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Research papers

HydroPredicT_Extreme: A probabilistic method for the prediction of extremal high-flow hydrological events

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ABSTRACT

Disastrous losses related to high-flow events have increased dramatically over the past decades largely due to an increase in flood-prone regions settlements and shift in hydrological trends largely due to Climate Change. To mitigate the societal impact of hydrological and hydraulic extremes, knowledge of the processes leading to these extreme events is vital. Hydrological modelling is one of the main tools in this quest for knowledge but comes with uncertainties. For that it is necessary to deeply study the impact of hydrological models' structure on the magnitude and timing of extreme rainfall-runoff events. This paper is mainly aimed to show the development of a method called "HydroPredicT_Extreme" based on Bayesian Causal Modelling (BCM), a technique within Artificial Intelligence (AI). This method may enhance predictive capacity of extreme rainfall-runoff events. "HydroPredicT_Extreme" follows an iterative methodology that comprise 2 main stages. First one comprises a mixed graphical/analytical method from Hydrograph. This stage is conditioned by two initial constraints which are, a) pluviometry station is representative of hydrograph downstream flow behaviour; b) there must be independence of events. This first stage comprises sub-phases such as: 1.1. Calculation of Response Time (RT) through a mixed graphical/analytical approach, 1.2 Subtraction of RT from the flow series to remove the Rainfall-Flow delay; 1.3 Calculation base flow rate; 1.4 Subtraction base-flow from flow series to work on absolute inputs. Second man stage is called Bayesian Causal Modelling Translation (BCMT) that comprises the 2.1 Learning, 2.2 Training, 2.3 Simulation through BCM modelling, 2.4 Sensitivity Analysis-Validation. This whole methodology will become a digital application and software that could be extrapolated to several similar case studies. This may be coupled with posterior devices for the prevention of catastrophic flood consequences in the form of MultiHazard-Early Warning System (MH-EWS) or others.

1. Introduction

The most recent studies on Climate Change (CC) project significant declines in water resources at global level, with the consequent impacts that water scarcity will have at environmental, economic, and social level (Zeng et al., 2021). Indeed, most studies forecast an intensification of the hydrological cycle, as well as an increase in temperatures and precipitations (Hegerl et al., 2019). Furthermore, in recent decades, the change of traditional hydrological patterns has already been increasingly more and more evident both worldwide and over a particular territory (Berg et al., 2013). This is leading to a worldwide increasing climatic variability and of its associated hydrological processes (Molina and Zazo, 2018). In addition, the spatio-temporal changes in weather patterns are likely to further aggravate the appearance and persistence of extreme events (Macian-Sorribes et al., 2020). Consequently, hydrologic cycles are being transformed rapidly (Chang et al., 2015), with negative consequences also on the spatio-temporal availability of water resources (Molina and Zazo, 2018), which may produce significant economic losses (Lopez-Nicolas et al., 2017). This global situation is highlighted in the increasing occurrence, intensity, magnitude and persistence of more unpredict extreme events such as rainfall, flood and drought (Marcos-Garcia et al., 2017).

Numerous studies link these negative effects to CC. Relevant studies have already shown a direct relationship among the intensification of

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hydrological events and CC (O'Gorman, 2015; Marotzke et al., 2017). It is well known that CC is present in a large number of processes relating to the water cycle such as larger-scale climate structures such as El Niño–Southern Oscillation (ENSO); anti-ENSO, also called La Niña; and the North Atlantic Oscillation (NAO), hydrologic and hydraulic events (floods and droughts), sea level rise and thermal expansion of sea water among others (Chang et al., 2015). This worldwide phenomenon is closely linked to the effect of global warming (IPCC, 2021), highly intensified by anthropogenic actions (Marotzke et al., 2017). O'Gorman (2015) suggested that precipitation extremes will be more intense because of warming climate. Pfahl et al. (2017) found that the variability of extreme precipitation between regions may be explained by different changes in the strength of local wind patterns. Donat et al. (2016) determined that a warming climate will produce an intensification of the hydrological cycle which will have consequences for flood risk, principally for the world's dry regions. In this sense, the North Atlantic Oscillation is the major cause of seasonal and interdecadal variability of atmospheric circulation on the European continent (Qian et al., 2000). Therefore, in this global scenario, on one side stationarity in hydrological time series (rainfall-runoff-droughts) no longer holds, or certainly not as strictly as in historical records (Donat et al., 2016), and on the other, climatic variations are not so natural (cyclic) and they are increasingly variable (Molina and Zazo, 2018). Hence, non-stationarity becomes a normal situation to deal with (Yoo et al., 2012).

However, not all the reasons that explain this increasing variability are brand new. Hence, there is a strong need to have powerful-reliable analytical methods to build accurate models that reproduce and forecast the future hydrological behaviour of water resources (Uysal et al., 2018), and that they are able of capturing the induced and widespread effects that these new hydrological phenomena lead to water resource availability (Vogel et al., 2018). This is essential not only for planning and development of effective water resource management strategies (Molina et al., 2019), but also for an optimal dimensioning of hydraulic infrastructure (Molina and Zazo, 2018). Indeed, accuracy in these hydrological models requires, on the one hand, dealing with the intrinsic hydrological time series randomness and, on the other hand, incorporating the uncertainty of those predictions (Kong et al., 2017). Also, there is a growing necessity of new strategies in the field of Early Warning and Decision Support Systems (EWS/DSS), which allow: (a) an increase of knowledge on temporal and spatio-temporal behaviour of the hydrological series (Macian-Sorribes et al., 2020) and (b) extracting the logical and non-trivial time-dependency structure (internal organization of hydrological records) that underlies them (Zazo et al., 2020). This internal organization comprises a set of trivial and nontrivial (induced and diffused) dependence relationships that explain its general temporal behaviour (Hao and Singh, 2016). Other key factors for advancing internal knowledge of hydrological time series are the growing global demand for water resources and the partial knowledge of the underlying relationships in complex natural systems such as water systems (Zazo, 2017). Advancing this knowledge is essential for the development of effective EWS to help mitigate and adapt to risks and damages due to increased climate variability.

Given the novelty that Bayesian Causal Modelling (BCM) suppose in the field of predictive hydrology, the foundations of this AI technique need to be highlighted. This novel hydrological approach is based on Causality, which has not yet been studied in depth (Macian-Sorribes et al., 2020). Causality is mainly characterized by searching reasoning patterns under different approaches such as Causal Reasoning (CR), Evidential Reasoning and Intercausal Reasoning (Koller and Friedman, 2009). CR is used when the approach is done from top to bottom. In this sense, the analysis is focused on the cause and the objective comprises the prediction of the effect or consequence. Consequently, the queries in form of conditional probability, where the "downstream" effects of various factors are predicted, are instances of causal reasoning or prediction. Evidential Reasoning comprises bottom-up reasoning, so the analysis is focused on the consequence (effect) and the cause is inferred (Bayesian Inference). For its part, Intercausal Reasoning comprises the interaction of different causes for the same effect (Macian-Sorribes et al., 2020).

On the other side, and from the works Molina et al. (2016) and Zazo (2017) the Causality, addressed in form of CR and supported by Bayesian modelling, has started to be applied to the behaviour of rivers as BCM (Macian-Sorribes et al., 2020). Under this powerful stochastic approach, the hidden logical temporal (in)dependence structure that inherently underlies into hydrological series is discovered and highlighted (Molina et al., 2019; Zazo et al., 2020). In this sense, BCM has led to an active line of research which is characterised by increasing not only the temporal but also the spatio-temporal knowledge of the water resources of a basin. In Molina and Zazo (2018), for first time, the temporally runoff fractions, named Temporally Conditioned Runoff (TCR, or fraction due to time) and Non-Conditioned Runoff (TNCR, or uninfluenced by time) were discovered and quantified. Molina et al. (2019) implemented, based on TCR and TNCR, a novel predictive model. Macian-Sorribes et al. (2020) addressed jointly the spatio-temporal dependence dimensions of inflows in hydrology through BNs for first time. Zazo et al. (2020) explored a hybrid causal–hydrological method to reduce the uncertainty of classical rainfall-runoff models. Finally, in Molina et al. (2021) described an innovative methodological approach, named Hybrid Causal Multivariate Linear Modelling (H-CMLM), which goal is empowering and hybridizing the analysis of temporal hydrological records behaviour.

On the other hand, it is noteworthy to highlight that BCM belongs to AI technique based on a Probabilistic Graphical Model (PGM; Pearl, 1988; Jensen, 1996; Cain, 2001). This provides relevant advantages such as no need for priori information of the process and use of raw data (Adamowski, 2008; Zounemat-Kermani and Teshnehlab, 2008), its usefulness for analysing non-linear physical systems (Aqil et al., 2007), ease of defining relationships in complex systems and offering a compact representation of the joint probability distribution over sets of random variables (Molina et al., 2013). In respect of climate and meteorology are concerned, at the European level, while the North and Northeast flood frequency tend to be increased, the South and South-East show a significant increase in the frequency of droughts (Zazo et al., 2020). This situation is leading to redefining the concept of drought and hydrological extreme events in general (Macian-Sorribes et al., 2020). This is even more serious, when there are already case studies where the situation is nearly irreversible (Segura Basin a paradigmatic example in Iberian Peninsula) (Molina et al., 2013), or water resource systems which show significant and alarming evidence of significant change (sub-basins of the southern Duero river).

On the other side, floods are probably one of the most hazardous natural event worldwide as well as the one of the main cause of numerous human being losses and severe economic damages (Grahn and Nyberg, 2017). From the years 2000 to 2012, the European Union experienced an average annual damage due to floods of 4.2 billion €, which could be increased up to 23.5 billion € by 2050 (Jongman et al., 2014). In particular, 2013 flood events in central Europe had an estimated cost of 12 billion € (Reynard et al., 2017) and, in Spain, floods are the natural hazard that causes the greatest social and economic losses (MAGRAMA, 2018) with estimated annual costs of 0.87 billion € predicted to occur from 2004 to 2033 (Zazo et al., 2018). Under such circumstances, reducing the flood hazard must be an absolute necessity. This is leading society to take protective measures (Zechner et al., 2018), which is mainly based on the analysis of the three components inherent to a natural hazard: (i) occurrence probability, (ii) level exposure, and (iii) vulnerability hazards (Reynard et al., 2017). Traditionally, the scientific community had focused its efforts on risk occurrence probability. However, recently, the focus is shifting to risk consequences (Grahn and Nyberg, 2017), its mitigation (Romali et al., 2018), and damage reductions (EU Directive, 2007), which is also as a consequence to the growing variability of the hydrological variables (Molina and Zazo, 2017, 2018).

Design storms developed using the Huff curve method differ from those developed by other procedures. Bonta (2004) showed that the Huff curves did not correspond to the NRCS design storm curves. Azli and Rao (2010) demonstrated significant differences between the Huff curves and the design storm developed for peninsular Malaysia as reported in the Urban Stormwater Management Manual for Malaysia. Huff (1990) reported that quartile I events often had durations of 6 h or less and quartile II events had durations of 6 to 12 h. Based on this, it was suggested that for hydraulic design applications, hyetographs for quartile I should be used for time scales of no >6 h and quartile II for 6 to 12 h. Bonta (2004) concluded that Huffś method has the following advantages as a procedure for rainfall storm generation: (1) hourly precipitation data gave nearly identical Huff curves as 3 min data, which suggested that the more widely available hourly data can be used to obtain Huff curves and generate intra-storm patterns to drive hydrologic and erosion models, such as SWIM (Ross, 1990) and WEPP (Lane and Nearing, 1989); (2) Huff curves appear relatively insensitive to the minimum dry period duration (MDPD) used to delineate individual storms; (3) there was relatively good stability with change of storm sample size; and (4) there was similarity between Huff curves developed over relatively long distances, which suggests potential for regionalization according to broad climatic regimes.

Huff curves have been developed by scientists from other areas in the world, such as the U.K. (NERC, 1975), Malaysia (Azli and Rao, 2010), and Santa Catarina State in Brazil (Back, 2011). As recognition of the utility of Huff curves, the National Oceanic and Atmospheric Administration (NOAA) released Huff curves for different areas of the U.S. (Perica et al., 2014). Many studies have confirmed that the differences among Huff curves over long distances in the same climatic region are often minor. Loukas and Quick (1996) compared Huff curves within the same climatic region in coastal British Columbia, Canada, and reported that the time distribution of the storms was similar regardless of the elevation, type of storm, storm duration, or storm precipitation depth. Al-Rawas and Valeo (2009) found that the differences between the mountainous and coastal regions were minor within arid Oman, where the annual rainfall ranged from 100 to 350 mm. The differences between Huff curves for Oman and Calgary (in Alberta, Canada) were also small. It was demonstrated that Huff curves from 13 stations in peninsular Malaysia were similar (Azli and Rao, 2010). Averaged Huff curve sets in peninsular Malaysia were also compared to those derived from 6 h storms in the Midwestern U.S.

To assess a flood hazard, it is widely accepted to analyze the conceptual scheme into three steps, which are exposed in de Moel et al. (2009). The three steps are: (i) to estimate discharge flows for particular return periods, adjusted to extreme value distributions or specific rainfall-runoff models, (ii) to translate discharge flows into water levels by 1D or 2D hydrodynamic models mainly, and (iii) calculate the inundated area supported by Digital Terrain Models (DTMs). Flood modelling involves multiple key aspects including such as hydrological model or flood wave characteristics (De Moel et al., 2009), fluvial geomorphology issues and sediment transport behaviour (Thompson et al., 2016), influence of infrastructures (bridges, dams or buildings; Sena Fael et al., 2016), structure of hydraulic model (Cea and Bladé, 2015), flow propagation methods (Moya Quirogaa et al., 2016), human-induced changes in land use (Thieken et al., 2016), roughness coefficient (Huang and Qin, 2014), vulnerability/damage curves (Arrighi et al., 2018) and topographic data (Zazo et al., 2015; Zazo et al., 2016). In this sense, Huang and Qin (2014) determine that the Manning's roughness coefficient (Manning's n) notably affect flood inundation predictions. For their part, Milanesi et al. (2015) argue that the flood assessment must be based on an appropriate combination of flow depth and velocity by using duly designed vulnerability curves. In Arrighi et al. (2018), the flood depth, velocity, flood duration, and the uncertainty in depth–damage curves are shown as relevant issues versus uncertainties in hydrological-hydraulic models and land uses. Md Ali et al. (2015) investigate the influence of elevation modelling on hydrodynamic modelling results and both determined that DTMs are one the most fundamental inputs for reliable flood modelling. According to Schanze et al. (2008), for reducing natural flood hazards, only two different actions may be applied through: "structural" measures based on works of hydraulic engineering, which modify hydrological-hydraulic characteristics of floods, and all other interventions called "non-structural". These latter are especially interesting due to the modify the susceptibility of the inundated area without acting on the flood flow itself (Albano et al., 2015), they are essentially focused on potential consequences (Escuder-Bueno et al., 2012) and they are an accessible way to reduce the flood hazard (Albano et al., 2017). Indeed, the most important non-structural measure is floodplain planning (Martín Vide, 2009). Thus, it is possible to define constraints of land uses on the floodplain and reduce the flood hazard (MAGRAMA, 2017). This involves the interplay between flow, the physical environment, and society (Zazo et al., 2018).

This paper is structured as follows:

- First, Introduction section is developed, where the latest references are included and analyzed.
- Second section on Materials and Methods is included, showing, and explaining the main mathematical techniques and the general research methodology.
- Third section is dedicated to show the main results drawn from this research. Results are organized according to the previous methodology.
- Fourth section is dedicated to discussing the main issues and concerns about this research.
- Fifth section addresses the main most important conclusions drawn from this research.
- References section includes the main and latest research work consulted for developing this study and cited throughout the manuscript.

2. Materials and methods

2.1. Materials

A stochastic extreme rainfall generator has been developed based on the real data as well as on the outcome from Huff method. Real rainfall and runoff data series were analyzed to identify main rainfall-runoff events as well as their patterns and recurrence. For instance, extreme rainfall events (storms) were analyzed through HUFF method. This information was useful to develop a strong pre-process for populating the HydroPredicT_Extreme tool able to identify dependencies through Conditional Probability (Eq. (4)) based on Bayesian Theorem. This tool is able to build a posterior distribution of extreme rainfall that may be useful to enhance the anticipation capacity of the system.

Furthermore, a previous rainfall-runoff mathematical adjustment was developed using several functions and picking Johnson SB distribution because of its best fitting. Consequently, this assures that the flow is highly representative from the rainfall. Main features of Johnson SB Distribution are explained as follows:

Johnson SB Distribution.

Parameters.

γ - continuous shape parameter.

δ - continuous shape parameter ($\delta > 0$).

λ - continuous scale parameter ($\lambda > 0$).

ζ -continuous location parameter.

$$\text{Domain}: \zeta \leq \chi \leq \zeta + \lambda \tag{1}$$

Probability Density Function.

$$f(x) = \frac{\delta}{\lambda\sqrt{2\pi}z(1-z)} exp\left(-\frac{1}{2}\left(\gamma + \delta ln\left(\frac{z}{1-z}\right)\right)^2\right) \tag{2}$$

Cumulative Distribution Function.

$$F(x) = \Phi\left(\gamma + \delta \ln\left(\frac{z}{1-z}\right)\right)$$

where

$$z \equiv \frac{x-\zeta}{\lambda}, and \Phi \text{ is the Laplace Integral}$$

Conditional Probability through Bayesian Theorem allows quantifying the variables relationship strength through Bayeś rule (Molina and Zazo, 2018). For events A and B:

$$P(A|B) = \frac{P(A,B)}{P(B)} = \frac{P(A \cap B)}{P(B)} \tag{4}$$

where: $P(A|B)$ is probability on event A assuming that event B is true, $P(A,B)$ is the joint probability on events A and B, $P(B)$ is probability on B.

2.1.1. Bayesian causal modelling (BCM)

The series from previous phase will be fed into the learning and training process of the Causal Bayesian model. This early BCM stage is crucial since it includes the discovery and characterization of the logical and non-trivial structure of temporal interdependence that underlies the hydrological (rainfall) series.

Calibration: The model has been continuously calibrated with historical extreme rainfall records, Huff modelling approach and real time data.

Validation: predictive rainfall-runoff simulator is finally validated through Artificial Intelligence and Information Theory indicators such as: P-Value, Mutual Information, Conditional Entropy and Total Entropy.

2.2. Methodology

This paper is mainly aimed to show the development of a method called "HydroPredicT_Extreme" based on Bayesian Casual Modelling (BCM), a technique within Artificial Intelligence (AI). This method may enhance predictive capacity of extreme rainfall-runoff events. "HydroPredicT_Extreme" follows an iterative methodology that comprise 2 main stages. First one comprises a mixed graphical/analytical method from Hydrograph. This stage is conditioned by two initial constraints which are, on one hand, a) pluviometry station is representative of hydrograph downstream flow behaviour so there is a representative rainfall of the basin response; on the other hand, b) there must be independence of events, so it is sure that events are equally comparable in terms of boundary conditions. This first stage comprises sub-phases such as: 1.1. Calculation of Response Time (RT) through a mixed graphical/analytical approach, 1.2 Subtraction of RT from the flow series to remove the Rainfall-Flow delay; 1.3 Calculation base flow rate; 1.4 Subtraction base-flow from flow series to work on absolute inputs due to event. Second main stage is called Bayesian Causal Modelling Translation (BCMT) that comprises the 2.1 Learning, 2.2 Training, 2.3 Simulation through BCM, 2.4 Sensitivity Analysis and Validation.

Specific stages are explained as follows:

The stage 1.1 "Calculation of Response Time (RT)" was crucial to identify the response of the system to the associated rainfall. This was largely done by the calculation of average time of response from rainfall to the associated rainfall response (Fig. 3).

Stage 1.2 involves deleting the delay between the cause (rainfall) and the effect (rainfall), to build as much symmetric hydrograph as possible.

Stage 1.3 comprises the identification and computation of the base flow in the hydrograph.

Stage 1.4 involves deleting the base flow from the data series to assure the total independence of rainfall-runoff events.

Stage 2.1 "Learning" process involved several stages that are briefly explained as follows:

1st) Data acquisition (importation) from a txt file.

2nd) Discretization of both variables of the Bayesian Causal Model (Rainfall and Runoff) into 5 intervals of equal range size.

3rd) Definition of structure constraints, where the logic structure was imposed.

4th) Structure learning, where the structured is learnt by using the Necessary Path Condition (NPC) algorithm. In this case, due to the simplicity of the structure, the algorithm choice process is not relevant.

5th) Data dependences visualizer, to show the strength of the dependence.

6th) EM-learning: this comprises the last part of the learning process where the conditional distributions from the data are extracted.

Stage 2.2 "Training" was done with the complete data series.

Stage 2.3 "Simulation through BCM" involved the establishment of two main scenarios to be simulated (Average and Maximum) (Fig. 4). For the maximum scenario, the probability associated to the highest interval of the variable "rainfall" was maximized, to get the maximum posterior runoff probability distribution.

Stage 2.4 Sensitivity analysis was performed using two types of measures: entropy and Shannon's measure of mutual information (Pearl, 1988). The entropy measure relies on the assumption that the uncertainty or randomness of a variable X, characterized by probability distribution P(x), can be represented by the entropy function H(X):

$$\boldsymbol{H}(\boldsymbol{X}) = -\sum_{x \notin X} \boldsymbol{P}(\boldsymbol{x}) \boldsymbol{logP}(\boldsymbol{x}) \tag{5}$$

Entropy of a probability distribution can be defined as a measure of the associated uncertainty to that random process that this distribution describes. Consequently, a score of uncertainty/certainty level of events can be made attending to this entropy, H(X).

Reducing H(X) by collecting information in addition to the current knowledge about variable $\boldsymbol{X}$ is interpreted as reducing the uncertainty about the true state of $\boldsymbol{X}$. The entropy measure therefore enables an assessment of the additional information required to specify a particular alternative.

On the other hand, Shannon's measure of mutual information is used to assess the effect of collecting information about one variable ($\boldsymbol{Y}$) in reducing the total uncertainty about variable $\boldsymbol{X}$ using:

$$\boldsymbol{I}(\boldsymbol{Y}.\boldsymbol{X}) = \boldsymbol{H}(\boldsymbol{Y}) - \boldsymbol{H}(\boldsymbol{Y}|\mathrm{X})$$

where $\mathbf{I}(\mathbf{Y}.\mathbf{X})$ is the mutual information between variables. This measure reports the expected degree to which the joint probability of $\boldsymbol{X}$ and $\boldsymbol{Y}$ diverges from what it would be if $\boldsymbol{X}$ were independent of $\boldsymbol{Y}$. If $\mathbf{I}(\mathbf{Y}.\mathbf{X}) = 0$, $\boldsymbol{X}$ and $\boldsymbol{Y}$ are mutually independent (Pearl, 1988).

$\mathbf{H}(\mathbf{Y}|\mathbf{X})$ is conditional entropy which means the uncertainty that remains about $\boldsymbol{Y}$ when $\boldsymbol{X}$ is known to be $\boldsymbol{x}$. This has been useful because if two variables have a mutual information $\neq 0$ involves that they are dependent (Pearl, 1988). On the contrary in case the mutual information is 0 means that they are independent. This analysis represents another way for characterizing and quantifying the temporal dependence and behaviour of hydrological series.

The final model comprises a joint bivariate system made of one independence (parent node) representing the "rainfall" and one conditional distribution probability (child node), representing the "runoff".

2.3. Case study

In recent years, the hydrological basins of the Iberian Peninsula have been increasingly experiencing flash and intense rainfall-flood events of a non-seasonal (non-cyclical) nature, which may be aggravated in the future due to the phenomenon of CC (Cantero et al., 2020). In this context, the Duero river basin (the largest in the Iberian Peninsula, in terms of the surface) is no exception.

This research has been focused on the Upper Basin of the Duero river (Fig. 1a), one inland sub-basin within the Duero river basin because

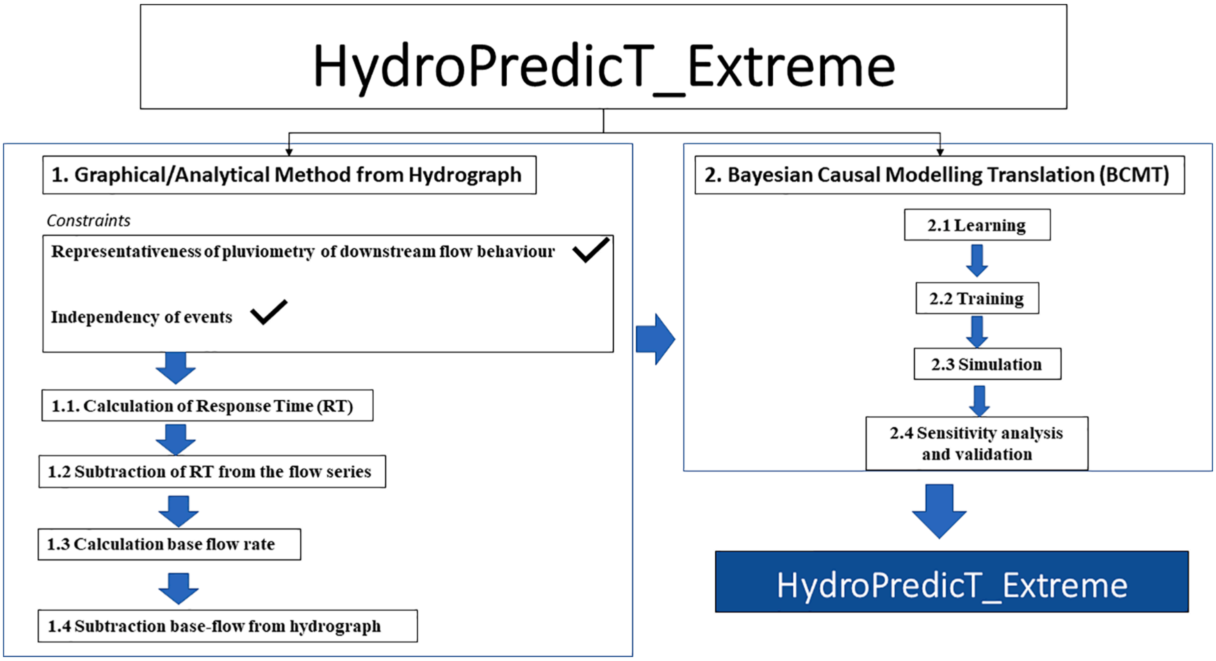

Fig. 1. General methodology.

these kinds of internal sub-basins are generally characterized by flash floods due mainly to intense and localized storms as well as massive snowmelt (Cantero et al., 2020). It is defined by the gauging station "Molinos de Duero", code number 2101, belonging to the gauging network of Duero River Basin Authority (Duero-RBA) and located upstream of the "La Cuerda del Pozo" reservoir, and defines a headwater of 132 Km^2 of extension with a Concentration Time (CT) of 6.9 h according to the legal requirement in Spain (Fig. 1b) and a calculated Response Time (RT) of 12 h.

As flash rainfall-runoff event was selected the extreme episodes occurred between on 20 and 30 January 2021 (AEMET, 2021). Hourly Rainfall-Runoff data were collected from the official database of Duero-RBA (IDE-Duero, 2021) from pluviometry station PL47 "Covaleda" and gauging station "Molinos de Duero" respectively (Fig. 1b). Flash hyetogram and hydrograph events are shown in Fig. 1c.

On the other hand, this area is characterized by a predominantly Mediterranean climate, highly continental, with moderately warm summers and severe winters, where the altitude conditions the temperature. This produces significant areas of the climate of the high mountains (CH-Duero, 2022). The hydrological regime is pluvio-nival of a temporary nature (MITECO, 2022), with an average of 30 days per year with precipitation in the form of snow, annual average rainfall of 935 mm (with mean values around 100 mm per month between November and February), and a mean temperature of the 9.4 °C (SIGA, 2022).

Regarding the area's geology, there are alternations in cycles of quartz sandstones and claystones, combined with conglomerates, gravels, sandstones, and marls (IGME, 2022).

3. Results

Results section is described and articulated following the main methodological stages. This is a clearer way of explaining the results obtained so the reader can better understand the whole process and the sectorial results achieved.

3.1. *Graphical/analytical method from hydrograph*

3.1.1. *Representativeness of pluviometry of downstream flow behaviour*

This is done through a mathematical adjustment between rainfall and runoff data series in the case study. Therefore, a Johnson SB distribution is fitted with the following results. Fig. 2 and Table 1 show the high association level between rainfall and runoff series and the good fit with Johnson SB distribution function through four representations which are a) Probability Density Function (PDF); b) Cumulative Distribution Function (CDF); c) Survival function; d) Risk Function (RF). Estimates of the four parameters, obtained through maximum likelihood method, are, $\hat{\gamma} = 1.9706$; $\hat{\delta} = 0.46334$; $\hat{\lambda} = 10.379$; $\hat{\xi} = -0.01896$.

A Cramer's V test was developed through SPSS (IBM). Cramer's V is an effect size measure for the chi-square test of independence. It measures how strong is the association of two fields. In this sense, obtained results strongly support the previous analysis and posterior causal analysis. The results drawn from the test are shown as follows (Table 1):

3.1.2. *Independency of events*

Independency of events are developed on the hydrograph, selecting those complete events that starts are finish in cero (baseflow) and they are separated enough from the previous event to lose the soil field capacity. This is the way to guarantee that those events are comparable, and the runoff process is not considerably affected by a previous moisture of the soil (Fig. 3a).

3.1.3. *Calculation and subtraction of response time*

To assure that a particular rainfall event produces effective runoff, we have calculated the average Response Time (RT) as an indicator that represents the time since starts raining and produce the corresponding runoff. This is developed through a graphic method directly in the hydrograph. Furthermore, to remove the Rainfall-Runoff delay and make rainfall and runoff series as more parallel as possible, the RT was removed from the time series (Fig. 3b).

3.1.4. *Calculation and subtraction base-flow rate*

To simplify the upcoming BCM and try to capture the maximum degree of causality, the base-flow was calculated from the hydrograph and then removed. Therefore, the beginning and the end of the

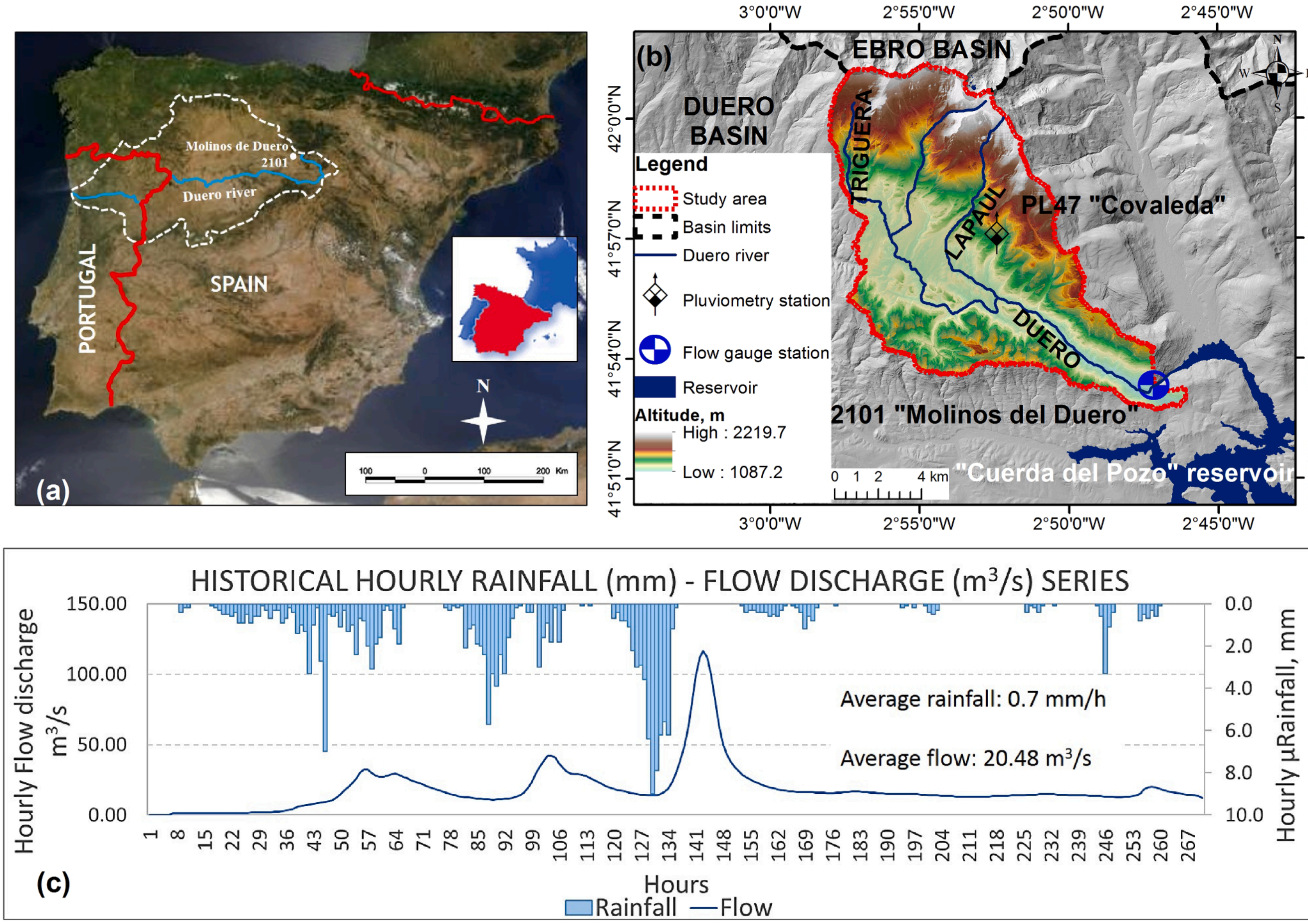

Fig. 2. (a) Case study location. (b) River basin, pluviometry station PL47 and gauging station code number 2101 "Molinos de Duero". (c) Flash hyetogram and hydrograph events.

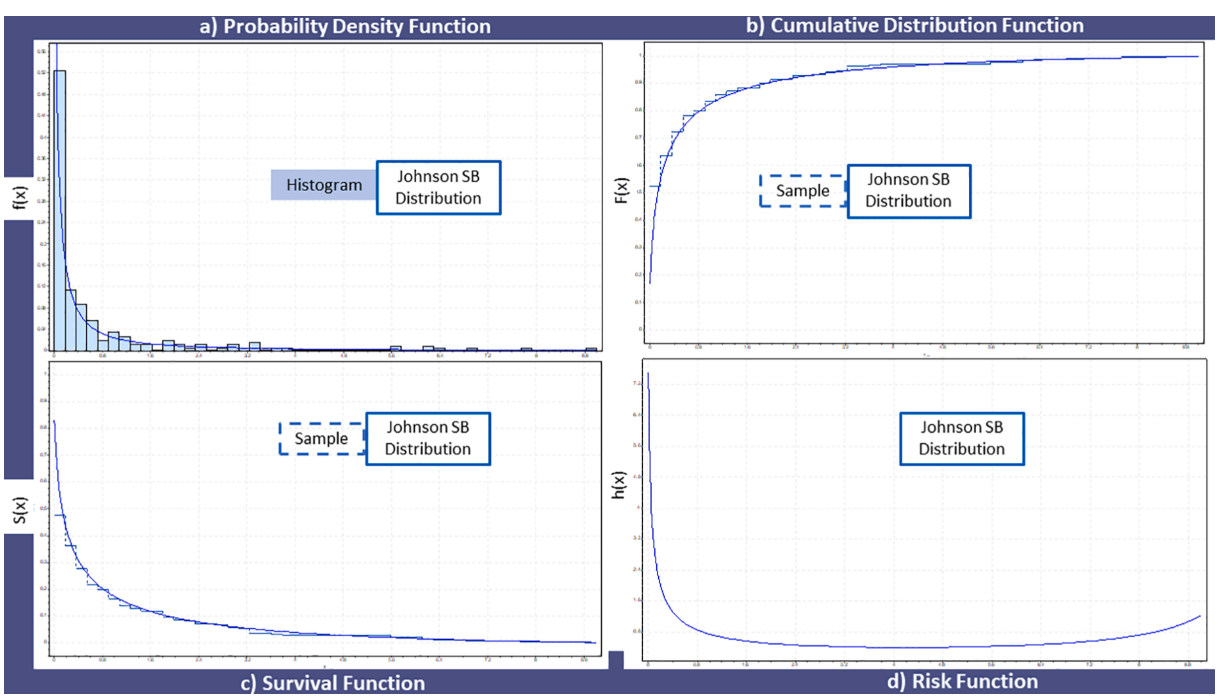

Fig. 3. Pluviometry mathematical adjustment. a) Probability Density Function (PDF); b) Cumulative Distribution Function (CDF); c) Survival function; d) Risk Function (RF).

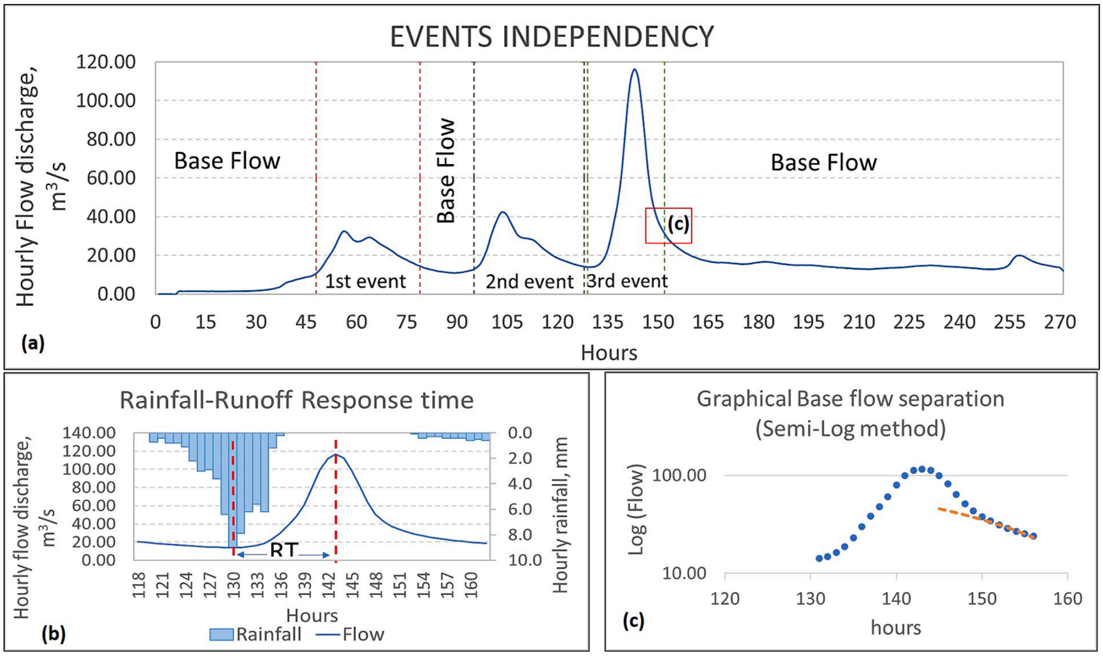

Fig. .4. Graphical method to data pre-process for BCMT. (a) Independence of events. (b) Calculation and subtraction of Response Time (RT). (c) Calculation and subtraction base-flow rate.

Table 1
Results from Cramer's V test for rainfall and runoff variables.

Symmetric Measures			
	Value	Approximate Significance	
Nominal by Nominal	Phi	5.742	0.001
	Cramerś V	0.971	0.001
N of valid cases	265		

hydrograph starts from the same plane (Fig. 3c).

3.2. *Bayesian causal modelling Translation (BCMT)*

3.2.1. *Learning and training*

Learning was done automatically through a learning wizard implemented in HUGIN ® Expert version 8.9 (HUGIN, 2021). Learning comprised two series of data "Rainfall" and "Runoff (WithoutBaseflow)", one series per variable involved in this model. Both series were discretized into five intervals and then, in the structure constraint phase, connect from "rainfall" node (parent) to "runoff" node which is the child (Fig. 4). Training phase was developed with the initial part of the series (20 h) and then compared to the mathematical adjustment developed through Johnson SB Distribution.

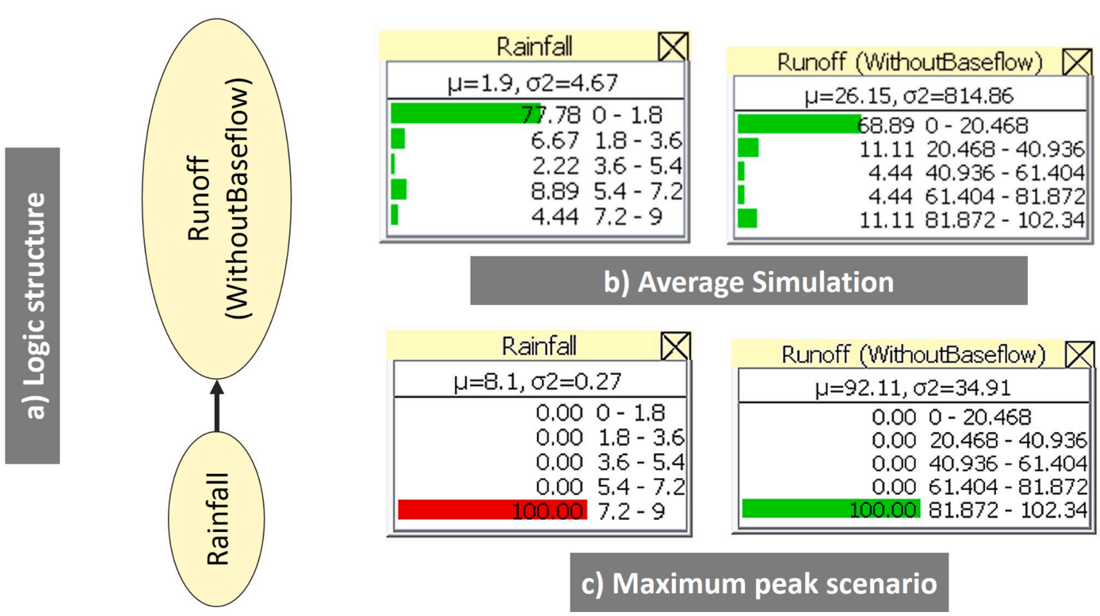

Fig. 5. (a) Logic structure of the bivariate causal model. (b) Average Simulation. (c) Simulation of the maximum event. Source: Hugin Expert. Version 8.9.

3.2.2. Simulation

The simulated event comprised 45 h of data representing the maximum rainfall of the year with 9 mm (l/m^2). As aforementioned, "Rainfall" node was discretized into five equal range intervals: 0–1.8 mm; 1.8–3.6 mm; 3.6–5.4 mm; 5.4–7.2 mm; 7.2–9 mm. Results show a very similar behaviour with the mathematical adjustment. In this sense, the average probability of runoff is 26.15 m^3/s (Fig. 5b) while in the maximum peak is 92.11 m^3/s (Fig. 4c).

3.2.3. Sensitivity analysis and validation

In this sense, p-value of the relation rainfall-runoff is 5*10−6; Mutual Information for Rainfall node is 0.74, for Runoff node is 0.59 and for the causal relationship is 0.6029. Furthermore, Total Entropy of rainfall node is 0.81 and for the runoff node has a value of 1.02. Consequently, Conditional Entropy is 0.07 for rainfall and 0.43 for the runoff node. The interpretation of these values is discussed in the next section.

On the other hand, for the validation process, the conditional probability function has been compared with the correlation analysis made in the previous section and mathematically adjusted with Johnson SB. It is worthy to highlight the great degree of probabilistic correlation reached between the different intervals in which the distribution probability function is discretized belonging to "runoff" variable in the bivariate causal modelling (Fig. 4).

4. Discussion

This paper is mainly aimed to show the development of a method called "HydroPredicT_Extreme" based on Bayesian Casual Modelling (BCM), a technique within Artificial Intelligence (AI). This modelling approach becomes a joint bivariate causal model, generated to predict the runoff in high-flow events. The simplicity of the BCM process should not be seen as a weakness of this method because the stronger the preprocess of the data is the simpler the BCM can become. In other words, the detailed analysis of information that feeds the BCM is crucial to develop a simple but robust causal model. One of the key issues here is the question about the need of developing a mathematical calibrate physical model for feeding with its output the BCM development. From a technical standpoint it is not compulsory because BCM can be fed by any type of data, but it is highly recommended because it is necessary a clear identification and understanding of the cause (rainfall) and its response/effect (flow).The values of probabilities for the posterior "Runoff" variable through the average simulation and the peak simulation (Fig. 4b,c) shows a very high similarity with the behaviour observed at the gauging station and then simulated through Johnson SB Distribution. The simulated event was an annual maximum with a Return Period of 25 years. Of course, this method and research is applicable to other even stronger hydrological events. This application is the starting point of a brand-new research line on the prediction of the hydrological extremal behaviour. Next steps will comprise, among others: to analyze and model the non-symetric hydrograph events, to develop a BCM including base-flow, to enrich the method and tool with the identification, characterization, analysis and modelling of other types of events, or to analyze and model in a probabilistic way, the climatic conditions so the main meteorological events that cause the main hydrological events can be predicted as well.

The values for sensibility analysis of the BCM proves the degree of accuracy of this method. Especially the extremely low rate of P-Value which is the degree of independency between the causal relationship of two variables, assures the dependence of the hydrological rainfall-runoff process. Furthermore, values of Mutual Information are very high when means that there are an important dependence and causality between rainfall and runoff in this water system. It is worthy to highlight the extremely low value of Total Entropy for the rainfall, which means that there is not significative uncertainty on the rainfall process prediction.

5. Conclusions

HydroPredicT_Extreme is a method that predict in a robust and simple way the runoff associated with a high rainfall event. This makes this method very powerful for anticipate future great flood risk as well as catastrophic impacts on the nature and human environment. The fact that values of probabilities are completely aligned with the mathematical extreme function called Johnson SB Distribution validates the method for this hydrological event type (Annual Maximum).

This tool is intended to take part of a broader developing package of tools based on BCM aimed to deliver knowledge for the anticipation of potential damaging processes due to natural or human driving factors.

This whole methodology will become a digital and technological package in the form of Digital Application and Software that could be extrapolated to several similar cases studies. This maybe coupled with posterior devices for the prevention of catastrophic flood consequences in the form of MultiHazard-Early Warning System (MH-EWS) or others

CRediT authorship contribution statement

Jose-Luis Molina: Conceptualization, Methodology, Formal analysis, Visualization, Investigation. **Fernando Espejo:** Methodology, Software, Formal analysis, Investigation. **Santiago Zazo:** Conceptualization, Methodology. **María-Carmen Molina:** Supervision, Validation. **Mohamed Hamitouche:** Supervision, Validation. **José-Luis García-Aróstegui:** Formal analysis.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Adamowski, J.F., 2008. Development of a Short-Term River Flood Forecasting Method for Snowmelt Driven Floods Based on Wavelet and Cross-Wavelet Analysis. J. Hydrol. 353 (3-4), 247–266.
AEMET, 2021. Available online: http://www.aemet.es/es/noticias/2021/02/enero_2021_extremo (accessed on 3 January 2021).
Albano, R., Mancusi, L., Sole, A., Adamowski, J., 2017. FloodRisk: "A Collaborative, Free and Open-Source Software for Flood Risk Analysis". Geomat. Nat. Hazards Risk 8 (2), 1812–1832.
Albano, R., Mancusi, L., Sole, A., Adamowski, J., 2015. Collaborative Strategies for Sustainable EU Flood Risk Management: FOSS and Geospatial Tools-Challenges and Opportunities for Operative Risk Analysis. ISPRS Int. J. Geo-Inf. 4, 2704–2727.
Al-Rawas, G.A., Valeo, C., 2009. Characteristics of rainstorm temporal distributions in arid mountainous and coastal regions. J. Hydrol. 376 (1–2), 318–326.
Aqil, M., Kita, I., Yano, A., Nishiyama, S.A., 2007. Comparative Study of Artificial Neural Networks and Neuro-Fuzzy in Continuous Modeling of the Daily and Hourly Behaviour of Runoff. J. Hydrol. 337, 22–34.
Arrighi, C., Brugioni, M., Castelli, F., Franceschini, S., Mazzanti, B., 2018. Flood Risk Assessment in Art Cities: The Exemplary Case of Florence (Italy). J. Flood Risk Manag. 2018 (11), S616–S631.
Azli, M., Rao, A.R., 2010. Development of Huff curves for peninsular Malaysia. J. Hydrol. 388 (1–2), 77–84.
Back, A.J., 2011. Time distribution of heavy rainfall events in Urussanga, Santa Catarina State, Brazil. Acta Sci. Agron. 33 (4), 583–588.
Berg, P., Moseley, C., Haerter, J.O., 2013. Strong Increase in Convective Precipitation in Response to Higher Temperatures. Nat. Geosci. 6 (3), 181–185.
Bonta, J.V., 2004. Development and utility of Huff curves for disaggregating precipitation amounts. Appl. Eng. Agric. 20 (5), 641–653.
Cain, J., 2001. Planning Improvements in Natural Resources Management; Centre for Ecology and Hydrology: Wallingford, UK, 2001.
Cantero, J.G., Maestre, R.G., Arellano, F.P., 2020. Las inundaciones en España: un problema que sube de nivel. bie3: Boletín IEEE 19, 425–454.
Cea, L., Bladé, E., 2015. A Simple and Efficient Unstructured Finite Volume Scheme for Solving the Shallow Water Equations in Overland Flow Applications. Water Resour. Res. 51 (7), 5464–5486.
Chang, B., Guan, J., Aral, M.M., 2015. Scientific discourse: Climate change and sea-level rise. J. Hydrol. Eng. 20 (1) https://doi.org/10.1061/(ASCE)HE.1943-5584.0000860, A4014003.
CH-Duero. 2022. Available online: https://www.chduero.es/la-cuenca-del-duero (accessed on 15 January 2022).

De Moel, H., van Alphen, J., Aerts, J.C.J.H., 2009. Flood Maps in Europe—Methods, Availability and Use. Nat. Hazards Earth Syst. Sci. 9, 289–301.
Donat, M.G., Lowry, A.L., Alexander, L.V., O'Gorman, P.A., Maher, N., 2016. More extreme precipitation in the world's dry and wet regions. Nat. Clim. Change 6 (5), 508–513.
Escuder-Bueno, I., Castillo-Rodriguez, J.T., Zechner, S., Joebstl, C., Perales-Momparler, S., Petaccia, G., 2012. A Quantitative Flood Risk Analysis Methodology for Urban Areas with Integration of Social Research Data. Nat. Hazards Earth Syst. Sci. 12, 2843–2863.
EU Directive. (2007). EU Directive of the European Parliament and the European Council on the Assessment and Management of Flood Risks. (2007/60/EU). Off. J. Eur. Union 2007, 15, 186–193.
Grahn, T., Nyberg, L., 2017. Assessment of Pluvial Flood Exposure and Vulnerability of Residential Areas. Int. J. Disaster Risk Reduct. 21, 367–375.
Hao, Z., Singh, V.P., 2016. Review of Dependence Modelling in Hydrology and Water Resources. Prog. Phys. Geogr. 40, 549–578.
Hegerl, G.C., Black, E., Allan, R.P., Ingram, W.J., Polson, D., Trenberth, K.E., 2019. Challenges in quantifying changes in the global water cycle. Bull. Am. Meteorol. Soc. 100 (10).
Huang, Y., Qin, X., 2014. Uncertainty Analysis for Flood Inundation Modelling with a Random Floodplain Roughness Field. Environ. Syst. Res. 2014 (3), 9.
Huff, F.A., 1990. Time distributions of heavy rainstorms in Illinois. Circular 173. Illinois State Water Survey, Champaign, IL.
HUGIN, 2021. Available online: http://www.hugin.com (accessed on 15 January 2021).
IDE-Duero, 2021. Available online: http://www.saih.chduero.es/ (accessed on 1 February 2021).
IGME, 2022. Available online: http://info.igme.es/cartografiadigital/geologica/ (accessed on 9 January 2021).
IPCC, 2021. Intergovernmental Panel on Climate Change. Sixth Assessment Report (AR6). In Press. https://www.ipcc.ch/reports/ (accessed on 3 May 2021).
Jensen, F.V., 1996. An Introduction to Bayesian Networks; UCL Press: London, UK.
Jongman, B., Hochrainer-Stigler, S., Feyen, L., Aerts, J.C.J.H., Mechler, R., Botzen, W.J. W., Bouwer, L.M., Pflug, G., Rojas, R., Ward, P.J., 2014. Increasing Stress on Disaster-Risk Finance due to Large Floods. Nat. Clim. Chang. 4, 264–268.
Koller, D., Friedman, N., 2009. Probabilistic Graphical Models: Principles and Techniques. The MIT Press, Cambridge, Massachusetts, USA.
Kong, X.M., Huang, G.H., Fan, Y.R., Li, Y.P., Zeng, X.T., Zhu, Y., 2017. Risk analysis for water resources management under dual uncertainties through factorial analysis and fuzzy random value-at-risk. Stochastic Environ. Res. Risk Assess. 31 (9), 2265–2280.
Lane, L.J., Nearing, M.A., 1989. USDA Water Erosion Prediction Project: Hillslope profile and watershed model documentation. USDA-ARS National Soil Erosion Research Laboratory, West Lafayette, IN.
Lopez-Nicolas, A., Pulido-Velazquez, M., Macian-Sorribes, H., 2017. Economic risk assessment of drought impacts on irrigated agriculture. J. Hydrol. 550, 580–589.
Loukas, A., Quick, M.C., 1996. Spatial and temporal distribution of storm precipitation in southwestern British Columbia. J. Hydrol. 174 (1), 37–56.
Macian-Sorribes, H., Molina, J.L., Zazo, S., Pulido-Velázquez, M., 2020. Analysis of spatio-temporal dependence of inflow time series through Bayesian causal modelling. J. Hydrol. 125722.
MAGRAMA, 2018. Gestión de los Riesgos de Inundación. Available online: http://www.magrama.gob.es/es/agua/temas/gestion-de-losriesgos-de-inundacion/ (accessed on 15 April 2018).
MAGRAMA, 2017. Guía Técnica de Apoyo a la aplicación del Reglamento del Dominio Público Hidráulico en las limitaciones a los usos del suelo en las Zonas Inundables de origen Fluvial; Ministerio de Agricultura, Alimentación y Medio Ambiente. Madrid, España, Gobierno de España.
Marcos-Garcia, P., Lopez-Nicolas, A., Pulido-Velazquez, M., 2017. Combined use of relative drought indices to analyze climate change impact on meteorological and hydrological droughts in a Mediterranean basin. J. Hydrol. 554, 292–305.
Marotzke, J., Jakob, C., Bony, S., Dirmeyer, P.A., O'Gorman, P.A., Hawkins, E.d., Perkins-Kirkpatrick, S., Quéré, C.L., Nowicki, S., Paulavets, K., Seneviratne, S.I., Stevens, B., Tuma, M., 2017. Climate Research must Sharpen its View. Nat. Clim. Chang. 7 (2), 89–91.
Martín Vide, J., 2009. Ingeniería De Ríos, 2nd ed.; Ediciones UPC: Barcelona, Spain, pp. 27–30, 121–123, ISBN 978-84-8301-900-9.
Md Ali, A., Solomatine, D.P., Di Baldassarre, G., 2015. Assessing the Impact of Different Sources of Topographic Data on 1-D Hydraulic Modelling of Floods. Hydrol. Earth Syst. Sci. 19, 631–643.
Milanesi, L., Pilotti, M., Ranzi, R.A., 2015. Conceptual Model of People's Vulnerability to Floods. Water Resour. Res. 51, 182–197.
MITECO, 2022. Available online: https://www.miteco.gob.es/es/agua/temas/delimitacion-y-restauracion-del-dominio-publico-hidraulico/Catalogo-Nacional-de-Reservas-Hidrologicas/informacion/duero/alto-duero/default.aspx (accessed on 8 January 2022).
Molina, J.L., Pulido-Velázquez, D., García-Arostegui, J.L., Pulido-Velazquez, M., 2013. Dynamic Bayesian Networks as a Decision Support tool for assessing Climate Change impacts on highly stressed groundwater systems. J. Hydrol. 479, 113–129.
Molina, J.L., Zazo, S., Rodriguez-Gonzalvez, P., Gonzalez-Aguilera, D., 2016. Innovative Analysis of Runoff Temporal Behaviour through Bayesian Networks. Water 8, 484.
Molina, J.L., Zazo, S., 2017. Causal Reasoning for the Analysis of Rivers Runoff Temporal Behaviour. Water Resour. Manag. 31, 4669–4681.
Molina, J.-L., Zazo, S., 2018. Assessment of Temporally Conditioned Runoff Fractions in Unregulated Rivers. J. Hydrol. Eng. 23 (5), 04018015.
Molina, J.L., Zazo, S., Martín, A.M., 2019. Causal reasoning: Towards dynamic predictive models for runoff temporal behaviour of high dependence rivers. Water 11 (5), 877.
Molina, J.L., Patino-Alonso, C., Zazo, S., 2021. Hybrid causal multivariate linear modelling (H_CMLM) method for the analysis of temporal rivers runoff. J. Hydrol. 599, 126501.
Quirogaa, V.M., Kurea, S., Udoa, K., Manoa, A., 2016. Application of 2D Numerical Simulation for the Analysis of the February 2014 Bolivian Amazonia Flood: Application of the New HEC-RAS Version 5. RIBAGUA-Rev. Iberoam. Del Agua 3 (1), 25–33.
NERC. (1975). Flood studies report, Vol. II: Meteorological studies. London, UK: Natural Environment Research Council.
O'Gorman, P.A., 2015. Precipitation Extremes under Climate Change. Curr. Clim. Chang. Rep. 1 (2), 49–59.
Pearl, J., 1988. Probabilistic reasoning in intelligent systems: Networks of plausible inference. Morgan Kaufmann.Pearl, J. (2009). Causality: Models, Reasoning and Inference, 2nd ed.; Cambridge University Press: New York, NY, USA, p. 484, ISBN 978-0-521-89560-6.
Perica, S., Dietz, S., Heim, S., Hiner, L., Maitaria, K., Martin, D., Yarchoan, J., 2014. NOAA atlas 14: Precipitation frequency atlas of the United States, Vol. 6. NOAA, Silver Spring, MD.
Pfahl, S., O'Gorman, P.A., Fischer, E.M., 2017. Understanding the regional pattern of projected future changes in extreme precipitation. Nat. Clim. Change 7 (6), 423–427.
Qian, B., Corte-Real, J., Xu, H., 2000. Is the North Atlantic Oscillation the most important atmospheric pattern for precipitation in Europe? J. Geophys. Res. Atmos. 105 (D9), 11901–11910.
Reynard, N.S., Kay, A.L., Anderson, M., Donovan, B., Duckworth, C., 2017. The Evolution of Climate Change Guidance for Fluvial Flood Risk Management in England. Prog. Phys. Geogr. 2017 (41), 222–237.
Romali, N.S., Yusop, Z., Is, A.Z., 2018. Application of Hec-Ras and Arc Gis for Floodplain Mapping in Segamat Town, Malaysia. Int. J. Geomate 14, 125–131.
Ross, P.J., 1990. SWIM: A simulation model for soil water infiltration and movement. CSIRO Division of Soils, Townsville, Queensland, Australia.
Schanze, J., Hutter, G., Olfert, A., Penning-Rowsell, E.C., Parker, D., Harries, T., Nachtnebel, H., Holzmann, H., Neuhold, C., Meyer, V. (2008). Systematisation, Evaluation and Context Conditions of Structural and Non-structural Measures for Flood Risk Reduction; CRUE Research Report No. I-1; CRUE Funding Initiative on Flood Risk Management Research: London, UK.
SIGA, 2022. Available online: https://sig.mapama.gob.es/siga/ (accessed on 10 January 2022).
Fael, C., Lança, R., Cardoso, A., 2016. Effect of Pier Shape and Pier Alignment on the Equilibrium Scour Depth at Single Piers. Int. J. Sediment Res. 31 (3), 244–250.
Thompson, C.J., Fryirs, K., Croke, J., 2016. The Disconnected Sediment Conveyor Belt: Patterns of Longitudinal and Lateral Erosion and Deposition during a Catastrophic Flood in the Lockyer Valley, South East Queensland, Australia. River Res. Appl. 32 (4), 540–551.
Thieken, A.H., Cammerer, H., Dobler, C., Lammel, J., Schöberl, F., 2016. Estimating Changes in Flood Risks and Benefits of Non-Structural Adaptation Strategies—A Case Study from Tyrol, Austria. Mitig. Adapt. Strateg. Glob. Chang. 21 (3), 343–376.
Uysal, G., Alvarado-Montero, R., Schwanenberg, D., Sensoy, A., 2018. Real-Time Flood Control by Tree-Based Model Predictive Control Including Forecast Uncertainty: A Case Study Reservoir in Turkey. Water 10, 340.
Vogel, K., Weise, L., Schröter, K., Thieken, A.H., 2018. Identifying driving factors in flood-damaging processes using graphical models. Water Resour. Res. 54 (11), 8864–8889.
Yoo, J., Kwon, H., Kim, T., Ahn, J., 2012. Drought frequency analysis using cluster analysis and bivariate probability distribution. J. Hydrol. 420, 102–111.
Zazo, S., Molina, J.L., Rodriguez-Gonzalvez, P., 2015. Analysis of Flood Modelling through Innovative Geomatic Methods. J. Hydrol. 524, 522–537.
Zazo, S., Rodriguez-Gonzalvez, P., Molina, J.L., Hernandez-Lopez, D., Gonzalez-Aguilera, D., 2016. Flood Analysis Supported by Low-Cost Geometric Modelling. River Res. Appl. 2017 (33), 620–631.
Zazo, S., 2017. Analysis of the Hydrodynamic Fluvial Behaviour through Causal Reasoning and Artificial Vision. Ph.D. Thesis, University of Salamanca, Ávila, Spain, 12 May 2017.
Zazo, S., Rodríguez-Gonzálvez, P., Molina, J.L., González-Aguilera, D., Agudelo-Ruiz, C. A., Hernández-López, D., 2018. Flood hazard assessment supported by Reduced Cost Aerial Precision Photogrammetry. Remote Sensing 10 (10), 1566.
Zazo, S., Molina, J.L., Ruiz-Ortiz, V., Vélez-Nicolás, M., García-López, S., 2020. Modeling River Runoff Temporal Behavior through a Hybrid Causal-Hydrological (HCH) Method. Water 12 (11), 3137.
Zechner, S., Grossmann, G., Pohl, R., Natale, L., Escuder Bueno, I., Bateman, A., 2018. Guidance. SUFRI Metodology for Investigation of Risk Awareness of the Population Concerned. 2nd ERA-Net CRUE Funding Initiative European Flood Risk. Available online: https://bit.ly/2DvTEoY (accessed on 27 September 2018).
Zeng, H., Wu, B., Zhang, M., Zhang, N., Elnashar, A., Zhu, L., Zhu, W., Wu, F., Yan, N., Liu, W., 2021. Dryland ecosystem dynamic change and its drivers in Mediterranean region. Curr. Opin. Environ. Sustain. 48, 59–67.
Zounemat-Kermani, M., Teshnehlab, M., 2008. Using Adaptive Neuro-Fuzzy Inference System for Hydrological Time Series Prediction. Appl. Soft Comput. 8 (2), 928–936.