Nat. Hazards Earth Syst. Sci. Discuss., 2, 27–79, 2014
www.nat-hazards-earth-syst-sci-discuss.net/2/27/2014/
doi:10.5194/nhessd-2-27-2014

Natural Hazards and Earth System Sciences
Open Access
Discussions

This discussion paper is/has been under review for the journal Natural Hazards and Earth System Sciences (NHESS). Please refer to the corresponding final paper in NHESS if available.

Estimation of flood design hydrographs using bivariate analysis (copula) and distributed hydrological modelling

A. Candela[1], **G. Brigandì**[2], **and G. T. Aronica**[2]

[1]University of Palermo, Dipartimento di Ingegneria Civile, Ambientale, Aerospaziale e dei Materiali, Palermo, Italy
[2]University of Messina, Ingegneria Civile, Informatica, Edile, Ambientale e Matematica Applicata, Messina, Italy

Received: 5 November 2013 – Accepted: 26 November 2013 – Published: 2 January 2014

Correspondence to: A. Candela (angela.candela@unipa.it)

Published by Copernicus Publications on behalf of the European Geosciences Union.

Abstract

In this paper a procedure to derive Flood Design Hydrographs (FDH) using a bivariate representation of rainfall forcing (rainfall duration and intensity) using copulas, which describe and model the correlation between these two variables independently of the marginal laws involved, coupled with a distributed rainfall-runoff model is presented. Rainfall-runoff modelling for estimating the hydrological response at the outlet of a watershed used a conceptual fully distributed procedure based on the soil conservation service – curve number method as excess rainfall model and a distributed unit hydrograph with climatic dependencies for the flow routing. Travel time computation, based on the definition of a distributed unit hydrograph, has been performed, implementing a procedure using flow paths determined from a digital elevation model (DEM) and roughness parameters obtained from distributed geographical information. In order to estimate the return period of the FDH which give the probability of occurrence of a hydrograph flood peaks and flow volumes obtained through R-R modeling has been statistically treated via copulas. The shape of hydrograph has been generated on the basis of a modeled flood events, via cluster analysis. The procedure described above was applied to a case study of Imera catchment in Sicily, Italy. The methodology allows a reliable and estimation of the Design Flood Hydrograph and can be used for all the flood risk applications, i.e. evaluation, management, mitigation, etc.

1 Introduction

Floods are a global problem and are considered the most frequent natural disaster world-wide. They may have serious socio-economic impacts in a community, causing victims, population displacement and damages in environment, ecology, landscape and services.

Flood risk analysis and assessment are required to provide information on current or future flood hazard and risks in order to accomplish flood risk mitigation, to pro-

NHESSD
2, 27–79, 2014

pose, evaluate and select measures to reduce risk. Thus, the European Parliament has adopted the new Directive 2007/60/EC (European Union, 2007) that requires Member State to assess if coastal areas and water courses are at risk from flooding, to carry out maps and take measures to reduce the evaluated risk. The objective of this directive is to establish a framework for the assessment and management of flood risk in Europe, emphasising both the frequency and magnitude of a flood as well as its consequences.

Reliable estimates of the likely magnitude of the extreme floods are essential in order to reduce future flood damage. Despite the occurrence of extreme floods is a problem across Europe, physical mechanisms responsible for the generation of floods will vary between countries and regions. As a result, no standardised European approach to flood frequency estimation exists. Where methods exist, they are often simple and their ability to accurately predict the effect of environmental change (e.g. urbanisation, land-use change, river training and climate change) is unknown.

Moreover, Mediterranean ephemeral streams have specific features compared to other river systems. Mediterranean basins are small, several hundred km^2, and highly torrential and may generate flash-floods (Camarasa-Belmonte and Soriano, 2012; Koutroulis and Tsanis, 2010). Runoff generation in semiarid zones is the final result of a lot of spatial and temporal complex processes that take place at the hillslope and catchment scale. The complexity of the processes involved derives from great heterogeneity of rainfall inputs, surface and subsurface characteristics, and strong nonlinear dependency on antecedent wetness which controls the infiltration capacity of the soil surface and the connectivity of surface and subsurface runoff pathways (Candela et al., 2005; Nicolau et al., 1996).

The flood frequency analysis (FFA) is the estimation of how often a specified event will occur (Hosking and Wallis, 1997) and aims at estimating the flood event in terms of maximum discharge value corresponding to a given return period and/or relative volume. The probability for future events can be predicted by fitting the past observations to selected probability distributions. The flood event estimation (hydrograph project) requires the use of different methods depending on whether it is enough to know the maximum discharge value, or it is necessary to know the full hydrograph. In both cases, the problem can be solved directly, starting from flow measurements available for the basin, or indirectly using rainfall data recorded under the basin using a rainfall-runoff model. This latter approach is the basis of the DDA methods (Derived Distributed Approach) that allows to derive FFC using rainfall-runoff models. Analytical difficulties associated with this approach are, often, overcome by adopting numerical Monte Carlo methods. In these cases, a stochastic rainfall generator is used in order to generate rainfall data for a single event or in continuous (Blöschl and Sivapalan, 1997; Loukas, 2002; Rahman et al., 2002; Aronica and Candela, 2007).

FFC analysis is, usually, based on the derivation of FFC to only define the maximum discharge value corresponding to a given return period. However, for flooding management, it is not enough to know information about flood peak only, but it is also useful to statistically value flood volume and duration. Since flood peaks and corresponding flood volumes are variables of the same phenomenon, they should be correlated and, consequently, multivariate statistical analyses must be applied (Grimaldi and Serinaldi, 2006; Aronica et al., 2012).

In general, multivariate probability models have been limited by mathematical difficulties due to the generation of consistent joint laws with ad hoc marginals. Actually, copulas has overcame many of these problems (Salvadori and De Michele, 2007), as they are able to model the dependence structure independently of the marginal distributions.

Several authors have presented hydrological applications with copulas implementation (Bacchi et al., 1994; Nelsen, 1999; Genest et al., 2007; Gaal et al., 2010; Balistrocchi and Baldassarre, 2011) as complex hydrological phenomena such as floods, storms, and droughts are characterised by correlated random variables. For all these phenomena it is of fundamental importance to be able to link the marginal distributions of different variables (De Michele and Salvadori; 2003; Favre et al., 2004; Salvadori and De Michele, 2004, 2010; Zhang and Singh, 2007; De Michele et al., 2005; Grimaldi and Serinaldi, 2006; Dupuis, 2007; Aronica et al., 2012). Particularly, Favre et al. (2004) re-

NHESSD
2, 27–79, 2014

view the general theory of copulas and describe in some detail certain families. They also apply the ideas to flow combination and joint modelling of flow and volume.

2 Case study

The Imera catchment with an area of about 2000 km^2 is located in the south-western part of Sicily, Italy (Fig. 1). The study was focused on the sub-catchment of Imera basin with an area of 1789 km^2 and delimited downstream by a flowgauge station named Imera at Drasi. The vegetation and the climate are Mediterranean with hot dry summer and rainy winter season from October to April. The hydrological response of the basin to a storm is, greatly, dependent on the soil water initial state which is highly variable because of the large range of weather conditions. The measurement network (Fig. 1) consists of eight raingauges (Canicattì, Caltanissetta, Delia, Mazzarino, Enna, Riesi, Petralia Sottana, Polizzi Generosa), located within the catchment and characterised by a temporal resolution of 10 min, and of one level gauge (Drasi), located few kilometers upstream the river mouth. Historical series of rainfall are available from 1960 on hourly basis and from 2001 on 10 min basis while discharges are available only on hourly basis.

3 Methodology

This section describes in details the procedure to derive design hydrographs in terms of flood peak and flood volume. The layout of the procedure can be resumed as follows: (1) stochastic generation of rainfall to derive rainfall events; (2) rainfall-runoff modelling for estimating the hydrological response at the outlet of the watershed using a conceptual fully distributed model; (3) derivation of design hydrographs (for given design return period) by bivariate analysis (copulas) of rainfall-runoff outputs.

3.1 Stochastic generation of rainfall

The hydrological input was derived by using a simple stochastic model to derive single synthetic sub-hourly rainfall events (Brigandí, 2009). Generated rainfall events are totally stochastic but with characteristics in terms of shape, duration and average intensity have to satisfy the parameters derived by statistical analyses of the available historic records.

Once extracted independent rainfall events from the available series of sub-hourly rainfall data, model is based on the two following modules:

- intensity–duration submodel (statistical description and generation of storm characteristics using a multivariate model).
- Temporal pattern submodel (generation of within-storm temporal characteristics as time step intensity variations using simple statistical descriptors).

3.1.1 Intensity–duration submodel

Since storm duration, average intensity or rainfall volumes are variables of the same phenomenon they should be correlated. Consequently, these variables have to be analyzed jointly through multivariate models and, particularly, those based on the theory of copulas.

Copula function C is a function which represents the joint distribution function of two dependent random variables uniformly distributed between 0 and 1:

$$C(u_1,u_2) = \Pr\{U_1 \leq u_1, U_2 \leq u_2\} \tag{1}$$

where u_1 and u_2 denote realizations. Let two random variables, X and Y, with their marginal distribution functions, $F_x(x)$ and $F_y(y)$, through a change of variables:

$$F_x(x) = U_1; \quad F_y(y) = U_2 \tag{2}$$

it is possible to obtain the multivariate distribution function:

$$C(F_x(x), F_y(y)) = F(x,y) = F(X \le x; Y \le y) \tag{3}$$

The advantage of the copula method is that no assumption is needed for the variables to be independent or have the same type of marginal distributions. More information and applications about copulas can be found in Nelsen (1999) and Genest and Favre (2007).

The Archimedean copula family is widely used for hydrological applications, given its easy construction and, particularly, the Frank's copula can be applied when the correlation amongst hydrologic variables is negative (Favre et al., 2004; Zhang and Singh, 2007). De Michele and Salvadori (2003) found how the Frank's copula is the best candidate to model the dependence between average rainfall intensity and storm duration in comparison with other families of copulas, and also to reproduce the asymptotic statistical distribution of the storm depth.

In the present study, Frank's family class of 2-copulas has been considered. Frank copula is a one parameter Archimedean copula:

$$C(u_1, u_2) = -\frac{1}{\theta} \ln \left[1 + \frac{(\exp(-\theta u_1) - 1)(\exp(-\theta u_2) - 1)}{\exp(-\theta) - 1} \right] \tag{4}$$

with generation function:

$$\phi(t) = \ln \left[\frac{\exp(\theta t) - 1}{\exp(\theta) - 1} \right] \quad \text{and} \quad t = u_1 \quad \text{or} \quad u_2 \tag{5}$$

where θ is the parameter of copula function that is related to the Kendall's coefficient of correlation τ between X and Y through the expression:

$$\tau = 1 - 4\frac{\Delta_1(-\theta) - 1}{\theta} \tag{6}$$

where Δ_1 is the first order Debye function defined as:

$$\Delta_1(\theta) = \frac{1}{\theta}\int_0^{\theta} \frac{t}{\exp(t)-1}\mathrm{d}t \tag{7}$$

and:

$$\Delta_1(-\theta) = \Delta_1(\theta) + \frac{\theta}{2} \tag{8}$$

According to the nonparametric method, the first step in determining a copula is to obtain its generating function from bivariate observations. The procedure to calculate the generating function and the resulting copula followed in this study was described by Genest and Rivest (1993). It assumes that for a random sample of bivariate observations (x_1, y_1), $(x_2, y_2), \ldots, (x_N, y_N)$ the underlying distribution function $H_{X,Y}(x,y)$ has an associated Archimedean copula $C(h)$ which also can be regarded as an alternative expression of the joint cumulative distribution function (CDF). The procedure involves the following steps:

1. Determine Kendall's τ from observations.

2. Determine the copula parameter θ from the above value of τ using Eqs. (5–7). For the Frank copula families introduced above, the θ parameter needs to be determined numerically, since there are no closed-form relations between τ and θ.

3. Obtain the copula having calculated the copula parameter θ. One can also obtain the generating function of each copula, since the generating function is expressed in terms of the copula parameter.

Use of copula requires the determination of marginal distributions based on univariate data. The marginal distributions here used were: exponential, gamma, Weibull and

NHESSD
2, 27–79, 2014

lognormal:

$$F(x) = 1 - e^{\frac{x}{a}} \tag{9a}$$

$$F(x) = \frac{1}{b^a \Gamma(a)} \int_0^x t^{a-1} e^{-\frac{t}{b}} \mathrm{d}t \tag{9b}$$

$$F(x) = 1 - e^{-\left(\frac{x}{a}\right)^b} \tag{9c}$$

$$F(x) = \frac{1}{b\sqrt{2\pi}} \int_0^x \frac{e^{-\frac{[\ln(t)-a]^2}{2b^2}}}{t} \mathrm{d}t \tag{9d}$$

3.1.2 Rainfall temporal pattern submodel

In order to define the temporal patterns of rainfall for each event, we used here the idea of mass curves followed by various authors (Huff, 1967; Garcia-Guzman and Aranda-Oliver, 1993; Chow et al., 1988). Following this kind of approach the variability of precipitation within a rainy period is represented by a dimensionless hyetograph $H(d)$, defined as follow:

$$H(\mathrm{d}) = \frac{1}{I \cdot D} \int_0^t h(t)\mathrm{d}t \tag{10}$$

that identifies the fraction of rainfall accumulated over the time interval $[0, d]$. In Eq. (10), $t (0 \le t \le D)$ is a fraction of the total duration D of the considered event and, consequently, $\mathrm{d} = t/D (0 \le \mathrm{d} \le 1)$ is the correspondent dimensionless duration, $h(t)$ is the rainfall depth at time $t (0 \le h \le V)$, $V = I \cdot D$ is the total storm volume and D the storm duration for the event.

The normalized events obtained are the input for selecting an appropriate probability function for the hyetograph shape. Any continuous density function could be appropriate to represents the shape for every analyzed time-step between 0–1, but here the

NHESSD
2, 27–79, 2014

choice has been orientated towards the Beta distribution because it is a very simple model that fits reasonably well the rainfall data.

The Beta cumulative distribution function for a given value, x, and given pair of parameters a and b is:

$$F(x) = \frac{1}{B(a,b)} \cdot \int_0^x t^{a-1}(1-t)^{b-1}\mathrm{d}t \tag{11}$$

where $B(a,b)$ is the Beta function:

$$B(a,b) = \int_0^1 t^{a-1}(1-t)^{b-1}\mathrm{d}t = \frac{\Gamma(a)\cdot\Gamma(b)}{\Gamma(a+b)} \tag{12}$$

and $\Gamma(*)$ represents the gamma function.

3.2 Rainfall–runoff modelling

In Mediterranean areas, intense weather phenomena, responsible for the flood events, are often characterised by high spatial variability. As consequence, here, starting from a semi-distributed model presented by Di Lorenzo (1993), a conceptual fully distributed model with climatic dependencies for the flow routing is used.

The proposed model is based on the representation in the form of linear kinematic mechanism of transfer of the full outflows coming from different contributing areas of the basin through the definition of a distributed hydrological response array with climatic characteristics.

Rainfall inputs are, also, distributed in space and time-varying. They are represented using a three-dimensional matrix, **P**, of order (A, B, N) where A and B are the number of cells in which the basin is divided in the direction x and y. N represents intervals number in which the rainfall event of duration Ω (with $N = \Omega/\Delta t$) is divided for each cell:

$$\mathbf{P}_{(A,B,N)} = \begin{bmatrix} P_{1,1,N} & P_{1,2,N} & \dots & P_{1,B,N} \\ & & P_{i,j,t} & \\ \vdots & & & \vdots \\ P_{A,1,N} & P_{A,2,N} & \cdots & P_{A,B,N} \end{bmatrix} \tag{13}$$

in which the generic term $P_{i,j,t}$ represents rainfall, expressed in mm, falling on the cell of coordinates i, j at time t.

The SCS-CN method, adopted by USDA Soil Conservation Service (1972, 1986), is used here to transform the gross rainfall in effective rainfall. This method allows to incorporate information on land use change as the CN is a function of soil type, land use, soil cover condition and degree of saturation of the soil before the start of the storm.

Since, a precipitation variable in time is considered, the runoff volume, $P_{e,i,j,t}$, is calculated in a dynamic form (Chow et al., 1988; Montaldo et al., 2007) as a function of the storm depth $P_{i,j,t}$, given initial abstraction, $I_{a,i,j} = cS_{i,j}$, in turn a function of the potential maximum soil moisture retention after runoff begins S according to the coefficient c, and the infiltrated volume, $F_{i,j,t}$, also variable over time, according to the following expression:

$$P_{e,i,j,t} = \begin{cases} 0 & P_{i,j,t} < c \cdot S_{i,j} \\ P_{i,j,t} - c \cdot S_{i,j} - F_{i,j,t} & P_{i,j,t} > c \cdot S_{i,j} \end{cases} \tag{14}$$

with $F_{i,j,t}$ calculated with the following expression:

$$F_{i,j,t} = \frac{S_{i,j} \cdot (P_{i,j,t} - c \cdot S_{a,i,j})}{P_{i,j,t} - c \cdot S_{a,i,j} + S_{i,j}} \tag{15}$$

and:

$$S_{i,j} = 254 \cdot \left(\frac{100}{\mathrm{CN}_{i,j}} - 1 \right) \tag{16}$$

NHESSD
2, 27–79, 2014
Estimation of flood design hydrographs using bivariate analysis
A. Candela et al.

Title Page
Abstract Introduction
Conclusions References
Tables Figures
◀| |▶
◀ ▶
Back Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

The $\mathrm{CN}_{i,j}$ parameter is, also, defined in a distributed form starting from a map of its spatial distribution obtained on the basis of the knowledge of soil types, land use and hydrologic soil types. Using Eqs. (14)–(16) the matrix of effective rainfalls P_e has been obtained with the same structure of the matrix (13).

The matrix $\mathbf{H}$, which describes the hydrological response of the basin, represents the space-time distribution of contributing areas (isochrones areas). It can be derived starting from concentration time and location of each cell within the catchment. Particularly, Wooding formula (1965) has been used to derive concentration time at cell scale:

$$\vartheta_{i,j} = \frac{L_{i,j\to \text{out}}^{3/5}}{k_{i,j\to \text{out}}^{3/5} \cdot s_{i,j\to \text{out}}^{3/10} \cdot r_{i,j}^{2/5}} \tag{17}$$

where $L_{i,j\to \text{out}}$ [m] is the hydraulic path length between the centroid of the cell of coordinates i,j and the outlet section of the catchment, $k_{i,j\to \text{out}}$ [$\text{m}^{1/3}\,\text{s}^{-1}$] is the Strickler roughness for the same path, $s_{i,j\to \text{out}}$ [$\text{m}\,\text{m}^{-1}$] is its slope, and $r_{i,j}$ [$\text{m}\,\text{s}^{-1}$] is the average rainfall intensity for the rainfall event over the cell of coordinates i,j. The paths lengths and their average slopes can be extracted starting from the catchment DEM (Noto and La Loggia, 2007). The DEM used for this study has a resolution of 200 m with a grid of 278 × 399 pixels (Fig. 1).

H matrix is of order (Θ, A, B) where Θ is the number of intervals in which catchment concentration time ϑ_{catch} is discretised:

$$\mathbf{H}_{(\Theta,A,B)} = \begin{bmatrix} H_{1,1,1} & H_{1,1,2} & \dots & H_{1,1,B} \\ & & H_{n,i,j} & \\ \vdots & & & \vdots \\ H_{\Theta,A,1} & H_{\Theta,A,2} & \cdots & H_{\Theta,A,B} \end{bmatrix} \tag{18}$$

where $H_{\Theta si,j}$ represents the cell surface of i, j-coordinates and a concentration time ϑ_n (with $\vartheta_n = \vartheta_{\text{catch}}/n \cdot \Delta t$, and $n = 1, 2, \dots, \Theta$).

The matrix of runoff Q is obtained by multiplying hydrological response matrix, $\mathbf{H}$ with the effective rainfall matrix, $\mathbf{P}_\mathrm{e}$:

$$Q_{(\Theta,N)} = \mathbf{H}_{(\Theta,A,B)} \times \mathbf{P}_{\mathrm{e}(A,B,N)} = \frac{1}{\Delta t} \cdot \begin{bmatrix} Q_{1,1} & Q_{1,2} & \dots & Q_{1,N} \\ & & Q_{i,j} & \\ \vdots & & & \vdots \\ Q_{\Theta,1} & Q_{\Theta,2} & \cdots & Q_{\Theta,N} \end{bmatrix} \tag{19}$$

in which $Q_{i,j}$ represents the available runoff for the ϑ isochrone zone at time t.

4 Application of the proposed methodology

4.1 Calibration of rainfall model

The calibration of the rainfall generation module was conducted using a sample of rainfall annual maximal rainfall events, extracted from the series of 10 min rainfall data recorded at raingauges above mentioned. Following De Michele and Salvadori (2003), two events are judged independent if they are separated by a dry period of at least 7 h. As consequence an inter-event time equal to 7 h was adopted to separate the single rainfall events and derive their average intensity and duration which represent the correlated variables modelled by Frank copula.

Kao and Govindaraju (2007) stated how the definition of annual maximal events for mutlivariate problems is somewhat ambiguous. As matter of fact, extreme events could be defined as those storms that have both high volume and peak intensity. Therefore here the definition of extreme rainfall based on events with annual maximum joint cumulative probability has been considered, where the joint cumulative probabilities of samples can be estimated directly via the empirical copula C_n as introduced by Yue (1999).

NHESSD

2, 27–79, 2014

Title Page
Abstract | Introduction
Conclusions | References
Tables | Figures
◀| |▶
◀ ▶
Back | Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

Moreover, as all raingauges are in a hydrologically homogeneous area (Cannarozzo et al., 1995) statistical analysis was performed by aggregating all selected events obtaining a final sample of 80 rainfall events whose characteristics are reported in Table 1.

The procedure described in the previous paragraph has been applied in order to derive θ parameter for the Frank copula and the generating function. The copula so obtained for the analyzed case study, is characterized by a parameter θ to -3.7573 calculated using the Eq. (6) where the Kendall's coefficient of correlation τ is equal to -0.381.

In order to indicate the goodness of fit of chosen copula, the empirical C_n and best fitted copula joint distribution were reported in a Q-Q plot (Fig. 2, left). To confirm the goodness of the chosen copula to describe the data, the parametric and nonparametric values of the function $K(z)$, as defined by Genest and Rivest (1993), are shown in Fig. 2 (right). These comparisons confirm how Frank 2-Copula is well suited to describe the dependence structure between the available intensity-duration data.

The parameters of the marginal distributions considered were estimated by applying the Maximum Likelihood method and the best fitted distribution was selected using various criteria. More in particular the AIC criterion, the Relative Root Mean Square Error (RRMSE), and the Anderson–Darling test were applied to verify the goodness of the fitting. The results, as shown in Tables 2 and 3, returned lognormal probability distribution as best marginal distribution for average storm intensity, and Weibull distribution as best marginal distribution for storm duration. Further, Fig. 3 show the two marginal distributions defined, respectively by Eqs. (9c–d) and empirical exceedances probabilities computed using Gringorten formula of the observed data.

Finally, the Beta distribution has been fitted to adimensional shape sample of each events. Model parameters are estimated by maximum likelihood (ML), while the goodness of fit was verified by the Pearson test. The historical normalized mass curves derived for all the events selected are plotted in Fig. 4. Then, these curves were sampled in 11 equal time-step (0; 0.1; 0.2; . . . ; 0.9; 1) and, for each time-step considered, the parameter estimation of the Beta distribution was carried out using the ML method (Table 4).

In order to test the model ability to reproduce rainfall events characteristics, 1000 events were generated using Monte Carlo procedure. Generated events have shown an excellent reproducibility of historical events characteristics both in terms of duration-intensity correlation and in terms of adimensional shapes (Fig. 5).

4.2 Calibration of rainfall-runoff model

Regarding the rainfall-runoff model, calibration is only required for three parameters: c and $\mathrm{CN}_{i,j}$, for the effective rainfall module (Eqs. 14–16), and the hydraulic roughness $k_{i,j\rightarrow \mathrm{out}}$ for the transfer module (Eq. 17). The latter two parameters are spatially distributed and their calibration should be carried out by considering both values as spatial correlation. To overcome the difficulties in considering also spatial correlation for the calibration a simple and efficient procedure proposed by Candela et al. (2005) has been implemented here.

In order to include its spatial distribution, the CN map has been rescaled according to some weights, $w_{\mathrm{CN}_{i,j}}$ allowing for CN spatial variability into the catchment, with regard to the a reference value $\overline{\mathrm{CN}}$, i.e. the spatially-averaged value of $\mathrm{CN}_{i,j}$:

$$\mathrm{CN}_{i,j} = w_{\mathrm{CN}_{i,j}} \cdot \overline{\mathrm{CN}} \tag{20}$$

In this way, it is not necessary to calibrate each single value of CN but only the reference value. Hence, the new CN spatial distribution can be easily obtained from Eq. (20) given the spatial distribution of $w_{\mathrm{CN}_{i,j}}$.

The spatially-averaged value of $\mathrm{CN}_{i,j}$ can be easily calculated starting from its effective spatial distribution, which is available for the entire Sicily at 100 m grid resolution (Fig. 6), by using standard GIS tools. Its value is equal to 82 for AMC condition II. This map was available starting the year 2000 (Regione Sicilia, 2004) and was used, here, also for the calibration of previous events because any significant changes of land uses in the Imera catchment were recognised.

Similarly, the Strickler roughness coefficients (Fig. 7) have been rescaled according to some weights, $w_{k_{i,j\rightarrow \text{out}}}$, allowing for roughness variability into the catchment, with regard to a reference roughness value $\overline{k}$, i.e. the spatially-averaged value of $k_{i,j\rightarrow \text{out}}$.

$$k_{i,j\rightarrow \text{out}} = w_{k_{i,j\rightarrow \text{out}}} \cdot \overline{k} \qquad (21)$$

The spatially-averaged value of $k_{i,j\rightarrow \text{out}}$ can be easily calculated starting from its effective spatial distribution of CN, in relation of soil type and land use by the modified Engmann's table (Engmann, 1986; Candela et al., 2005) (Table 5), by using standard GIS tools. Its value is equal to $20.5\,\text{m}^{-1/3}\,\text{s}^{-1}$.

The calibration of the three model parameters has been carried out comparing observed and predicted variables in terms of discharges for the event of 21 December 1976, registered at Imera meridionale at Drasi station (Fig. 8).

Particularly, in calibration it is not difficult to get optimal fittings to the observations by adjusting parameter values but rather that there are many sets of parameter values that will give acceptable fits to the data (Beven, 1993). Often, there are no techniques available for estimating or measuring the values of effective parameters required at the grid element or catchment scale. These values will therefore be subject to some uncertainty, especially in semiarid areas for which data are not always adequate and there is an extreme variability in space and time of all factors controlling the runoff processes (Yair and Lavee, 1982).

In this study the uncertainty in the identification of model parameters has been assessed using the Generalised Likelihood Uncertainty Estimation (GLUE) procedure of Beven and Binley (1992). GLUE is a Monte Carlo based technique that allows for the concept of equifinality of parameter sets in the evaluation of modelling uncertainty. It transforms the problem of searching for an optimum parameter set into a search for the sets of parameter values, which would give reliable simulations for a wide range of model inputs. Following this approach there is no requirement to minimise or maximise any objective function, but the performance of individual parameter sets are characterised by a likelihood weight, computed by comparing predicted to observed responses using some kind of likelihood measure. The likelihood distribution reflects type of sets of parameters, parameter interaction and insensitivity, moreover likelihood measure increase with increasing levels of performance (Freer et al., 1996). Table 6 lists parameters required for the model and the ranges assigned to each for the Monte Carlo simulations; particularly each interval has been chosen as wide as possible on order to explore a feasible parameter space.

This analysis has been carried out generating 5000 uniform random sets of parameters and using these sets to perform model simulation. The results presented in this study use the sum of squared errors as basic likelihood measure, in the form of Nash and Sutcliffe (1970) efficiency criterion:

$$L(\Theta_i/Y) = \left(1 - \sigma_i^2/\sigma_{\text{obs}}^2\right) \sigma_i^2 < \sigma_{\text{obs}}^2 \tag{22}$$

where $L(\Theta_i/Y)$ is the likelihood measure for the ith model simulation for parameter vector Θ_i conditioned on a set of observations Y, σ_i^2 is the associated error variance for the ith model and σ_{obs}^2 is the observed variance for the event under consideration.

Figure 9 shows scatter plots for the likelihood based on Eq. (22) for each of the three parameters, c, CN and k. Each dot represents one run of the model with different randomly chosen parameter values within the ranges of Table 6. These dotty plots are projections of the surface of the likelihood measure within a three dimension parameter space into single parameter axes. Scatter plots for the three parameters are very close, in terms of form of likelihood surface and level of performance.

It is readily seen from the plots that, consistent with the concepts that underlie the GLUE approach to model evaluation, there is considerable overlap in performance between simulations and that there are many different parameter sets that give acceptable simulations.

NHESSD
2, 27–79, 2014

Moreover a best fit parameter set has been fixed corresponding to maximum efficiency values and in Fig. 10 comparison between observed and simulated hydrographs is reported for the event of 21 December 1976.

5 Results

The capability of the proposed procedure was tested in reproducing the joint statistics of both peak discharges and corresponding discharge volumes through the generation of 5000 synthetic hydrographs starting from 5000 synthetic rainfall events of assigned shape, average intensity and duration. Figure 11 shows the scatter plot of the pairs $(Q_{\max}, V)$ derived from synthetic hydrographs generated.

Comparison with pairs of observed $(Q_{\max} - V)$ values at Drasi station (Aronica et al., 2012) shows a good ability of the procedure to reproduce both observed values and their correlative structure for all range of values.

The final phase of the work was the derivation of Flood Design Hydrographs (FDH) via synthetic generation by using the output from the rainfall–runoff model. The derivation of FDH was carried out by following procedure: (a) modelling of the statistical correlation between flood peak and volume pairs generated by the R-R model via copulas; (b) definition of the normalised hydrograph shape in probabilistic form; (c) final derivation of the FDH by rescaling the selected shape (i.e., for a fixed return time) given the synthetic flood peak and volume values.

The first step of the procedure involves the choice of the best copula for the bivariate analysis of the output data from the R-R model. Three copula families (namely Gumbel–Hougard, Frank and Clayton) were adapted to the 5000 generated pairs of flood peak discharges and volumes. These two series are characterised by a Kendal's correlation coefficient equal to 0.932. The parameter of the studied copulas has been estimated using the inversion of Kendall's Tau method (Table 4).

In order to select the copula that best represents the dependence structure of observed variables graphical tools and statistical tests were used here. In Fig. 12 the K-

plot, as defined by Genest and Rivest (1993), are shown for the three copula families considered. For a best detection of modelling the correlation structure, the normalised scatter plot of the empirical and theoretical 5000 pairs are reported in Fig. 13. In addition, more rigorous tests base on statistical analisys have been performed. Specifically, the AIC criterion and the Log-Likelihood test were applied to verify the goodness of the fitting. The graphical tools and the statistical test returns how Gumbel–Hougard copula family is the best choice for describing the dependence structure between the flood peaks and volume data.

The parameters of the marginal distributions here used (exponential, gamma, Weibull, lognormal, and GEV) these distributions were estimated by applying the Maximum Likelihood method and the best fitted distribution was selected using various criteria. Again, the AIC and Anderson–Darling test (Kottegoda and Rosso, 1997) have been applied to verify the goodness of the fitting (Tables 8 and 9). The goodness-of-fit criteria return gamma distribution as best marginal distribution for both univariate variables. Further, Fig. 14 shows the marginal distribution defined by Eq. (9b) compared with the exceedances probabilities computed using Gringorten formula of the empirical data.

A comparison between a sample generated from the Gumbel–Hougard copula and the empirical ($Q_{\max} - V$) pairs is plotted in Fig. 8 (left). Also, contours of the fitted copula that represent the events with the same probability of occurrence are shown (Fig. 8, right).

The second step of the procedure is devoted to the derivation of the shape of the FDH generated via cluster analysis with Ward method (1963) using the procedure proposed by Aronica et al. (2012). The procedure consists in normalising the empirical hydrographs (5000 in this study) that a unit peak flow and a unit flood volume have been resulted. The normalised hydrographs are then grouped in various clusters according with Ward method (1963) (minimum variance algorithm that minimizes increments in sums of squares of distances of any two clusters that can be formed at each step). The results of this cluster analysis are the three shapes of hydrograph showed in Fig. 16. In

NHESSD
2, 27–79, 2014

relation to the number of hydrographs belonging to each cluster, a probability of about 0.11 (Shape 1), 0.5 (Shape 2) and 0.39 (Shape 3) has been assigned to these shapes.

The final step of the procedure allows to obtain the FDH for any return time by merging the non-dimensional hydrographs (for specific probability) and the generated peak-volume pairs derived using copula. The choice of a joint (bivariate) return period (JRP) is the core problem of the final step. Several authors found (see for instance, Requena et al., 2013; Vandenberghe et al., 2012) how different methods can be considered for defining joint return periods estimated by fitted copulas. Here, following the approach proposed by Vandenberghe et al., (2012) the joint return period can be easily calculated by means of a bivariate copula $C(u_1,u_2)$ as:

$$T = \frac{1}{1-C(u_1,u_2)} = \frac{1}{1-C(F_x(x),F_y(y))} \tag{23}$$

As matter of fact, this method is an extension of the classical definition of a univariate return period. All couples (u_1,u_2) that are on the same contour (corresponding with a isoline p) of the copula C will have the same bivariate return period.

Hence, for a given design return period T, the corresponding level $p = C(u_1,u_2)$ can easily be calculated using the Eq. (23) and all the pairs (u_1,u_2) on the isoline p have the same return period. In order to select the single design point $(u_{1,T},u_{2,T})$ Vandenberghe et al. (2012) suggest the select the point with the largest joint probability:

$$(u_{1,T},u_{2,T}) = \underset{C(u1,u2)=p}{\arg\max}\ f_{XY}\left(F_X^{-1},F_Y^{-1}\right) \tag{24}$$

The corresponding design values $Q_{\max,T}$ and V_T can be easily calculated by inverting the marginal CDF:

$$Q_{\max,T} = F_{Q_{\max}}^{-1}(u_{1,T}); \quad V_T = F_V^{-1}(u_{2,T}) \tag{25}$$

As example the FDH with a design return period of $T = 100$ yr is calculated. For $T = 100$ yr, the corresponding copula level $p$equals 0.99 and corresponds with an isoline (Fig. 17).

The Eq. (24) can be solved to find the single design point $(u_{1,T}, u_{2,T})$ with the largest joint probability, i.e. (0.9949, 0.990). Using the inverse marginal CDFs the design event pair is obtained: $(Q_{\max,T}, V_T) = (4929.3\,\mathrm{m^3\,s^{-1}}, 162.2\,\mathrm{M\,m^{-3}})$. Finally, the design hydrograph can be obtained using the shape 3 and de-normalising the time and the discharge by multiplying for the values of the pair (Fig. 18).

6 Conclusions

In this study a procedure to derive Flood Design Hydrographs (FDH) using a bivariate representation of rainfall forcing (rainfall duration and intensity) described by copulas coupled with a distributed rainfall-runoff model is presented. In order to estimate the return period of the FDH which give the probability of occurrence of a hydrograph flood peaks and flow volumes obtained through R-R modeling has been statistically treated via copulas. The choice of copulas is motivated by the strong capability to describe the statistical correlation between variables which allows to obtain the return period related to the FDH and not only to a single variable (usually the peak flow) as in the univariate analysis. This circumstance have a significant importance in all those case where all the hydrological variables (flood volume, flood peaks, etc.) included in a Design Hydrograph plays an important role (i.e, flood propagation modeling for the delimitation of inundate areas with hazard/risk classification).

In addition, a statistical label (in terms of probability of occurrence) has been give also to the hydrograph shape through the cluster analysis of the R-R model generated hydrographs. This completes the statistical definition of the FDH which can be identified with a specific return period (Joint Return Period, JRP).

The procedure described above applied to the case study of Imera catchment in Sicily, Italy, shows how this approach methodology allows a reliable and estimation of the Design Flood Hydrograph in a way which can be easily implemented also in the practical situations.

These results, hence, underline the necessity of considering JRP estimation methods in the definition of design events for all practical purposes.

Further research efforts will be devoted to move from one-design-event methods to ensemble-design-event methods by considering uncertainty via a complete application of GLUE procedure.

Acknowledgements. This research has been developed in the framework of COST Action ESF0901 "European Procedures for Flood Frequency Estimation" (FloodFreq) activities. Authors wish to thank the Sistema Informativo Agrometorologico Siciliano and, particularly, Luigi Pasotti for supplying the rainfall data and the Osservatorio delle Acque for supplying the discharge data.

References

Aronica, G. T. and Candela, A. Derivation of flood frequency curves in poorly gauged Mediterranean catchments using a simple stochastic hydrological rainfall-runoff model, J. Hydrol., 347, 132–142, 2007.

Aronica, G. T., Candela, A., Fabio, P., and Santoro, M.: Estimation of flood inundation probabilities using global hazard indexes based on hydrodynamic variables, Phys. Chem. Earth, 42–44, 119–129, 2012.

Bacchi, B., Becciu, G., and Kottegoda, N. T.: Bivariate exponential model applied to intensities and duration of extreme rainfall, J. Hydrol., 155, 225–236, 1994.

Balistrocchi, M. and Bacchi, B.: Modelling the statistical dependence of rainfall event variables through copula functions, Hydrol. Earth Syst. Sci., 15, 1959–1977, doi:10.5194/hess-15-1959-2011, 2011.

Beven, K. J.: Prophecy, reality and uncertainty in distributed modeling, Adv. Water Resour., 16, 41–51, 1993.

Beven, K. J. and Binley, A. M.: The future of distributed models – model calibration and uncertainty prediction, Hydrol. Process., 6, 279–298, 1992.

Blöschl, G. and Sivapalan, M.: Process Control on Flood Frequency. Runoff Generation, Storm Properties and Return, Centre for Water Research Environmental Dynamics Report, ED

1159 MS, Department of Civil Engineering, The University of Western Australia, Perth, Australia, 1997.
Brigandí, G.: Il preavviso delle piene in bacini non strumentati attraverso l'uso di precursori idro-pluviometrici, Ph.D. dissertation, University of Palermo, Palermo, Sicily, Italy, 2009 (in Italian).
Camarasa-Belmonte, A. M. and Soriano-Garcia, J.: Flood risk assessment and mapping in peri-urban Mediterranean environments using hydrogeomorphology. Application to ephemeral streams in the Valencia region (eastern Spain), Landscape Urban Plan., 104, 189–200, 2012
Candela, A., Noto, L. V., and Aronica, G. T.: Influence of surface roughness in hydrological response of semiarid catchments, J. Hydrol., 313, 119–131, 2005.
Cannarozzo, M., D'Asaro, F., and Ferro, V.: Regional rainfall and flood frequency analysis for Sicily using the two component extreme value distribution, Hydrological Sciences Journal, J. Hydrol. Sci., 40, 19–42, 1995.
Chow, V. T., Maidment, D. R., and Mays, L. W.: Applied Hydrology, McGraw-Hill International Edn., Singapore, 1988.
Chowdhary, H., Escobar, L. A., and Singh, V. P.: Identification of suitable copulas for bivariate frequency analysis of flood peak and flood volume data, Hydrol. Res., 42, 193–216, 2011.
De Michele, C. and Salvadori, G.: A generalized Pareto intensity-duration model of storm rainfall exploiting 2-copulas, J. Geophys. Res., 108, 4067, doi:10.1029/2002JD002534, 2003.
De Michele, C., Salvadori, G., Canossi, M., Petaccia, A., and Rosso, R.: Bivariate statistical approach to check adequacy of dam spillway, J. Hydrol. Eng., 10, 50–57, 2005.
Di Lorenzo, M.: Modello afflussi-deflussi per lo studio delle piene del fiume salso a Drasi, M.Sc. thesis, University of Palermo, Palermo, Sicily, Italy, 1993 (in Italian).
Dupuis, D. J.: Using copulas in hydrology; benefits, cautions and issues, J. Hydrol. Eng., 12, 381–393, 2007.
Engman, E. T.: Roughness coefficients for routing surface runoff, J. Irrig. Drain. E-ASCE, 112, 39–54, 1986.
Favre, A. C., El Adlouni, S., Perreault, L., Thiemonge, N., and Bobee, B.: Multivariate hydrological frequency analysis using copulas, Water Resour. Res., 40, W01101, doi:10.1029/2003WR002456, 2004.
Freer, J., Beven, K. J., Ambroise, B.: Bayesian estimation of uncertainty in runoff prediction and the value of data: an application of the GLUE approach, Water Resour. Res., 32, 2161–2173, 1996.

NHESSD
2, 27–79, 2014

Estimation of flood design hydrographs using bivariate analysis

A. Candela et al.

Gaál, L., Viglione, A., Szolgay, J., Blöschl, G., Bacigál, T., and Rogger, M.: Bivariate at-site frequency analysis of simulated flood peak-volume data using copulas, CD Rom, EGU2010–13441, EGU General Assembly, Vienna, 2010.

Garcia-Guzman, A. and Aranda-Oliver, E.: A stochastic model of dimensionless hyetograph, Water Resour. Res., 29, 2363–2370, 1993.

Genest, C. and Favre, A. C.: Everything you always wanted to know about copula modeling but were afraid to ask, J. Hydrol. Eng., 12, 347–368, 2007.

Genest, C. and Rivest, L.: Statistical inference procedures for bivariate Archimedean copulas, J. Am. Stat. Assoc., 88, 1034–1043, 1993.

Gräler, B., van den Berg, M. J., Vandenberghe, S., Petroselli, A., Grimaldi, S., De Baets, B., and Verhoest, N. E. C.: Multivariate return periods in hydrology: a critical and practical review focusing on synthetic design hydrograph estimation, Hydrol. Earth Syst. Sci., 17, 1281–1296, doi:10.5194/hess-17-1281-2013, 2013.

Grimaldi, S. and Serinaldi, F.: Design hyetograph analysis with 3-copula function, Hydrolog. Sci. J., 51, 223–238, 2006.

Hosking, J. R. M. and Wallis, J. R.: Regional Frequency Analysis: an Approach Based on L-Moments, Cambridge University Press, Cambridge, 1997.

Huff, F. A.: Time distribution of rainfall in heavy storms, Water Resour. Res., 3, 1007–1019, 1967.

Kao, S. C. and Govindaraju, R. S.: A bivariate frequency analysis of extreme rainfall with implications for design, J. Geophys. Res., 112, D13, doi:10.1029/2007JD008522, 2007.

Koutroulis, A. G. and Tsanis, I. K.: A method for estimating flash flood peak discharge in a poorly gauged basin: case study for the 13–14 January 1994 flood, Giofiros Basin, Crete, Greece Original, J. Hydrol., 385, 150–164, 2010.

Koutsoyiannis, D. and Foufoula-Georgiou, E.: A scaling model of a storm hyetograph, Water Resour. Res., 29, 2345–2361, 1993.

Loukas, A.: Flood frequency estimation by a derived distribution procedure, J. Hydrol., 255, 69–89, 2002.

Montaldo, N., Ravazzani, G., and Mancini, M.: On the prediction of the Toce alpine basin floods with distributed hydrologic models, Hydrol. Process., 21, 608–621, 2007.

Nash, J. E. and Sutcliffe, J. V.: River flow forecasting through conceptual models 1. A discussion of principles, J. Hydrol., 10, 282–290, 1970.

NHESSD

2, 27–79, 2014

Nelsen, R. B.: An Introduction to Copulas. Lecture Notes in Statistics, Springer-Verlag, New York, 1999.
Nicolau, J. M., Solé-Benet, A., Puigdefabregas, J., and Guitiérrez, L.: Effects of soil and vegetation on runoff along a catena in semiarid Spain, Geomorphology, 14, 297–309, 1996.
Noto, L. V. and La Loggia, G.: Derivation of a distributed unit hydrograph integrating GIS and remote sensing, J. Hydrol. Eng., 12, 639–650, 2007.
Rahman, A., Weinmann, P. E., Hoang, T. M. T., and Laurenson, E. M.: Monte Carlo simulation of flood frequency curves from rainfall, J. Hydrol., 256, 196–210, 2002.
Requena, A. I., Mediero, L., and Garrote, L.: A bivariate return period based on copulas for hydrologic dam design: accounting for reservoir routing in risk estimation, Hydrol. Earth Syst. Sci., 17, 3023–3038, doi:10.5194/hess-17-3023-2013, 2013.
Regione Siciliana: Piano stralcio di bacino per l'assetto idrogeologico della Regione Sicilia – Relazione Generale, Assessorato Territorio e Ambiente della Regione Siciliana, Palermo, 2004 (in Italian).
Salvadori, G. and De Michele, C.: Frequency analysis via copulas: theoretical aspects and applications to hydrological events, Water Resour. Res., 40, W12511, doi:10.1029/2004wr003133, 2004.
Salvadori, G. and De Michele, C.: Multivariate multiparameter extreme value models and return periods: a copula approach, Water Resour. Res., 46, W10501, doi:10.1029/2009WR009040, 2010.
Salvadori, G., De Michele, C., Kottegoda, N. T., and Rosso, R.: Extremes in Nature. An Approach Using Copulas, Water Sciences and Technology Library 56, Springer, Dordrecht, The Netherlands, 2007.
US Department of Agriculture, Soil Conservation Service: National Engineering Handbook, Hydrology,. Vol. 4, Washington, DC, 1986.
Ward, J. E.: Hierarchical grouping to optimize an objective function, J. Am. Stat. Assoc., 58, 236–244, 1963.
Wooding, R. A.: A hydraulic model for the catchment-stream problem: 1. Kinematic wave theory, J. Hydrol., 3, 254–267, 1965.
Yair, A. and Lavee, H.: Application of the concept of partial area contribution to small arid watersheds, in: Rainfall-Runoff Relationship, edited by: Singh, P. V., Water Res. Publ., Colorado, 335–350, 1982.

NHESSD
2, 27–79, 2014

Estimation of flood design hydrographs using bivariate analysis

A. Candela et al.

Yue, S., Ouarda, T. B. M. J., Bobèe B., Legendre, P., and Bruneau, P.: The Gumbel mixed model for flood frequency analysis, J. Hydrol., 226, 88–100, 1999.
Zhang, L. and Singh, V. P.: Bivariate rainfall frequency distributions using Archimedean copulas, J. Hydrol., 332, 93–109, 2007.

NHESSD
2, 27–79, 2014

NHESSD
2, 27–79, 2014

Estimation of flood design hydrographs using bivariate analysis

A. Candela et al.

Table 1. Information and statistics of the rainfall data for 80 events registered from 2010 to 2011.

	Intensity ($mm\,h^{-1}$)	Volume (mm)	Duration (min)
Max	26.02	156.2	2060.0
Min	1.62	18.0	170.0
Mean	5.04	66.9	975.0
Standard deviation	3.76	27.6	453.0

Table 2. Marginal distribution parameters and goodness of fit results for average intensity (I).

	a	b	AIC	RRMSE	$A-D^*$
Exponential	5.03644	–	420.672	13.890	10.557
Gamma	3.31078	1.52123	376.565	7.91708	3.099
Weibull	5.67845	1.57408	394.866	10.3672	4.928
Lognormal	1.45814	0.51516	357.209	5.84947	1.411

* Critical value for 95 % significance level = 2.492.

NHESSD
2, 27–79, 2014

NHESSD
2, 27–79, 2014

Table 3. Marginal distribution parameters and goodness of fit results for duration (*D*).

	a	*b*	AIC	RRMSE	*A – D* *
Exponential	16.2542	–	608.136	56.130	9.588
Gamma	3.84882	4.22315	554.563	10.590	0.808
Weibull	18.3596	2.32434	549.195	6.842	0.451
Lognormal	2.65285	0.56908	564.288	18.451	1.522

* Critical value for 95 % significance level = 2.492.

Table 4. Parameters estimation of the Beta distribution.

d	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
α	1.070	1.369	1.706	2.029	2.029	3.629	4.643	5.600	9.558
β	8.127	4.727	3.456	2.790	2.790	2.543	2.151	1.649	1.198

NHESSD
2, 27–79, 2014

Table 5. Engmann modified table reported Strickler's coefficient values related to Imera catchment land use.

Land use	Urban	Bare rocks	Arable land	Untilled	Vineyard	Clear forest
Strickler coefficient	100.0	50.0	22.0	20.0	7.69	6.67

NHESSD
2, 27–79, 2014

Table 6. Ranges of parameters considered for the calibration.

Parameter	Lower limit	Upper limit	Max eff value
c	0	1	0.68
$\overline{CN}$	70	90	87
$\overline{k}$	50	100	75.8

NHESSD

2, 27–79, 2014

Table 7. Goodness of fit results for copula (Q_{max}, V).

Copula family	θ	LL	AIC
Gumbel	14.792	9581.66	19 163.32
Frank	57.476	10 354.17	20 708.35
Clayton	27.585	10 140.84	20 281.68

NHESSD
2, 27–79, 2014

Table 8. Marginal distribution parameters and goodness of fit results for flood peaks (Q_{max}).

	a	b	c	AIC	$A-D^*$
Exponential	985.84	–	–	7.895	1.110
Gamma	1.04	944.78	–	7.895	1.089
Weibull	982.33	0.99	–	7.895	1.130
Lognormal	6.34	1.16	–	7.913	2.819
GEV	425.29	438.01	0.51	7.916	1.204

* The critical values for the Anderson–Darling test is 2.492.

NHESSD
2, 27–79, 2014

Table 9. Marginal distribution parameters and goodness of fit results for flood volumes (V).

	a	b	c	AIC	$A-D$*
Exponential	39.66	–	–	4.6816	3.745
Gamma	1.27	31.18	–	4.6649	0.680
Weibull	41.41	1.12	–	4.6716	1.199
Lognormal	3.24	1.03	–	4.6856	2.804
GEV	17.8733	20.327	0.39014	4.6824	0.944

* The critical values for the Anderson–Darling test is 2.492.

NHESSD
2, 27–79, 2014

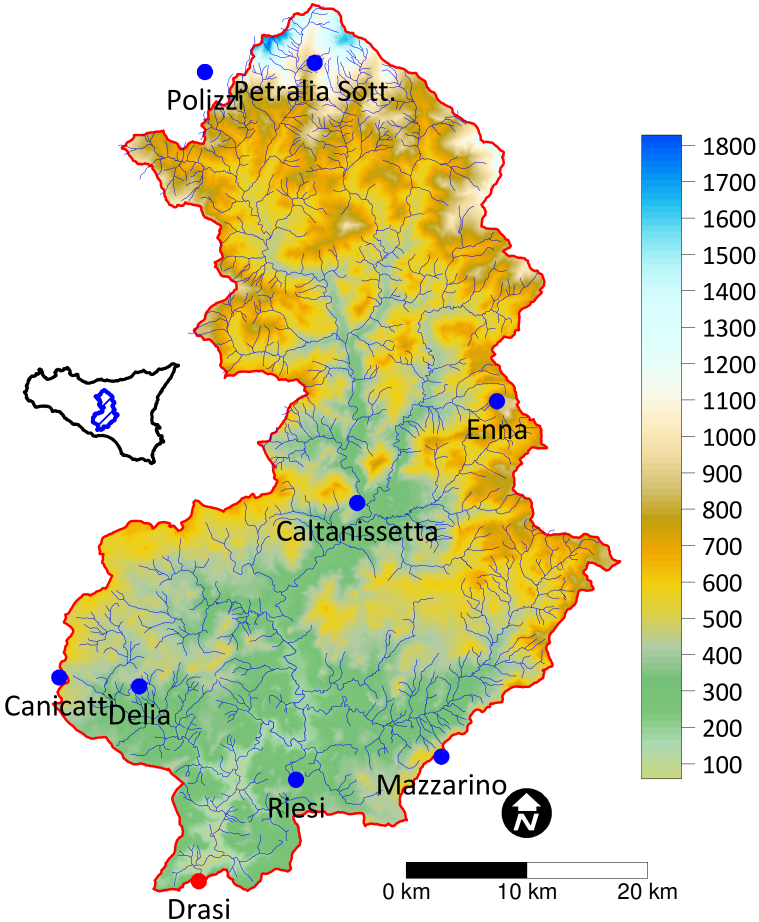

Fig. 1. Imera catchment layout.

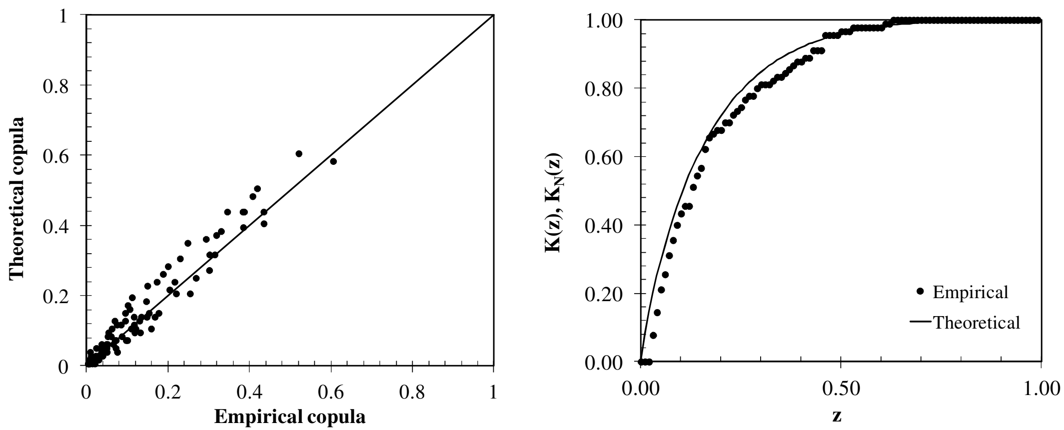

Fig. 2. Comparison between empirical joint distribution and best fitted copula. Goodness test for Frank's copula.

NHESSD
2, 27–79, 2014

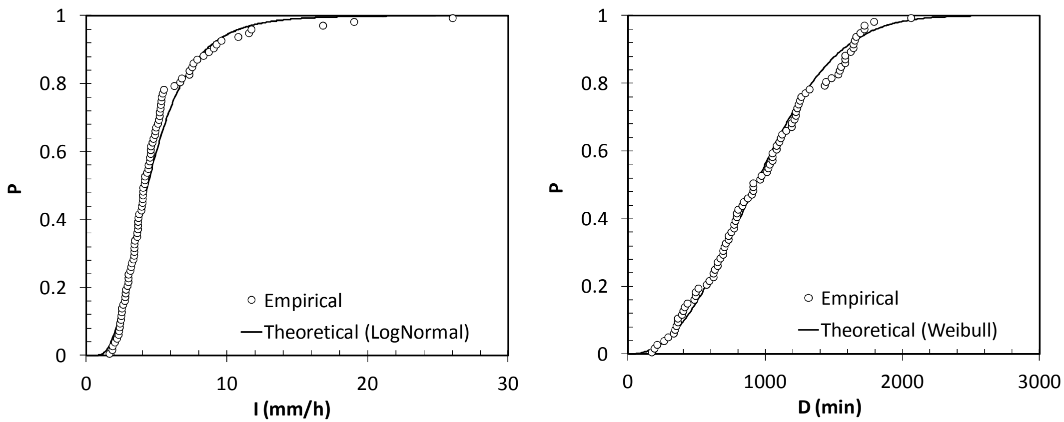

Fig. 3. Plotting position: average intensity and duration.

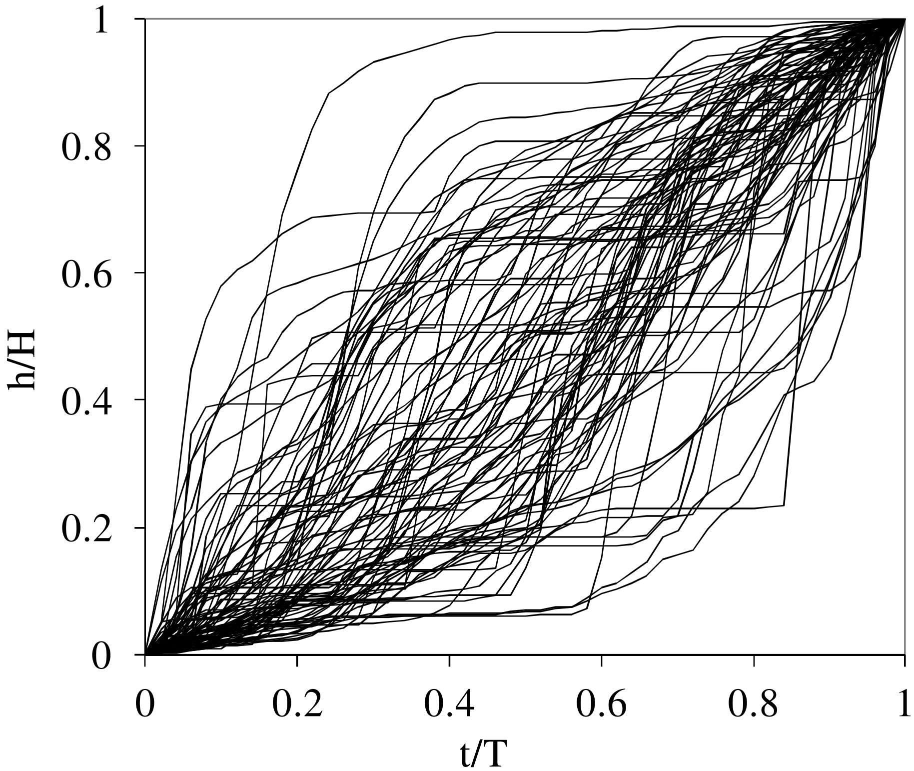

Fig. 4. Historical normalized mass curves derived for all the events selected.

NHESSD
2, 27–79, 2014

Estimation of flood design hydrographs using bivariate analysis

A. Candela et al.

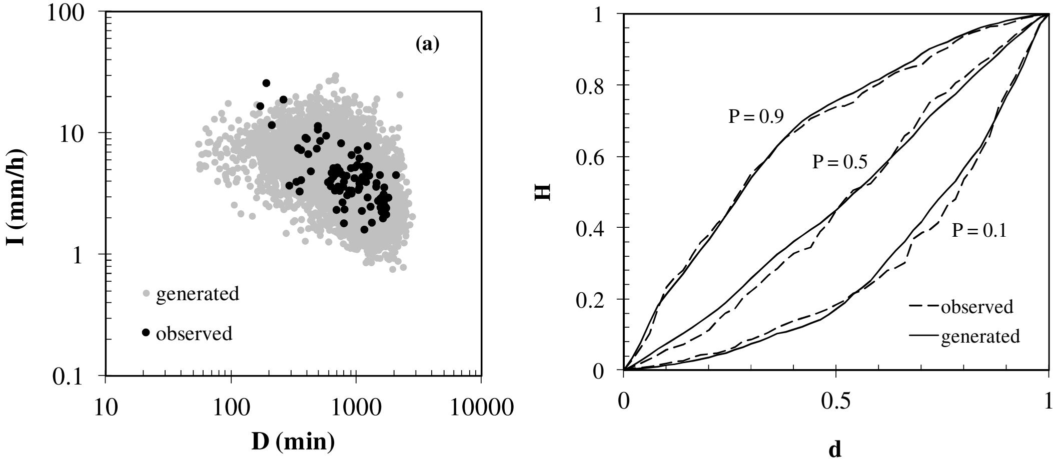

Fig. 5. Duration-intensity correlation (left) and adimensional shapes (right).

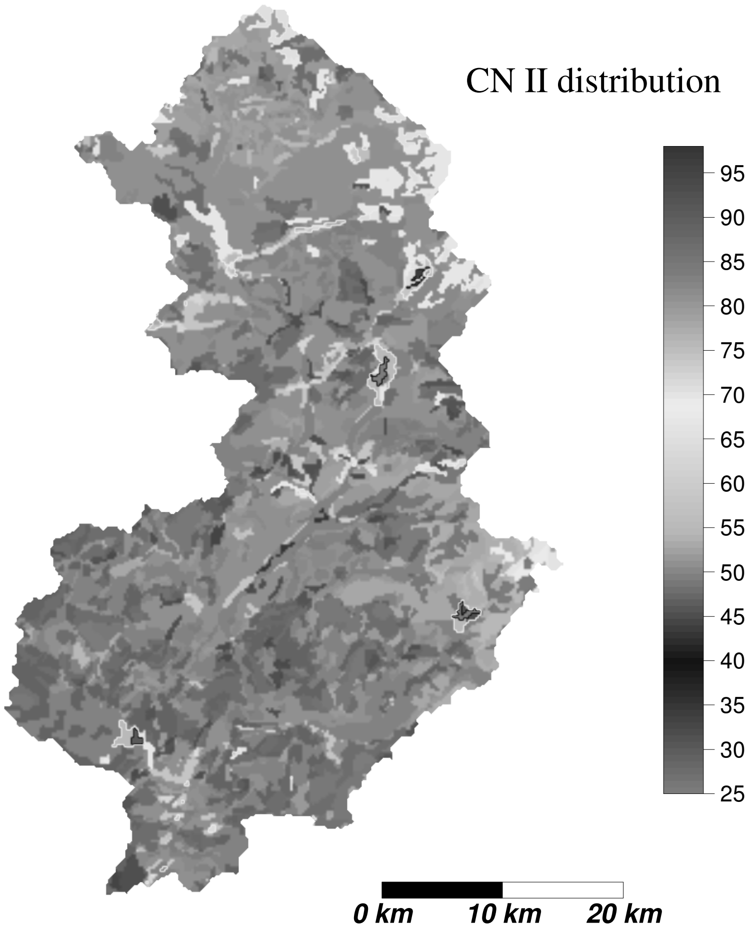

Fig. 6. Spatial distribution of CN_{II} for the Imera catchment.

NHESSD
2, 27–79, 2014

Estimation of flood design hydrographs using bivariate analysis

A. Candela et al.

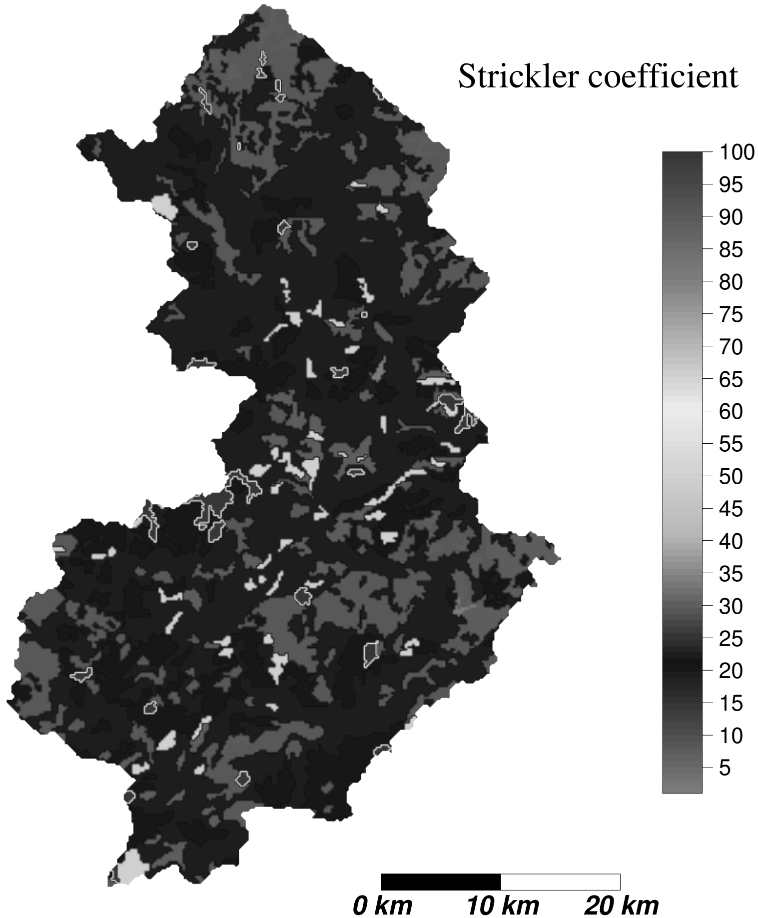

Fig. 7. Spatial distribution of roughness coefficient k.

NHESSD
2, 27–79, 2014

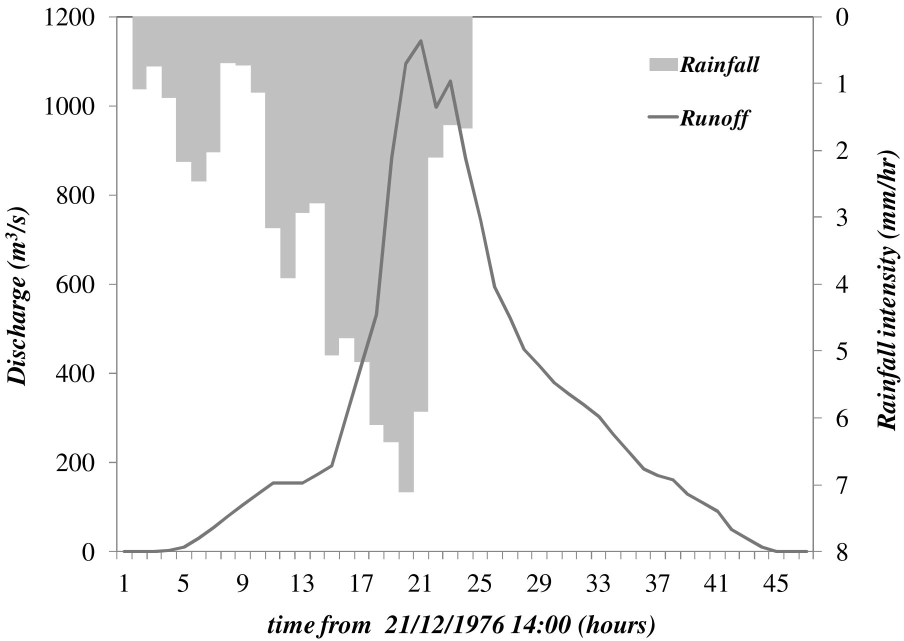

Fig. 8. Event of 21 December 1976 registered at Drasi flowgauge.

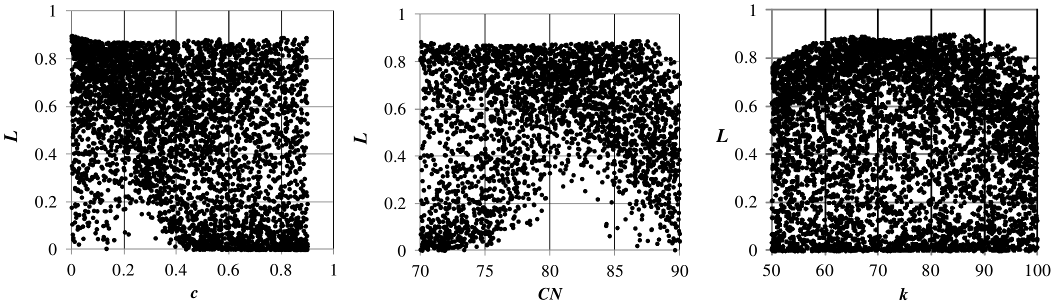

Fig. 9. Scatter plots illustrating the distribution of likelihood weighted hydrological parameter values distribution.

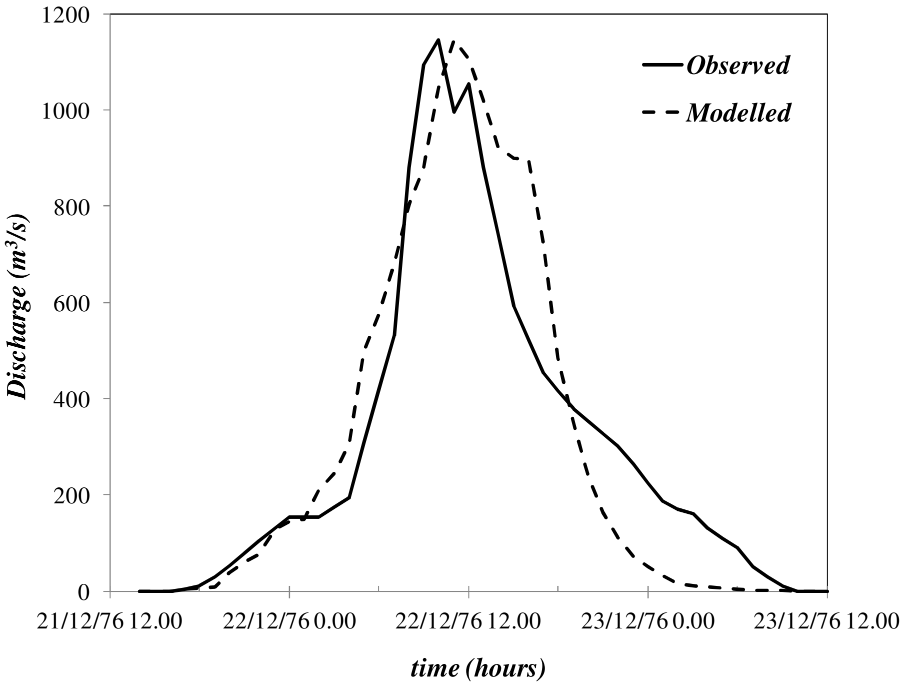

Fig. 10. Comparison between observed and modelled hydrographs for the event of 21 December 1976.

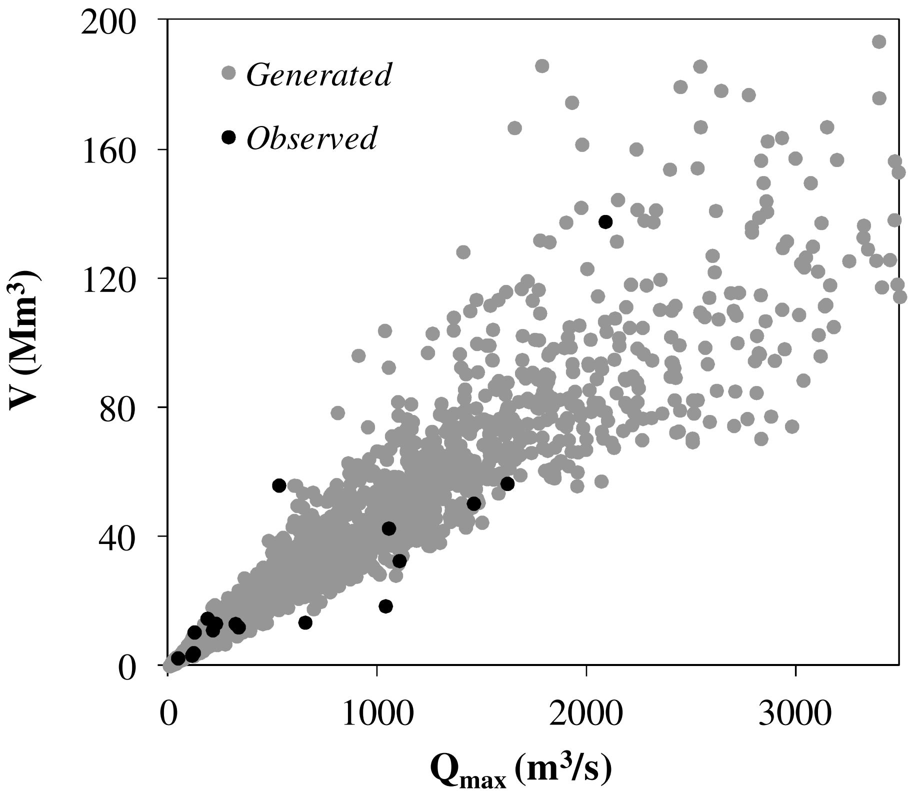

Fig. 11. Comparison between scatter plot of the observed and generated pairs (Q_{max}, V).

NHESSD
2, 27–79, 2014

Estimation of flood design hydrographs using bivariate analysis

A. Candela et al.

Title Page
Abstract
Introduction
Conclusions
References
Tables
Figures
◀▮ ▶▮
◀ ▶
Back
Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

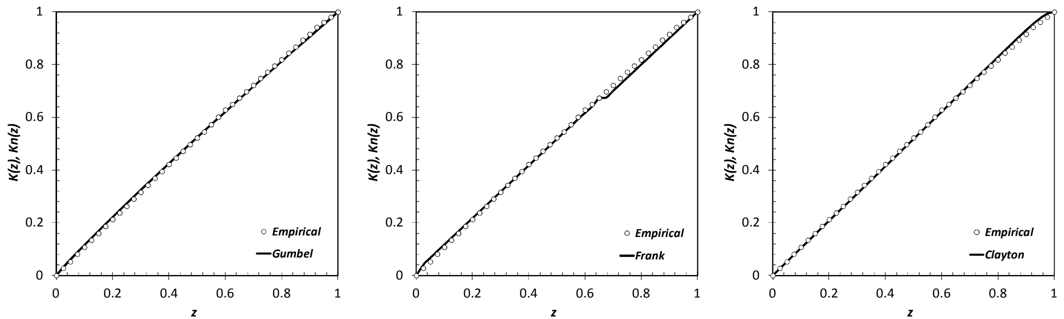

Fig. 12. K-plot for the copula models. The "empirical" points represent the pairs coming from the R-R model.

NHESSD
2, 27–79, 2014

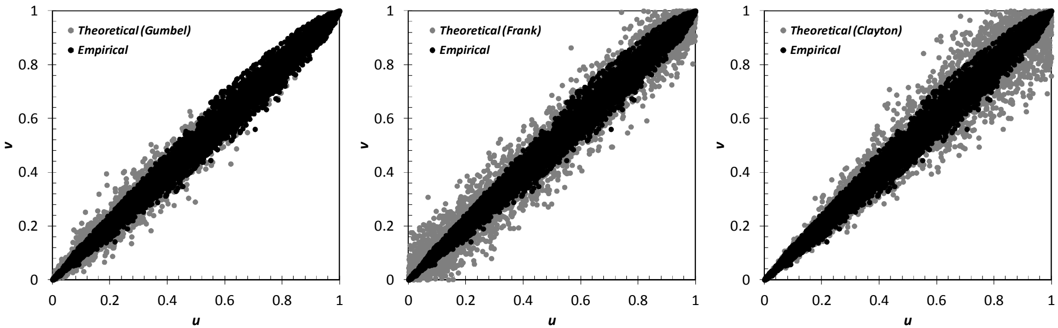

Fig. 13. Normalised scatter plot of for the different copula models considered. The “empirical” points represent the pairs coming from the R-R model.

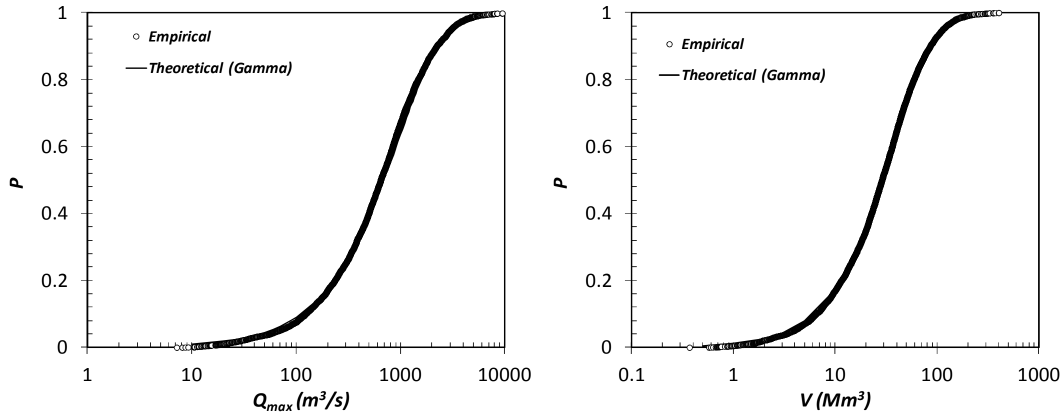

Fig. 14. Plotting position: flood peak and volume.

NHESSD

2, 27–79, 2014

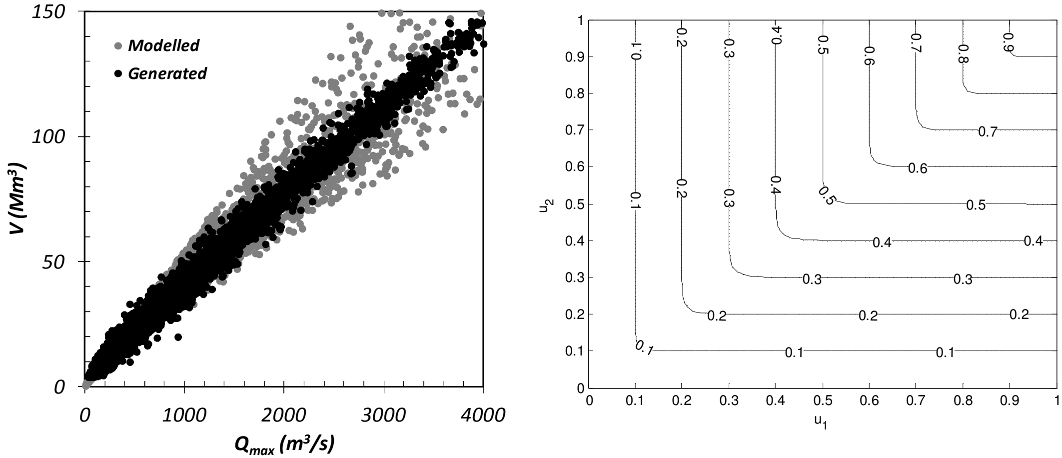

Fig. 15. Comparison between a sample generated from the Gumbel copula and the observed data (left) with the copula contours (right).

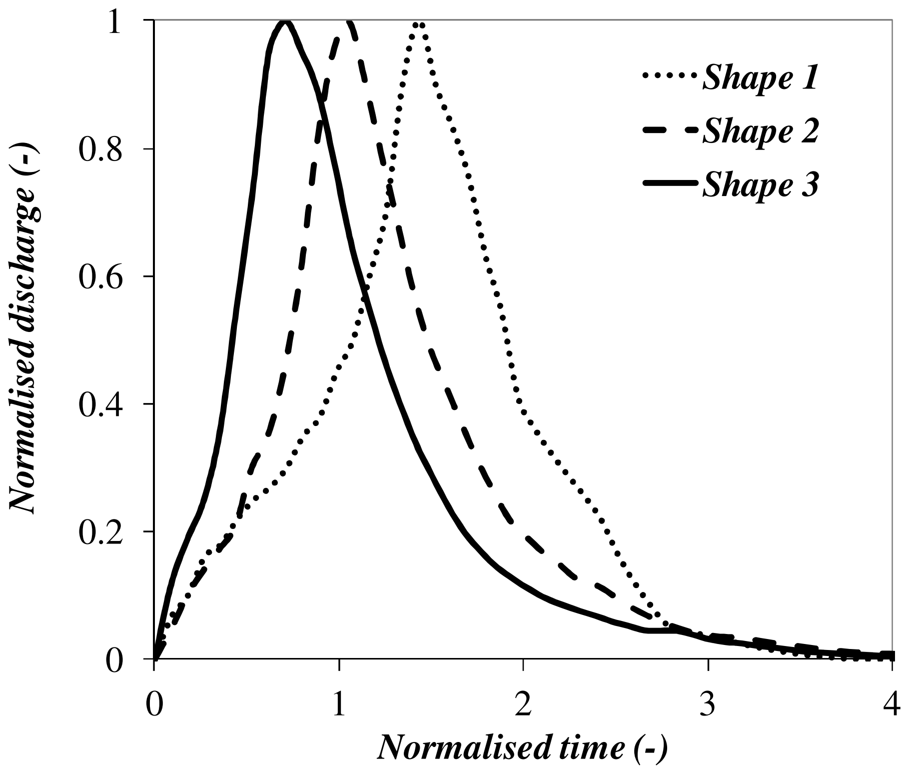

Fig. 16. Non-dimensional clustered hydrographs.

NHESSD
2, 27–79, 2014

Estimation of flood design hydrographs using bivariate analysis

A. Candela et al.

Title Page
Abstract
Introduction
Conclusions
References
Tables
Figures
◄I
►I
◄
►
Back
Close
Full Screen / Esc
Printer-friendly Version
Interactive Discussion

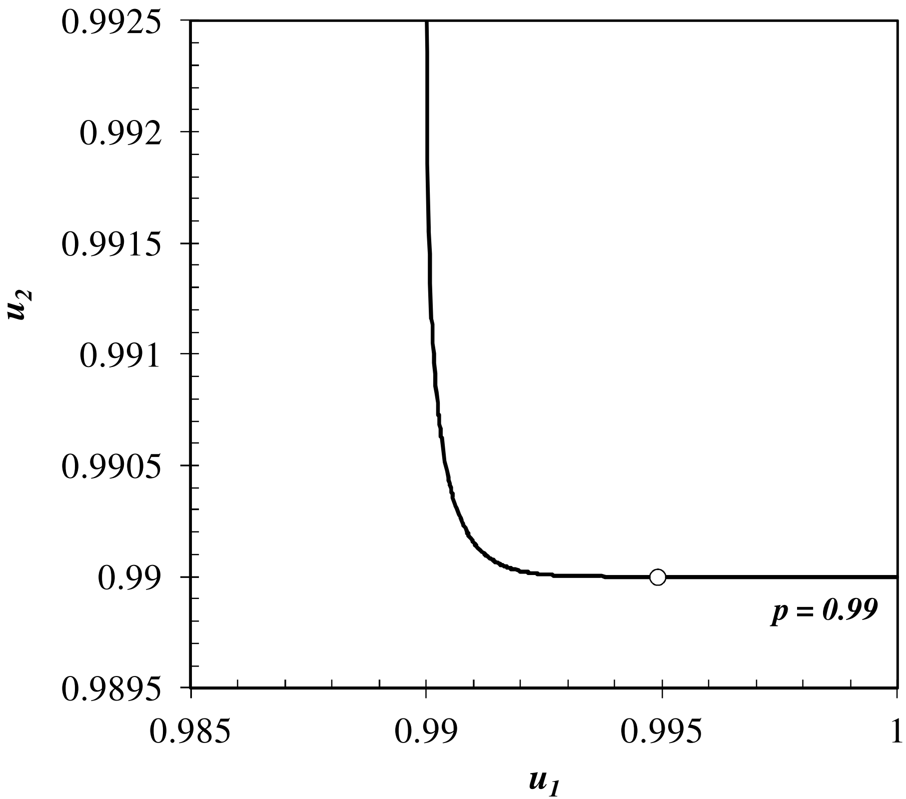

Fig. 17. p level of the copula $C(u_1, u_2)$ corresponding to a JRP = 100 yr, with indication of the single design point (white dot).

NHESSD
2, 27–79, 2014

Estimation of flood design hydrographs using bivariate analysis

A. Candela et al.

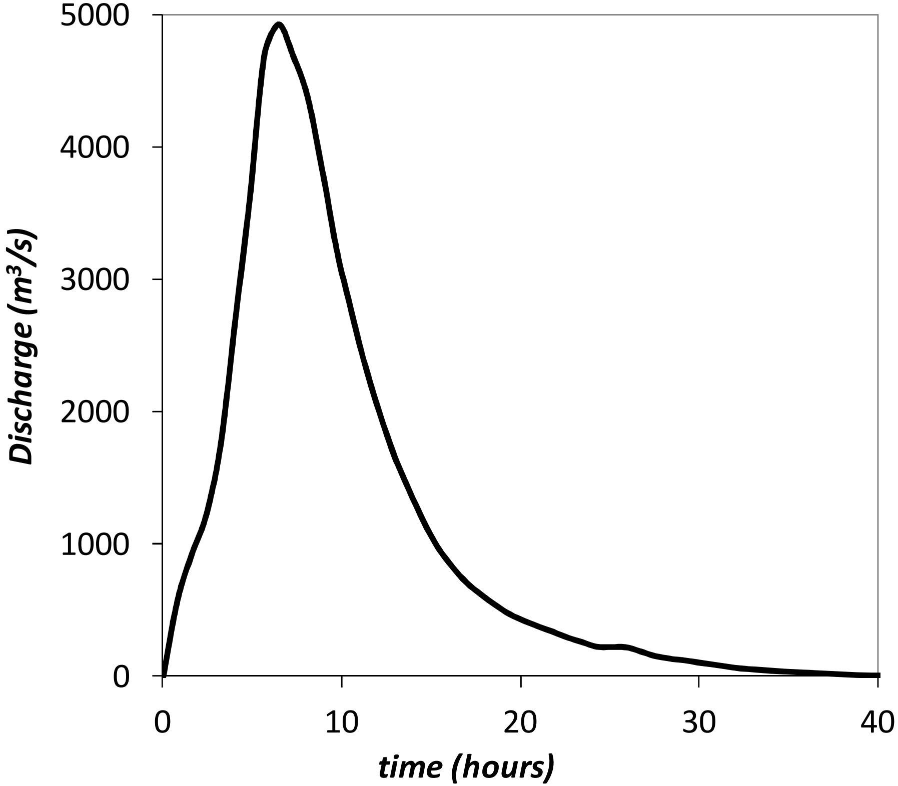

Fig. 18. Flood Design Hydrograph corresponding to a JRP = 100 yr.

NHESSD
2, 27–79, 2014