Book Chapter

A Continuous Drought Risk Monitoring System, CDRMS, Based on Copulas

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Abstract

From the drought indices, the Standardized Precipitation Index, SPI, is the most used one. However, it is difficult to use to monitor the ongoing drought characteristics because it cannot be expeditiously related to precipitation deficits. It also does not provide information regarding the drought risk nor the temporal evolution of the droughts. By using the SPI, a copula-based Continuous Drought Risk Monitoring System, CDRMS, was developed aiming to monitor the droughts, including the risk of having a drought event as the rainy season advances. In climates with very pronounced rainy seasons, the absence of precipitation along the same is the fundamental booster of droughts. After presenting the CDRMS, the paper describes its application to Mainland Portugal, which showed that the system has an increased capability of anticipating the drought risk by the end of the rainy season as new precipitation records are known. The good performance of the system results from the ability of the copula to model complex dependence structures as those existing between precipitations in different time intervals. CDRMS is an innovative and user-friendly tool to monitor the precipitation and, consequently, the drought risk, allowing to anticipate mitigation and adaptation measures or even to issue alarms.

Keywords

Drought; SPI; Copulas; Risk Assessment

Introduction

Drought is a natural hazard with a clear onset inherently difficult to identify. It is the world's costliest natural disaster and can provide impacts in a global perspective, not restricted to places

with low average precipitation amounts [1–3]. Alone in Europe, the total cost of droughts from 1976 to 2006 amounted to 100 billion € [4]. Therefore, drought risk monitoring is fundamental to mitigate its impacts.

Considerable disagreement exists about the concept of drought. Common to all definitions is the fact that it results from a below-the-average precipitation over a period of time. If this period is long enough, it can affect progressively soil moisture, water resources availability, and, consequently, social development. According to its consequences, the droughts can be clustered into four categories - meteorological, agricultural, hydrological, and socioeconomic [1,5].

Drought indices are the most suitable tool for drought monitoring and evaluation. Many different indices have been proposed in the last decades. Among the hydrological variables used to detect and characterize drought occurrences, precipitation is the most used, not only due to its natural link with the phenomenon and its consequences, but also because precipitation is widely monitored and there are relatively long precipitation records.

In 2009, the World Meteorological Organization (WMO) recommended the Standardized Precipitation Index (SPI) [6] to monitor and follow meteorological drought conditions. Since then, SPI is used worldwide to detect anomalous values of precipitation at different time scales. The index has the advantages of being independent of the magnitude of the mean precipitation, because it is a standardized index, and hence, able to compare the droughts under different climatic zones. However, because it provides a standardized numerical value, it is difficult to connect it expeditiously to precipitation deficits, and, consequently, to use it to recognize or to anticipate drought occurrences.

Droughts had been traditionally studied in a univariate context, mostly aiming at recognizing their occurrence. However, as many of the hydrological phenomena, they are characterized by multiple aspects some of them expectably correlated. Because a

univariate approach ignores the dependence structure among those aspects, it may result in a poorer representation of the phenomenon.

Some multivariate techniques were introduced in hydrological studies, such as in the case of floods, droughts, and storms. Those techniques contributed to improve the accuracy of the estimates and to provide information about the dependence structure among characteristics. Most of the studies focused on bivariate cases using bivariate distributions with the same marginal, such as bivariate gaussian, exponential, gamma, and extreme value distributions. The disadvantages of these types of distribution are that a same family is needed for each marginal distribution and extensions to more than the bivariate case are not clear [7,8]. Multivariate distributions using copulas, however, can overcome such difficulties [9]. The advantages in using copulas to model joint distributions are manifold: (1) flexibility in choosing arbitrary marginals and structure of dependence, (2) extensions to more than two variables, and (3) splitting of marginal and dependence structure analysis [7,8,10,11].

Although multivariate analysis based on copulas is possible, the bivariate analysis is more recommended because of the complexity of fitting the dependence among multiple random variables to the predefined shapes of the common copulas. To address the multivariate analysis more advanced copulas are needed such as the vine-copulas that are capable of coupling multiple variables into a pair-to-pair manner [12]. Due to these capabilities, application of copulas in hydrology has gained some relevance in the last decades. Regarding droughts analysis, one of the main uses of copulas is the frequency analysis which combines different characteristics of the drought events, e.g., intensity, duration, magnitude, and spatial distribution [13–17]. Another important use is to integrate the drought index to couple different drought categories, such as meteorological, hydrological and agricultural [18–20].

In climates, like Mainland Portugal, where insufficient precipitation during the short and well-defined rainy season is

the main booster of the drought events, an innovative use of copulas could be its application in a multivariate context to monitor the evolution of the drought risk along that season, based on the continuous updating of the precipitation deficits or surpluses. Such application can be easily decoded into a typical a problem of conditional probability taking advantage of the flexibility of copulas to model dependence structure between the precipitation that already occurred and the one that needs to occur, so that there is no drought during a reference period – in the example, the rainy season. The conditional probability theory coupled with copulas is highly used in hydrological applications to analyze multivariate dependence [17,21,22] and will be applied in this study.

Aiming at exploring copula's forecasting capabilities in the drought monitoring context, the concept of a precipitation threshold for drought recognition developed by [23–25] was used. In each rain gauge, if the cumulative precipitation in a given timespan falls below the precipitation threshold for that timespan, a drought with a severity (from moderate to extreme), defined by the threshold, will occur. Figure 1 exemplifies the application to Mainland Portugal of the precipitation surface threshold concept applied to the recognition of moderate to extreme droughts in the period from October to March, the rainy season. If in a certain location the precipitation registered falls below the value given by one of the maps, then such location experiences a drought with the intensity given by the threshold to which the map relates.

Surfaces of precipitation thresholds, R_N^* , for the 6-month period from October to March (SPI6), from the right to the left, for moderate (-0.84), severe (-1.28) and extreme (-1.96) droughts. Adapted from [23].

The application of the precipitation threshold concept in the scope of the present study can be formulated as follows: for a season of N months to which the time scale of the SPI and the precipitation threshold, R_N^* , refer, let R_n denote the observed precipitation in the first n months ($1 \leq n \leq N$) and R_N the total seasonal precipitation.

A drought will occur by the end of the N -month period if R_n added to the (unknown) precipitation in the remaining ($N - n$) months, $R_{(N-n)}$, is not enough to meet the threshold, R_N^* , i.e.:

$$R_n + R_{(N-n)} \leq R_N^* \Leftrightarrow R_N \leq R_N^* \quad (1)$$

Consider, for example, the six-month season, $N=6$, from October to March (during which most of the precipitation in Portugal occurs) and, that at the end of December of a given year, an estimate of the probability of a moderate, severe or extreme drought occurrence is envisaged. Given the observed precipitation from October to December (R_n with $n=3$), the question to tackle is: for each drought intensity, what is the probability the precipitation from January to March (still

unknown) added to the precipitation from October to December being below the drought threshold? The answer to this question is the drought risk given by the following equation:

$$P(R_N \leq R_N^* | R_n) \Leftrightarrow P(R_6 \leq R_6^* | R_3) \quad (2)$$

By coupling a copulas approach with the precipitation threshold concept, the main objectives of this study were as follow: 1) to develop a methodology for a Continuous Drought Risk Monitoring System, CDRMS; 2) to evaluate the performance of CDRMS, and 3) to apply the CDRMS in a study area. For this purpose, Mainland Portugal and the rainy season, from October to March, were selected. In Portugal the precipitation regime is characterized by a high seasonality, in average with 80% of the precipitation occurring from October to March, which makes it relevant to be able to anticipate if drought conditions are expected by the end of that period.

Materials and Methods

The development of the CDRMS was based on the following stepwise approach (Figure 2): (a) definition of the drought threshold for a given time span or scale of the SPI, N , and drought severity; (b) evaluation of the copula candidates aiming at modeling the precipitation correlation structure, and selection of the copulas with best-fit, and (c) monitoring of the drought risk given by Equation (2). Having in mind that the aim of the CDRMS is to continuously monitor the risk of a drought by the end of the N -month period, steps (b) and (c) of Figure 2 are repeated from $n=1$ to $n=N-1$. The Leave-One-Out Cross-Validation (LOOCV) methodology (steps b and c repeated from $x=1$ until the length x of time series) was used to evaluate model performance using the Brier and the Brier Skill scores (step d).

The CDRMS was applied to Mainland Portugal based on precipitation records at 45 rain gauges (section 3).

Figure 2: Development of the CDRMS and evaluation of its performance.

CDMRS Model Definition

Seasonal Threshold Definition

The precipitation in mainland Portugal is mainly concentrated in the semester from October to March: on average, almost 70% (North) and 85% (South) of the annual precipitation occurs in that period. Therefore, it was considered relevant to obtain the probability of drought occurrence starting in October (also beginning of the hydrological year) and adopting March as the end of the rainy season. The precipitation thresholds for that period were obtained based on the corresponding value of SPI6 for the different drought intensities proposed by Agnew [26] and presented in table 1.

Table 1: Drought class and associated probability and SPI value according to [26].

Drought class	Probability	SPI value
Moderate Drought	0.20	Less than -0.84
Severe Drought	0.10	Less than -1.28
Extreme Drought	0.05	Less than -1.65

Adapted from [26]

For a given rain gauge, period and drought severity, the precipitation thresholds, R_N^* , are obtained by inverting the SPI calculation, which means that they give the SPI value back to the precipitation field.

Copula Fitting

The analysis of the dependency structure between two or more random variables can be used to indicate predictive relationships between them. The most common method is to measure linear relation in the form of the Pearson correlation coefficient. One of the main weaknesses of using linear correlation is that it tends to detect only the degree of dependence despite of its dependence structure.

The consideration of non-linear dependence is possible by using a rank correlation coefficient such as Spearman rank correlation and Kendall's Tau. This coefficient is more used because its value indicates directly the probability of observing concordant or discordant pairs. There exists a relationship between the rank correlation coefficient and copula function that allows the use of copulas to study non-linear dependences.

According to Sklar's theorem [27], if the random variables $x_1, \dots, x_m$ follow a marginal distribution function $F_1(x_1), \dots, F_m(x_m)$, respectively, there exists a copula, C , that can join these marginal distribution functions in the form of a joint distribution function (Eq. 3),

$$\begin{aligned} H(x_1, x_2, \dots, x_m) &= C[F_1(x_1), F_2(x_2), \dots, F_m(x_m)] \\ &= C(u_1, u_2, \dots, u_m) \end{aligned} \tag{3}$$

where, $F_k(x_k) = u_k$ for $k = 1, \dots, m$, with $u_k \sim u(0,1)$ and $C(u_1, \dots, u_m)$ being the copula function.

Although copulas may be implemented in multiple dimensions only bivariate copulas were considered in the present study.

Different families of copulas have been described by Nelsen [27]. The families are commonly classified in four main groups:

Meta-elliptical copulas (Gaussian and t Student), Archimedean copulas (Clayton, Gumbel, Frank, and Joe), Extreme value type (Gumbel, Husler-Reiss, Galambos, Tawn, and t-EV), and miscellaneous type (Plackett and Farlie–Gumbel–Morgenstern).

The Archimedean copulas are very popular for hydrological analyses as they allow modeling a great diversity of dependence structures, especially for dependent tail structures, and because of its accessible generation properties [8,14,28]. At higher orders, the use of Archimedean copulas is limited because their structure imposes restrictions related to dependence characteristics that are extremely difficult to satisfy for more than two variables [29]. Meta-Elliptical copulas, on the other hand, can model higher order due to their simple structure that can better fit complex dependence of multi-dimensional problems [9,30].

The parameters for the copulas families can be estimated either by the method of moments, inversion of Kendall's Tau or by Maximum Likelihood Estimation (MLE). The first method has the disadvantage of being applicable only to one-parameter copulas. As for the MLE method, two possibilities exist: the Inference Functions from Margins (IFM) [31] or the Maximum Pseudo-Likelihood Method (MPL)[32]. How the transformation to $[0,1]$ interval was made will dictate which is the best method, parametric for IFM and MPL for rank-based [33].

To model the dependence structure between the precipitation in a given sub period of the rainy season and the seasonal precipitation itself, as is the case of the current application, the most popular Meta-Elliptical copulas (Gaussian and t Student), and Archimedean copulas (Clayton, Gumbel, and Frank) were tested as candidates. The copula formulation for each candidate family and its parameters' interval are presented in Table 2. For each month of the rainy season, the bivariate model is constructed based on the two variables: precipitation in its initial n months, R_n , and the total seasonal precipitation, R_N .

The parameters θ for Archimedean copulas and ρ and ν for Meta-Elliptical copulas, with ν standing for the degrees of

freedom (only needed for t Student copulas) were estimated for the candidate copulas. The MPL method was used as in [9]. This method was chosen because it can estimate both one and two parameters of the copula without requiring the establishment of the marginal distributions.

The Akaike Information Criterion (AIC) was used to compare the bivariate copula models for the candidate families. The AIC method penalizes the models with the highest number of parameters, allowing to find the model with maximum explanatory power and fewer parameters, according to the parsimony principle.

Table 2: Copula candidate family formulation and parameter range.

Class	Family	$C(u_1, u_2)$	Parameter range
Archimedean	Gumbel	$\exp\{-[(-\ln u_1)^\theta + (-\ln u_2)^\theta]^{\frac{1}{\theta}}\}$	$\theta \in [1, +\infty)$
Archimedean	Frank	$\frac{1}{\theta} \log\left(1 + \frac{(e^{\theta u_1} - 1)(e^{\theta u_2} - 1)}{(e^\theta - 1)}\right)$	$\theta \in (-\infty, +\infty)$
Archimedean	Clayton	$(u_1^{-\theta} + u_2^{-\theta} - 1)^{-\frac{1}{\theta}}$	$\theta \in (0, +\infty)$
Meta-Elliptical	Gaussian	$\phi_\rho(\phi^{-1}(u_1), \phi^{-1}(u_2))$	$\rho \in (-1, 1)$
Meta-Elliptical	t Student	$T_{\rho, v}(T_v^{-1}(u_1), T_v^{-1}(u_2))$	$\rho \in (-1, 1), v > 2$

Conditional Probability

The conditional probability theory associated with copulas is highly used in hydrological applications to analyze multivariate dependence [17,21,22] and can be expressed by Equation (5). Let two random variables X and Y with $U_1 = F_x(x)$, $U_2 = F_y(y)$ and u_1 and u_2 being specific values. The conditional distribution of X given Y = y is given by:

$$\begin{aligned}
 H(X \leq x | Y = y) &= C_\theta(U_1 | U_2 = u_2) = \\
 &= \frac{\partial}{\partial u_2} C_\theta(u_1, u_2)
 \end{aligned}
 \tag{5}$$

CDRMS Performance Assessment

The CDRMS performance was measured by the Brier Score based on the previous computation of the probability of the joint

events for all the years with data but one ($x-1$), according to the LOOCV. The probabilistic prediction skill was evaluated by the Brier Skill Score. In the LOOCV method, each of the x observed years is evaluated by withdrawing one year of the time series, by fitting the model to the remaining $x-1$ years, and by estimating the withdrawal observation [34]. The process is repeated x times to exclude any bias in the performance verification. It is important to state that LOOCV is not part of CDRMS, as it was used only to assess model's performance, as represented in Figure 2. The model skill is compared against a random reference forecast.

Brier Score (BS)

The drought probability provided by the proposed copula-based model for each month can be analyzed using the Brier Score (BS), a verification measure of binary events (yes/no) that is used in multivariate models [35,36]. BS is mainly the mean squared error between the probability of the drought prediction (p_i), and a value of a binary variable associated to the observations (o_i) by assigning 1, if the event occurs, and 0, if it does not, where x is the length of the time series. The BS takes values in the range 0 to 1, with 0 meaning perfect prediction, according to [34]:

$$BS = \frac{1}{x} \sum_{i=1}^x (p_i - o_i)^2 \quad (6)$$

Brier Skill Score (BSS)

The Brier Skill Score (BSS) was used to evaluate the probabilistic prediction skill. The score is calculated from the BS for the CDRMS (BS_{CDRMS}) and the BS for a reference forecast (BS_{REF}) according to Equation 7, whose results range from $-\infty$ to 1. No skill, in comparison to the reference, is given by $BSS = 0$ and perfect skill by $BSS = 1$.

$$BSS = 1 - \frac{BS_{CDRMS}}{BS_{REF}} \quad (7)$$

In the application done, the reference forecast selected for the evaluation of the prediction performance is the random probability of occurrence of a drought with a given intensity. Because this score was only applied to *moderate* droughts ($SPI < -0.84$, corresponding to the 20th percentile [26]) the p_i for the BS_{REF} was set equal to 0.20.

Precipitation Data

In order to construct a reliable bivariate statistical model for joint precipitation distributions, long historical continuous observations are needed. In the application presented herein, 45 rain gauges evenly distributed over mainland Portugal were selected – Figure 3 and Table 3.

The monthly precipitation records were acquired by the Portuguese Environmental Agency, APA, and made available via the SNIRH database (*Sistema Nacional de Informação de Recursos Hídricos*, <http://snirh.pt>), which has high data quality standards and is the main source of Portuguese hydrological and hydrometeorological data used by researchers and practitioners of water resources engineering and science.

Some of the precipitation series had missing values that were filled by applying an approach based on a linear regression analysis. For each monthly gap in a given rain gauge, the approach identifies the candidate rain gauges that can be used for filling it. These gauges are next ranked according to the correlation coefficient between paired series for that month at the rain gauge with the gap and the candidate rain gauges. The one with higher correlation coefficient is used to fill the gap based on a linear regression model that is specific for each gap [37]. The length of the series after filling the missing values was $x=100$ hydrological years, from 1918/19 to 2017/18. In Portugal, the hydrological year starts in October.

Figure 3: Schematic location of the 45 rain gauges adopted in the study.

Table 3: Name, code, identification (ID) and geographic coordinates (WGS84 system) of the 45 rain gauges of Figure 3.

Name	Code	ID	Lat (°)	Long (°)	Name	Code	ID	Lat (°)	Long (°)
Merufe	01G03UG	RG01	42.0180	-8.3890	Bemposta	17I02UG	RG24	39.3490	-8.1410
Travancas	03N01G	RG02	41.8280	-7.3056	Alter do Chão	18L01UG	RG25	39.2182	-7.6844
Leonte	03I03UG	RG03	41.7650	-8.1470	Pragança	18C01G	RG26	39.1990	-9.0640
Soutelo (Chaves)	03L02UG	RG04	41.7530	-7.5348	Pavia	20I01G	RG27	38.8965	-8.0136
Campo de Vitoras	04R03UG	RG05	41.5240	-6.5580	Caia (Monte Caldeiras)	20C02UG	RG28	38.8873	-7.0898
Cabeceiras de Basto	04J06UG	RG06	41.5127	-7.9792	Santo Estevão	20B02UG	RG29	38.8600	-8.7460
Santa Marta da Montanha	04K02G	RG07	41.5008	-7.7460	Estremoz	20L01G	RG30	38.8416	-7.6159
Folgares	06N01C	RG08	41.3032	-7.2828	Colares (Sarrazola)	21A01C	RG31	38.8020	-9.4570
Carviçais	06P02UG	RG09	41.1790	-6.8900	Évora-Monte	21K02UG	RG32	38.7690	-7.7161
Moncorvo	06O04UG	RG10	41.1650	-7.0510	São Manços	23K01UG	RG33	38.4605	-7.7505
Adorigo	07L01U	RG11	41.1460	-7.6070	Barragem de Pego do Altar	23C01C	RG34	38.4196	-8.3952
Pindelo dos Milagres	09J02U	RG12	40.8060	-7.9630	Amieira	24L01C	RG35	38.2793	-7.5605
Freixedas	09O02U	RG13	40.6880	-7.1630	Barrancos	25P01UG	RG36	38.1321	-7.0013
Gouveia	11L01UG	RG14	40.4940	-7.5930	Santa Vitória	26B01UG	RG37	37.9645	-8.0227
Santo Varão	12F02C	RG15	40.1840	-8.6020	Serpa	26L01UG	RG38	37.9426	-7.6038
Góis	13I01G	RG16	40.1568	-8.1133	Relíquias	27G01G	RG39	37.7030	-8.4825
Soure	13F01G	RG17	40.0521	-8.6250	Castro Verde	27I01G	RG40	37.6976	-8.0933
Penha Garcia	13O01UG	RG18	40.0420	-7.0180	Mértola	28L01UG	RG41	37.6371	-7.6619
Alvaizere	15G01UG	RG19	39.8270	-8.3810	Rosário (Almodôvar)	28B02U	RG42	37.6020	-8.0810
Ladoeiro	14N02UG	RG20	39.8269	-7.2660	Barragem de Mira	28G01C	RG43	37.5101	-8.4433
Nisa	16I03UG	RG21	39.5160	-7.6690	Santa Catarina (Tavira)	31K01UG	RG44	37.1487	-7.7847
Castelo de Vide	17M01G	RG22	39.4116	-7.4525	Valverde	31B03C	RG45	37.0820	-8.7180
Pernes	17F01UG	RG23	39.3910	-8.6630					

CDRMS for Mainland Portugal: Definition and Performance

The following items describe the stepwise development and the performance assessment of the CDRMS aiming at monitoring continuously the drought risk over Mainland Portugal during the rainy season, from October to March, based on the precipitation records at the 45 rain gauges of Figure 3. The application to a specific site is presented in item 5.

Precipitation Thresholds for Drought Recognition

Table 4 presents the precipitation thresholds, R_N^* , in the 45 rain gauges obtained by inverting the SPI for the time span of 6 months (SPI6), from October to March, for the different drought intensities (moderate, severe and extreme). By the end of March, a drought with a given intensity occurs in a given rain gauge whenever the precipitation from October to March is smaller than the precipitation threshold for that intensity.

Table 4: Precipitation thresholds, R_N^* , (mm) for the six-month period, from October to March, for the different drought intensities.

Rain gauge ID	Drought intensity			Rain gauge ID	Drought intensity		
	Moderate	Severe	Extreme		Moderate	Severe	Extreme
RG01	745.2	550.64	411.71	RG24	307.4	226.87	165.02
RG02	429.86	351.89	297.57	RG25	269.87	189.95	126.19
RG03	1250	933.9	701.38	RG26	442.08	357.14	294.9
RG04	338.88	272.4	228.68	RG27	245.44	181.41	132.09
RG05	252.7	212.22	189.92	RG28	228.59	169.37	122.54
RG06	624.02	467.59	350.53	RG29	272.29	208.88	160.37
RG07	774.35	614.67	500.81	RG30	281.62	208.11	151.76
RG08	250.85	197.33	158.84	RG31	371.68	309.26	263.11
RG09	290.02	221.5	172.2	RG32	265.59	201.47	152.4
RG10	225.01	175	137.3	RG33	238.9	178.12	130.74
RG11	280.15	223.04	182.17	RG34	269.57	214.9	174.57
RG12	601.35	479.3	393.19	RG35	256.2	202.44	162.62
RG13	311.57	232.75	170.58	RG36	260.57	204.39	159.99
RG14	517.33	419.07	345.06	RG37	251.94	197.65	155.93
RG15	446.41	361.03	294.17	RG38	237.88	182.39	140.58
RG16	557.52	449.03	364.89	RG39	311.31	242.33	191.1
RG17	415.41	320.11	246.56	RG40	267.89	215.71	175.71
RG18	383.71	310.81	255.61	RG41	184.49	146.78	120.91
RG19	586.6	468.64	378.47	RG42	284.41	223.21	176.28
RG20	288.63	234.72	194.22	RG43	292.29	225.79	173.24
RG21	331.49	256.71	199.37	RG44	318.5	239.46	180.25
RG22	370.68	284.5	221.82	RG45	289.52	228.98	182.32
RG23	379.64	288.83	218.22				

Copula Fitting

In each rain gauge, the bivariate model was constructed by “coupling” the seasonal precipitation, from October to March, R_N for $N=6$, with the precipitation at the beginning of the first n months of the rainy season, R_n , i.e., the precipitation in October, for $n=1$, from October and November, for $n=2$ and so on until $n=5$, from October to February. The length of each coupled (R_N , R_n) series is equal to the length of the recording period ($x=100$ years). The parameters were estimated using maximum likelihood, and the candidate copula families were selected based on the AIC.

For the 45 rain gauges, Figure 3 presents the frequency of the copula families chosen for each value of n . Considering, for example, $n=1$, the percentage of rain gauges where the different types of families were selected is as follows: 31% - copula Frank, a symmetric Archimedean copula; 38% - Clayton copula, an asymmetric copula with lower tail dependence; 4% - Survival Clayton copula, a 180 degrees rotated Clayton with upper tail dependence; 18% - Gumbel copula, an asymmetric copula with upper tail dependence; and 9% - Gaussian copula, a symmetric Meta-Elliptical copula.

As n increases, the percentage of rain gauges where the Frank copula is selected decreases from 31 ($n=1$) to 7% ($n=5$). This is explained by the increase of the linear dependency between variables as the precipitation in additional months of the rainy season is progressively added. The same applies to the Meta-Elliptical copulas, Gaussian and t Student: less than 10% of the rain gauges for $n=1$ to approximately 60% of the rain gauges for n from 3 to 5.

Figure 3: Distribution (in percentage) of the selected copulas by the 45 rain gauges as a function of the number of initial months of the rainy season.

Drought Risk Monitoring

After the bivariate model has been set up for each rain gauge, the CDRMS was applied to estimate the drought risk, according to Equation (2) (conditional probability of drought occurrence given the observations).

The results obtained are shown in Figure 4 that characterizes the spatial distribution of the moderated drought risk for the rainy season of Oct/2012 to Feb/2013, chosen as example. The figure was obtained by averaging the results at the 45 rain gauges according to the Inverse Distance Weighting (IDW) method with exponent 2.

Figure 4: Example of the application of the CDRMS to the continuous monitoring of the risk of moderate drought at the end of the six months period from Oct/2013 to Mar/2013. Drought risk from the end of October (n=1) to the end of February (n=5). The last map identifies the rain gauges that in fact did or did not experience a drought by the end of March of 2013.

It is possible to see that, for n=1 (that is, by the end of October), two regions presented a higher risk of drought occurrence: northwest and southeast regions. For n=3 (end of December), the risk of drought in those regions increased and even expanded to some of the central areas. As the precipitation in the following months is progressively known, only a few regions of the country have a drought risk smaller than 50%. This could justify the issue of an alarm warning for the risk of having a drought by the end of March – with caution in December (n=3), for sure in January (n=4) and definitely in February (n=5). Such an early alarm could raise the awareness of the water resources managers and of the civil protection authorities, urging some anticipatory measures adequate to smoothen the consequences of a possible scenario of drought and water scarcity.

The last map of Figure 4 relates to what happened by the end of March. The almost perfect match between the areas where the drought risk progressively increased with n (areas shaded from blue to orange and red) and those that in fact experienced a drought by the end of March (red circles) clearly confirms the ability of the model to identify the increasing drought risk.

CDRMS Performance Assessment

The performance of the CDRMS was assessed based on the BSS computed for each one of the 45 rain gauges and values of n , according to the LOOCV methodology (section 2.2).

The results achieved for moderate droughts, adopted as example, are presented in Table 5. The values closer to 1, the best the model performs, and the negative values indicate that the reference forecast outperformed the CDRMS. The ability of the CDRMS to monitor the drought risk increases as the number of months, n , with known precipitation increases: for $n=1$ the average performance for the complete set of rain gauges is 0.03 while for $n=5$ is 0.70.

Table 5: Moderate droughts. BSS values for $n=1$ to $n=5$.

Rain gauge ID	n = 1	n = 2	n = 3	n = 4	n = 5	Average	Rain gauge ID	n = 1	n = 2	n = 3	n = 4	n = 5	Average
RG01	0.15	0.27	0.46	0.57	0.69	0.43	RG24	0.03	0.23	0.38	0.56	0.81	0.40
RG02	-0.02	0.10	0.13	0.37	0.55	0.23	RG25	0.02	0.15	0.30	0.57	0.73	0.35
RG03	0.05	0.19	0.47	0.63	0.83	0.44	RG26	-0.05	0.12	0.25	0.60	0.78	0.34
RG04	0.04	0.10	0.25	0.44	0.65	0.30	RG27	0.03	0.17	0.30	0.41	0.67	0.32
RG05	0.00	0.18	0.35	0.51	0.65	0.34	RG28	0.03	0.18	0.29	0.47	0.72	0.34
RG06	0.15	0.27	0.44	0.55	0.77	0.44	RG29	0.02	0.10	0.14	0.41	0.55	0.24
RG07	0.06	0.18	0.35	0.52	0.66	0.35	RG30	-0.04	0.11	0.27	0.40	0.54	0.25
RG08	0.04	0.11	0.23	0.41	0.56	0.27	RG31	0.03	0.07	0.24	0.51	0.73	0.32
RG09	-0.03	0.25	0.27	0.53	0.62	0.33	RG32	0.05	0.15	0.25	0.49	0.62	0.31
RG10	0.01	0.16	0.22	0.41	0.52	0.27	RG33	0.08	0.21	0.37	0.48	0.67	0.36
RG11	0.02	0.14	0.22	0.53	0.64	0.31	RG34	0.01	0.13	0.27	0.41	0.68	0.30
RG12	0.01	0.13	0.28	0.44	0.59	0.29	RG35	0.01	0.11	0.32	0.57	0.71	0.34
RG13	-0.03	0.14	0.39	0.71	0.79	0.40	RG36	0.04	0.19	0.29	0.54	0.68	0.35
RG14	0.00	0.11	0.23	0.52	0.66	0.30	RG37	-0.01	0.14	0.29	0.57	0.84	0.36
RG15	0.02	0.19	0.32	0.44	0.70	0.33	RG38	0.07	0.24	0.31	0.48	0.57	0.33
RG16	0.01	0.11	0.23	0.50	0.73	0.32	RG39	0.04	0.17	0.15	0.54	0.71	0.32
RG17	0.02	0.13	0.31	0.54	0.81	0.36	RG40	0.03	0.13	0.31	0.61	0.80	0.37
RG18	0.00	0.12	0.23	0.44	0.58	0.27	RG41	0.10	0.28	0.47	0.70	0.81	0.47
RG19	-0.02	0.09	0.21	0.50	0.70	0.29	RG42	0.07	0.16	0.42	0.66	0.78	0.42
RG20	0.01	0.07	0.21	0.33	0.65	0.25	RG43	0.08	0.20	0.37	0.54	0.70	0.38
RG21	0.01	0.10	0.29	0.42	0.74	0.31	RG44	0.03	0.08	0.35	0.66	0.82	0.39
RG22	0.00	0.13	0.31	0.47	0.69	0.32	RG45	0.01	0.14	0.19	0.47	0.76	0.32
RG23	0.01	0.31	0.44	0.74	0.83	0.47	Average	0.03	0.16	0.30	0.51	0.70	0.34

The stations with better performance for $n=1$ are RG01, RG06, RG33, RG41, RG42, and RG43. This better performance means that the correlation between the precipitation in October and from October to March in these rain gauges is higher than in the other rain gauges. Only for $n=1$ and for seven rain gauges (RG26, RG30, RG09, RG13, RG02, RG19, and RG37) did the CDRMS perform worse than the reference forecast ($BBS < 0$). This means that, in those rain gauges, the knowledge of the precipitation in October does not allow trustful forecasts about the risk of having or not a drought by the end of March. However, the CDRMS performance skills increases every month, indicating sustained improved monitoring capabilities as new precipitation data is being known.

Figure 5 shows BSS values for all 45 rain gauges for $n=5$. It allows to identify the areas with higher values of BSS, meaning better monitoring capabilities of the CDRMS. The spatial interpolation technique was also the Inverse Distance Weighting (IDW) with exponent 2.

Figure 5: Moderate droughts. BSS values for $n=1$ to $n=5$. The closer to 1, the better the CDRMS performance.

In order to further analyze the variance of the performance measure, the box plots shown in Figure 6 were drawn based on the values of BSS for the 45 rain gauges. In those plots, the whiskers have a maximum length of $1.5 \times \text{IQR}$ (interquartile range) and the values outside the whiskers are outliers.

Figure 6 shows that the variance of the performance measure, BSS, increases in the last two months ($n=4$ and $n=5$) indicating that, in some cases, a high risk may not result in a drought event as there is still some precipitation to occur. The opposite is also true: a low risk does not mean drought cannot happen because the above threshold precipitation tendency presented in the initial months of the rainy season may not be enough to compensate dry last months. However, both specific cases are less likely to occur.

Figure 6: Moderate droughts. BSS values for all the rain gauges as a function of the number of initial months of the rainy season with known precipitation (n).

Drought occurrence in mainland Portugal is associated with a substantial interannual and decadal variability, strongly linked to precipitation shortage during the rainy season [38,39]. The dynamic interactions among weather types associated with mainland Portugal due to its location between the Atlantic Ocean and the Mediterranean Sea, strong orographic influence and small size contribute to explain high spatial variability and relative disconnection from general circulation [39–42]. The

complex interactions between different weather types during the rainy season, also as a result of the different geographic conditions, might explain the variability between the model performances.

Overall, due to copula's high flexibility, a great variety of copula families can be chosen to model the temporal dependence structure of the precipitation in each specific rain gauge, and, by this way, to represent its spatial variability.

The increasing performance of the CDRMS over time means that it consistently “learns” with the addition of the precipitation in the following months. It also consistently outperforms the reference forecasts, indicating that it can be a valuable source for assessing drought risk.

The application of the LOOCV excluded any bias in the performance verification by not choosing specific years that could best fit the expected performance, such as very dry or very wet years. Therefore, the CDRMS proved to be a valuable tool for drought risk monitoring. However, its application to mainland Portugal to monitor under real-time conditions the risk of drought by the end of the rainy season, requires a continuous updating of the precipitation records at the rain gauges of Figure 2, which may not be an easy task. Alternatively, the CDRMS can be applied to a specific site, as exemplified in the next item.

CDRMS Applied to a Single Site

This item refers to the CDRMS development and application to a single site in mainland Portugal aiming at exemplifying how the system can be operated as a drought monitoring, but also forecasting tool. For this purpose, the rain gauge of Santa Marta da Montanha (RG07) and the rainy season of the hydrological year of 2017/18 (Oct/2017 to Mar/2018) were selected as examples. It was assumed that the precipitation from Oct/2017 onwards, until Mar/2018 was being progressively known and that the application of the system ended in Feb/2018. As already said, the knowledge of the drought occurrence probability – that is, of the drought risk – is extremely relevant to anticipate actions and mitigate impacts related to water scarcity.

CDRMS Development for Santa Marta da Montanha

The dependence structure for each coupled (R_N , R_n) series in RG07 was modeled by the Archimedean (Frank) or Meta-Elliptical copulas (Gaussian and t Student). Table 6 identifies the bivariate models adopted for each n, from October (n=1) to February (n=5). The parameters θ (for the Archimedean copulas) and ρ and ν (for the Meta-Elliptical copulas) were estimated using MPL, and the copula families were selected based on the AIC, as described in section 2.1.2. The Kendall's Tau was applied to verify the non-linear dependence between R_N and R_n modeled by copulas. A hypothesis test was applied to determine whether R_N and R_n presented a relevant dependence structure; a small p-value provides strong evidence against the null hypothesis that they are independent, for the 95% confidence level.

Table 6: RG07. Bivariate models for each coupled (R_N , R_n) series, their parameters, Kendall Tau correlation (according to the model and empirical), AIC, and p values.

R_n	Family	Parameters		Kendall's Tau		AIC	p-value
		θ or ρ	ν	Model	Empirical		
n = 1	Frank	1.75	-	0.19	0.19	-6.16	< 0.05
n = 2	Gaussian	0.60	-	0.41	0.40	-37.86	< 0.05
n = 3	t Student	0.76	30.00	0.55	0.53	-75.34	< 0.05
n = 4	Gaussian	0.91	-	0.72	0.72	-161.84	< 0.05
n = 5	Gaussian	0.96	-	0.83	0.83	-251.14	< 0.05

The values of the empirical Kendall Tau correlation coefficient presented in Table 6 indicate that as the precipitation in the rainy season is progressively known, the dependence between R_N and R_n becomes stronger. In fact, for n=1 the precipitation in October explains only 19% of the precipitation of the rainy season; while for n=2 it explains 40%, and for n=5, 83%. The small differences between model and empirical Kendall's Tau values show that the dependence between R_N and, R_n was properly modeled by the copulas.

Figure 7 presents the bivariate models adopted for each coupled (R_N, R_n) series in Santa Marta da Montanha. The axes in the figure were graduated in terms of the standard normal deviates that correspond to the non-exceedance probability given by the marginal distributions. It can be seen that the copulas become narrower as n increases due to stronger correlations between R_N and R_n .

Figure 7: RG07. Bivariate models for each coupled (R_N, R_n) series along the rainy season of 2017/18, from $n=1$ to 5.

CDRMS Application – Drought Risk Monitoring

After the bivariate model has been set up, the CDRMS was applied to monitor the drought risk in Santa Marta da Montanha along the rainy season of 2017/18. The results obtained are exemplified in Table 7 for the three categories of droughts - moderate, severe and extreme droughts. Besides the precipitation thresholds, R_N^* , for the different droughts categories, the table includes the precipitation that took place along the season (monthly and cumulative precipitations), as well as the average monthly precipitations, according to the historical series.

Table 7: Santa Marta da Montanha (RG07). Risk of moderate, severe, and extreme drought events along the rainy season of 2017/18 according to the CDRMS (dashed cells).

		Oct	Nov	Dec	Jan	Feb	Mar
Mean monthly precipitation (mm)		133.3	160.9	190.1	197.5	135.2	161.7
Observed precipitation (mm)	Monthly	43.1	40.4	173.0	109.0	58.6	273.5
	Acumulated	43.1	83.5	256.5	365.5	424.1	697.6
Drought category (Threshold)		Drought risk					
Moderate (779.93 mm)		0.31	0.57	0.56	0.71	0.97	Drought
Severe (618.83 mm)		0.16	0.36	0.30	0.31	0.61	No Drought
Extreme (503.49 mm)		0.08	0.21	0.13	0.09	0.14	No Drought

From Oct/2017 to Mar/2018, the precipitation during the rainy season was 697.6 mm, i.e., below the threshold for moderate drought and above the thresholds for the other drought categories, meaning that a moderate drought event really occurred by the end of March.

In what concerns the moderate droughts, the CDRMS model proved to be able to detect the increasing risk of drought: 31% (in Oct/2017), 57% (in Nov/2017), 56% (in Dec/2017), 71% (in Jan/2018), and 97% (in Feb/2018) which could justify issuing a drought alarm, at least in January and for sure in February. Despite the considerable above-the-average precipitation that occurred in March, there was a moderate drought, confirming the tendency detected by the CDRMS.

The CDRMS also identified an increasing risk of severe drought by the end of March, though with much smaller probabilities: only 31% in January and 61% in February. However there was not a severe drought event, which suggests a poorer performance of the CDRMS. This circumstance can be explained by the anomalous and unforeseeable precipitation that took place in March, which countered the expectations of a severe drought in the season.

Regarding the extreme droughts, the risk given by the CDRMS was always too small, as it was confirmed when the precipitation by the end March was known.

The example confirms the good performance of the CDRMS in detecting moderate droughts. However, it was not capable of distinguishing the severity of the event, once severe and extreme droughts are very sensitive to an individual precipitation in the months of analysis. Precipitation thresholds for the droughts with higher intensity are lower and can be easily exceeded by a few millimeters of precipitation.

Discussion and Conclusion

Drought is a harsh natural disaster also because its onset is difficult to perceive. Therefore, it is relevant and challenging to

develop a trustful trigger tool able to recognize its occurrences and to initiate actions aiming at mitigating its impacts. This study developed such tool based on copulas applied to the continuous monitoring of the drought risk based on precipitation data – the CDRMS.

Such system uses a kind of stepwise procedure applied to each specific location where the drought risk evaluation is wanted. It starts with the computation of the precipitation thresholds, which enable assigning precipitations to the drought categories given by the SPI [23]. The next step refers to the setting up of the copula-based bivariate model that, by using historical monthly precipitation data, “couples” the seasonal precipitation of rainy season (R_N) with the precipitation until the last but one month of such season (R_n), according to the dependence structure between R_N and R_n .

The last step relates to the application of the CDRMS under real time conditions, to monitor the drought risk along the rainy season, that is, to answer the following question: will there be a drought by the end of the rainy season? Once the precipitation in each month of the current rainy season is progressively known and incorporated into the CDRMS, the system returns the probability of the precipitation being smaller than the one required to avoid drought conditions by the end of the season, that is, the drought risk. Based on that risk, drought alarms can be issued and anticipatory drought mitigation and adaptation measures implemented. The application based on a single rain gauge was exemplified for the rainy season of 2017/2018.

The CDRMS can also be applied to monitor the evolution of the drought risk along the rainy season in a region, instead of a single site, based on the continuous updating of the precipitation deficits or surplus over the region. Such innovative application was exemplified by the application of the CDRMS to Mainland Portugal to monitor the drought risk along the rainy season from Oct/2012 to Mar/2013, based on 100-year of precipitation data at 45 rain gauges evenly distributed over the country. The application evidenced that the CRDMS is able to anticipate the regions that later experienced, in fact, drought conditions.

The study proved that the Continuous Drought Risk Monitoring System has the ability to detect the drought events simply based on precipitation data. However, it has a poorer capability to distinguish among drought intensities, probably because the differences among precipitation thresholds for the different intensities are too small and can be easily exceeded by also small, but unforeseeable, amounts of precipitation during the rainy season. The dynamic interactions among weather types associated with mainland Portugal due to its location between the Atlantic Ocean and the Mediterranean Sea, the strong orographic influence in the precipitation spatial and temporal patterns and its small area may result in the CDRMS performing better in some regions than in others.

Notwithstanding, the CDRM can help decision-makers to anticipate actions and, thus, to decrease potential negative impacts, due to its inherent capacity to assign a quantitative measure – the risk – to the imminence of a drought event. It also contributes to a progressive alert of the water managers and civil protection authorities, allowing them to gradually adjust the public awareness as the threat of a possible drought event becomes more reliable.

Drought occurrences in mainland Portugal are associated with a substantial interannual and decadal variability, strongly linked to precipitation shortage during the rainy season. The addition of other variables linked to climate such as teleconnection indexes – sea surface temperature and North Atlantic Oscillation - could improve the performance of any drought risk monitoring model [43,44]. In addition, the use of other climatic and hydrological variables such as temperature and runoff should be analyzed aiming at increasing the forecasting capabilities of the continuous drought risk monitoring system. Future studies could also try to implement a time varying copula model for bivariate modeling precipitation (R_N and R_n) designed to address the nonstationary behavior of some of the hydrological variables that are expected to result from climate change.

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