

1 Article

2 The effect of sample size on bivariate rainfall 3 frequency analysis of extreme precipitation

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13 **Abstract:** The objective of this study is to compare univariate and joint bivariate return periods of
14 extreme precipitation that all rely on different probability concepts in selected meteorological
15 stations of Cyprus. Pairs of maximum rainfall depths with corresponding durations are estimated
16 and compared using annual maximum series (AMS) for the complete period of the analysis and 30-
17 year subsets for selected data periods. Marginal distributions of extreme precipitation are examined
18 and used for the estimation of typical design periods. The dependence between extreme rainfall and
19 duration is then assessed by an exploratory data analysis using K-plots and Chi-plots, and the
20 consistency of their relationship is quantified by Kendall's correlation coefficient. Copulas from
21 Archimedean, Elliptical and Extreme Value families are fitted using a pseudo-likelihood estimation
22 method, evaluated according to the corrected Akaike Information Criterion and verified using both
23 graphical approaches and a goodness-of-fit test based on the Cramér-von Mises statistic. The
24 selected copula functions and the corresponding conditional and joint return periods are calculated
25 and the results are compared with the marginal univariate estimations of each variable. Results
26 highlight the effect of sample size on univariate and bivariate rainfall frequency analysis for
27 hydraulic engineering design practices.

28 **Keywords:** bivariate analysis; copulas; rainfall frequency analysis; extreme precipitation; design
29 return period

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32 1. Introduction

33 Rainfall frequency analysis is an important area of hydraulic engineering design, water
34 resources planning and management. This involves the selection of the variables of interest, the
35 sampling of a sample series and the choice of the most appropriate population distribution. Analysis
36 of extreme rainfall events has conventionally been performed by prespecifying rainfall duration as a
37 filter to abstract annual maximum rainfall depths as the only variable for analysis. However, this
38 univariate approach does not account for dependence between rainfall properties. Rainfall
39 characteristics, such as total depth, duration, and peak intensity exhibit high variability and a
40 multivariate approach should be studied for extreme rainfall analysis.

41 The interdependency of extreme rainfall characteristics urged scientists and water managers to
42 derive a joint law in order to successfully describe the main characteristics of the observed
43 hydrological events. The first bivariate frequency distributions were generated based to the
44 hypothesis that the variables of interest either have the same marginal probability distribution, or

45 that their joint relationship is normally distributed (or become normally distributed after a
46 transformation) [1]. In recent years, several studies were focused in finding a method which would
47 assess in the investigation of the statistical behavior of dependent hydrological variables, without the
48 need of the assumptions that classical bivariate frequency distributions use. The first paper on
49 copulas in hydrology was published by De Michele and Salvadori [2], and in the next few years,
50 several other studies further expanded the theory, such as Favre et al. [3]; Salvadori and De Michele
51 [4], Salvadori and De Michele [5] and Genest and Favre [6].

52 The main concept of the copula approach is that a joint distribution function can be divided into
53 two independent parts, the one describing the marginal-univariate behavior and the other the
54 dependence structure [7,8]. Copulas are the functions that describe the dependence between random
55 variables and as a result, are able to couple the marginals of these variables into their joint distribution
56 function [9]. The importance of this approach in the field of engineering and water science is
57 noticeable. Copula method offers an efficient way in finding reasonable multivariate estimates for
58 hydrological events that have a certain likelihood of occurrence. These estimates are used as design
59 variables of the hydraulic structures. Design variables are characterized by a return period
60 (recurrence interval) defined as the average time elapsing between two successive realizations of an
61 event whose magnitude exceeds a defined threshold [10,11]. In practice, the selection of a reliable
62 return period is crucial as it is the fundamental parameter in the design of hydraulic structures.

63 To analyse extreme rainfall events and the effect of sample size on rainfall frequency results, a
64 bivariate analysis is conducted in this study using daily precipitation data from selected
65 meteorological stations in Cyprus. Samples of extreme rainfall events are chosen (using annual
66 maximum rainfall depth with corresponding storm durations) and analyzed using copulas to
67 describe the dependence structures between rainfall variables and to construct their joint distribution
68 for extreme rainfall events. With the marginal distributions selected according to the methodology of
69 traditional univariate analysis using two different types of extreme rainfall series, a set of copula
70 based bivariate distributions for rainfall peak–storm duration are determined and compared for
71 selected design return periods.

72 2. Study Area and Rainfall Database

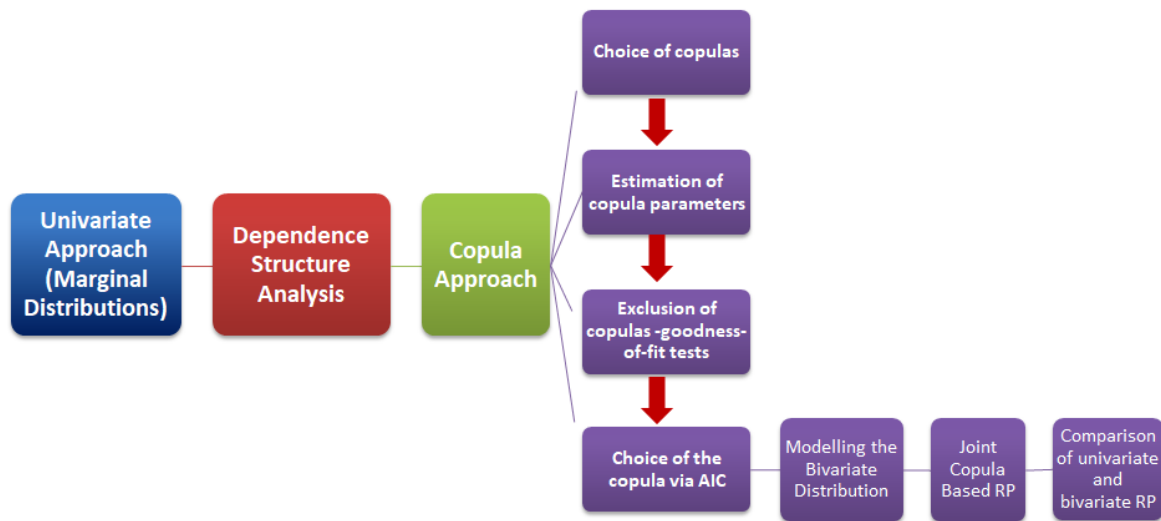
73 During the last century remarkable variations and trends were observed in precipitation.
74 Pashiardis [12] published a comprehensive study of rainfall extremes presenting rainfall intensity –
75 duration – frequency (IDF) distribution curves for Cyprus. According to this study, the curves for the
76 period 1971-2007 are more intense and extreme than the curves developed in an earlier study for the
77 period 1931-1970 [13]. The average precipitation of 541 mm in the period 1901 to 1970 dropped to 463
78 in the period 1971 to 2009 [12]. Analysis of precipitation data for Cyprus led to the conclusion that
79 the mean annual rainfall is decreasing whilst the rainfall intensity of extreme events is increasing.
80 Hence, this study's primary objective is the application of the copula method and the evaluation of
81 its results to extreme rainfall. To that end, approaches to specify the marginal distribution functions
82 for the study rainfall characteristics (rainfall depth and storm duration) are initially applied.

83 Daily rainfall data for 90 years (October 1920 – September 2010) were obtained for three
84 meteorological stations (Limassol, Larnaca and Nicosia) located in the wider area of Cyprus from the
85 European Climate Assessment and Dataset (ECA&D, www.ecad.eu). The sample size of rainfall
86 extreme characteristics can be a major uncertainty factor when dealing with the estimation of rainfall
87 design values. As a general rule, small sized samples cannot correctly interpret the statistical
88 properties of the population distribution. Hence, in order to evaluate the uncertainty of return period
89 estimation in copula method when small data samples are used, each of the 90 years length time-
90 series were divided into 3 sub-datasets and return periods for both univariate and bivariate models
91 were calculated. The 100 and 500 years return periods were selected for comparison, as they are often
92 used as design variables in the construction of hydraulic structures.

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95 **3. Methodology**

96 This study’s primary objective is the application of the copula method and the evaluation of its
 97 results. Figure 1 presents the flow diagram of the methodology and shows the steps for rainfall
 98 frequency analysis to the three meteorological stations. The first step is the return period estimation
 99 for each variable (depth and storm duration) based on the typical univariate approach. Then, the
 100 dependence between the two variables of interest is assessed. This could be done either by visualizing
 101 dependence or by the performance of statistical tests. The Chi-plot and K-plot are the most common
 102 graphical tools for detecting dependence. The statistical tests of dependence were performed by
 103 computing Kendall’s correlation coefficient (Kendall’s tau) and both graphical methods were taken
 104 into consideration for better visualization of the results.
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 107 **Figure 1.** Flow diagram of the methodology.

108 After the dependence between the variables was evaluated, copulas from three different families
 109 were selected as candidate models. In the present work we considered only bivariate distributions
 110 and made use of Archimedean (Gumbel–Hougaard, Clayton, Frank and Joe), extreme value
 111 (Gumbel–Hougaard and Tawn) and elliptical (Normal or Gaussian) models. The maximization of the
 112 pseudolikelihood, a generally applicable method which does not have limitations regarding the
 113 dependence parameter, was selected for estimating the model’s parameters for this study. The
 114 exclusion of non-admissible copulas was based to Cramér-von Mises statistic test, computed using a
 115 bootstrap procedure as described in Genest et al. [14]. Graphical tests for a visual description of the
 116 copula fitting and complementary analysis were also used. Finally, the (corrected) Akaike
 117 Information Criterion (AIC) [15,16] among the non-rejected copulas determined the most appropriate
 118 model.

119 After the choice of the most efficient copula model, the bivariate distributions needed to be
 120 constructed. A copula is a joint distribution function of standard uniform random variables able to
 121 connect univariate marginal distribution functions with the multivariate probability distribution, as
 122 stated in Sklar Theorem [9]:

123 Let F_{XY} be a joint distribution function with marginals F_X and F_Y . Then there exists a copula C
 124 such that :

$$F_{XY}(x, y) = C(F_X(x), F_Y(y)), \tag{1}$$

126 for all reals x, y . If F_X, F_Y are continuous, then C is unique; otherwise, C is uniquely defined on $\text{Range}(F_X) \times \text{Range}(F_Y)$. Conversely, if C is a copula and F_X, F_Y are distribution functions, then F_{XY} given by Eq. (1) is a joint distribution function with marginals F_X and F_Y .

129 After modeling the bivariate distribution the copula based return periods were computed. In
 130 this study the bivariate joint (primary) return periods called OR operator “ \vee ” (union of events - wither

131 of the variables u and v exceed the defined thresholds-) and AND operator “ \wedge ” (intersection of events
 132 –both of the variables u and v exceed the defined thresholds) [5,10], were computed and are defined
 133 as:

$$134 \quad T_{u,v}^{OR} = \frac{\mu}{1 - C_{u,v}(u,v)}, \quad (2)$$

$$135 \quad T_{u,v}^{AND} = \frac{\mu}{1 - u - v + C_{u,v}(u,v)}, \quad (3)$$

136 where u and v follow a uniform distribution $U(0,1)$. The U denotes $F_X(X)$ and V denotes $F_Y(Y)$ and
 137 were constructed after applying the probability integral transform to X and Y , a transformation which
 138 allowed us to simplify our work by using an equivalent set of values which follow the standard
 139 uniform distribution.

140 In comparison to the univariate return periods, the joint bivariate estimates are not unique, but
 141 instead, they have infinite combinations of values, described with the level curve. All pairs (u, v) that
 142 lie on the same level curve of the copula have the same return period $T(p)$, however, these
 143 combinations of values for u and v have various probabilities of occurrence and can have significant
 144 differences from one another. For the purposes of the present study the most-likely design realization
 145 method [17], was used to select a unique return period. This method introduces a weighting function
 146 which specifies the point over the critical layer with the greatest value of the joint probability density
 147 function f_{xy} . It is also known as “typical” critical realization, and is described with the following
 148 equation:

$$149 \quad (u, v) = \underset{C(u,v)=t}{\operatorname{argmax}} f_{XY}(F_X^{-1}(u), F_Y^{-1}(v)), \quad (4)$$

150 where u and v depict the converted via the probability integral transform realizations of the marginal
 151 distributions F_X and F_Y of the random variables X and Y . After the identification of the maximization
 152 point, the pair (u,v) was used in order for the exceedance probability to be calculated. As a final step,
 153 a comparison of the different return periods coming from univariate and bivariate analysis was
 154 performed in order to investigate the results of the copula method.

155 4. Results

156 4.1 Univariate Analysis

157 After the selection of extreme events, a univariate rainfall frequency analysis was performed for
 158 annual maximum rainfall depths and corresponding storm durations. Different probability models
 159 such as Generalized Extreme Values (GEV), Gumbel (EVI) and Generalized Pareto Distribution
 160 (GPD) for peak discharge and GEV, Gamma, Exponential, and Log-normal were applied to the
 161 datasets. The distribution’s parameters were estimated with the help of maximum likelihood method,
 162 a method which will be as well used in copula’s parameters estimation process [18]. Subsequently,
 163 the Kolmogorov-Smirnov Goodness-of-Fit and graphical tests were produced to select the
 164 distributions that produced an adequate fit to the data and finally, AIC [15] values among the non-
 165 rejected copulas determined the most appropriate statistical model. In conclusion, the generalized
 166 extreme value distribution (GEV) was selected for modelling annual maximum rainfall depth and
 167 storm duration. Table 1 presents the results of the univariate approach for Limassol meteorological
 168 station for the complete period of analysis and for the three subperiods. Finally, when the appropriate
 169 model was selected, the univariate return periods were calculated for 2, 5, 10, 25, 50, 100, 200 and 500
 170 years.
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Table 1. Results of univariate and bivariate approaches for annual maximum rainfall depths and corresponding storm durations for the complete data period and the 3 sub-periods of Larnaka Station.

	1st Data Sample	2nd Data Sample	3rd Data Sample	4th Data Sample
Station	LIMASOL	LIMASOL	LIMASOL	LIMASOL
Years	1920-2010	1920-1950	1950-1980	1980-2010
Length (In Years)	90	30	30	30
Number Of Events	90	30	30	30
Kendall's tau	0.35	0.33	0.26	0.59
RAINFALL DEPTH VARIABLE				
Sampling Method	AMS	AMS	AMS	AMS
Marginal Distribution	GEV	GEV	GEV	GEV
Distribution Parameters (μ, σ, ξ)	7.79, 3.47, -0.07	8.70, 3.39, -0.19	6.87, 2.82, 0.14	7.74, 3.80, -0.06
Kolmogorov smirnov Test($p>0.05$)	0.7835	0.9878	0.9412	0.8746
RAINFALL DURATION VARIABLE				
Sampling Method	Corresponding value	Corresponding value	Corresponding value	Corresponding value
Marginal Distribution	GEV	GEV	GEV	GEV
Distribution Parameters (μ, σ, ξ)	5.42, 2.65, -0.02	5.52, 2.89, -0.20	6.12, 2.85, -0.07	4.83, 2.18, 0.10
Kolmogorov smirnov Test($p>0.05$)	0.4212	0.5704	0.5942	0.6988
Copula Model	Gaussian (par = 0.54, tau = 0.36)	Clayton (para=0.81, tau=0.29)	Frank (para=2.34, tau=0.25)	Gumbell (para=2.63, tau=0.62)
Von Mises (bootstrap) ($p>0.05$)	0.18	0.4400	0.9700	0.2400

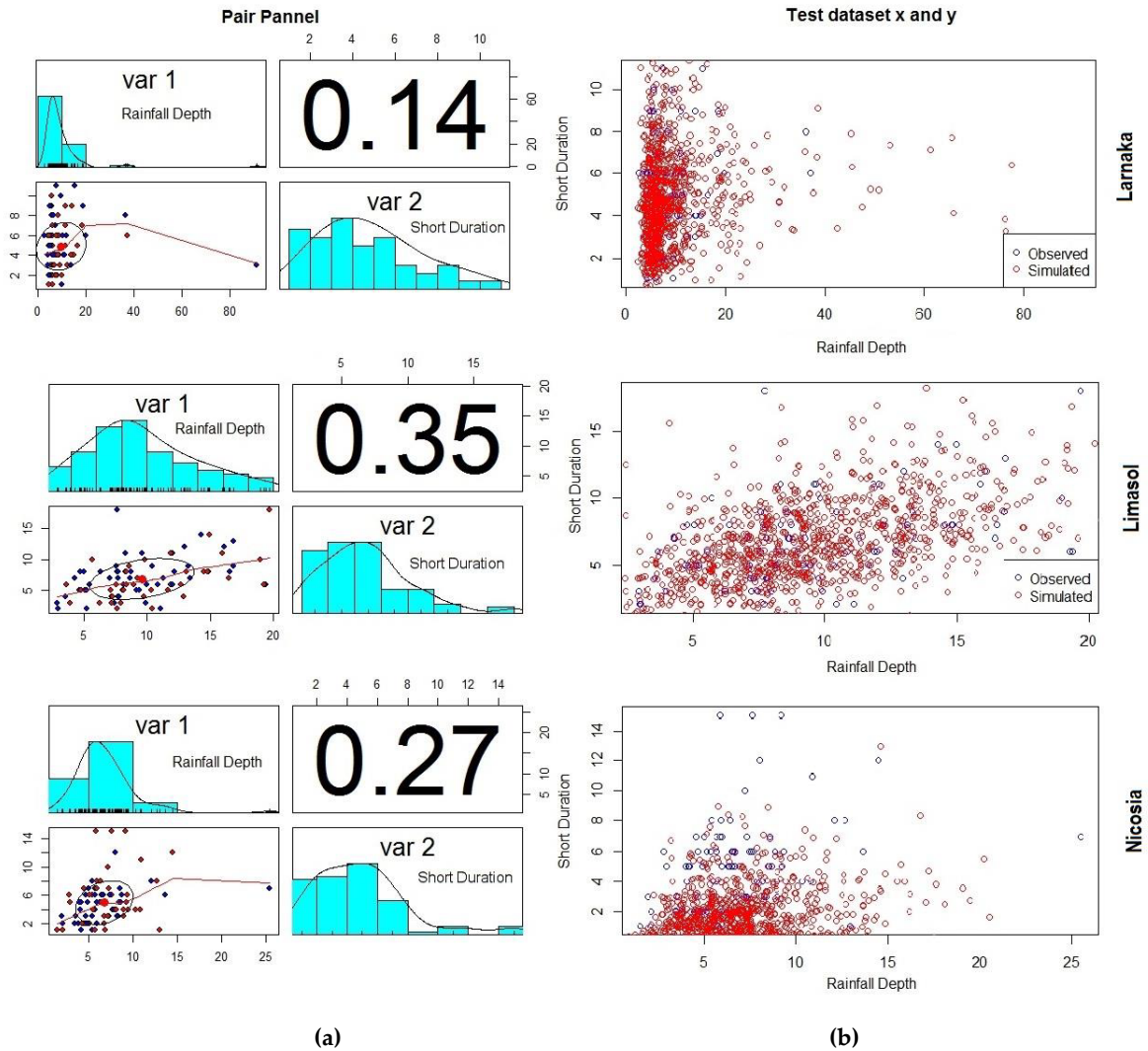
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175 *4.2 Bivariate Analysis*

176 After the univariate analysis was performed, a formal assessment of the dependence between
 177 the pairs of the considered variables was tested with the help of Kendall correlation coefficient.
 178 Histograms and a scatterplot of the Rainfall Depth (X) - Duration (Y) pair are presented in Figure 2a,
 179 in which a weak correlation between the two variables can be easily noticed. In the next step, the
 180 different copulas from the three families were fitted to X-Y pair. The parameters of the copulas were
 181 estimated with the maximum pseudolikelihood method and the considered functions were
 182 compared with different goodness-of-fit tests. Table 1 shows the best copulas selected for Larnaca
 183 meteorological station for all sample periods. For example, for the complete period of analysis (1920-
 184 2010) the Gaussian copula with parameter = 0.54 was selected for the AMS sample, as it had the lowest
 185 AIC value, and at the same time had an adequate fit. The statistical test p-value was 0.18 for the
 186 bootstrapped p-value of the goodness-of-fit test using the Cramer-von Mises statistic (95%
 187 significance level). Furthermore, Figure 2b shows the graphical tests of the selected copulas for a
 188 sample size of 1000 simulations for the X-Y pair (Rainfall Depth-Duration). The Kendall's tau
 189 extracted from the comparison between observed and simulated values was 0.36 for the copula and
 190 0.35 for the actual data, indicating that the correlation of the real data was preserved in the copula.
 191 Similar results are observed for the other sub-periods and the other two meteorological stations
 192 (Larnaca and Nicosia). It should be mentioned that in these two stations lower correlations are
 193 observed between annual maximum rainfall depth and corresponding storm durations (Figure 2).

194 After copula selection, the bivariate distribution function was constructed and the selected
 195 marginals were taken into consideration. Figure 3 illustrates the level curves for the bivariate return
 196 periods for Limassol station and the complete data period of 90 years and Table 2 shows the derived
 197 joint return (primary) periods for the OR (union) and AND (intersection) cases, constructed following
 198 the Equations 2 and 3, and the most likely realization method as described in Equation 4. The T^{OR} and
 199 T^{AND} joint return periods express the possible conditions of failure in case of having two variables
 200 which are considered important for design purposes. To be more comprehensive, the variables of
 201 interest can either work together or simultaneously in order to cause failure. In case that the condition
 202 of failure is met when either or both rainfall depth (X) and rainfall duration (Y) variables exceed their
 203 threshold, the cooperative risk T^{OR} should be taken into consideration. On the other hand, in case that
 204 failure occurs when both X and Y variables exceed their threshold simultaneously (or dually), the
 205 dual return period T^{AND} needs to be calculated. The calculation of the two different joint return period
 206 cases is important as if the two variables X and Y can cooperate (OR case) then the marginal
 207 probabilities must be considerably higher.
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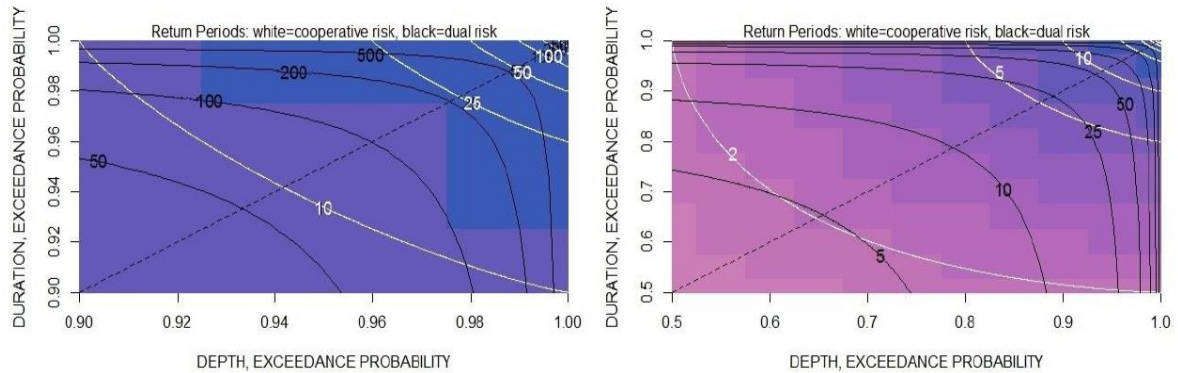
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Figure 2. a. A scatterplot matrix of the selected variables and their Kendall correlation coefficient for the study meteorological stations; b. Comparison between the observed and simulated values (sample size 1 000) (Rainfall Depth-Duration) for Frank (Larnaca) and Gaussian (Limassol, Nicosia) copulas for 1000 simulations, indicating an adequate fit between the simulating and observed values.

Table 2. Results of the Bivariate Return Periods 2, 5, 10, 25, 50, 100, 200 and 500 for Rainfall Depth and Storm Duration – Limassol meteorological station.

Station	RETURN LEVEL							
	2	5	10	25	50	100	200	500
Limassol								
Depth (cm)/ dual	7.58	10.83	13.10	16.65	18.94	20.98	22.70	25.05
Depth (cm)/ cooperative	10.62	14.20	16.41	19.04	20.88	22.60	24.24	26.79
Duration (d)/ dual	5.19	7.61	9.12	9.88	10.22	10.50	11.98	11.61
Duration (d)/ cooperative	7.55	10.47	12.36	14.72	16.45	18.16	19.81	21.60

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Figure 3. Level curves for the bivariate return periods, white for cooperative risk T^{OR} and black for dual risk T^{AND} . The color range changes as the probability reaches from 0 to 1. U denotes $F_X(X)$ which represents the random variable from the marginal distribution of the rainfall depth values and V denotes $F_Y(Y)$ which represents the random variable from the marginal distribution of the storm duration values. Each of the lines refer to a specific return period and the values on the two axis are equivalent to the probabilities of occurrence of the random variables X (annual maximum rainfall depths) and Y (corresponding storm durations), respectively.

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The analysis of the samples at Limassol meteorological station showed that GEV distribution is the most appropriate for modeling both duration and rainfall depth. The parameters of the fitted distributions had differences from one another, and at the same time, Kendall's correlation coefficient indicated that the last thirty years had much stronger correlation (0.59) than the others (approximately 0.30). The copula models used were different in every sample and can be seen in Table 1. The return periods (not shown due to paper length limitations), have relatively small differences in the 100yrs return period, whereas in the 500yrs period there were differences in AND and OR cases, with values ranging from 9.94 to 25.05 and 21.74 to 40.05, respectively.

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4. Concluding Remarks

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In the present study, a bivariate rainfall frequency analysis is performed using an extensive selection of bivariate copulas, as well as different statistical and graphical tests. Annual Maximum Series are followed in order to collect the data samples and then, the corresponding univariate and bivariate return periods are evaluated and compared. In total, the return periods obtained are in consensus with Salvadori et al. [5] who showed that the relationship between univariate and primary (bivariate) return periods can be written as $T^{OR} < T^{UNI} < T^{AND}$.

The correlation analysis in the two data samples confirms that a slight dependence exists between the extreme rainfall characteristics (rainfall depth and duration). It is worth noting that even though the correlation pattern changed when different samples are selected, the return period estimates did not have significant differences. In conclusion, the existence of dependence among hydrological variables, indicate the need for multivariate distributions to be constructed, especially when dealing with design values. As a result, more studies should be performed in order to investigate the importance of copula application in rainfall frequency analysis and the effect of sample size in design return periods.

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