9	−54.3	−16.8	13.1	139.0

Note: (1) The means of all variable are equal to zero. (2) The summary statistics of the varying time-windows of cumulative rainfall for the robustness checks are presented in Table S2 and the summary statistics of the initial data (in absolute terms; before detrending) are illustrated in Tables S3–S6.

the diversification effect in the main text, we consider crop pairs of winter wheat with another crop (winter barley, winter rapeseed, sugar beet, and grain maize), as winter wheat is the most important cash crop in Germany. The results of the remaining crop pairs (e.g., winter barley + winter rapeseed; sugar beet + grain maize) are presented in the supplementary material as part of the robustness checks.

We use weather data on daily precipitation provided by the German Weather Service (DWD) as 1 × 1 km grid, which we aggregate to the municipality level (DWD, 2021). The information on the municipality of each farm allows us to match the farm yield data with the rainfall information. We proxy drought shocks by cumulative rainfall during a predefined period critical for crop yields and derive the percentage deviation from the long-term municipality mean (see Figure S2, Table 1 and Tables S2–S6). Specifically, we set a common timeframe for the drought variable for all crops, as we need a "common denominator" across all crops to operationalize the weather variable for the copula estimation and the subsequent comparison of the crop-pair specific results. As all crops analyzed have important phenological growth phases from 1st of April to 30th of June, we focus on these three months in the main specification. We express different severity levels of drought by the 2nd, 5th, 10th, and 20th percentiles of the percentage deviation of cumulative rainfall from the respective long-term municipality mean. This allows us to estimate the situation of an extreme drought (2nd percentile—one in 50 years event), severe drought (5th percentile—one in 20 years event), strong drought (10th percentile—one in 10 years event), and moderate drought (20th percentile—one in 5 years event).[17]

6 | RESULTS

The results are presented in five parts. First, we examine descriptively the bivariate relationship between farm-level crop yield deviations and cumulative rainfall deviations. Second, we present the copula results on the probabilities of simultaneous yield losses. Third, we analyze how the probabilities of simultaneous yield losses change under different drought conditions. Fourth, we compare the results across regional subsamples. Fifth, we present the results of robustness checks, including the comparison with elliptical copulas.

[17] In the robustness checks, we varied the time window for cumulative rainfall to the time windows "1st of March–30th of June" and "1st of March–31st of July".

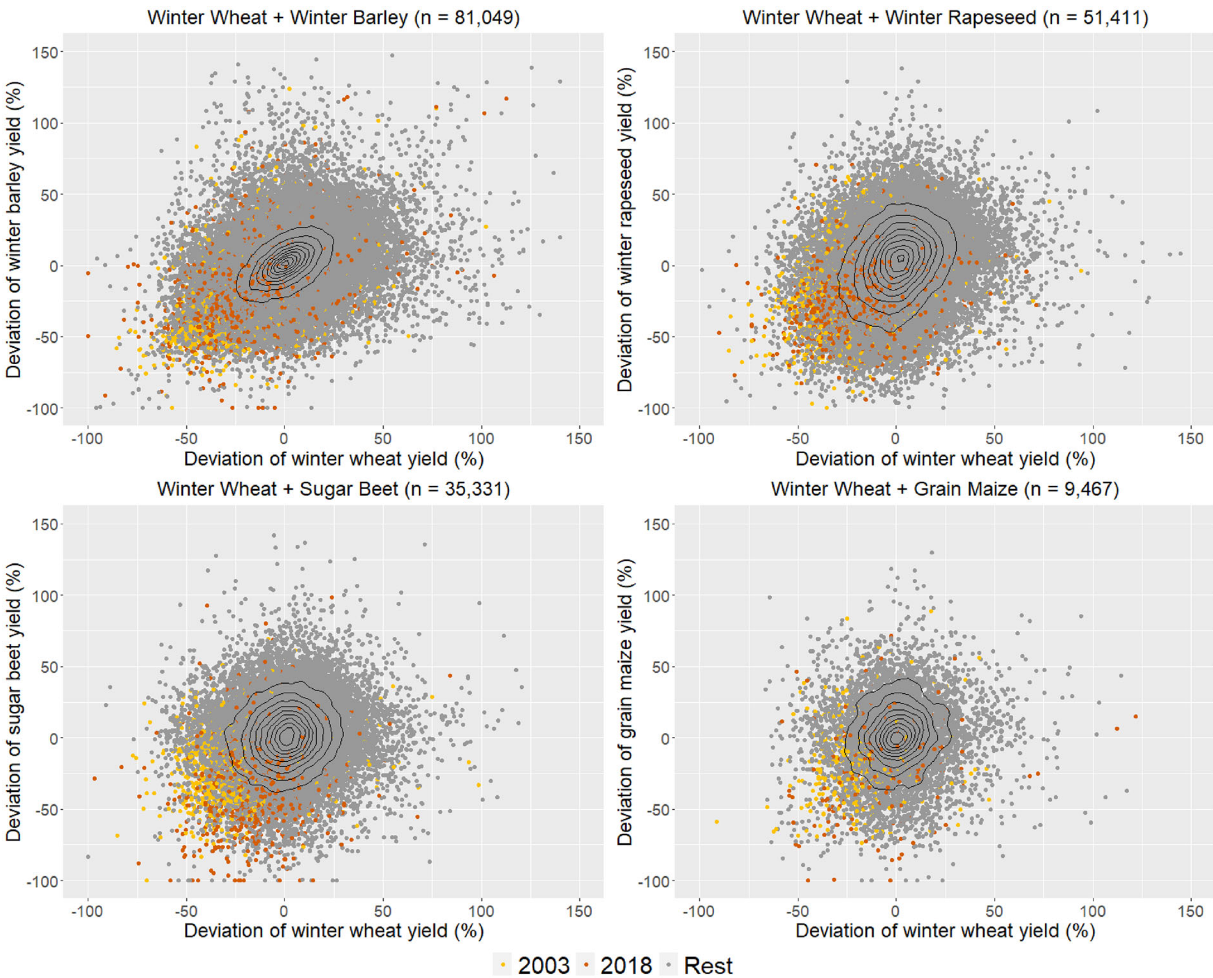

FIGURE 1 Simultaneous deviations of detrended yields of winter wheat, winter barley, winter rapeseed, sugar beet and grain maize (in %) between 1995 and 2019, expressed as the deviation from the detrended average yield at farm level (with ten bins).

Note: (1) The observations of the years 2003 and 2018 are highlighted as examples. (2) Figure 1 only includes farms with at least 11 yield observations of the respective crop in each analyzed combination (sample of the whole of Germany).

6.1 | Pairwise relation of crop yields and cumulative rainfall

The descriptive data analyses start with observations of yield deviations from the long-term mean at farm level (Figure 1: crop–crop) and cumulative rainfall deviations (Figure 2: crop–cumulative rainfall), which are also the basis for our copula analyses.[18] In addition, we highlight the observations from the years 2003 and 2018, when Germany experienced severe droughts that even led to disaster payments from the government (BMEL, 2018).[19] Highlighting these 2 years gives an indication of how farm-level yield deviations of different crops are correlated to each other in a drought year.

In Figure 1, the correlation of negative yield deviations between winter wheat and winter barley is particularly strong (upper left plot), whereas the correlation of negative yield deviations between winter wheat and grain maize is comparatively lower (lower right plot). We can also see that in about 70% of the observation pairs (area within the inner 7 bins) the negative yield deviation from the long-term farm level yield mean of at least one of two analyzed crops does not fall below −20% in a harvest season. However, many farms experienced that the yield deviations of both crops considered simultaneously fell below −20% in years such as 2003 (yellow dots) and 2018 (orange dots), as illustrated by the accumulation of orange and yellow dots in the bottom left-hand corner of all four plots.

Figure 2 shows the simultaneous anomalies of detrended crop yields at farm level and the corresponding cumulative rainfall. In the year 2003, negative deviations

[18] Further descriptive statistics of the (initial) yield data and cumulative rainfall are illustrated in Figures S1.1, S1.2, S2, in Table 1 and in Tables S2–S6.

[19] See Figure A2 for the spatial distribution of drought in Germany in 2003 and 2018.

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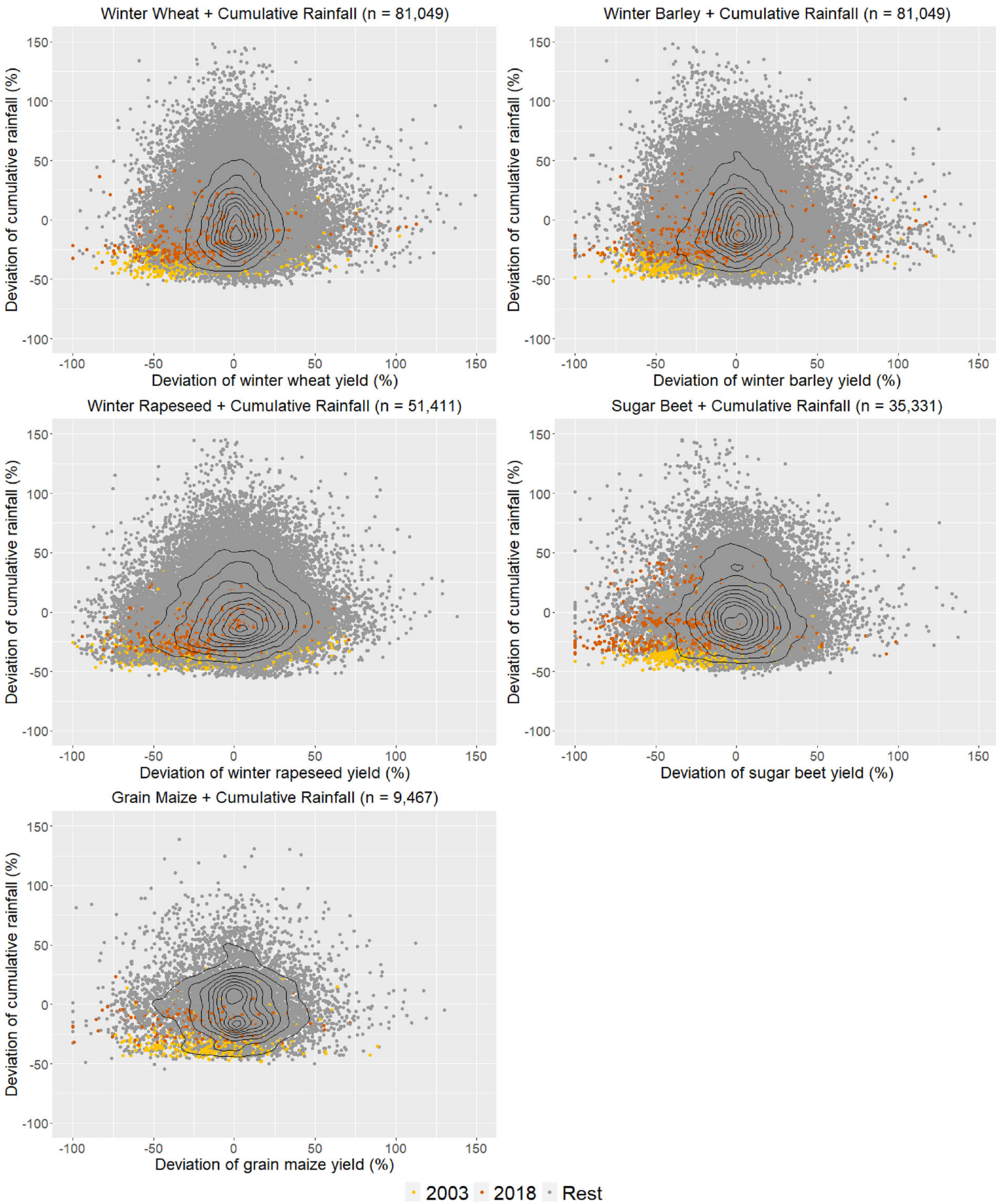

FIGURE 2 Deviations of detrended yields and of cumulative rainfall during the period April 1st to June 30th between 1995 and 2019 (with 10 bins).

Note: (1) The observations of the years 2003 and 2018 are highlighted as examples. (2) Figure 2 only includes farms with at least 11 yield observations of the respective crops in each analyzed combination (sample of the whole of Germany).

of yields and of cumulative rainfall are highly correlated for winter wheat, winter barley, and grain maize. In 2018, however, negative deviations of cumulative rainfall were not as strong as negative deviations of yields. This suggests that there are additional determinants influencing the occurrence of large yield losses under drought (e.g., additional weather anomalies, pests, and diseases) that are beyond the scope of the present study (e.g., Iglesias et al., 2012; Ribeiro et al., 2020; Haqiqi et al., 2021). Furthermore, Figure 2 shows that many farms experienced quite similar relative rainfall deficits, but significantly different levels of yield losses, as indicated by the horizontal structure of the points (particularly strong in the case of sugar beet for the year 2018). An important determinant of this structure may be the different soil/climate conditions in the four main production regions of German agriculture, which underlines the importance of regionally differentiated analyses. More specifically, farms across Germany appear to have different exposure to drought risk. This may be due to different precipitation patterns (see Figure A2) and to different water storage capacities of soils in the different German regions.

As summary statistics of Figures 1 and 2, we provide the relative deviations of farm-level yields and relative deviations of cumulative rainfall for the period April 1st to June 30th in Table 1.

6.2 | Probabilities of concurrent yield losses

The contour plots in Figure 3 illustrate the bivariate Clayton copula joint distributions of farm level yield deviations in the East German sub-sample. The stronger the asymmetry of the bivariate relationship, the higher is the Clayton dependence. We observe that simultaneous yield deviations in the case of winter wheat & winter barley are concentrated in the lower left corner, suggesting greater probabilities of joint lower extremes (simultaneous crop yield losses). In contrast, the correlation between winter wheat and winter barley is less strong in the "gain" region, that is, for above-average yields. Compared to winter wheat & winter barley, the contour plots of the crop pairs winter wheat & sugar beet and winter wheat & grain maize do not show such pronounced negative tails.

The probability of simultaneous yield losses (exceeding a given threshold) can be calculated using the estimated copula parameters (see Equation 5). For example, to estimate the probability that winter wheat and winter barley simultaneously experience ≤−20% yield losses for the East German sub-sample (see Figure 3, upper left plot), we translate the threshold value into the percentile of the respective empirical cumulative distribution function. In the case of winter wheat, the −20% corresponds to .1306 and in the case of winter barley, the −20% corresponds to .1635. The two derived percentile values and the bivariate Clayton copula coefficient (see Figure 3 upper left plot) can now be inserted into Equation (8):

$$(.1306^{-.71} + .1635^{-.71} - 1)^{\left(\frac{-1}{.71}\right)} = .066 \qquad (8)$$

Thus, the estimated probability of simultaneous yield losses of ≤−20% for winter wheat and winter barley in East Germany, based on the bivariate Clayton copula, is 6.6%. This means that the farm-level risk of a yield loss of ≤−20% is crop-individually equal to 13.1% for winter wheat and equal to 16.4% for winter barley, but the risk of a farm experiencing such a loss at the same time is only 6.6%. In comparison, the estimated probability of simultaneous yield losses of ≤−20% for winter wheat + winter rapeseed is 5.9%, the estimated probability of simultaneous yield losses of ≤−20% for winter wheat + sugar beet is 4.5% and for winter wheat + grain maize is 4.3%.[20]

6.3 | Probabilities of concurrent yield losses conditional on drought

Beyond the descriptive analyses and the bivariate Clayton copula dependence, we now present the estimated copula coefficients for the trivariate relationship by additionally considering the role of drought on simultaneous yield deviations of two crops. For the demonstration of the different copula procedures, we focus on the sub-sample of East Germany, as this region has been particularly vulnerable to drought in the past (see e.g., Webber et al., 2020; Schmitt et al., 2022).

Figure 4 shows the nested Clayton copula tree structure and the estimated theta coefficients (θ). In the case of winter wheat & winter barley and winter wheat & winter rapeseed, we observe that the crop-crop pairs show stronger dependence than the crop-rainfall pairs (Figure 4: upper left and upper right plots). For example, the strongest dependence structure applies to the crop pair of winter wheat & winter barley (θ = .71). Furthermore, the coefficients for estimating the nested trivariate copula, which takes into account the additional influence of drought on the probability of simultaneous crop yield losses, are θ = .32 for winter wheat & winter barley and θ = .31 for winter wheat & winter rapeseed.

For the crop pairs winter wheat & sugar beet and winter wheat & grain maize a different dependence structure is observed. More specifically, in both cases, winter wheat yield deviations have a stronger dependence on the rain-

[20] The regional percentiles expressing the −20% yield deviations for each crop are shown in Table A1.

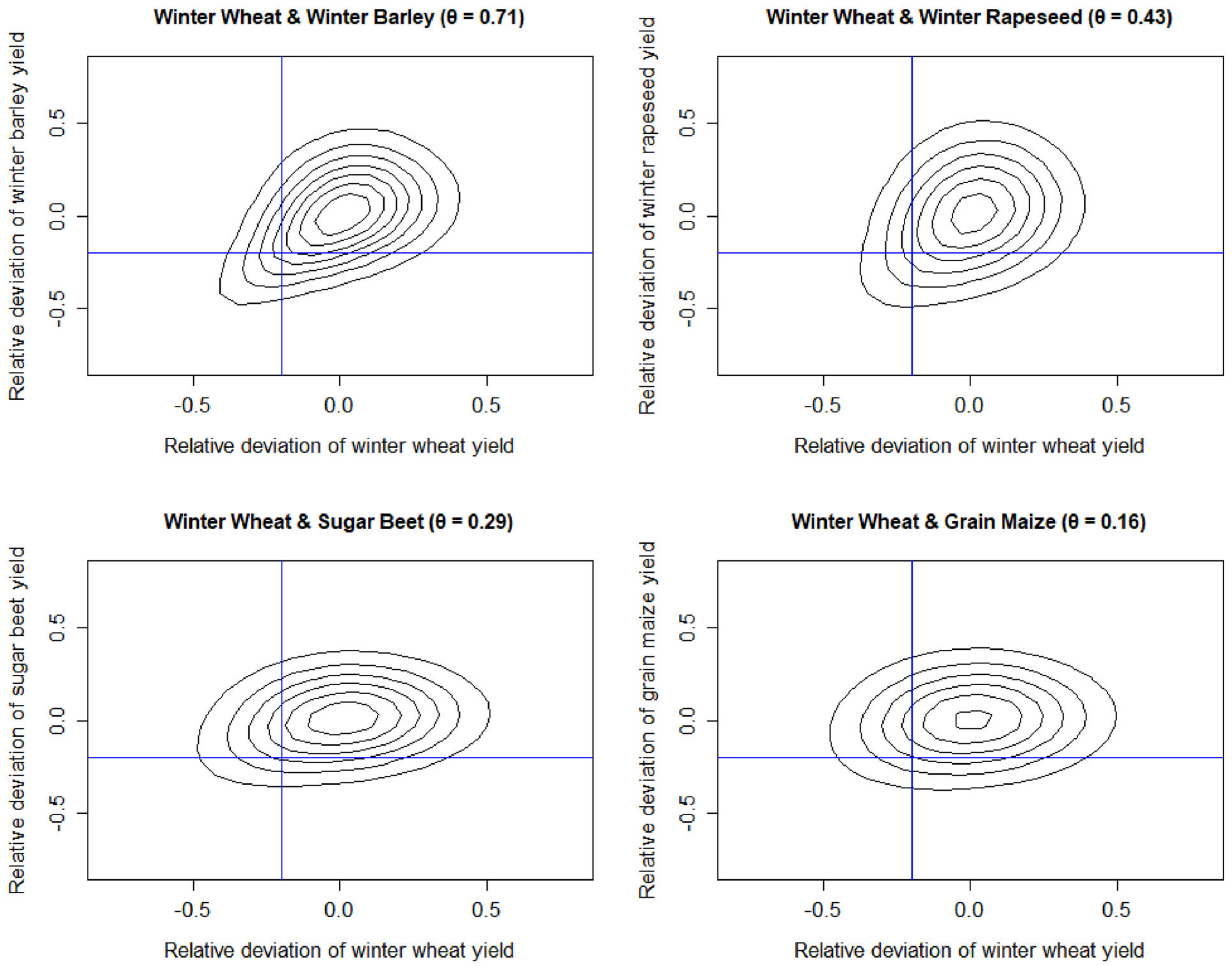

FIGURE 3 Sub-sample of Eastern Germany—contour plots of estimated bivariate Clayton copulas for exemplary crop pairs illustrating the dependence structure between the analyzed cash crop yield deviations.

Note: Yield deviations corresponding to −20% are highlighted as blue lines.

fall deviation ($\theta = .32$ in lower left plot and $\theta = .37$ in lower right plot) than on the other crop. The additional coefficients considering the dependence with the second crop are slightly lower with $\theta = .26$ in the case of sugar beet and $\theta = .2$ in the case of grain maize.[21]

In the following, we calculate the joint probability of simultaneous yield losses conditional on different levels of drought in the East German sub-sample by combining it with the cumulative rainfall deviations (and Figure 4) and illustrate the probabilities in Figure 5 (red lines). For the case of moderate drought (one in 5 years event – 20th percentile) and the crop pair winter wheat & winter barley, we use Equations (7) and (8) to obtain Equation (9):

$$\frac{\left(.066^{-.32} + .2^{-.32} - 1\right)^{\left(\frac{-1}{.32}\right)}}{.2} = .152 \tag{9}$$

Thus, for a moderate drought (one in 5 years event) in eastern Germany, the probability of simultaneous yield losses for winter wheat and winter barley is about 15.2%. In the case of a severe drought (one in 20 years event – 5th percentile), the probability increases to about 26.4% based on the calculation in Equation (10):

$$\frac{\left(.066^{-.32} + .05^{-.32} - 1\right)^{\left(\frac{-1}{.32}\right)}}{.05} = .264 \tag{10}$$

In the same way, we can calculate the probabilities of simultaneous yield losses for the crop pair winter wheat & winter rapeseed. For instance, during a moderate drought (one in 5 years event), the probability of simultaneous yield

[21] Combining the Clayton copula parameters of Figure 4 (and Figures A3–A6 for the remaining regional sub-samples and the samples for the whole of Germany) and the regional- and crop-specific percentiles of the −20% yield deviations in Table A1, it is possible to reproduce all the main Clayton copula results of this article by following the working steps of Equations (5)–(7) (for the strongest bivariate dependence of crop-crop) or Equations (A1)–(A4) in the Appendix (for the strongest bivariate dependence of crop-rainfall).

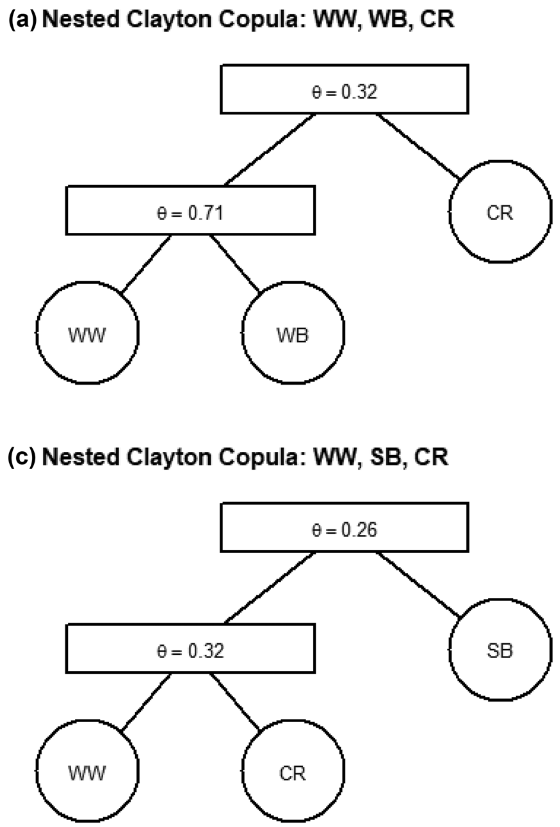

FIGURE 4 Sub-sample of East Germany—structure of nested Clayton copulas to model the probabilities of simultaneous crop yield losses at the farm level, conditional on cumulative rainfall deviations.

Note: (1) WW, winter wheat yield deviation; WB, winter barley yield deviation; WR, winter rapeseed yield deviation; SB, sugar beet yield deviation; GM, grain maize yield deviation; CR, cumulative rainfall deviation.

losses for winter wheat and winter rapeseed is 13.7%, rising to 24.1% during a severe drought.

Under moderate drought conditions, 10.4% of the farms observe simultaneous yield losses of winter wheat and sugar beet, and this value changes to 19.1% under severe drought conditions. Finally, if we compare the situation under moderate and severe drought conditions for the crop pair winter wheat + grain maize, we observe an increase from 11.3% to 20.3%.[22]

The uncertainties associated with the statistical modeling are quantified by the corresponding confidence intervals for the probabilities estimated above, generated by repeated sampling (10,000 times) of the fitted model with sample sizes equal to the number of observations. In Figure 5, we observe that the confidence intervals around the red lines become larger in the left part of each plot, reflecting the higher uncertainty due to the decreasing number of observations in the tails. As a graphical robustness check, we plot the probabilities based on the observations obtained by counting exceedances (Figure 5, green line). We observe that most of the probabilities based on the observations for the sub-sample of East Germany (green lines) are within the 99% confidence intervals of the Clayton copula estimates. Furthermore, we illustrate the probability by counting the exceedances of single crop yield losses of $\leq -20\%$ for winter wheat (blue lines) and the second crop of each plot (purple line: winter barley, winter rapeseed, sugar beet or grain maize) conditional on different drought severities. For the sub-sample of eastern Germany, we observe for all crop pairs that the gaps between the probabilities of single crop yield failures (blue and purple lines) and the (estimated) probabilities of simultaneous failures of two crops (red and green lines) become smaller as drought events become more severe.

6.4 | Regional comparison of drought susceptibility

Figure 6 illustrates the results for the spatial sub-sample of West Germany. In the case of winter wheat and winter barley, the probability of simultaneous yield losses

[22] Considering the stronger dependence of winter wheat on the cumulative rainfall deviation in the case of the crop pairs winter wheat & sugar beet and winter wheat & grain maize in the sub-sample of East Germany, the calculations follow in principle the same steps (see Appendix, Equations A1–A4).

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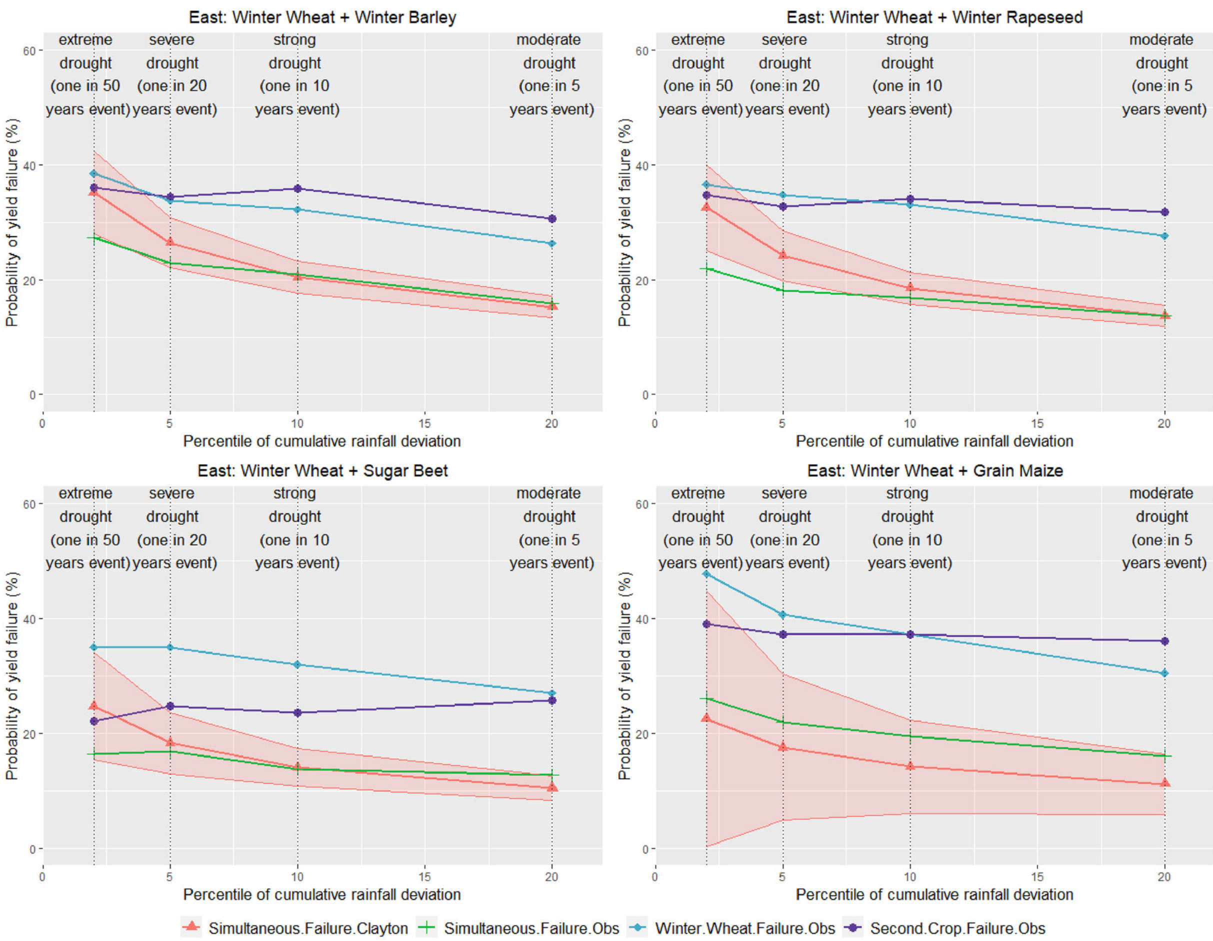

FIGURE 5 Sub-sample of Eastern Germany—probabilities of simultaneous yield losses under different drought levels based on the nested Clayton copula estimates compared to the (single crop) observations.

Note: (1) Absolute numbers of observations are presented in Tables S15–S18. (2) The 99% confidence intervals are derived from repeated sampling (10,000 times) of the fitted model with sample sizes equal to the number of observations.

under moderate drought conditions is 3.6% based on the nested Clayton copula estimation, and this value does not increase under severe drought conditions. We also observe no increase in probability for the crop pairs winter wheat & sugar beet (1.6%) and winter wheat & grain maize (2.8%). Only in the case of winter wheat & winter rapeseed does the probability of simultaneous yield losses increase slightly from 4.1% during moderate drought to 5.3% during severe drought. Furthermore, the difference between the probabilities of single-crop and multi-crop yield losses does not decrease significantly with the severity of the drought in western Germany.

The results of the Clayton copula estimation of the spatial sub-sample of Northern Germany (Figure A7) show quite similar results as in the case of Western Germany, as we do not observe a considerable increase in the risk of simultaneous yield losses when drought events become more severe. However, the overall level of risk in northern Germany is slightly higher than in western Germany. For example, in the case of a severe drought, the estimated risk of simultaneous yield losses of winter wheat & winter barley is 6.9% and the risk of simultaneous yield losses of winter wheat & sugar beet is 3.8%.

In southern Germany (Figure A8), there is a considerable increase in the estimated probabilities of simultaneous yield losses for the crop pairs winter wheat & winter barley (moderate drought: 9.4%; severe drought: 15.4%) and winter wheat & winter rapeseed (moderate drought: 10.2%; severe drought: 19.4%). There are also slight increases in the estimated probabilities of simultaneous yield losses for the combination of winter wheat & sugar beet (moderate drought: 5.3%; severe drought: 8.8%) and winter wheat & grain maize (moderate drought: 4.0%; severe drought: 5.2%).

In summary, the risk of simultaneous yield losses at farm level is significantly influenced by regional growing conditions and by the severity of the drought event. This is in line with the results of other studies such as Webber et al.

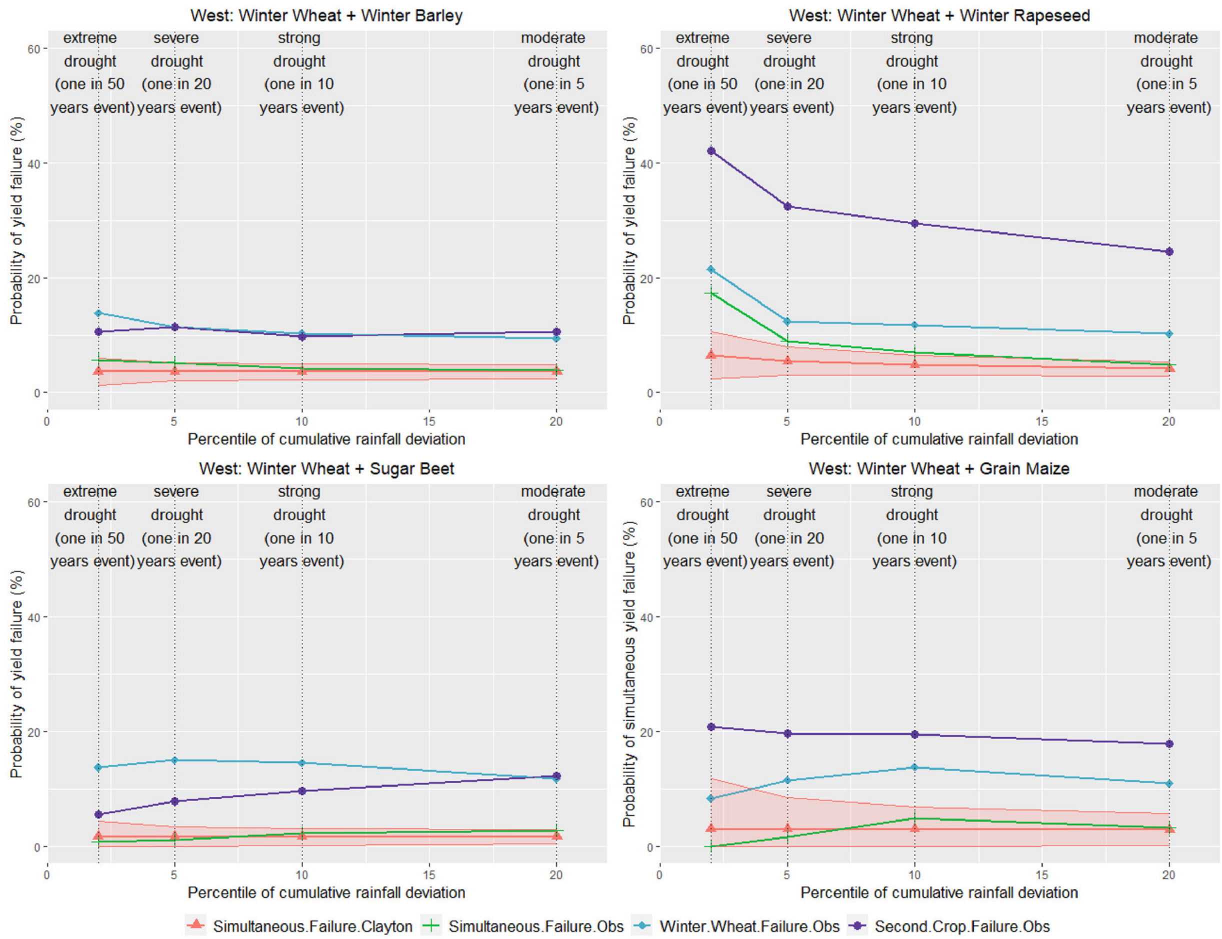

FIGURE 6 Sub-sample of Western Germany—probabilities of simultaneous yield losses under different drought levels based on the nested Clayton copula estimates compared to the (single crop) observations.

Note: (1) Absolute numbers of observations are presented in Tables S19–S22. (2) The 99% confidence intervals are derived from repeated sampling (10,000 times) of the fitted model with sample sizes equal to the number of observations.

(2020) and Beillouin et al. (2020), which illustrated simultaneous yield losses of different crops at higher spatial scales.

6.5 | Results from robustness checks

We also conducted six robustness checks and present the main results here. First, we graphically compared the results of the nested Clayton copulas with the results of the Gaussian and Student-t copulas, both of which represent elliptical copulas, and the Frank copula. As an example, Figure 7 illustrates the comparison of the nested Clayton copula and Student-t copula for East Germany. We observe that the Student-t copula is characterized by a lower tail dependence than the nested Clayton copula. This can also be observed for the estimates of the remaining sub-regions (see Figures S3–S5). Furthermore, the estimates of the Gaussian and Frank copulas suggest even less tail dependence than the Student-t copula (see Figures S6–S9 and S11–S14).

Second, we varied the time window for cumulative rainfall to "1st of March–30th of June" and "1st of March–31st of July" (see Tables S31 and S32). Changing the time window for cumulative rainfall only slightly alters the results of the Clayton copula coefficients. Third, we carried out the copula estimations only with rainfed farms (by excluding the farms with irrigation), which does not change the results of our analyses. Fourth, we implemented the estimations also for the German-wide sample and could observe an increase in probabilities of simultaneous yield losses for all crop pairs and especially for those with similar daily water demand and overlapping phenological phases such as winter wheat and winter barley (Figure S10). However, we have to be aware that these effects for the German-wide sample are mainly driven by farm observations from east-

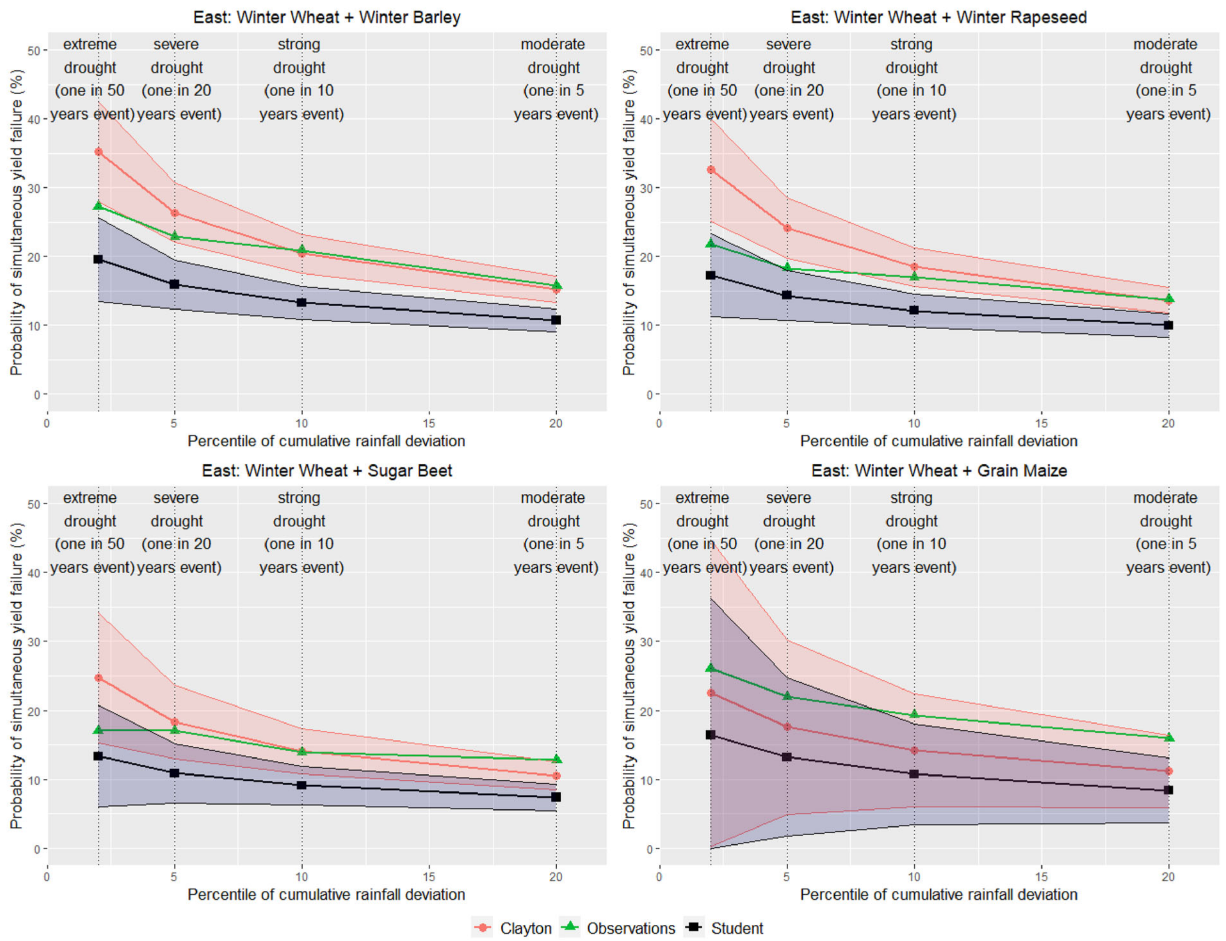

FIGURE 7 Sub-sample of Eastern Germany—probabilities of simultaneous yield losses under different drought levels based on the nested Clayton copula estimates, the observations and the Student-t copula estimates ($P(X \leq x, Y \leq y \mid CR \leq cr)$).

Note: (1) The absolute numbers of observations are presented in Tables S15–S18. (2) The 99% confidence intervals are derived from repeated sampling (10,000 times) of the fitted model with sample sizes equal to the number of observations.

ern and southern Germany. Fifth, the temporal splitting of the samples for whole Germany shows some differences in the dependence structure of yield losses and drought over time (see Table S33). These changes are more pronounced for the crop pairs of winter wheat & sugar beet and winter wheat & grain maize, which show a weaker dependence in the recent past. Sixth, the exemplary results of other crop pairs without winter wheat in Figure S15 support our findings that crops with temporally similar/overlapping growing phases throughout the year (e.g., sugar beet & grain maize) show stronger correlations of yield losses than crop pairs that temporally differ in their important growing phases.

7 | DISCUSSION

In our analyses, we compared the dependence structure of simultaneous crop yield losses and changes at the farm level under different levels of drought severity across the main agricultural production regions in Germany, defined on the basis of similar growing conditions and farm structure. We estimated the probability and confidence intervals of simultaneous yield losses on farms in the predefined production regions, which illustrate a range of simultaneous-yield-loss-risk considering the natural heterogeneity of farms.

As described in Section 2, crop diversification can have a direct impact on the production risk of individual crops, for example by controlling pest populations and/or pest damage. These effects are particularly evident in crop rotation (temporal diversification) and intercropping (in-field diversification), which cannot be analyzed with the available data. It is important to bear in mind that the estimated diversification effects of our analyses reflect the observed crop diversification at farm level (i.e., crop shares) and may therefore underestimate the effect of increasing diversification. With respect to our case study, we consider the quantitative impact of these effects to be small (especially with respect to our focus on yield risk under drought), as on-farm crop diversification is the norm in Germany (see e.g., Jänicke et al., 2022; Thuenen Earth Observation, 2023), not only to control pests (e.g., sugar beet is only grown once during a 3-year crop rotation on a field), but also to meet the respective policy requirements on crop rotation and/or crop shares in order to receive subsidies.

We show that the effectiveness of crop diversification as a risk management instrument against (different severities of) drought depends on the crop-pair. Choosing crops that differ (significantly) in their daily water requirements and phenological phases throughout the year, such as winter wheat and grain maize, can effectively reduce the probability of large simultaneous yield losses on a farm compared to choosing crops with more similar daily water requirements throughout the year, such as winter wheat and winter barley. Thus, the portfolio effect works at farm level in many cases, but the effectiveness varies between crop pairs due to different correlations of their yield deviations. Therefore, the commonly used indices, which only take into account the absolute number of different crops and not the crop asynchrony, such as the Shannon or Margalef indices, are not sufficient to illustrate that the effectiveness of crop diversification depends on the crop composition. Moreover, these indices cannot analyze the effectiveness of crop diversification when a risk factor such as drought varies in its severity. However, this information is very important for farmers in order to decide whether complementary risk management measures such as drought insurance are needed on their farms.

In addition, we demonstrate that the risk-reducing potential of crop diversification varies greatly by region. For example, in western and northern Germany, on-farm yield losses of different crops are less correlated and the probabilities of simultaneous yield losses do not increase considerably under severe drought conditions. In contrast, in the East and South of Germany we observe stronger correlations between yield losses of different crops and an increasing risk of simultaneous yield losses under severe drought levels. One explanation for the regional differences could be the variation in soil quality and soil composition across Germany, which affects the water-holding capacity of the soil (e.g., Bormann & Klaasen, 2008). For example, rainfall tends to infiltrate more quickly in the sandy soils of eastern and part of southern Germany than in other regions due to the lower soil water holding capacity of sandy soils (Morgan et al., 2001), which could lead to a stronger effect of variations in cumulative rainfall on simultaneous yield losses between crop pairs. Furthermore, it is important to stress that the percentage deviations in cumulative rainfall take into account the different mean cumulative rainfall values across municipalities in Germany (see Figure A2). Therefore, the percentiles of deviations of cumulative rainfall in East Germany (Figure 5) represent lower absolute rainfall levels compared to, for instance, West Germany (Figure 6). Thus, the 20th percentile of deviations in cumulative rainfall in the eastern sub-sample could already lead to a critical water supply for the analyzed cash crops compared to the 20th percentile in the western sub-sample. However, this aspect does not change the implications for agricultural stakeholders that crop diversification is less effective as a risk management instrument against severe droughts in eastern Germany compared to western Germany.

In addition to assessing the effectiveness of diversification as a risk management instrument across regions, our results highlight the great potential of copula modeling in agricultural (weather) risk modeling. For instance, copulas can be a useful complement to "traditional" bio-economic modeling approaches (e.g., Reidsma et al., 2010; Ewert et al., 2015) when research is more interested in weather extremes. Furthermore, copulas can be used as an additional tool for climate change analyses to model the impact of extreme weather events on crop yields (see, e.g., Gaupp et al., 2019, Hasegawa et al., 2021). Copulas allow us to extend these models by additionally modeling more extreme variability of weather, rather than just adding/subtracting a certain amount of, for instance, temperature or precipitation. This is important because climate change consists not only of an "average" change in weather, but also of a change in frequency and severity (see e.g., Trnka et al., 2014; Grillakis, 2019). As the analyses presented here are applied to a dataset that already includes "extreme weather shocks", such as the droughts of 2003 and 2018 (see Figure S2), and presumably adaptation measures on the farms to these "extreme weather shocks," the modeling presented here of, for example, 1-in-50-years events provides helpful indications of the resilience of crop farming in the future. However, our dataset is too short to determine what proportion of these "extreme weather shocks" is due to climate change and what proportion is due to normal weather anomalies in the past.

Furthermore, we provide interesting methodological insights regarding the goodness-of-fit procedure of copulas. In our analyses, we choose two goodness-of-fit tests. First, we consider the AIC. Second, we graphically compare the estimated probabilities of nested Clayton copulas with Student-t copulas (see Figure 7 and Figures S3–S5), Gaussian copulas (see Figures S6–S9) and nested Frank

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copulas (see Figures S10–S14) and the probabilities of the underlying data in the lower tail.[23] The graphical comparison allows us to illustrate the distance between estimated and observed probabilities and the corresponding uncertainties of the estimates associated with limited sample sizes in the (extreme) tails. We show that the graphical goodness-of-fit test can be an important addition, since the AIC refers to the full range of data, from the most negative to the most positive. However, in our study we are "only" interested in the best fit for the lower tail. For instance, if we had only considered the AIC, the Gaussian copula or the nested Frank copula would have been the better fit for the crop pair winter wheat + winter barley in eastern Germany (see Table S11), which is misleading as shown in Figures S6 and S11.

Moreover, we show that the estimation of tail dependencies by Clayton copulas has an additional value, since uncertainties associated with limited observations, which is often the case when analyzing extreme values, can be robustly quantified and illustrated by confidence intervals. In our case, a limitation of the yield data is that the German Farm Accountancy Data Network only considers the area actually harvested for each crop. Thus, yield losses in extreme drought years may be underestimated because farmers may decide that it is not worth harvesting the most affected field(s) (Cui, 2020) and/or replant a field of a winter crop with a summer crop. This could explain why the probability of observed simultaneous yield losses is lower for extreme droughts than for severe droughts for some crop pairs (see e.g., Figures A7 and A8), while the estimated parametric Clayton copula more realistically imposes strictly increasing tail dependencies.

8 | CONCLUSION

In this article, we provide and apply a new approach for the probabilistic assessment of simultaneous yield losses of different cash crops at farm level under drought stress exposure by using multivariate copulas. Using a case study of German crop production, we find considerable differences in the probabilities of simultaneous yield losses between crop pairs. Furthermore, we show that more severe drought conditions can increase the probability of simultaneous yield failures at the farm level. However, these probabilities are strongly influenced by regional environmental (e.g., soil-climate) conditions, which both lead to considerable differences in the probabilities of simultaneous yield failures and in how/if more severe drought levels increase the probabilities of simultaneous yield failures. Therefore, the risk-reducing effectiveness of crop diversification in coping with drought events (of different severity levels) is highly dependent on crop choice and regional soil-climate conditions.

As a result, farmers can more effectively mitigate risk through diversification by growing crops that differ (as much as possible) in their phenological needs and water requirements throughout the year. However, farmers make these decisions in the context of natural and economic constraints such as harvesting peeks, machinery and knowledge requirements, phytosanitary concerns, or the availability of a sugar factory (see, e.g., Bradshaw et al., 2004; Revoyron et al., 2022; Roesch-McNally et al., 2018). Therefore, (additional) crop diversification is mostly associated with costs (Vroege & Finger, 2020), which need to be taken into account in potential diversification requirements of agricultural policies. Furthermore, since crop diversification as a traditional on-farm risk management instrument is not effective on many farms when drought becomes severe, off-farm risk management measures such as insurance should be considered as a complementary strategy.

Our analysis also has important policy implications. For example, policy makers should use our results to create a framework in which farmers are empowered to implement crop diversification in the most effective way to reduce their risk. For instance, policy makers could encourage and (financially) reward the diversification of crops with more diverse phenological requirements and different water needs throughout the year, which has the potential to make agricultural systems more resilient to weather extremes. So far, the current rationale for crop diversification in the European Union's agricultural policy is mainly related to biodiversity. However, our results underline that it also has significant implications for risk management at farm level. Therefore, there is a great opportunity to consider diversification simultaneously from a biodiversity and risk management perspective in order to exploit synergies. For example, linking public support for risk management (e.g., insurance subsidies) and disaster payments to crop diversification requirements could increase the resilience of cropping systems, improve biodiversity, and increase the cost-effectiveness of public support. In addition, policy makers could encourage the expansion of "traditional crop portfolios" on farms by valuing the cultivation of

[23] It should be noted that there is still a huge range of copula specifications that we have not yet tested for goodness-of-fit and we cannot exclude the possibility that there is a copula specification with a better fit available for our case.

"non-traditional" crops, which could unfold more effective diversification combinations of new crop pairs.

Further research should also investigate the effect of crop diversification by considering the asynchrony of different crops (see, e.g., Egli et al., 2020). Furthermore, exploring the potential of copulas to combine (farm-level) yield variability with climate change models could have important implications for climate change adaptation. This could be of particular interest for modeling of weather extremes under climate change, and could provide information on the conditional probabilities of (simultaneous) yield failures under different levels of (simulated) future weather extremes. In addition, further research could investigate how/if the portfolio effect of crop diversification could be used in agricultural weather insurance products. Finally, further research should apply copulas to other extreme weather events, such as heat or waterlogging, and other yield risks, such as pest or disease pressure. These analyses should also be carried out with plot-level yield data to investigate local effects such as landscape structure on the risk of simultaneous yield losses of different crops.

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REFERENCES

Anastassiadis, F., Feil, J. H., Musshoff, O., & Schilling, P. (2014). Analysing farmers' use of price hedging instruments: An experimental approach. *Journal of Agricultural & Food Industrial Organization*, *12*(1), 181–192. https://doi.org/10.1515/jafio-2014-0007

Barkley, A., Peterson, H. H., & Shroyer, J. (2010). Wheat variety selection to maximize returns and minimize risk: An application of portfolio theory. *Journal of Agricultural and Applied Economics*, *42*(1), 39–55. https://doi.org/10.1017/S107407080000328X

Beillouin, D., Ben-Ari, T., & Makowski, D. (2019). Evidence map of crop diversification strategies at the global scale. *Environmental Research Letters*, *14*(12), 123001. https://doi.org/10.1088/1748-9326/ab5ffb

Beillouin, D., Schauberger, B., Bastos, A., Ciais, P., & Makowski, D. (2020). Impact of extreme weather conditions on European crop production in 2018. *Philosophical Transactions of the Royal Society B*, *375*(1810), 20190510. https://doi.org/10.1098/rstb.2019.0510

BMEL. (2018). Gemeinsame Dürrehilfe durch landwirtschaftliche Betriebe stark gefragt. Das Bundesministerium für Ernährung und Landwirtschaft zu den Zahlen der in Anspruch genommenen Dürrehilfe durch existenziell in Not geratene landwirtschaftliche Betriebe. *Pressemitteilung Nr. 207/2018*. https://www.bmel.de/SharedDocs/Pressemitteilungen/DE/2018/207-duerrehilfe.html

BMEL. (2020). Die wirtschaftliche Lage der landwirtschaftlichen Betriebe. Buchführungsergebnisse der Testbetriebe des Wirtschaftsjahres 2019/2020. https://www.bmel-statistik.de/landwirtschaft/testbetriebsnetz/testbetriebsnetz-landwirtschaft-buchfuehrungsergebnisse/archiv-buchfuehrungsergebnisse-landwirtschaft/buchfuehrungsergebnisse-landwirtschaft-201920

Bokusheva, R., Kogan, F., Vitkovskaya, I., Conradt, S., & Batyrbayeva, M. (2016). Satellite-based vegetation health indices as a criteria for insuring against drought-related yield losses. *Agricultural and Forest Meteorology*, *220*, 200–206. http://doi.org/10.1016/j.agrformet.2015.12.066

Bormann, H., & Klaassen, K. (2008). Seasonal and land use dependent variability of soil hydraulic and soil hydrological properties of two Northern German soils. *Geoderma*, *145*(3-4), 295–302. http://doi.org/10.1016/j.geoderma.2008.03.017

Bowles, T. M., Mooshammer, M., Socolar, Y., Calderón, F., Cavigelli, M. A., Culman, S. W., Deen, W., Drury, C., Garcia y Garcia, A., Gaudin, A., Harkcom, W., Lehman, R., Osborne, S., Robertson, G., Salerno, J., Schmer, M., Strock, J., & Grandy, A. S. (2020). Long-term evidence shows that crop-rotation diversification increases agricultural resilience to adverse growing conditions in North America. *One Earth*, *2*(3), 284–293. https://doi.org/10.1016/j.oneear.2020.02.007

Bradshaw, B., Dolan, H., & Smit, B. (2004). Farm-level adaptation to climatic variability and change: Crop diversification in the Canadian prairies. *Climatic Change*, *67*(1), 119–141. https://doi.org/10.1007/s10584-004-0710-z

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

Bucheli, J., Dalhaus, T., & Finger, R. (2021). The optimal drought index for designing weather index insurance. *European Review of Agricultural Economics*, *48*(3), 573–597. https://doi.org/10.1093/erae/jbaa014

Bucheli, J., Dalhaus, T., & Finger, R. (2022). Temperature effects on crop yields in heat index insurance. *Food Policy*, *107*, 102214. https://doi.org/10.1016/j.foodpol.2021.102214

Chavas, J.-P., Rivieccio, G., Di Falco, S., De Luca, G., & Capitano, F. (2022). Agricultural diversification, productivity, and food security across time and space. *Agricultural Economics*, 1–18. https://doi.org/10.1111/agec.12742

Ciais, P., Reichstein, M., Viovy, N., Granier, A., Ogée, J., Allard, V., Aubinet, M., Buchmann, N., Bernhofer, C., Carrara, A., Chevallier, F., De Noblet, N., Friend, A. D., Friedlingstein, P., Grünwald, T., Heinesch, B., Keronen, P., Knohl, A., Krinner, G., … Valentini, R. (2005). Europe-wide reduction in primary productivity caused by the heat and drought in 2003. *Nature*, *437*(7058), 529–533.

Cui, X. (2020). Beyond yield response: Weather shocks and crop abandonment. *Journal of the Association of Environmental and Resource Economists*, *7*(5), 901–932. https://doi.org/10.1038/nature03972

Di Falco, S., & Perrings, C. (2005). Crop biodiversity, risk management and the implications of agricultural assistance. *Ecological Economics*, *55*(4), 459–466. https://doi.org/10.1016/j.ecolecon.2004.12.005

Di Falco, S., & Chavas, J. P. (2009). On crop biodiversity, risk exposure, and food security in the highlands of Ethiopia. *American Journal of Agricultural Economics*, *91*(3), 599–611. https://doi.org/10.1111/j.1467-8276.2009.01265.x

Du, X., Hennessy, D. A., Feng, H., & Arora, G. (2018). Land resilience and tail dependence among crop yield distributions. *American Journal of Agricultural Economics*, *100*(3), 809–828. https://doi.org/10.1093/ajae/aax082

Durante, F., & Sempi, C. (2016). *Principles of copula theory* (Vol., 474). CRC press.

DWD. (2021). Climate Data Center. http://www.dwd.de/DE/klimaumwelt/cdc/cdc_node.html

Egli, L., Schröter, M., Scherber, C., Tscharntke, T., & Seppelt, R. (2020). Crop asynchrony stabilizes food production. *Nature*, *588*(7837), E7–E12. https://doi.org/10.1038/s41586-019-1316-y

European Union. (2021). Regulation (EU) 2021/2115 of the European Parliament and the Council. Article 76(5).

Ewert, F., Rötter, R. P., Bindi, M., Webber, H., Trnka, M., Kersebaum, K. C., … Asseng, S. (2015). Crop modelling for integrated assessment of risk to food production from climate change. *Environmental Modelling & Software*, *72*, 287–303. https://doi.org/10.1016/j.envsoft.2014.12.003

Finger, R. (2012). Biases in farm-level yield risk analysis due to data aggregation. *German Journal of Agricultural Economics*, *61*(1), 30–43. https://doi.org/10.1016/j.envsoft.2014.12.003

Finger, R. (2013). Investigating the performance of different estimation techniques for crop yield data analysis in crop insurance applications. *Agricultural Economics*, *44*(2), 217–230. https://doi.org/10.1111/agec.12005

Gaudin, A. C., Tolhurst, T. N., Ker, A. P., Janovicek, K., Tortora, C., Martin, R. C., & Deen, W. (2015). Increasing crop diversity mitigates weather variations and improves yield stability. *PloS one*, *10*(2), e0113261. https://doi.org/10.1371/journal.pone.0113261

Gaupp, F., Pflug, G., Hochrainer-Stigler, S., Hall, J., & Dadson, S. (2017). Dependency of crop production between global breadbaskets: A copula approach for the assessment of global and regional risk pools. *Risk Analysis*, *37*(11), 2212–2228. https://doi.org/10.1111/risa.12761

Gaupp, F., Hall, J., Mitchell, D., & Dadson, S. (2019). Increasing risks of multiple breadbasket failure under 1.5 and 2 C global warming. *Agricultural Systems*, *175*, 34–45. https://doi.org/10.1016/j.agsy.2019.05.010

Glauber, J., Baldwin, K., Antón, J., & Ziebinska, U. (2021). Design principles for agricultural risk management policies, OECD Food, Agriculture and Fisheries Papers. No. 157, OECD Publishing. https://doi.org/10.1787/1048819f-en

Goodwin, B. K. (2015). Agricultural policy analysis: The good, the bad, and the ugly. *American Journal of Agricultural Economics*, *97*(2), 353–373. https://doi.org/10.1093/ajae/aau105

Goodwin, B. K., & Hungerford, A. (2015). Copula-based models of systemic risk in US agriculture: Implications for crop insurance and reinsurance contracts. *American Journal of Agricultural Economics*, *97*(3), 879–896. https://doi.org/10.1093/ajae/aau086

Grillakis, M. G. (2019). Increase in severe and extreme soil moisture droughts for Europe under climate change. *Science of The Total Environment*, *660*, 1245–1255. https://doi.org/10.1016/j.scitotenv.2019.01.001

Gupta, A., Rico-Medina, A., & Caño-Delgado, A. I. (2020). The physiology of plant responses to drought. *Science*, *368*(6488), 266–269. https://doi.org/10.1126/science.aaz7614

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

Hasegawa, T., Sakurai, G., Fujimori, S., Takahashi, K., Hijioka, Y., & Masui, T. (2021). Extreme climate events increase risk of global food insecurity and adaptation needs. *Nature Food*, *2*(8), 587–595. https://doi.org/10.1038/s43016-021-00335-4

Hofert, M., & Mächler, M. (2011). Nested Archimedean copulas meet R: The nacopula package. *Journal of Statistical Software*, *39*(9), 1–20. https://doi.org/10.3929/ethz-b-000032555

Iglesias, A., Quiroga, S., Moneo, M., & Garrote, L. (2012). From climate change impacts to the development of adaptation strategies: Challenges for agriculture in Europe. *Climatic Change*, *112*(1), 143–168. https://doi.org/10.1007/s10584-011-0344-x

Jänicke, C., Goddard, A., Stein, S., Steinmann, H. H., Lakes, T., Nendel, C., & Müller, D. (2022). Field-level land-use data reveal heterogeneous crop sequences with distinct regional differences in Germany. *European Journal of Agronomy*, *141*, 126632. https://doi.org/10.1016/j.eja.2022.126632

JKI. (2009). Netz Vergleichsbetriebe Pflanzenschutz—Jahresbericht 2009. (No. 156).

Kojadinovic, I., & Yan, J. (2010). Modeling multivariate distributions with continuous margins using the copula R package. *Journal of Statistical Software*, *34*, 1–20. https://doi.org/10.18637/jss.v034.i09

Kornhuber, K., Lesk, C., Schleussner, C. F., Jägermeyr, J., Pfleiderer, P., & Horton, R. M. (2023). Risks of synchronized low yields are underestimated in climate and crop model projections. *Nature Communications*, *14*(1), 3528. https://doi.org/10.1038/s41467-023-38906-7

Kuwayama, Y., Thompson, A., Bernknopf, R., Zaitchik, B., & Vail, P. (2019). Estimating the impact of drought on agriculture using the US Drought Monitor. *American Journal of Agricultural Economics*, *101*(1), 193–210. https://doi.org/10.1093/ajae/aay037

Larsen, R., Mjelde, J. W., Klinefelter, D., & Wolfley, J. (2013). The use of copulas in explaining crop yield dependence structures for use in geographic diversification. *Agricultural Finance Review*, *73*(3), 469–492. https://doi.org/10.1108/AFR-02-2012-0005

Leng, G., & Hall, J. (2019). Crop yield sensitivity of global major agricultural countries to droughts and the projected changes in the future. *Science of the Total Environment*, *654*, 811–821. https://doi.org/10.1016/j.scitotenv.2018.10.434

Lin, B. B. (2011). Resilience in agriculture through crop diversification: Adaptive management for environmental change. *BioScience*, *61*(3), 183–193. https://doi.org/10.1525/bio.2011.61.3.4

Madadgar, S., AghaKouchak, A., Farahmand, A., & Davis, S. J. (2017). Probabilistic estimates of drought impacts on agricultural production. *Geophysical Research Letters*, *44*(15), 7799–7807. https://doi.org/10.1002/2017GL073606

Markowitz, H. (1952). Modern portfolio theory. *Journal of Finance*, *7*(11), 77–91.

Markowitz, H. M. (2010). Portfolio theory: As I still see it. *Annual Review of Financial Economics*, *2*(1), 1–23. https://doi.org/10.1146/annurev-financial-011110-134602

Marra, M. C., & Schurle, B. W. (1994). Kansas wheat yield risk measures and aggregation: A meta-analysis approach. *Journal of Agricultural and Resource Economics*, *19*(1), 69–77.

Mehrabi, Z., & Ramankutty, N. (2019). Synchronized failure of global crop production. *Nature Ecology & Evolution*, *3*(5), 780–786. https://doi.org/10.1038/s41559-019-0862-x

Mijatović, D., Van Oudenhoven, F., Eyzaguirre, P., & Hodgkin, T. (2013). The role of agricultural biodiversity in strengthening resilience to climate change: Towards an analytical framework. *International Journal of Agricultural Sustainability*, *11*(2), 95–107. https://doi.org/10.1080/14735903.2012.691221

Morgan, K. T., Parsons, L. R., & Adair Wheaton, T. (2001). Comparison of laboratory-and field-derived soil water retention curves for a fine sand soil using tensiometric, resistance and capacitance methods. *Plant and Soil*, *234*(2), 153–157.

Nagler, T., Schepsmeier, U., Stöber, J., Brechmann, E. C., Graeler, B., & Erhardt, T. (2020). *VineCopula: Statistical Inference of Vine Copulas*.

Nelsen, R. B. (2003). Properties and applications of copulas: A brief survey. *Proceedings of the First Brazilian Conference on Statistical Modeling in Insurance and Finance* (pp. 10–28). São Paulo: University Press USP.

Nelsen, R. B. (2006). *An introduction to copulas*. Springer Science & Business Media.

Okhrin, O., Odening, M., & Xu, W. (2013). Systemic weather risk and crop insurance: The case of China. *Journal of Risk and Insurance*, *80*(2), 351–372. https://doi.org/10.1111/j.1539-6975.2012.01476.x

Okhrin, O., & Ristig, A. (2014). Hierarchical Archimedean copulae: The HAC package. *Journal of Statistical Software*, *58*, 1–20. https://doi.org/10.18637/jss.v058.i04

Okhrin, O., Ristig, A., & Xu, Y. F. (2017). Copulae in high dimensions: An introduction. *Applied Quantitative Finance*, 247–277. https://doi.org/10.1007/978-3-662-54486-0_19

Paut, R., Sabatier, R., & Tchamitchian, M. (2019). Reducing risk through crop diversification: An application of portfolio theory to diversified horticultural systems. *Agricultural Systems*, *168*, 123–130. https://doi.org/10.1016/j.agsy.2018.11.002

Paut, R., Sabatier, R., & Tchamitchian, M. (2020). Modelling crop diversification and association effects in agricultural systems. *Agriculture, Ecosystems & Environment*, *288*, 106711. https://doi.org/10.1016/j.agee.2019.106711

R Core Team. (2022). R: A language and environment for statistical computing. R Foundation for Statistical Computing. http://www.R-project.org

Reidsma, P., Ewert, F., Lansink, A. O., & Leemans, R. (2010). Adaptation to climate change and climate variability in European agriculture: The importance of farm level responses. *European Journal of Agronomy*, *32*(1), 91–102. https://doi.org/10.1016/j.eja.2009.06.003

Revoyron, E., Le Bail, M., Meynard, J. M., Gunnarsson, A., Seghetti, M., & Colombo, L. (2022). Diversity and drivers of crop diversification pathways of European farms. *Agricultural Systems*, *201*, 103439. https://doi.org/10.1016/j.agsy.2022.103439

Ribeiro, A. F., Russo, A., Gouveia, C. M., & Páscoa, P. (2019). Copula-based agricultural drought risk of rainfed cropping systems. *Agricultural Water Management*, *223*, 105689. https://doi.org/10.1016/j.agwat.2019.105689

Ribeiro, A. F. S., Russo, A., Gouveia, C. M., Páscoa, P., & Zscheischler, J. (2020). Risk of crop failure due to compound dry and hot extremes estimated with nested copulas. *Biogeosciences*, *17*(19), 4815–4830. https://doi.org/10.5194/bg-17-4815-2020

Roesch-McNally, G. E., Arbuckle, J. G., & Tyndall, J. C. (2018). Barriers to implementing climate resilient agricultural strategies: The case of crop diversification in the US Corn Belt. *Global Environmental Change*, *48*, 206–215. https://doi.org/10.1016/j.gloenvcha.2017.12.002

Salvadori, G., & De Michele, C. (2007). On the use of copulas in hydrology: Theory and practice. *Journal of Hydrologic Engineering*, *12*(4), 369–380. https://doi.org/10.1061/(ASCE)1084-0699(2007)12:4(369)

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. https://doi.org/10.1016/j.foodpol.2022.102359

Sklar, M. (1959). Fonctions de repartition an dimensions et leurs marges. *Publications de l'Institut Statistique de l'Université de Paris*, *8*, 229–231.

Smit, B., & Skinner, M. W. (2002). Adaptation options in agriculture to climate change: A typology. *Mitigation and Adaptation Strategies for Global Change*, *7*(1), 85–114.

Statistisches Bundesamt. (2022). Ackerland nach Hauptfruchtgruppen und Fruchtarten. https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Landwirtschaft-Forstwirtschaft-Fischerei/Feldfruechte-Gruenland/Tabellen/ackerland-hauptnutzungsarten-kulturarten.html

Thuenen Earth Observation. (2023). National-scale crop type maps for Germany from combined time series of Sentinel-1, Sentinel-2 and Landsat data (2017 to 2021). https://geoserver-bw.thuenen.de/atlas_thuenen_rs/index.html

Trnka, M., Rötter, R. P., Ruiz-Ramos, M., Kersebaum, K. C., Olesen, J. E., Žalud, Z., & Semenov, M. A. (2014). Adverse weather conditions for European wheat production will become more frequent with climate change. *Nature Climate Change*, *4*(7), 637–643. https://doi.org/10.1038/nclimate2242

Vroege, W., & Finger, R. (2020). Insuring weather risks in European agriculture. *EuroChoices*, *19*(2), 54–62. https://doi.org/10.1111/1746-692X.12285

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

World Bank. (2023). Cereal Production—Germany. https://data.worldbank.org/indicator/AG.PRD.CREL.MT?locations=DE&most_recent_value_desc=true

Xu, W., Filler, G., Odening, M., & Okhrin, O. (2010). On the systemic nature of weather risk. *Agricultural Finance Review*, *70*(2), 267–284, https://doi.org/10.1108/00021461011065283

SUPPORTING INFORMATION

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

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APPENDIX

Sub-sample of East Germany: Exemplary calculation of the Clayton probability of simultaneous yield losses of winter wheat and sugar beet in the case of moderate and severe drought:

$$\left(.1269^{-.32} + .2^{-.32} - 1\right)^{\left(\frac{-1}{.32}\right)} = .05 \tag{A1}$$

$$\frac{\left(.05^{-.26} + .1816^{-.26} - 1\right)^{\left(\frac{-1}{.26}\right)}}{.2} = .104 \tag{A2}$$

$$\left(.1269^{-.32} + .05^{-.32} - 1\right)^{\left(\frac{-1}{.32}\right)} = .0192 \tag{A3}$$

$$\frac{\left(.0192^{-.26} + .1816^{-.26} - 1\right)^{\left(\frac{-1}{.26}\right)}}{.05} = .191 \tag{A4}$$

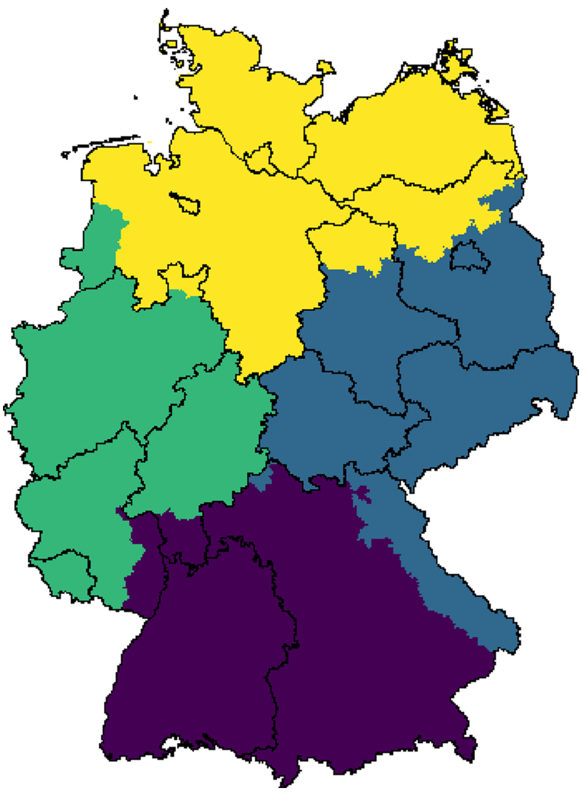

FIGURE A1 Classification of main arable production regions in Germany.

Note: The colors represent the main agricultural production regions across Germany (based on JKI, 2009). The subdivision of these main agricultural productions regions is based on similar soil-climate-conditions and farm structures.

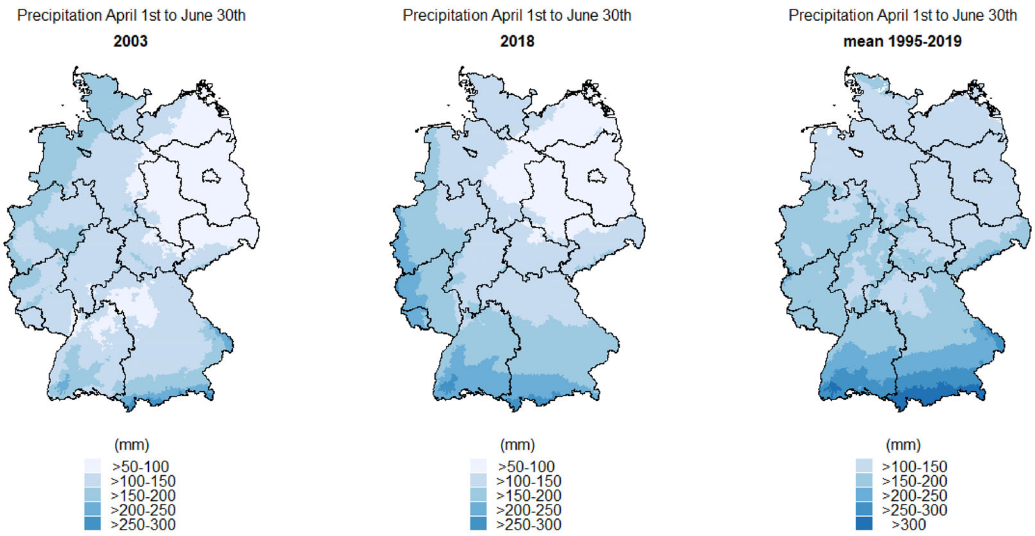

FIGURE A2 Spatial distribution of annual cumulative rainfall during from 1st of April to 30th of June in 2003, 2018 and mean of the whole observation period 1995–2019.

TABLE A1 Percentiles corresponding to −20% yield loss of each crop across the different regional sub-samples.

Crop-pair	−20% yield loss	South	East	West	North	Whole Germany
Winter wheat (u_X)	Percentile of u_X	.0989	.1306	.0881	.1161	.1051
winter barley (u_Y)	Percentile of u_Y	.1163	.1635	.1050	.1461	.1277
Winter wheat (u_X)	Percentile of u_X	.1008	.1331	.0875	.1172	.1105
winter rapeseed (u_Y)	Percentile of u_Y	.1920	.1997	.1798	.1851	.1891
Winter wheat (u_X)	Percentile of u_X	.1096	.1269	.0867	.0972	.1053
sugar beet (u_Y)	Percentile of u_Y	.1596	.1816	.1354	.1376	.1537
Winter wheat (u_X)	Percentile of u_X	.0995	.1331	.1083	.1243	.1071
grain maize (u_Y)	Percentile of u_Y	.1611	.2237	.1811	.1899	.1742

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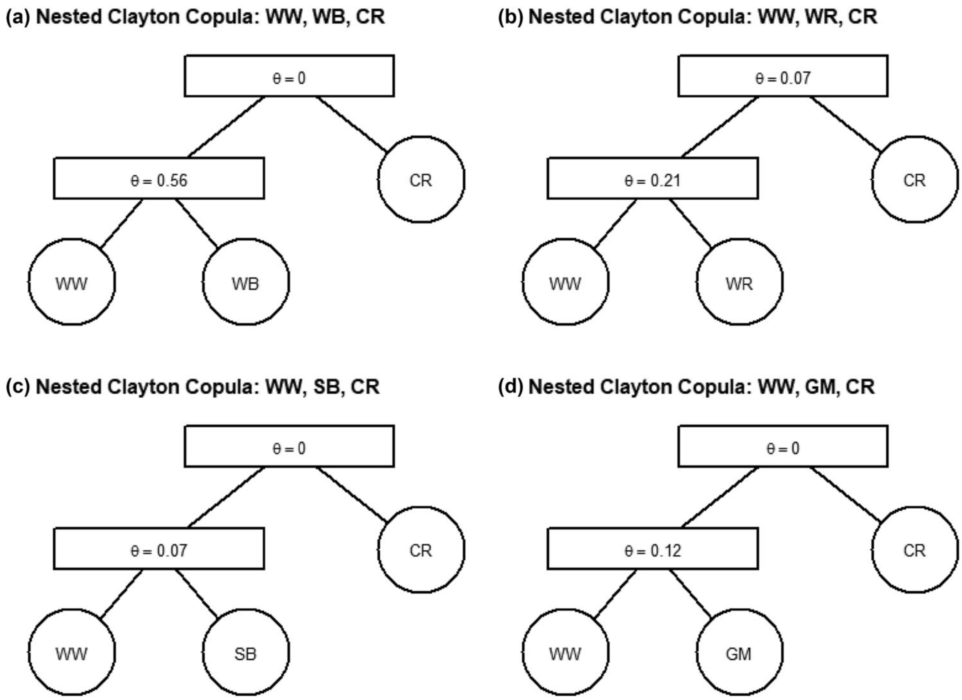

FIGURE A3 Sub-sample of West Germany—structure of nested Clayton copulas to model probabilities of simultaneous farm level crop yield losses conditional on cumulative rainfall deviations.

Note: (1) WW, winter wheat yield deviation; WB, winter barley yield deviation; WR, winter rapeseed yield deviation; SB, sugar beet yield deviation; GM, grain maize yield deviation; CR, cumulative rainfall deviation.

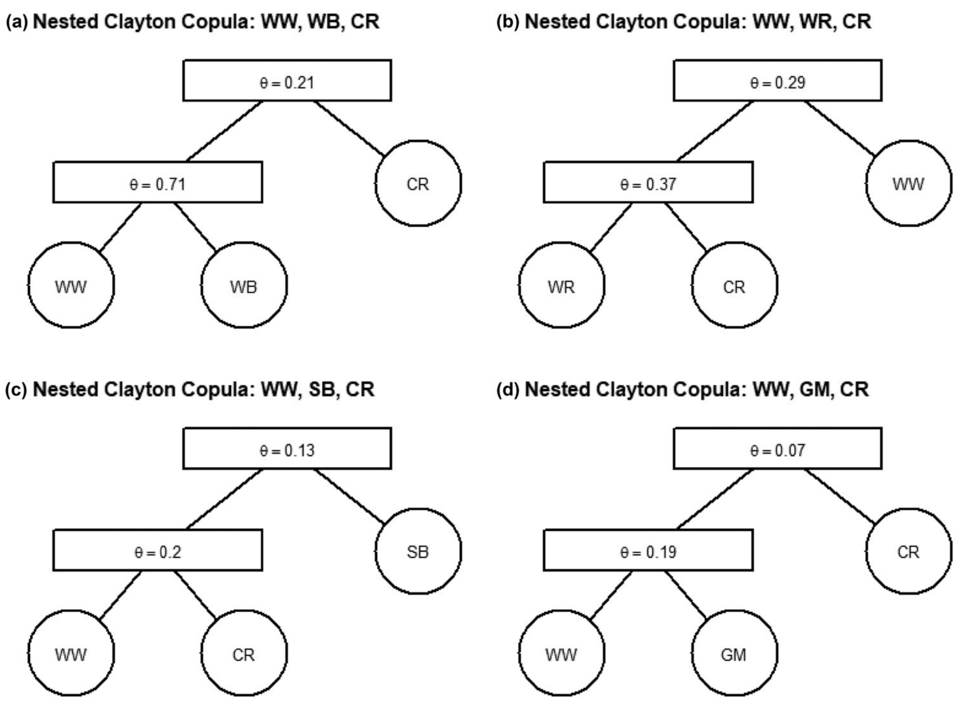

FIGURE A4 Sub-sample of South Germany—structure of nested Clayton copulas to model probabilities of simultaneous farm level crop yield losses conditional on cumulative rainfall deviations.

Note: (1) WW, winter wheat yield deviation; WB, winter barley yield deviation; WR, winter rapeseed yield deviation; SB, sugar beet yield deviation; GM, grain maize yield deviation; CR, cumulative rainfall deviation.

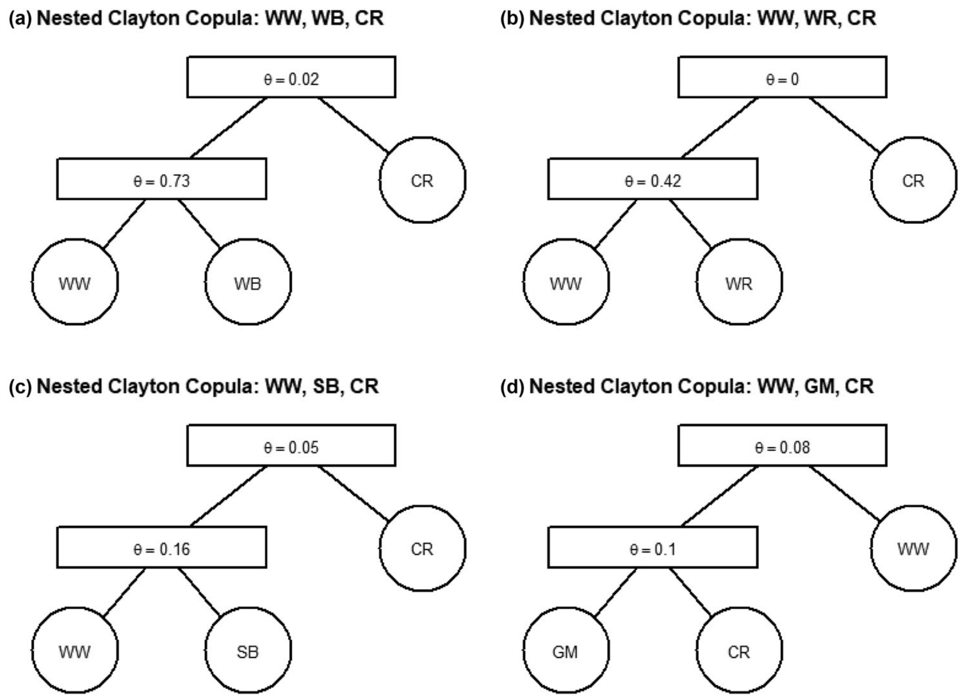

FIGURE A5 Sub-sample of North Germany—structure of nested Clayton copulas to model probabilities of simultaneous farm level crop yield losses conditional on cumulative rainfall deviations.

Note: (1) WW, winter wheat yield deviation; WB, winter barley yield deviation; WR, winter rapeseed yield deviation; SB, sugar beet yield deviation; GM, grain maize yield deviation; CR, cumulative rainfall deviation.

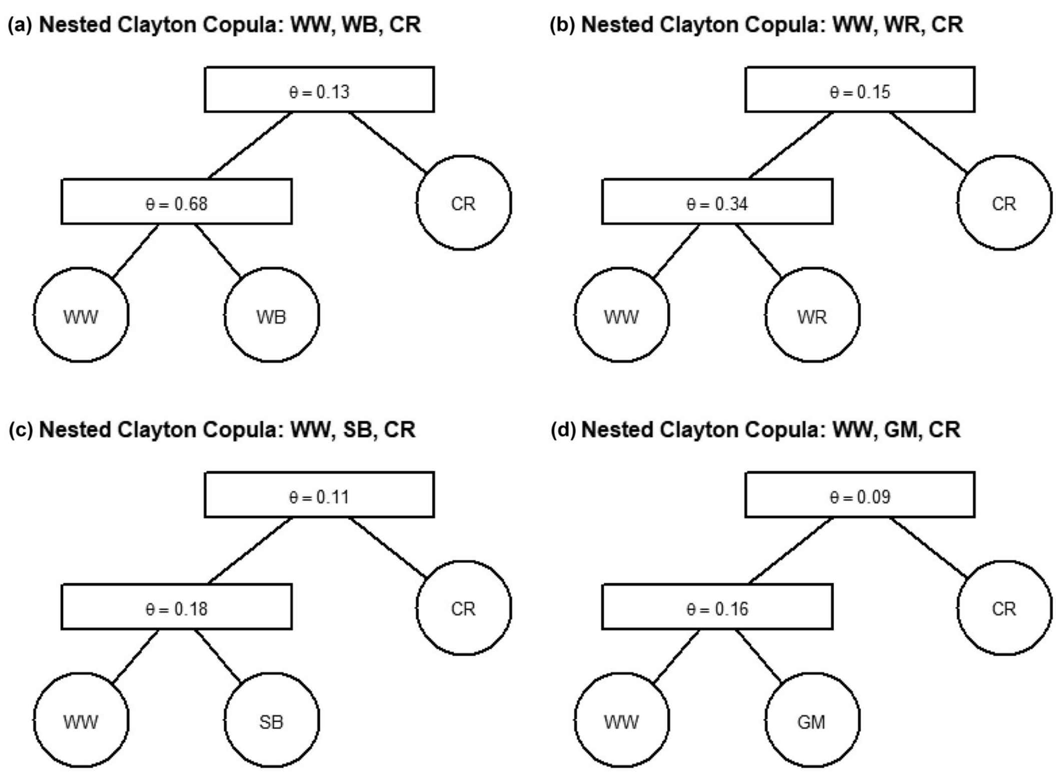

FIGURE A6 Whole Germany—structure of nested Clayton copulas to model probabilities of simultaneous farm level crop yield losses conditional on cumulative rainfall deviations.

Note: (1) WW, winter wheat yield deviation; WB, winter barley yield deviation; WR, winter rapeseed yield deviation; SB, sugar beet yield deviation; GM, grain maize yield deviation; CR, cumulative rainfall deviation.

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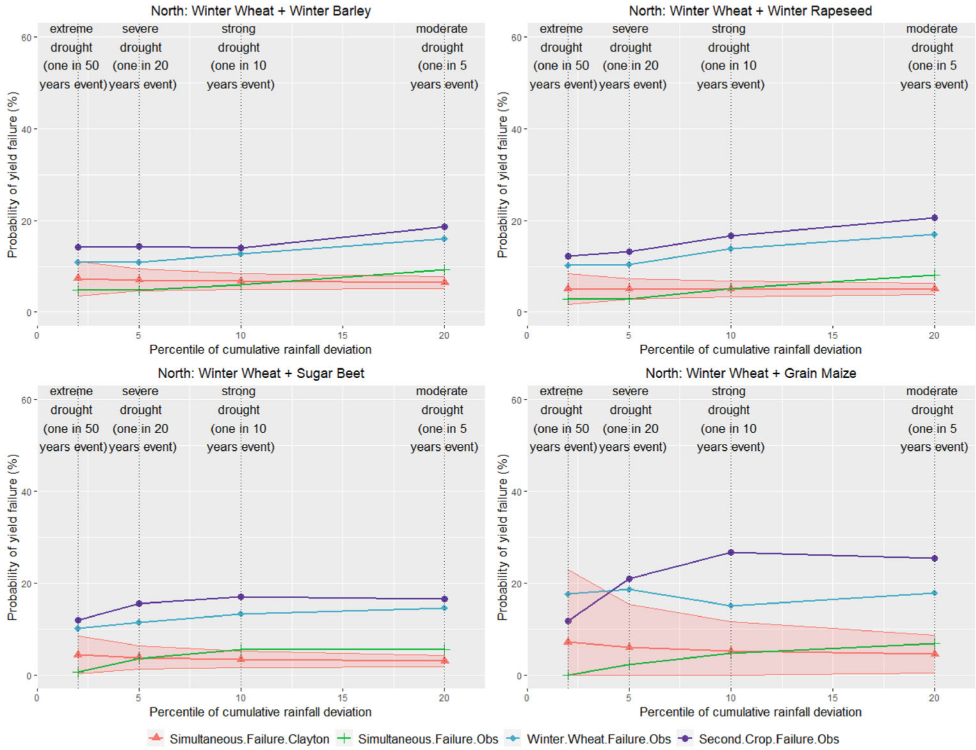

FIGURE A7 Sub-sample of Northern Germany—Probabilities of simultaneous yield losses under different drought levels based on the nested Clayton copula estimations compared to the (single-crop) observations.

Note: (1) Absolute numbers of observations are illustrated in Tables S21–S24. (2) The 99% confidence intervals are derived from repeated sampling (10,000 times) of the fitted model with sample sizes equal to the number of observations.

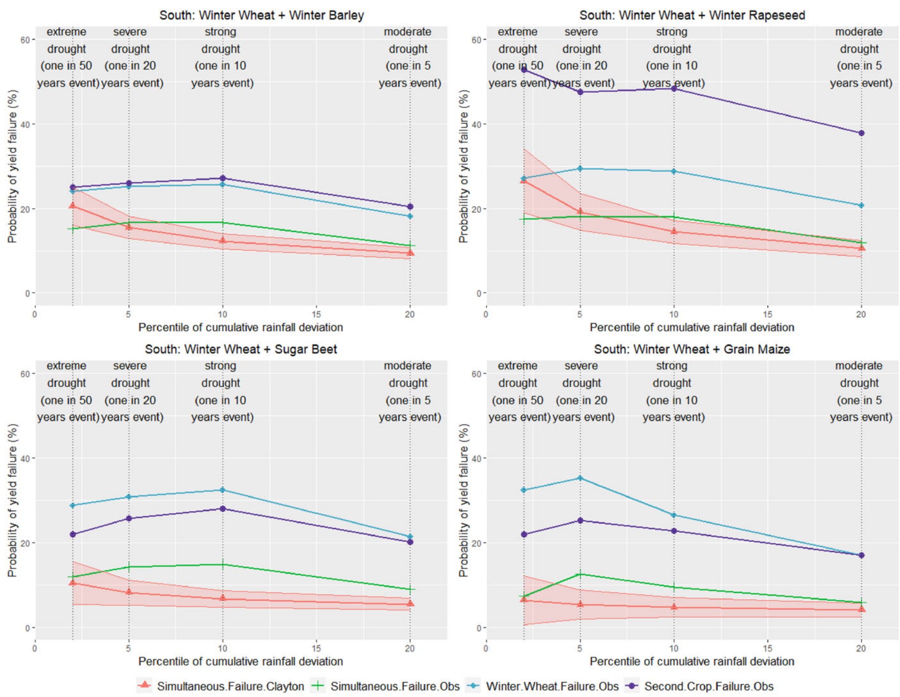

FIGURE A8 Sub-sample of Southern Germany—Probabilities of simultaneous yield losses under different drought levels based on the nested Clayton copula estimations compared to the (single-crop) observations.

Note: (1) Absolute numbers of observations are illustrated in Tables S25–S28. (2) The 99% confidence intervals are derived from repeated sampling (10,000 times) of the fitted model with sample sizes equal to the number of observations.