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Abstract: In this paper a Monte Carlo procedure for deriving frequency distributions of extreme discharges starting from a simplified description of rainfall and surface runoff processes and using regional data is presented. The procedure is based on two modules: a stochastic rainfall generator module and a catchment response module. In the rainfall generator module the rainfall storm, i.e. the maximum rainfall depth for a fixed duration, is assumed to follow the Two Components Extreme Value (TCEV) distribution whose parameters have been estimated at regional scale for Sicily. The catchment response has been modelled by using the Soil Conservation Service – Curve Number for the total-effective rainfall transformation and the classical rational formula for the flood routing. This method allows incorporation of information on soil type, land use, soil cover condition and Antecedent Soil Moisture (AMC). Furthermore, to take in account for the spatial variation of CN within the catchment, a semi-distributed approach of the rainfall-runoff model was implemented. Finally, the Generalised Likelihood Uncertainty Estimation (GLUE) procedure has been used to explore the estimation of the uncertain knowledge of AMC affecting derivation of FFC.

Keywords: Flood; frequency analysis; Extreme events; Monte Carlo simulation, Uncertainty, PUB

1. INTRODUCTION

For engineering applications the estimation of the peak discharge at the basin outlet for a given return time is important especially because the planning and design of water resource projects and floodplain management depend on the frequency and magnitude of peak discharges. In gauged basins, this is possible through a statistical analysis of data or the calibration of a rainfall-runoff model of varying degrees of complexity. In ungauged basins the modelling of flood formation process must be built up using simplified descriptions of the hydrological processes characterised by a reduced number of robust parameters in order to ensure a reduced uncertainty in model predictions.

Eagleson [1972] developed the idea of deriving flood statistics from a simplified schematisation of storm and basin characteristics proposing the so-called Derivation Distribution Technique. The approach allows consideration of the knowledge about the hydrological processes generating streamflow, i.e. developing the chain of events in the runoff formation process that lead to a certain frequency of streamflow. Streamflow variables are related to precipitation data (which have longer record history, spatially more dense and more uniform), antecedent moisture conditions in the drainage basin and the basin response to a precipitation input. [Hebson and Wood 1982; Diaz-Granados et al.,1984; Gottschalk and Weingartner, 1998; Iacobellis and Fiorentino, 2000; De Michele and Salvadori, 2002]. The Derived Distribution Approach can be used to derive, analytically, or numerically, the cumulative distribution function of the flood runoff.As the analytical methods to derive the probability distribution of peak streamflow showed mathematical complexity, i.e. difficulties in parameter estimation, availability of long series of hystorical data some authors [among others Loukas, 2002; Blöschl and Sivapalan, 1997; Muzik, 2002; Rahman et al., 2002] adopted Monte Carlo simulation approach to determine the flood probability distribution. This methodology involves random sampling from continuous distributions of input variables to obtain the flood hydrographs. The procedure is mathematically simple, despite having a heavy computational demand. Therefore, from the consideration of practical applicability and flexibility, the Monte Carlo simulation technique appears to be the most promising method to determine derived flood frequency distributions, and thus has been adopted in this study.

2. MONTE CARLO PROCEDURE FOR DERIVING FFC

This section describes the Monte Carlo procedure used in the present study to derive the flood frequency curves. The procedure is based on two modules: a stochastic rainfall generator module and a catchment response module. It was the intention of the authors to develop a method as simple as possible requiring limited data and suited for ungauged or partially gauged catchments. In the next paragraphs the rainfall and the catchment modules will be presented.

2.1 The stochastic rainfall generator module

In the rainfall generator module the storm *h* is assumed to follow the Two Components Extreme Value (TCEV) distribution [Rossi et al. 1984]. This distribution has been adopted by the Italian National Research Group for the Prevention of Hydro-Geological Disasters for the analysis of extreme rainfall in Italy. The main advantage of this distribution lies in using two components to model the observed hydrological variable. This capability is significant in Mediterranean catchments where maximum rainfalls and floods are often due to storms with different meteorological characteristics [Rossi and Villani, 1992].

The Cumulative Distribution Function (CDF) of the TCEV distribution written using a dimensionless variable *h'* equal to the ratio between the hydrological variable *h* and the mean value μ of the distribution is the following:

$$F(h') = exp\left[-\Lambda_1 (exp\,\alpha)^{-h'} - \Lambda^* (\Lambda_1)^{\frac{1}{\Theta^*}} \left(exp\left(\frac{\alpha}{\Theta^*} \right) \right)^{-h'} \right] \quad (1)$$

In order to apply this distribution to ungauged catchments Cannarozzo et al., [1995] estimated the five parameters α, Λ_1, Λ^*, Θ^*, μ at regional scale for Sicily. In their work the authors proposed a division of the Sicily into three hydrologically homogeneous sub-regions for which the parameters α, Λ_1, μ have been estimated using Maximum Likelihood (ML) method using the annual maximum rainfall with 1,3,6, 12 and 24 hours duration recorded at raingauges located in each sub-region. In comparison, the two parameters Λ^*, Θ^* have been estimated using the data recorded in the entire region.

Furthermore, these five parameters were observed to be dependent on the rainfall duration and simple relationships were proposed for their estimation (Cannarozzo et al., 1995):

for the entire region:

$$\begin{aligned} \Theta^* &= 1.95 + 0.0285 \cdot t \\ \Lambda &= 0.175 \cdot t^{0.301} \end{aligned} \quad (2)$$

depending on the sub-regions:

$$\begin{aligned} \Lambda_1 &= p \cdot t^q \\ \alpha &= r \cdot t^s \end{aligned} \quad (3)$$

depending on raingauge site:

$$\mu = a \cdot t^n \quad (4)$$

Again, to allow a simple estimation of the parameter μ in ungauged or partially gauged sites two maps reporting contour lines with constant *a* or *n* values were also produced.

2.2 The catchment response module

For modelling the catchment response a parsimonious hydrological approach was preferred over more complex models because of its simplicity and ability to approximate catchment runoff behaviour characterised by a fast hydrological response, a small area and inadequate streamflow data. Again, in the model we consider the rainfall duration as constant and uniformly distributed in space over the catchment. Such an hypothesis is physically accepted for small-medium size catchments, which are more usually ungauged or partially gauged.

The classical 'rational formula' [Dooge, 1957], although an old concept, remains a practical tool in engineering hydrology. From the rational formula, the peak runoff Q_{peak}, caused by an effective uniform rainfall $h_e(t_c)$ for a duration t_c which leads, for a given return period, to the maximum peak discharge (critical duration) can be calculated from:

$$Q_{peak} = \frac{h_e(t_c)}{t_c} \cdot A \qquad (5)$$

where A is the catchment area.

The SCS-CN method, adopted by USDA Soil Conservation Service [1986], is used to transform the rainfall depth h to effective rainfall h_e. This method allows us to incorporate information on soil type, land use, soil cover condition and antecedent soil moisture (AMC). The total depth of effective rainfall h_e can be expressed in terms of the rainfall depth h as:

$$h_e = \begin{cases} \dfrac{(h - 0.2 \cdot S)^2}{(h + 0.8 \cdot S)} & h > 0.2 \cdot S \\ 0 & h \le 0.2 \cdot S \end{cases} \qquad (6)$$

where S is the maximum soil potential retention given by the following expression:

$$S = 254 \cdot \left(\frac{100}{CN} - 1 \right) \qquad (7)$$

Now, to take in account for the spatial variation of CN within the catchment, a semi-distributed probabilistic approach was implemented for the modelling of the runoff production from (6). Using GIS, a classified map of the Curve Number, reporting the number of pixels in each class of CN, can be easily obtained given the land use and the soil type. In this perspective the effective rainfall can be computed by applying (6) in a way to include the information from this type of map. Following these premises, equation (6) can be rewritten in the form:

$$h_{e,i} = \begin{cases} \dfrac{(h - 0.2 \cdot S_i)^2}{(h + 0.8 \cdot S_i)} & h > 0.2 \cdot S_i \\ 0 & h \le 0.2 \cdot S_i \end{cases} \qquad (8)$$

and, consequently, the equation (5):

$$Q_{peak} = \sum_{i=1}^{N} \frac{h_{e,i}(t_c)}{t_c} \cdot a_i \qquad (9)$$

where $h_{e,i}$ is the runoff produced the *i-th* CN class, S_i is the maximum soil potential retention in *i-th* CN class, a_i is the area of the catchment characterised by a particular value of CN with $A = \sum_{i=1}^{N} a_i$ and N is the number of CN classes in the GIS map.

The SCS-CN method assumes that the CN values vary with the degree of saturation of the soil before the start of the storm. Particularly, the soil conditions are described through the definition of three AMC classes (I, II and III) depending on the total 5-days antecedent rainfall. To take into account the catchment prior-to-storm conditions and to relax the classical hypothesis of iso-frequency between rainfall input and peak discharges, the AMC has been treated as a random variable with a discrete probability distribution:

$$\begin{cases} \lambda_1 = Prob[AMC = I] \\ \lambda_2 = Prob[AMC = II] \\ \lambda_3 = Prob[AMC = III] \\ \sum_{i=1}^{3} \lambda_i = 1 \end{cases} \qquad (10)$$

where $\{\lambda_1, \lambda_2, \lambda_3\}$ are the probabilities of occurrence of the three different moisture conditions of the catchment [De Michele and Salvadori, 2002].Finally, the distribution of peak flood conditioned by the AMC distribution is thus given by:

$$Q_{peak} = \sum_{i=1}^{3} \lambda_i \sum_{j=1}^{N} \frac{h_{e,i,j}(t_c)}{t_c} \cdot a_j \qquad (11)$$

3. IMPLEMENTATION OF MONTE CARLO PROCEDURE

The procedure above outlined was applied for the derivation of the FFC in a relatively small catchment located in the north-western part of Sicily, Italy (Figure 1): Oreto River (catchment area = 75.6 km^2).

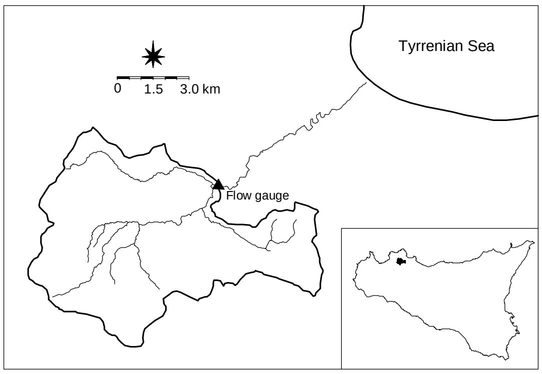

Figure 1. Location of Oreto catchment.

In this catchment the heavy storm rainfall is the only flood producing factor and the presence of streamflow gauging station with a long recording period (N=57 yrs) at outflow allowed derivation of the AMC probability distribution using daily data (Figure 2). The TCEV parameters were evaluated using (2)-(4) with the parameters p, q, r, s, specified for the catchment sub-region and the parameters a, n obtained by the iso-*a*, iso-*n* contour lines [Cannarozzo et al., 1995] (Table 1). The critical storm duration t_c was assumed to be equal to the concentration time of the catchment. For its evaluation we used the simple relationship $t_c = 0.46 \cdot \sqrt{A} / v$ (t_c in hours, A in square kilometres and v = 1-2 $m \cdot s^{-1}$) deduced by Agnese and D'Asaro [1990] by applying the Geomorphological Instantaneous Unit Hydrograph theory to several Sicilian catchments. The CN spatial distribution map has been produced in a GIS environment with a 100m grid resolution (Figure 3).

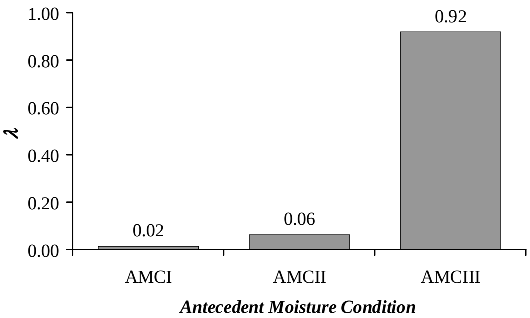

Figure 2. AMC discrete probability distribution from historical data

Table 1. Parameter values for the TCEV distribution

Parameters	Values
p	14.55
q	0.2419
r	3.5208
s	0.1034
a	26.2
n	0.372
t_c (hours)	2.7

10000 Monte Carlo runs were performed to obtained synthetic FFC with a return time range from 1 to 500 years. The implementation can be described by the following steps:

(a) 10000 values of total rainfall depth *h* for the storm duration t_c were randomly drawn from TCEV distribution by solving (1); (b) for the three AMC conditions (I, II, III) 10000 effective rainfall values have been calculated using (8) for each CN class; (c) the final values of the peak flood discharges conditioned by the AMC distribution were obtained using (11); (d) the return time for each generated peak flood value has been computed from the plotting position formula:

$$T_m = \left(1 - \frac{m - 0.4}{NG + 0.2}\right)^{-1} \quad (12)$$

where NG is the number of simulated peaks and *m* is the rank of the *m*-th peak flood value arranged in increasing order of magnitude.

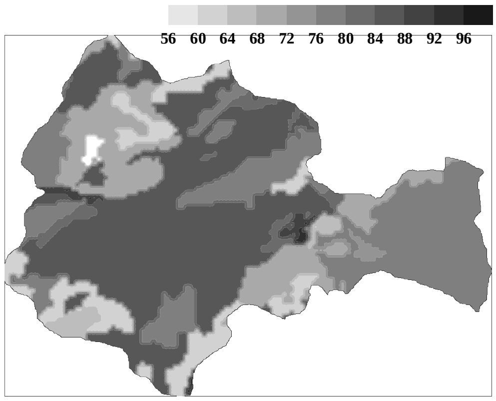

Figure 3. CN spatial distribution map

The resulting Flood Frequency Curve is reported in Figure 4 and compared with the observed annual maximum peak flood values plotted using the same plotting position. The agreement is fairly good and this shows that the Monte Carlo simulation technique can reproduce observed flood frequency curves with reasonable accuracy over a wide range of return time using a simple and parsimonious approach.

4. UNCERTAINTY ANALYSIS USING GLUE

As many authors pointed out [Wood, 1976, Muzik et. al., 2002, De Michele and Salvadori, 2002] the soil moisture condition of the basin could be the most important factor influencing the estimation of flood frequency distribution and hence, the uncertainty of the distribution. The Generalised Likelihood Uncertainty Estimation (GLUE) procedure [Beven and Binley, 1992] is used here to explore the estimation of the uncertain knowledge of AMC affecting the predictions of the rainfall-runoff model. GLUE is a Monte Carlo simulation-based approach developed as an attempt to recognise more explicitly the underlying uncertainties of models simulating environmental processes. 1000 numbers of λ_i values of (corresponding to different AMC conditions) were generated, each value being drawn within range from 0 to 1 with the condition $\sum_{i=1}^{3} \lambda_i = 1$.

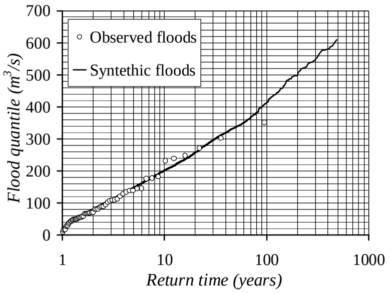

Figure 4. Flood Frequency Curve for Oreto catchment compared with observed values

Simulations were performed for each parameter set $\theta_i = \{\lambda_1, \lambda_2, \lambda_3\}_i$ for comparison with the measured flood peak values at catchment outlet. Due to the different sample size for the generated and the observed values the comparison was carried out with the generated discharge values characterised by the same return time of the historical values (a linear interpolation was used to extract the value of the discharge from the generated sample). Each simulation was evaluated using a performance index in the form of the classical Nash and Sutcliffe Efficiency Criterion (1970):

$$L(\theta_i / Y) = (1 - \sigma_i^2 / \sigma_{obs}^2) \qquad \sigma_i^2 < \sigma_{obs}^2 \qquad (13)$$

where $L(\theta_i/Y)$ is the likelihood measure for the *i*-th model simulation for parameter vector θ_i conditioned on a set of observations *Y*, σ_i^2 is the associated error variance for the *i*-th model and σ_{obs}^2 is the observed variance of the observed peak floods.

Figure 5 shows scatter plots for the likelihood based on (13) for each of the AMC parameters sampled for the Flood Frequency Curve. Each dot represents one run of the model with different randomly chosen parameter values within the ranges. The generation of the likelihood surface involves a decision about the criterion for model rejection and, particularly, simulations that achieve a likelihood value less than zero are rejected as non-behavioural. The remaining are rescaled between 0 to 1 in order to calculate the cumulative distribution of the predictive variables from which the chosen discharge quantiles, 5 and 95%, have been calculated to represent the model uncertainty in the model predictions (Figure 6). As might be expected these plot show how the model response is highly sensitive to variation of antecedent moisture condition in the catchment.

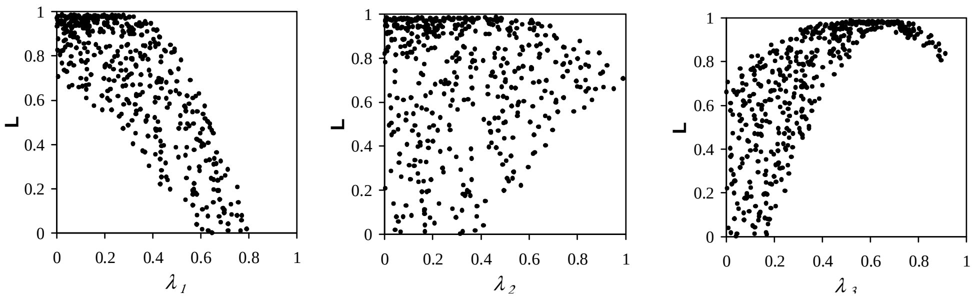

Figure 5. Scatter plots illustrating the distribution of likelihood weighted qualitative parameter values

It worth to point out how the higher values of rescale likelihood were found for high value of λ_3 (AMC_{III}). In the limitation of a single application this is a typical behaviour of Mediterranean catchments in which extreme events occur when the soil is close to saturation and hence the soil moisture is the main factor affecting the flood formation process.

Figure 6 illustrates the 90% likelihood weighted uncertainty flood frequency bounds derived from the 1000 *behavioural* simulations parameter sets, In addition to above stated the estimates of the higher return period floods are subject to the greatest amounts of uncertainty.

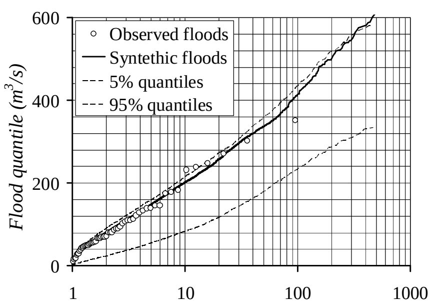

Figure 6. 90% uncertainty bounds derived from annual maximum peaks of 1000 *behavioural* parameter set with 10000-year simulation length

5. CONCLUSIONS

This paper presents a Monte Carlo procedure for deriving frequency distributions of extreme discharges starting from a simplified description of rainfall and surface runoff processes. The procedure is tailored for small-medium size ungauged or partially gauged catchments It focuses on a parsimonious rainfall-runoff modelling approach and a stochastic rainfall generator both fed by data at regional scale, as CN maps and spatial interpolation of maximum rainfall depth over the study area. The application of this procedure to a Mediterranean catchment showed how Monte Carlo simulation technique can reproduce the observed flood frequency curves with reasonable accuracy over a wide range of return time (Figure 4) using a simple and parsimonious approach and limited data input.

In addition to this we put the emphasis on the importance of the soil moisture conditions for flood formation process and the uncertainty in their knowledge as common in ungauged catchments. The application of GLUE procedure for exploring this uncertainty showed the importance of the prior-to-storm conditions to derive the FFC and the sensitivity of the rainfall-runoff model (despite, its simplicity) to soil moisture variations.

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