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RESEARCH ARTICLE

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Analysis of future changes in meteorological drought patterns in Fulda, Germany

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Abstract
Meteorological droughts have large impacts on society and the environment. A better understanding and quantification of their occurrences can be highly relevant for the development of proper climate change mitigation, adaptation and resilience strategies. Here we examine meteorological droughts from observed data covering the 1971–2000 period for the Fulda catchment in Germany by means of the Standardized Precipitation Index. The joint dependency of drought duration and severity is modelled by a copula function, which relates their univariate distributions in a functional relationship. Recurrence intervals are further calculated as a function of the joint relationship and univariate marginals. Future projections are investigated in which downscaled EURO-CORDEX Regional Climate Model (RCM) projections for the period 2021–2050 are used together with the three Representative Concentration Pathways (RCP) 2.6, 4.5, and 8.5, in order to analyse and compare future joint patterns of duration and severity of events. We find that drought duration and severity present a clear interdependency supporting the choice of a bivariate model. Results suggest substantial differences in the future joint relationship duration–severity. Depending on the RCM and RCP, drought patterns show different magnitude of changes in the future. The projected changes are different for the different returns periods. RCP8.5 shows more severe events and longer drought durations than RCP2.6 and RCP4.5. The uncertainties of the projected patterns also depend on the RCP and RCM and are larger for higher return periods.

KEYWORDS
climate change, copulas, drought duration and severity, drought events, extremes, Fulda catchment, Standardized Precipitation Index

1 | INTRODUCTION

Meteorological droughts have large impacts on society and the environment (Sheffield, Wood, & Roderick, 2012). Droughts are normal, recurrent features of climate that occurs in virtually all climate zones (Mpelasoka et al., 2008). One of the related environmental phenomena associated to droughts is desertification, which not only has an impact on the environment but can also have severe consequences on society (e.g., Trnka et al., 2018, and references therein). Naumann, Spinoni, Vogt, and Barbosa (2015) used drought damage functions relating drought characteristics and their impacts and found an increasing relationship between reduction in cereal crop production and an increase in drought severity.

Depending on the application context, different drought categories exist (Dracup, Lee, & Paulson, 1980; Spinoni, Naumann, Carrao, Barbosa, & Vogt, 2014; Wilhite & Glantz, 1985). Definitions embrace water supply deficit in stream flows; water storages in lakes and reservoirs as well as in groundwater (hydrological drought); shortage in soil moisture that affects average crop production by causing a lack in water supply (agricultural drought); and precipitation deficit relative to a normal or average condition in a certain region (meteorological drought). A drought event in one of these types does not automatically imply the occurrence of a drought event in another type. For example, meteorological droughts do not necessarily coincide with periods of agricultural droughts (Wilhite & Glantz, 1985).

Droughts can be defined in terms of different characteristics (Yoo, Kwon, Kim, & Ahn, 2012). A well-known index to describe meteorological droughts is the Standardized Precipitation Index (SPI; McKee, Doesken, & Kleist, 1993). As the SPI is based only on precipitation time series, other processes that affect the water balance, such as evaporation, run-off or soil water content dynamics, are ignored. Therefore, alternative indices have been proposed. The Standardized Precipitation-Evapotranspiration Index (SPEI) requires precipitation and evapotranspiration data (Beguería, Vicente-Serrano, Reig, & Latorre, 2014; Vicente-Serrano, Beguería, & López-Moreno, 2010) and the Palmer Drought Severity Index (PDSI) implements meteorological as well as soil-related information. As for the PDSI, the SPI relies on various assumptions, in particular the statistical distribution of the precipitation data (Lloyd-Hughes & Saunders, 2002; Mishra & Singh, 2010; Wu, Svoboda, Hayes, Wilhite, & Wen, 2007). Recently, Farahmand and AghaKouchak (2015) suggested a nonparametric normalization procedure for the SPI. Descriptions of these and further indices can be found in Keyantash and Dracup (2002) and Heim (2002). Although several indices exist, there seems to be scientific consensus that there is not a best index to define droughts and that the quest for a best index is useless (Van Loon, 2015). Nevertheless, Raible, Baerenbold, and Gómez-Navarro (2017) tested different water balance models (differing in the number of hydrological fluxes included) to define various drought indices of diverse complexity for several regions in Europe. The comparison of these different drought indices provides insight about regions where indices with simpler water balance models (i.e., reduced number of hydrological fluxes included) are sufficient to characterize a drought. Raible et al. (2017) showed that the simplest index, the SPI, performs well for Western Europe, including Germany.

The effect of anthropogenic climate change on drought events has been investigated using specialized indices that characterize droughts. For example, Zhang and Zhang (2016) studied the Drought Hazard index as a function of the SPEI in different regions in China. The analysis was carried out for the present and for climate change scenarios using three Representative Concentrations Pathways (RCP). They concluded that the drought hazard increases in all regions analysed for the RCP8.5 scenario. Tölle, Moseley, Panferov, Busch, and Knohl (2013) investigated climate change impacts on water supply patterns over Germany using the SPI index on a seasonal (6 months) time scale based on an ensemble of 24 Regional Climate Model (RCM) simulations. Projections for two periods in the future showed wetter winters during both periods. Wetter summers during 2036–2065 were projected while drier summers were estimated for the period 2071–2100 toward the southwest of Germany. The authors concluded that the SPI is a useful tool for climate change research.

We examine drought events by their duration and severity derived from the SPI and hence consider them as a multivariate phenomenon. To model drought duration and severity jointly, copulas (see section 2.3) offers an attractive method as they display the interdependence between variables in its essential form (Bárdossy & Pegram, 2009). A major advantage and key point in using copulas is the ability of constructing the dependence structure between random variables, independently of the marginal distributions (Genest & Favre, 2007). In hydrology, copulas have been introduced more than a decade ago (Favre, El Adlouni, Perreault, Thiémonge, & Bobée, 2004; Salvadori, 2004). Shiau and Modarres (2009) used the Clayton copula to represent the relationship between drought duration and severity and to calculate the conditional recurrence intervals for two gauge stations in Iran. Shiau (2006) modelled the joint severity and duration in which six parametric families of copulas were tested. The copula selection criterion was based on the log-likelihood function and the Galambos copula was found to provide the best fit. Vandenberghe, Verhoest, and De Baets (2010) analysed different storm characteristics at Uccle, Belgium. They tested seven different copula families commonly used to describe hydrological phenomena. Vandenberghe et al. (2010) put emphasis on symmetrical Archimedean copulas and suggested applying asymmetric copulas for a more detailed analysis. Recently, Halwatura, Lechner, and Arnold (2015) quantified the relationship severity–duration–frequency of droughts considering three drought indices, namely the SPI, the SPEI and the Reconnaissance Drought Index (RDI) for different time scales in 11 locations in eastern Australia. The authors used Frank and Gumbel copulas and found that the correlation between SPI and SPEI or RDI was stronger for tropical and temperate locations than for arid locations.

The purpose of this paper is to characterize meteorological droughts in the Fulda region (Figure 1), Germany, and to estimate and compare future patterns of these drought events under anthropogenic climate change scenarios. We concentrate on the short-term period 2021–2050 for practical considerations as potential changes will directly affect today's society. We focus on three main issues in our work: first, we define the SPI index; second, we characterize drought events as bivariate phenomenon in the historical period; and third, we investigate the joint behaviour duration–severity of future projections for different return periods. Regarding to this last point, the different projected joint patterns are compared and the uncertainties induced by an ensemble of EURO-CORDEX simulations and RCPs are quantified. For this, five different EURO-CORDEX simulations and three RCPs (RCP8.5, RCP2.6, and RCP4.5) are used. The study is organized as follows. Section 2 introduces the observed and modelled data and describes the methods. In section 3, the results are presented and discussed followed by conclusions in section 4.

2 | MATERIAL AND METHODS

2.1 | Study area and data

The study area is Fulda located in the Federal state of Hesse, Germany, with coordinates: latitude 50.53°N, longitude 9.67°E, elevation 225 m.a.s.l. and can be seen in Figures 1 and S1, Supporting Information. Daily precipitation time series are provided by the Climate Data Center (CDC) of the German Weather Service (Deutscher Wetterdienst [DWD]) for the period 1971–2000. Figure 1 also shows the monthly average precipitation in the area. A clear cycle is observed in which the maximum aggregated monthly precipitation is higher in spring and summer. Precipitation time series simulations for 1971–2000 and for 2012–2050 were obtained from an ensemble of five bias-corrected EURO-CORDEX runs (Jacob et al., 2014a), namely, EC-EARTH_RCA4 (M1), MPI-ESM_CCLM (M2), CNRM-CERFACS_ALADIN (M3), CNRM-CERFACS_ALARO (M4), and MPI-ESM_REMO (M5) for three RCPs (RCP2.6, RCP4.5, and RCP8.5; Moss et al., 2010). The EURO-CORDEX precipitation data are based on daily model output. The precipitation data refer to the location of the Fulda DWD weather station and were derived by nearest neighbour interpolation from the

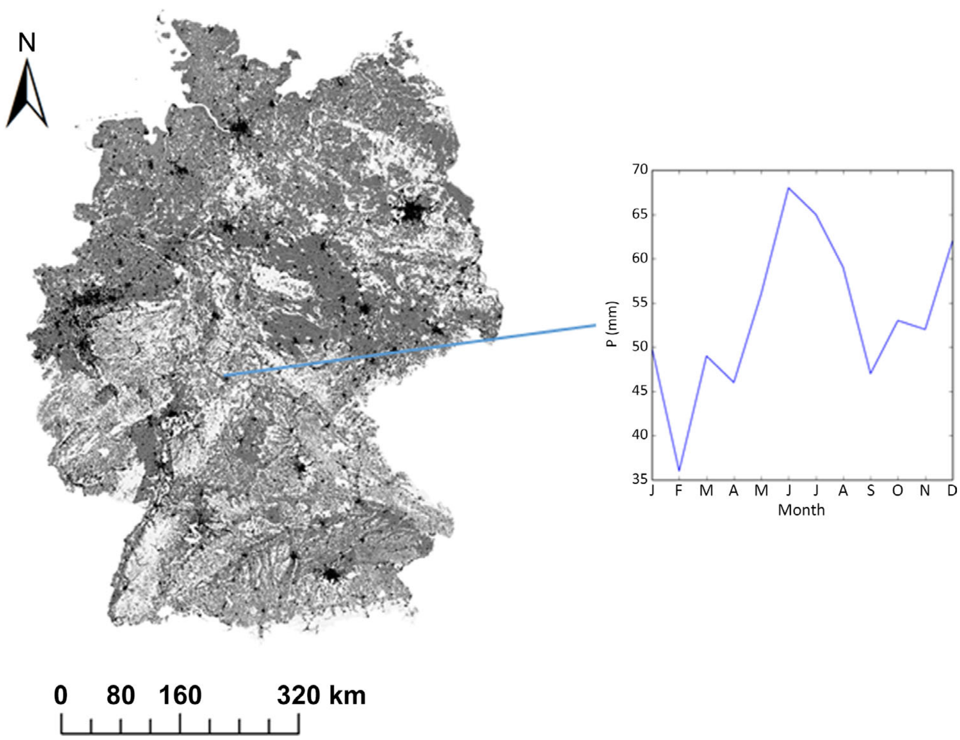

FIGURE 1 Location and monthly average precipitation for the period 1971–2000 (data provided by the German Meteorological Service [DWD]), Fulda station, Germany

model grid. The choice of RCMs was based on availability of information. The full range of simulations was not available, and therefore only a subset was chosen based on: (a) availability of all three RCP scenarios; (b) previous evaluation papers, which examined the statistical characteristics of regional climate simulation results compared to observed precipitation (see, e.g., Jacob et al., 2014a or Kotlarski et al., 2014); (c) were not too wet or dry for the Fulda region. To alleviate systematic biases, they are bias-corrected and downscaled by the empirical quantile mapping method given in Ivanov and Kotlarski (2017).

2.2 | Characterization of drought

The SPI index is used to characterize drought duration and severity in both historical and projected period. SPI depends solely on precipitation data. Its calculation involves applying the quantile function of the standardized normal distribution to the distribution of the data. Given a specific time scale (e.g., 1, 3, 6, 12, or more months), a probability model (distribution function) is fit to the long term precipitation time series so that the transformed series are defined in the unit interval. In the present study the Gamma probability model is used which has been applied and proposed by many authors (McKee et al., 1993; Wu et al., 2007). A further transformation is then carried out by applying the inverse of the standard normal distribution. This implies zero mean and unit standard deviation. For more details, refer to McKee et al. (1993). SPI can take both positive and negative values. Positive (negative) values indicate observed precipitation larger (smaller) than the median. Depending on the magnitude of the SPI, droughts can be classified on the spectrum from mild to extreme severe (McKee et al., 1993). The main advantage of the SPI is that it can be calculated for several time scales (McKee, Doesken, & Kleist, 1993McKee et al., 1993). Often used time scales for precipitation deficit are 3, 6, 12, 24, 48 months (McKee et al., 1993). As defined by McKee et al. (1993) a drought event is defined as a period in which the SPI is continuously negative and the SPI reaches a value of −1.0 or less.

To compare joint patterns of drought events in the projected period as well as joint patterns of droughts between projected and historical period, different RCM–RCP combinations are used in this study. We analyse drought events considering a seasonal 3-month time scale to account for seasonal effects in the evaluation of dryness conditions. It is important to stress that we are comparing different patterns which can be defined independently in both, historical and projected period. This will tell us, for example, how the bivariate relationship duration–severity may change between periods (historical and projected) and between different scenarios given by the ensemble of projections (RCM–RCP). Drought severity S (Equation (1)) is defined as the cumulated SPI during a drought as follows:

$$S = -\sum_{i=1}^{D} \mathrm{SPI}(i), \tag{1}$$

in which D represents the duration of the drought event in months. As the SPI is negative during the drought event, S is a positive real number. Drought duration is defined as the aggregated time in which a drought event occurs.

2.3 | Selection of a copula model

Copulas are tools that aim to model dependence of random variables. In the two-dimensional case, they are functions defined on the unit square with uniformly distributed marginals. Here, we consider a two-dimensional copula, in which the dimensions represent duration D and severity S of the drought events. An important aspect is that a link between a joint distribution function and a copula function can be established that permits to model the association between the variables regardless of their univariate marginal distributions (see, e.g., Nelsen, 2006). More specifically, Sklar's theorem (Sklar, 1959) states that if X and Y are two random variables with corresponding marginals F_1 and F_2 and joint distribution function H, there exists a copula given by Equation (2)

$$P(X \le x, Y \le y) = H(x,y) = C_\theta\{F_1(x), F_2(y)\}, \tag{2}$$

in which x, $y \in R$ and P denotes the probability of the event. Writing $u_1 = F_1(x)$ and $u_2 = F_2(x)$, the copula function C_θ can be defined as

$$C_\theta(u_1,u_2) = P(U_1 \le u_1, U_2 \le u_2). \tag{3}$$

Continuity of the marginals entails the uniqueness of C. This result allows expressing the dependence structure of drought properties S and D in terms of a two-dimensional copula. The main advantage of this approach is that the selection of an appropriate model to describe the association between the random variables can be carried out independently of the choice of the marginal distributions. If in a parametric framework we choose $F_{1,\,\alpha}$, $F_{2,\,\beta}$, C_θ, with α, β, θ representing the parameters (or parameter sets) of the marginals

TABLE 1 Copula models and associated parameter space

Family	Model	Parameter space
Frank	$C_\theta(u,v)=-\frac{1}{\theta}\log\left\{1+\frac{(e^{-\theta u}-1)(e^{-\theta v}-1)}{e^{-\theta}-1}\right\}$	$\theta\in(-\infty,\infty)$
Gumbel	$C_\theta(u,v)=e^{-\left\{(-\log u)^\theta+(-\log v)^\theta\right\}^{\frac{1}{\theta}}}$	$\theta\in[1,\infty)$
Clayton	$C_\theta(u,v)=\max\left\{\left(u^{-\theta}+v^{-\theta}-1\right)^{-\frac{1}{\theta}},0\right\}$	$\in[-1,\infty]\backslash\{0\}$
FGM	$C_\theta(u,v)=uv+\theta uv(1-u)(1-v)$	$\theta[-1,1]$
AMH	$C_\theta(u,v)=\frac{uv}{1-\theta(1-u)(1-v)}$	$\theta\in[-1,1)$

and the copula respectively, then a joint model for X and Y can be constructed. For more details see Genest and Favre (2007). Among the parametric copulas, most of the models can be associated to a family with one or more parameters. In this paper, five frequently used copula families for hydrological applications (Vandenberghe et al., 2010) are considered, namely Gumbel, Frank, Clayton, Ali-Mikhail-Haq (AMH), and Farlie-Gumbel-Morgenstern (FGM) family. Their formulations are shown in Table 1. The first four belong to the Archimedean copula class, which is characterized by a convex generator function (Equation (4)) expressed as

$$C_\theta(u_1,u_2)=\phi^{-1}(\phi(u_1)+\phi(u_2)), \quad (4)$$

in which ϕ is known as the generator function, so that ϕ: $(0,1]\mapsto[0,\infty)$ and ϕ^{-1} is the pseudo-inverse of ϕ. Conditions on this function can be found elsewhere (Genest, Quessy, & Remillard, 2006; Nelsen, 2006).

2.4 | Parameter estimation and duration–severity model for different return periods

Given a continuous model C_θ with associated density c_θ, a rank-based maximum pseudo-likelihood method is used (Genest & Favre, 2007) for parameter estimation (Equation (5)):

$$l(\theta)=\sum_{i=1}^{n}\ln\left[c_\theta\left(\frac{R_i}{n+1},\frac{S_i}{n+1}\right)\right], \quad (5)$$

in which n is the number of pairs and (R_i, S_i) represents a pair of ranks for duration and severity. The optimum parameter set maximizes l. An important step is to identify an appropriate kind of dependence structure from the set of copula models. In this study, the empirical copula (Equation (6)) is used to approximate the theoretical copula in terms of the root mean square error (RMSE; Equation (7)):

$$C_n(u_{1,j},u_{2,j})=\frac{1}{n}\sum_{i=1}^{n}1\left(\frac{R_i}{n+1}\le u_{1,j},\frac{S_i}{n+1}\le u_{2,j}\right), \quad (6)$$

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(C_\theta(u_{1,i},u_{2,i})-C_n(u_{1,i},u_{2,i})\right)^2}, \quad (7)$$

in which $1(\cdot)$ represents the indicator function. Another goodness-of-fit criteria used in this study is the Akaike information criterion (AIC; Akaike, 1974) which has been applied in copulas and hydrological assessments (see Hao, Zhang, & Yao, 2015; Zhang & Singh, 2007) to identify the appropriate probability distribution. The AIC selects a model among a set of models and includes a penalty term linearly related to the number of parameters in the calculation. It can be calculated as

$$\text{AIC}=-2\log(L_{\text{op}})+2k, \quad (8)$$

with L_{op} representing the optimized likelihood and k the number of parameters in the model. The higher the absolute value of AIC, the better the model. More about the methods for parameter estimation is given in Genest and Favre (2007) and Genest et al. (2006). The RMSE as well as the AIC for the five copulas, each regional model and RCP are given in Table S1. The values correspond to the post-fitting procedure outcomes. The best copula model is chosen so that it minimizes these two indicators.

In order to graphically see the goodness of fit of all models and the best performing model, two graphical analyses are performed. First, the empirical distributions are plotted against the theoretical copula distributions. For a good fit, plotted pairs are expected to lie near the 1.1 line. Second, the best performing model is used to simulate synthetic events which can be compared to the observed drought events. We generate the artificial data set (Genest & Favre, 2007) given by simulated ordered pairs (u, v) that represent the transformed drought characteristics duration and severity, respectively. We generate a large (n = 500) number of samples $\{(u,v)\}_{i=1}^{n}$ from the fitted Frank model by means of the conditional distribution $\frac{\partial}{\partial u}C_\theta(u,v)$ for a fixed v and randomly generated

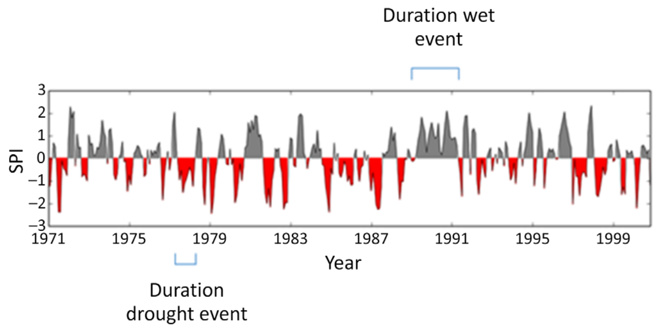

FIGURE 2 Standardized precipitation index (SPI) from the MPI-ESM_CCLM model, period 1971–2000. Periods of droughts are indicated in red. Grey areas indicate periods of precipitation higher than normal condition (median)

TABLE 2 Projected number of drought events for each RCM and RCP

	M1	M2	M3	M4	M5
RCP26	47	49	46		48
RCP45	45	51	46	52	48
RCP85	41	49	49	43	45

u values from the uniform distribution. We want to highlight that the fitting process and selection of the best copula model was carried out according to the ranked-based maximum pseudo-likelihood method and selection criteria according to Equations (6)–(8) respectively, as explained previously. The graphical representation is intended to graphically show the goodness of fit of the three best (Figure 4) and best copula (Figure 5) for the model MPI-ESM_CCLM.

The recurrence interval T_{DS} for the bivariate event ($D \geq d \wedge S \geq s$) can be defined as the expected time interval (or mean time interval) for the event to occur and can be expressed as a function of the marginals and joint distribution for drought duration D and drought severity S. Mathematically (Shiau, 2003),

$$T_{DS} = \frac{E(L)}{P(D \geq d, S \geq s)} = \frac{E(L)}{1 + F_{\mathrm{DS}}(d,s) - (F_D(d) + F_S(s))}, \quad (10)$$

in which $E(L)$ represents the expected value of the inter-arrival time L of a drought event and $F_{DS}(d, s)$ is the joint distribution modelled by the fitted copula.

3 | RESULTS AND DISCUSSION

3.1 | Drought occurrences

The SPI time series of the model M2 is displayed exemplarily in Figure 2 corresponding to the time period 1971–2000. Periods of dry conditions are depicted in red and of wet conditions in grey. It can be seen, for instance, that the duration of the wet period in 1989–1991 is much longer than the drought period between 1977–1978. For comparison purposes, Figures S2–S4 show the SPI time series for all EURO-CORDEX models, RCP8.5. Clear differences can be observed in the projected drought events indicating the differences in projections associated to climate models. Further, severity is calculated as the sum of SPI values. From the SPI-based drought characterization of present and projected events, the posterior joint models are built.

A first relevant analysis of these SPIs values is the difference between the number of droughts events (N_{events}) particularly between the different RCMs and RCPs in the projected period. Results are shown in Table 2. The first observation is that there is not a single model which projects an upper limit for N_{events} for each RCP when compared to the other models. Nonetheless we see that model M2, with the exception of model M4 for RCP4.5 always projects a higher number of drought events. We also see that the maximum difference in N_{events} occurs in scenario RCP8.5. For this case model M1 projects 41 events in contrast to models M2 and M3 which project 49 events. Important to note is the spread (difference) in the N_{events} projections. The higher the peak in GHG (greenhouse gases) emissions the more spread is observed in N_{events}. While RCP2.6 shows a spread of $d = 3$ in which model M3 and model M2 project 46 and 49 events, respectively, this difference increases to $d = 8$ in the RCP8.5 calculated from the models M1 and M2-M3 with 41 and 49 events, respectively.

Figure 3 shows a scatterplot of drought duration and severity for all regional models for the present period as well as RCPs. The small scatter indicates a strong duration–severity interdependence suggesting the use of a joint model for further analysis. Although the relationship may seem to be similar between different RCPs for a specific climate model, the scatterplots show different spread and different maximum values. For example,

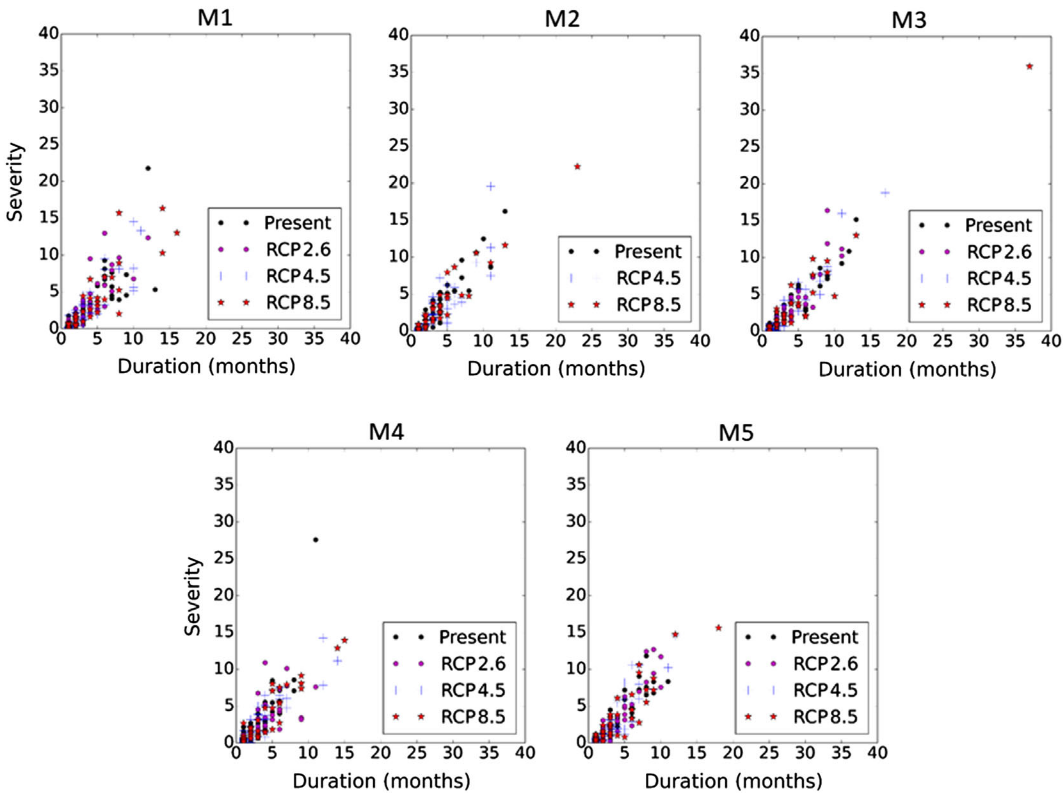

FIGURE 3 Duration versus severity scatterplots

model M3 in combination with RCP8.5 (red stars) shows the highest duration–severity drought event (point around [37, 36]), considerably higher than any other. RCP4.5 shows the second highest value (blue crosses). The present period and RCP2.6 display clearly smaller maximum values.

3.2 | Probabilistic model fitting

The theoretical copula is fit by the rank-based maximum pseudo-likelihood method given by Equation (5). The fitted theoretical model is further compared to its empirical counterpart. Table S1 shows the average RMSE and AIC over RCMs for all RCPs and copula models. Results indicate a good agreement for the copula families Clayton, Frank, and Gumbel. The worst results are found for the FGM model with a substantially larger error than the other models. A clearly better performance of the Frank family in terms of the RMSE and AIC is observed in all cases with exception of model M1 (EC-EARTH_RCA4) for RCP4.5 and model M4 (CNRM-CERFACTS_ALARO) for the present period, with small differences. The goodness of fit for the Gumbel model is, although not the optimum, close to the Frank model in terms of both the RMSE and AIC.

The goodness of fit of the copula models can be seen in Figure 4 for all cases, that is, present, RCP2.6, RCP4.5, and RCP8.5 for the model M1. This figure displays the empirical cumulative against the theoretical copula function for the three best performing models Clayton, Frank, and Gumbel. As Table S1 indicates, the other copula models show a clearly worse performance and hence are not shown. As expected and based on the fitting results (Table S1), a good agreement is confirmed for all these three copula families given in Table 1. For the subsequent analysis, we present results using the Frank model as it shows the best fit.

Figure 5 exemplarily shows the historical and simulated dependency from the conditional Frank copula for the periods 1971–2000 and 2021–2050, model M2 as a scatterplot. The fitted copula model C_θ adequately reproduces the bivariate dependency between u and v as expected, since the simulated points are drown from the best performing copula model (according to Equations (6)–(8)).

It is important to mention that the functional relation between drought duration and severity cannot be assumed a priori. Often, different models are found to represent the joint behaviour. For instance, Shiau (2006) identified the Galambos copula fitting best out of seven models, while for a drought analysis for 50 rain-gauge

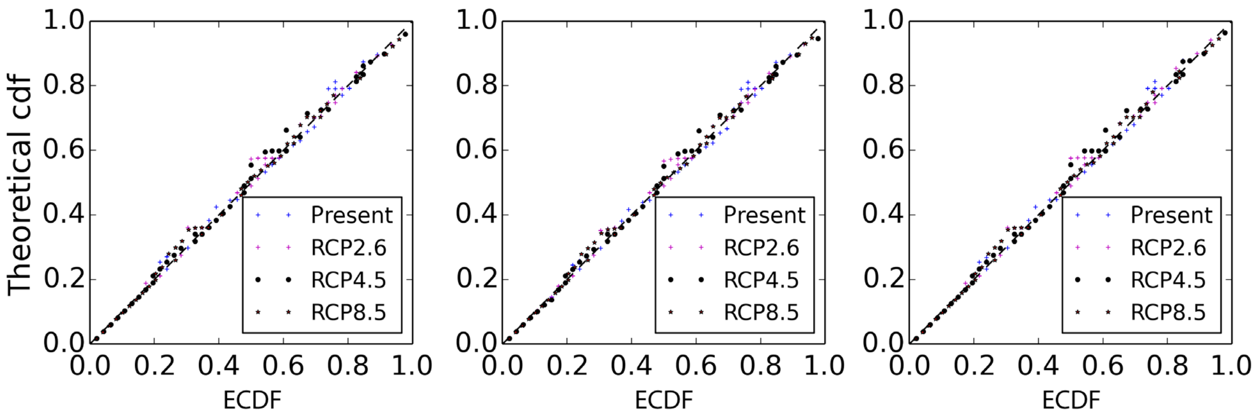

FIGURE 4 Empirical (ECDF) versus the fitted theoretical cumulative distribution function (CDF) for the models Clayton, Frank, and Gumbel

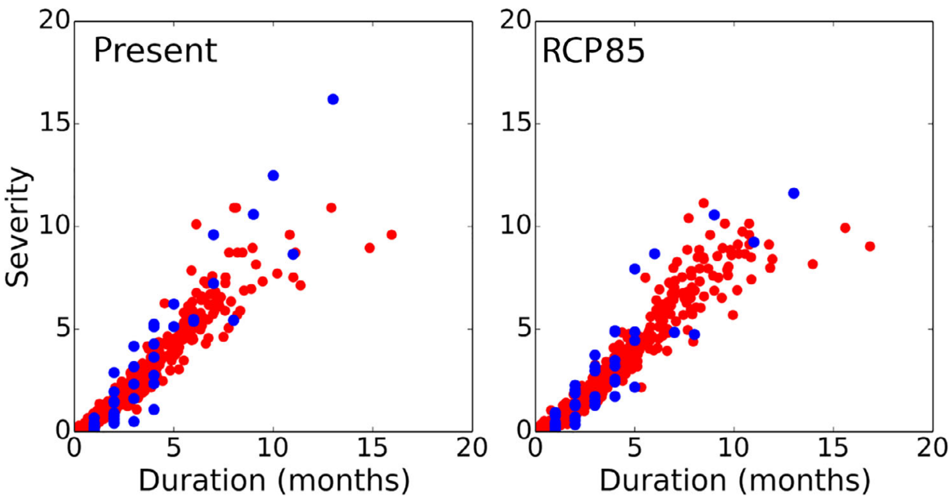

FIGURE 5 Comparison of calculated dependence (blue) and simulated dependence (red) from fitted Frank copula model. The left panel shows present period (1971–2000) and the right panel the future period (2021–2050), for RCP8.5 and M2

stations in Malaysia the Joe copula performed best (Zin, Jemain, & Ibrahim, 2013). Abdul Rauf and Zeephongsekul (2014) found the Gumbel-Hougaard copula more appropriate in representing the relationship between severity and duration. All this indicates that first the appropriate model is case dependent, so that an assumption of a predefined model could lead to a poor fit, and second the selection should be based out of several choices.

3.3 | Joint analysis of drought duration, severity, and recurrence intervals

The association of drought duration and severity to their frequency in terms of recurrence intervals is calculated using Equation (10). The return period is expressed as a function of the marginals (duration and severity) and the fitted bivariate copula model. Figure 6 shows the joint relationship duration–severity for different recurrence intervals for both the historical and projected periods. For each return period of 1, 2, 5, and 10 years, three different curves representing the RCP2.6, RCP4.5, and RCP8.5 are shown. The associated uncertainties in the joint behaviour are characterized by the spread of the estimates for the different RCMs and RCP.

Results show that for short return periods of 1 and 2 years, only small changes in the associated duration–severity relationship are projected for all RCMs. The difference is clearly larger for longer return periods and is most accentuated for a return period of 10 years. The magnitude of these differences substantially depends on the RCM. Comparing all five CORDEX models (Figure 6), the patterns of recurrence intervals for models M1, M2, and M5 are rather similar. Larger spreads of projections are found for the other two models.

For a fixed return period, the curves associated to different concentration pathways also show variations. Consider, for example, the model M1 for the return period of

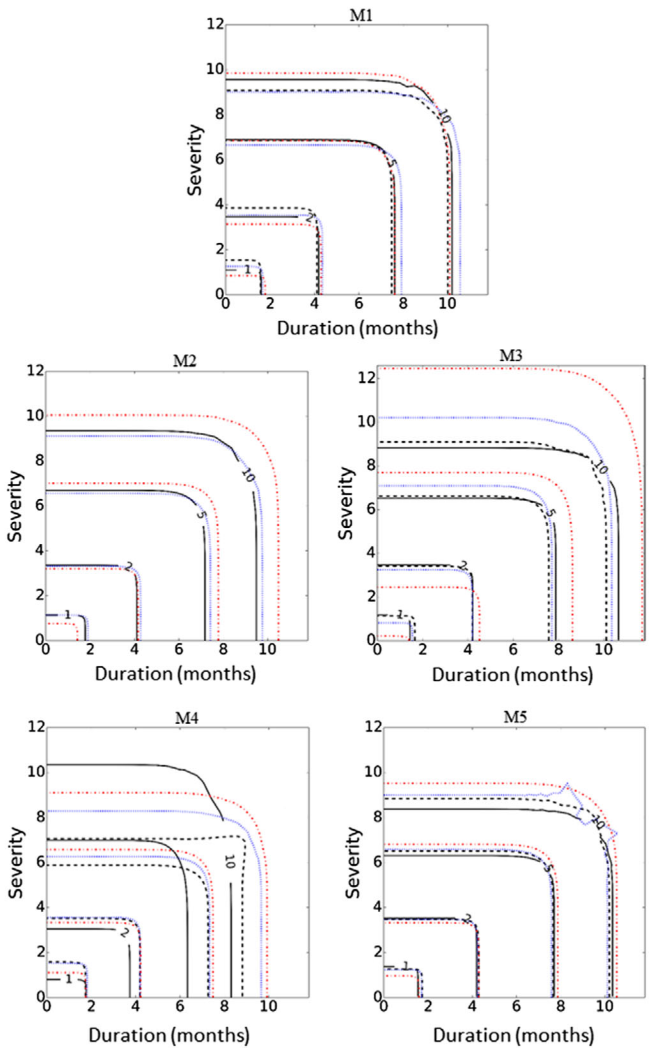

FIGURE 6 Recurrence intervals of 1, 2, 5, 10 years for the observed period (solid line), RCP2.6 (dashed line), RCP4.5 (blue line), and RCP8.5 (dash-dotted red line) for all five CORDEX models

10 years. Compared to the present period, the RCP2.6 projects a joint pattern in which the severity is smaller and the durations are shorter (dashed line). RCP4.5 and RCP8.5 show, however, opposite trends. While RCP4.5 projects smaller severity together with a longer duration, RCP8.5 indicates larger severity and shorter duration (seen as a bivariate dependency). The model M3 suggests a different association between drought duration and severity for the same return period. In this case, for RCP2.6 and RCP4.5, severity shifts upwards and duration shifts downwards. In contrast, for RCP8.5, both duration and severity shift upwards. This also shows that projected patterns are strongly related to the RCPs. On the whole, uncertainties associated to RCPs are substantial and their magnitude of variations are RCM-dependent. The largest uncertainties are shown by the models M3 and M4.

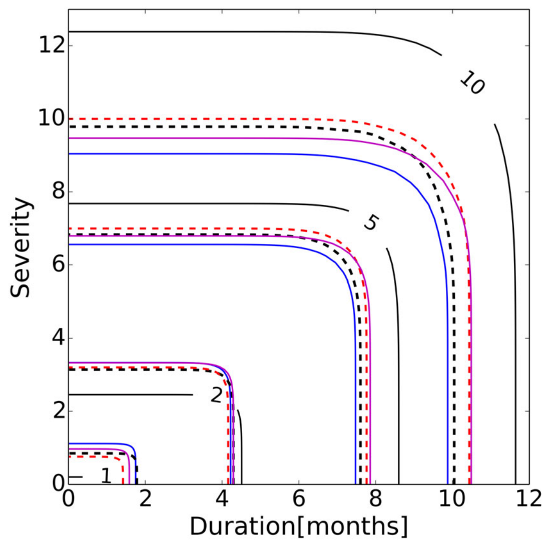

FIGURE 7 Recurrence intervals 1, 2, 5, 10 for RCP8.5 showing the different joint relationships duration–severity for the driving models: M1 (black dashed line), M2 (red dashed line), M3 (black solid line), M4 (blue solid line), M5 (magenta solid line)

The most important source of uncertainty are the RCMs (Figure 6). In order to better compare the magnitudes of the differences between the five regional models independent of the RCPs, Figure 7 shows the duration–severity joint pattern for RCP8.5 considering all RCMs. An increasing uncertainty with increasing return periods is clearly observed from the model ensemble. The projected differences in the drought patterns are not negligible and are much more accentuated for return periods of 10 years, particularly for the model M3.

Anthropogenic climate change effects on drought characteristics have also been the object of other studies that support the findings of this work. For example, changes in the precipitation patterns across the year, changes in intensity and occurrence of dry days can influence the joint behaviour duration–severity of drought events. The Special Report on Emission Scenarios (SRES) projected an increase of precipitation in winter and decrease in summer for Germany, which could explain the pattern changes shown in this work. Meehl et al. (2007) projected a larger number of dry days together with an increase in variability of precipitation intensity. Tölle et al. (2013) analysed the SPI drought index for Germany and detected a statistically significant increase of the upper quantiles of the SPI for winter. They concluded that strong precipitation will intensify and the number of dry months will decrease in the winter season in the future. All this evidence is consistent with our results that suggest a change in the interrelation between drought duration and severity in the study region.

4 | CONCLUSIONS

In the present study, we investigate droughts in the Fulda catchment (Germany) under current climatic conditions and for the near future. We show that the characteristics duration and severity of drought events are strongly interrelated. Based on this, we model them as a bivariate phenomenon fitting different bivariate copula models. The Frank model shows the best performance in terms of the RMSE and AIC and is used to model the dependence structure duration–severity. Potential differences in the duration–severity interdependence for the next decades are quantified for the RCM–RCP combinations. Altogether, we considered 15 different scenarios. The uncertainty of projections corresponding to different RCMs and RCPs are also investigated. We find clear tendencies in the different RCMs despite the inherent uncertainty of the RCM ensemble, as the dependency between the magnitudes of variations and frequencies. We conclude that (a) the drought duration–severity interdependence may change in the period 2021–2050 as RCMs project and (b) that the duration–severity relationships shows different patterns depending on return period, RCM and RCP. Finally (c), the uncertainty associated with the RCMs is larger than that associated with the RCPs. The most important sources of uncertainty is given by the RCMs. Concentration pathways also present important uncertainties and the largest differences are observed by the models M3 and M4. We can suggest that future work should consider an even larger ensemble of RCMs to see whether the projected spread of results is even wider. Other uncertainty sources as those related to improving model bias or the analysis of other joint models may also be incorporated.

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