Improving Flash Flood Forecasting with a Bayesian Probabilistic Approach: A Case Study on the Posina Basin in Italy

Zviad Ghadua, Biswa Bhattacharya

Abstract**—**The Flash Flood Guidance (FFG) provides the rainfall amount of a given duration necessary to cause flooding. The approach is based on the development of rainfall-runoff curves, which helps us to find out the rainfall amount that would cause flooding. An alternative approach, mostly experimented with Italian Alpine catchments, is based on determining threshold discharges from past events and on finding whether or not an oncoming flood has its magnitude more than some critical discharge thresholds found beforehand. Both approaches suffer from large uncertainties in forecasting flash floods as, due to the simplistic approach followed, the same rainfall amount may or may not cause flooding. This uncertainty leads to the question whether a probabilistic model is preferable over a deterministic one in forecasting flash floods. We propose the use of a Bayesian probabilistic approach in flash flood forecasting. A prior probability of flooding is derived based on historical data. Additional information, such as antecedent moisture condition (AMC) and rainfall amount over any rainfall thresholds are used in computing the likelihood of observing these conditions given a flash flood has occurred. Finally, the posterior probability of flooding is computed using the prior probability and the likelihood. The variation of the computed posterior probability with rainfall amount and AMC presents the suitability of the approach in decision making in an uncertain environment. The methodology has been applied to the Posina basin in Italy. From the promising results obtained, we can conclude that the Bayesian approach in flash flood forecasting provides more realistic forecasting over the FFG.

Keywords**—**Flash flood, Bayesian, flash flood guidance, FFG, forecasting, Posina.

I. Introduction

FLOODING is the leading cause of damage and distress from natural hazards. At least one third of all losses due to natural hazards can be attributed to flooding. Flood damages have been extremely severe in recent decades and it is likely that both the frequency and the intensity of floods are increasing [1]. Among different types of floods, flash floods can be characterized as the most deadly floods [2]. The most common flash flood forecasting system is the FFG, which is mostly used in North America. FFG is defined as the numerical estimate of the rainfall over a specified area and time duration required to initiate flooding on small streams.

When using physically based or lumped conceptual rainfall-runoff models, rainfall and in some cases, soil moisture state are input variables to compute runoff. Computing FFG works in the opposite direction. From rainfall-runoff curves, which are developed for a particular catchment, the rainfall corresponding to the threshold discharge that causes flooding is determined and is known as the FFG (for a specific time duration) [3]. Information regarding the current soil moisture condition may be obtained from a hydrologic model to update the rainfall-runoff curves, so that the FFG is updated to the current catchment condition.

The FFG has limitations as it is a lumped value across a given (sub-) catchment. It is influenced by catchment conditions (soil moisture state, slope, soil texture and land cover) and meteorological conditions [3]. Moreover, changes in vegetation or seasonal changes (e.g. in deciduous forests) may decrease or increase the hydrologic response associated with similar rainfall events. In these cases, the flash flood potential changes dramatically on an event-by-event basis [4]. Therefore, there may not be a unique rainfall threshold for flash flood occurrence and production of several rainfall thresholds may be needed. However, the relationship between antecedent soil moisture condition and varying rainfall intensity is non-linear, which on the other hand indicates the necessity to develop separate rainfall runoff curves for rainfalls with different ranges of intensities. Furthermore, events with the same rainfall and antecedent soil moisture condition may still have varying basin response which ultimately may influence the occurrence or non-occurrence of flooding depending on spatial and temporal distribution of rainfall.

An alternative, much less used, approach is the statistical distributed (SD) model, which uses the ensemble of antecedent model predictions (obtained from previous events) to rank the severity of the predictions [5]. The SD approach requires running a distributed model using archived radar-rainfall grids to derive flood probability characteristics of simulated flows for all cells in the distributed model. When subsequently running the distributed model in forecast mode, the flooding flow threshold for each grid cell is defined in terms of a flood probability level rather than an absolute value of flow. In this manner, the flooding flow computed from simulated data is different than that computed from observed data because it takes into account the hydrologic model uncertainty [6]. Reference [7] discussed quantifying the uncertainties of the SD model in forecasting flash floods given currently available precipitation data and continuous,

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distributed modeling software (HL-RMS). The authors claimed that the proposed approach offered advantages over the current National Weather Service (NWS) FFG method which is based on a lumped model.

Reference [8] has introduced Distributed Hydrologic Model - Threshold Frequency (DHM-TF) Flash Flood Forecasting System, which produces gridded flow forecasts. This method is similar to FFG and another newer gridded approach called Gridded Flash Flood Guidance (GFFG) [3]. GFFG relies on static runoff thresholds to identify flood producing discharges using a hydrologic model fed with observed or forecast rainfall in real time. Operating on the Hydrologic Rainfall Analysis Project (HRAP) grid [9] at a 4 km resolution and hourly time step, DHM-TF produces gridded flow forecasts, from which gridded frequency forecasts are derived using historical simulations. These frequency forecasts are then compared against flood threshold frequency grids to determine where flooding is occurring. In the absence of locally customized flood threshold grids, a uniform 2-year out-of-bank threshold value is used to indicate flooding. That is, if DHM-TF simulates a return period value of 2 years or greater, flooding is taken to be occurring within that particular grid cell [8]. Independent reports of flash flooding from trained spotters confirmed DHM-TF was more skillful than FFG and GFFG, but several shortcomings were mentioned. Despite a number of approaches mentioned above, the current FFG system is the primary tool still being developed in many countries around the globe for flash flood forecasting, that reached project coverage of close to 1 billion people worldwide.

Hydrologic models used in operational water management are typically deterministic and complex. They are built of numerous sub-models, each mimicking some physical processes such as soil moisture accounting, transformation of excess rainfall to runoff, flood routing, etc. Forecasts produced via such models are typically in the form of time series of estimates. These estimates are not error-free. From the viewpoint of a decision maker who receives such estimates and must make a decision, for example, to issue flood warnings, or to operate a barrage/sluice, or to release water from a reservoir, there remains uncertainty about the actual realization of the output being forecast [10]. Probabilistic forecast, at least partly, resolves this issue [11], [12].

Reference [13] (FLOODSite Project), used statistical analysis of long series of synthetic data in developing joint and conditional probability functions, which were then used within a Bayesian context to determine the appropriate rainfall thresholds. To estimate water stages (or discharges) at the relevant river section, three continuous time series had been analysed: (i) the precipitation averaged over the catchment area, (ii) the mean soil moisture value, (iii) the river stage (or the discharge) in the target river section. The forecast rainfall totals were accumulated progressively, starting from the measured rainfall volume and the value was then compared to the appropriate AMC (Antecedent Soil Moisture Condition) threshold value. The approach presented an improvement over the current forecasting systems. However, it does not distinguish between short duration high intensity events and long duration low intensity ones, whereas FFG values are estimated based on average rainfall and specified time duration required to initiate flooding. Therefore, as expected, high accuracy was obtained for the first 6 h to 8 h; followed by quick drop in accuracy after 9 h [13].

In this paper, we propose to use Bayesian probabilistic estimates to determine the occurrence of flash flood. The Bayesian probabilistic estimate is computed using rainfall amounts in a specified time duration and three AMC classes. The Bayesian model can be directly used in flash flood forecasts. We do not aim to replace the standard FFG system but to develop a complementary tool in increasing the confidence level of decision makers in issuing or not issuing flash flood alerts.

II. Methodology

The current FFG system is a deterministic tool based on threshold exceedances. A threshold is defined as the level or the value (e.g. a rainfall amount) that must be exceeded to produce a given effect or result (a flash flood). Implied in this definition is an inherently deterministic view: The state of the system can be predicted by comparing the input value (or a set of input values) with the threshold [12]. The system response often may not be so simplistic. For example, distribution of rainfall varies over a basin, which influences the basin response and flash flood occurrence.

When different outputs can be obtained for the same input (e.g. a given rainfall event), a deterministic approach is no longer applicable and a probabilistic model is needed [12]. There are two broad approaches for deducing formal statistical inference from noisy empirical data: Frequentist and Bayesian approach [14]. Frequentists define probability as the frequency of a certain observation. To a Bayesian, there is no Platonic truth out there which (s)he wants to access through data collection (or perhaps we should say there may be a Platonic truth, but it will always remain outside our experience). For a Bayesian, there is just data which we can use as evidence for a particular hypothesis. A Bayesian coin-tosser just observes a series of coin tosses and then uses this information to make deductions about, for example, how likely it is that the coin is fair [15].

The proposed methodology is based on the application of Bayes' theorem in developing Bayesian probabilistic FFG. Bayesian probability may be defined as the probability of an event F (for example, a flash flood) given the occurrence of another event R (for example, a rainfall event with a rainfall amount higher than a threshold). Bayesian (or posterior) probability is written as P(F|R) and it is read as the probability that flood F occurs given a rainfall event R occurs. This posterior probability can be computed using the Bayes' theorem:

$$P(F|R) = \frac{P(R|F)\cdot P(F)}{P(R)} \quad (1)$$

where, P(R|F) is the likelihood of observing rainfall event R when flash flood F occurs. P(F) is the prior probability of flash flood F (without considering rainfall event R). P(R) is the marginal probability of rainfall event R (without considering flash flood event F). We can use relative frequencies to compute the Bayesian probability. This approach can be used in computing the Bayesian estimate for any considered forecast horizon, which usually are 1, 3, 6, 9 and 12. However, model accuracy decreases as rainfall event duration increases, due to varying rainfall hyetograph and a basin response. Therefore, for most basins, forecasting with six and less hourly steps is needed.

Equation (1) can be extended to two-dimensional applications by considering catchment soil moisture or AMC:

$$P(F|R, AMC) = \frac{P(R,AMC|F)\cdot P(F)}{P(R,AMC)} \quad (2)$$

where P(R, AMC) indicates the joint probability of event R and AMC. By considering antecedent soil moisture as AMC I, II or III together with a range of rainfall values (R), the Bayesian probability of a flash flood event F can be computed using (2).

In most cases, Bayes' approach is considered as a good solution even with limited data and it provides a rational method for updating beliefs by introducing new data in the model. However, with limited data, many conditioning cases may be represented by too few or no data records and they do not offer a sufficient basis for learning conditional probability distributions [16].

A. 1D Bayesian FFG

In 1D Bayesian FFG, we considered varying rainfall ranges in computing the Bayesian probability of flooding. This is done by modifying (1) in the following way:

$$P(F|R_x) = \frac{P(R_x|F)\cdot P(F)}{P(R_x)} \quad (3)$$

where Rx refers to a rainfall amount within a range specified by x (e.g. 20-30 mm). By considering different values of x we can compute varying probability of flooding. In this research we have considered rainfall ranges of 5 mm.

The variation of the Bayesian probabilistic estimate presents the uncertainties associated with the threshold based approach and will help decision making.

B. 2D Bayesian FFG

In 2D Bayesian estimates, we used rainfall and varying AMCs, illustrating the capability of the model in further increasing the model accuracy by adding new parameters into the model.

C. 3D Bayesian FFG

The Bayesian FFG may further be extended with new input parameters into the model which may play a significant role in Bayesian forecasting such as: Seasonality, leaf stage, wind speed, wind direction, and atmospheric pressure. However, in this work, we used 1D, 2D and the preceding rainfall episode as the third input parameter (3D), which is explained in paragraph 4.

III. Case Study

The Posina River basin is located at the foothills of Central-Eastern Italian Alps, close to Venice and Padua and has an area of 116 km^2 (Fig. 1). The elevation ranges from 387 m to 2232 m. Posina River is a tributary of Astico River that flows into the Adriatic Sea. About 75% of the catchment is covered by deciduous forests, especially beeches and hornbeams, thereby saturation-excess is the main runoff generation mechanism of the basin. The forest area expanded significantly during the last decades due to land use changes; mainly due to abandonment of some agricultural practices. The annual precipitation is estimated to be in the range of 1,600-1,800 mm. Rainfall is concentrated particularly in the spring (April and May) and fall. The basin is situated in one of the rainiest areas of Veneto (in Italy) and is monitored by five meteorological and three hydrometric stations. Basin-averaged precipitation was estimated using Thiessen polygons. We used hourly rainfall data for the time period 1992-2000. Hourly discharge data at the outlet of the basin were collected for the time period 1985-2000. The threshold discharge, that causes flood in the basin, was considered as 24m^3/sec.

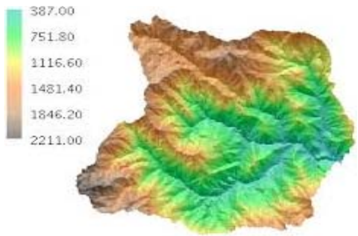

Fig. 1 Posina Basin, Elevations in (m)

A. Observed and Simulated Data

In total, 23 separate rainfall events were identified, which led to a river discharge above the threshold discharge level – 24 m^3/s. These rainfall events were considered in building the Bayesian model. As in our case, the second input parameter was AMC, and we used seasonal rainfall limits for AMC classes [17] to determine the AMC class in relation to 5-day antecedent rainfall. In total, eight events with AMCI (dry), two with AMCII (average) and 13 with AMCIII (wet) condition were identified.

This work introduces a new approach in the application of simulated data in Bayes' computation when observed data are not sufficient; whereas the minimum data set required for Bayes' computation depends on expert judgment and may vary from case to case. Though, it is important to mention that Bayesian inferences depend on prior and likelihood of observed data, and not on other data that might have been observed. To solve this dilemma, we provide an example in the proposed approach based on data records of the Posina basin.

As mentioned earlier, the lumped FFG is derived based on the current AMC and forecast rainfall amounts for a specified time duration. Therefore, we have identified six-hourly flood causative rainfall episodes for each flood event built in the hydrological model. To generate the simulated data, we used a lumped conceptual rainfall-runoff modelling tool Hydrologic Modelling System (HEC-HMS) from Hydrologic Engineering Center-Hydrologic Modelling System (HEC-HMS). It is a freely available tool developed by the US Army Corps of Engineers and is designed to simulate the precipitation-runoff processes of a variety of catchments.

In order to perform Bayes' computations, we need to define the input variables for (2). Firstly we found that all 23 flood causative rainfall episodes fall within the 16.5 mm to 60mm constraint, regardless the AMC condition, which is called a probability area. Then we identified 78 separate rainfall events above 16.5mm regardless of whether the runoff exceeded the flood threshold or not and computed the prior probability of flash flood P(F)=23÷78 = 0.294872.

As a next step, since we had limited number of flood events for Bayes' computations, especially under AMCII, we built event-based hydrological models in HEC-HMS for all 23 flood events to enlarge the dataset and generated simulated data for varying AMC conditions. Basically, we used the same pattern of 23 rainfall events distributed over the basin and changed only the AMC to find out what would be the result if the same rainfall had fallen under the varying AMC and defined the rainfall amount that would lead in exceeding the flood threshold under the selected AMC. In other words, we used HEC-HMS to increase or decrease the rainfall amounts proportionally over the basin until peak discharge was just above $24m^3/s$. Eventually, instead of e.g. two flood separate events under AMCII, we obtained 23 event points with rainfall amount that led in exceeding the flood threshold, which we used further in Bayes' computations.

B. Application of Simulated Data in Bayes' Computation

As mentioned above, three AMCI, AMCII and AMCIII conditions were defined and the hydrological model was used to estimate the rainfall amounts necessary to initiate flooding corresponding to other two of the AMC conditions (out of I, II and III) by simply increasing or decreasing proportionally the original pattern of rainfall amounts over the basin for selected AMC. With this approach, we generated 46 simulated events, which together with the 23 observed events, gave the rainfall thresholds of 69 events.

At this point, we needed to update the value of a prior. As we had obtained 69 flood event points, according to frequentists' principle we also had to increase the total number of separate rainfall events or the marginal probability, respectively. Thus, if initially we had 23 flood points and the total number of rainfall events within the probability area was 78 regardless the AMC condition, we proportionally derived the total number of these rainfall events for 69 event points, which is 234. Note that with this approach, prior values are not changed 23÷78 = 69÷234 whereas we have significantly increased number of flood event points for Bayes' computations.

With the same approach we also derived the values of joint probability P(R, AMC) and as a result computed posterior probabilities, which is illustrated in Fig. 2. This way, we used simulated data obtained through hydrological models in improving the reliability of Bayes' computations, without disobeying the fundamentals of Bayesian theorem.

IV. Results and Discussion

The FFG System provides a collection of real-time data products in graphical and various text file formats. The text products are available for direct review as well as download using the web interface and file transfer accessibility of the FFG Dissemination Interface. Each hour, the FFG system provides images and text tables related to the various stages of data processing carried out by the system. Even though the FFG Systems' primary product is the FFG data, the other products are made available to the forecaster for leveraging their information in their efforts for quality control and in their assessments regarding degree of belief when further applying and modifying the FFG data in their operational forecasting activities [18].

In the following, Bayesian probabilistic estimates of flash flood occurrence are provided, which will allow reducing uncertainty by adding probabilistic value to current FFG. It is a supplementary tool to the deterministic FFG system, which does not require expert knowledge in the operational environment, and has visual aids for improved communication. The calculations are provided with the 5 mm increments of rainfall amounts within the six hourly rainfall episodes. For better illustration of the calculation results we used two steps of six hourly rainfall episodes, which makes the first episode the predecessor and the next episode the successor. The preceding rainfalls for this example are given in the constraints of probability area of flood occurrence, ranged between 0 mm, 0mm-20mm, 20mm-40mm and 40mm-60mm. However, in the operational environment high-density ranges may be selected.

A. 1D/2D Bayesian FFG

As we can see from Fig. 2 and Table I, we arbitrarily set up rainfall ranges with 5 mm steps for the probability distribution in flood forecasting. Therefore, the Bayesian calculations in this work are performed based on runoff generation just exceeding the flood threshold 24 m^3/sec according to a given rainfall range and AMC as input parameters. However, in practice, Fig. 2 in the same or other form may be expanded with estimates for varying flood thresholds, since, for example, an additional input variable of river stage may play a significant role in estimating flood occurrence.

In Fig. 2, we can see the probability distribution for the one dimensional case, without antecedent soil moisture condition and may observe changes when introducing AMCs as the second input parameter. We may also notice that the Posina basin has very high initial abstraction and saturation-excess is the main rainfall-runoff generation mechanism of the basin. Probability of flood occurrence is zero under AMCI condition until rainfall amount is higher than 50 mm/6 hours. As expected, probabilities of flood occurrences increase significantly under AMCII and AMCIII, which is explained with rapid runoff routing due to the topography and morphology of the basin.

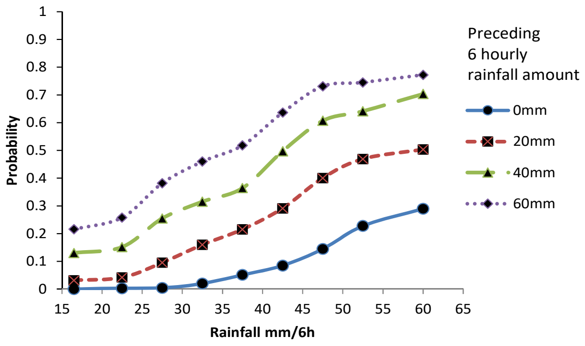

Fig. 2 (a) 1D Bayesian FFG vis-à-vis conventional FFG corresponding to varying rainfall ranges and varying rainfall amount in the preceding six hours (without AMC)

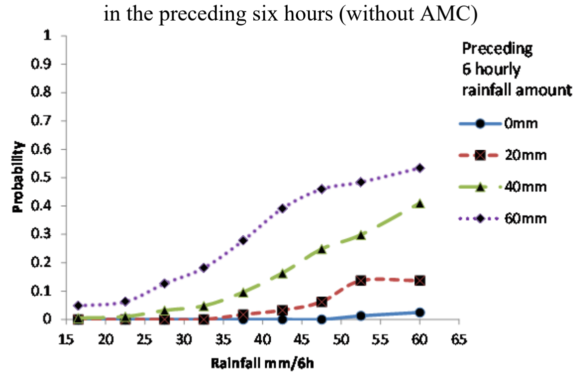

Fig. 2 (b) 3D Bayesian FFG vis-à-vis conventional FFG corresponding to varying rainfall ranges and varying rainfall amount in preceding six hours corresponding to AMC I

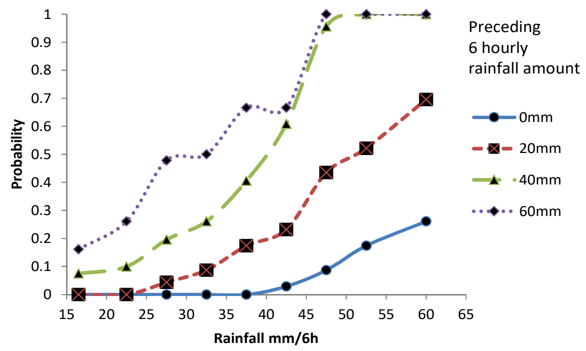

Fig. 2 (c) Bayesian FFG corresponding to rainfall ranges and preceding six hourly episode, under AMC II

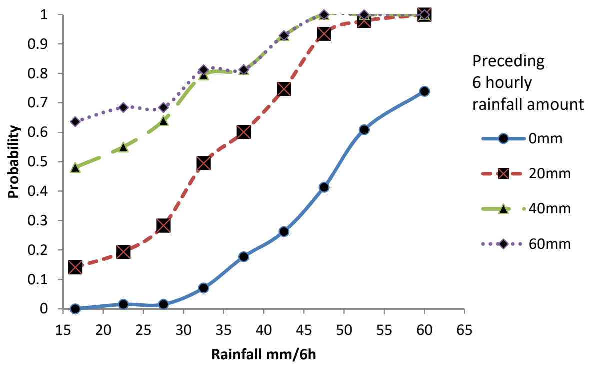

Fig. 2 (d) Bayesian FFG corresponding to rainfall ranges and preceding six hourly episode, under AMC III

TABLE I
BAYESIAN ESTIMATES OF FLASH FLOOD OCCURRENCE IN POSINA BASIN FOR TWO CONSECUTIVE 6-HOURLY RAINFALL EPISODES

AMC/Preceding rainfall mm/6h	Rainfall (mm/6h)/Posterior probability								
	16.5-20	**20-25**	**25-30**	**30-35**	**35-40**	**40-45**	**45-50**	**50-55**	**55-60**
Without AMC									
0mm	0	0	0	0.02	0.05	0.08	0.14	0.23	0.29
20mm	0.03	0.04	0.10	0.16	0.22	0.29	0.40	0.47	0.50
40mm	0.13	0.15	0.25	0.32	0.36	0.50	0.61	0.64	0.70
60mm	0.22	0.26	0.38	0.46	0.52	0.64	0.73	0.74	0.77
AMCI									
0mm	0	0	0	0	0	0	0	0.01	0.02
20mm	0	0	0	0	0.02	0.03	0.06	0.14	0.14
40mm	0	0.01	0.03	0.05	0.10	0.16	0.25	0.30	0.41
60mm	0.05	0.06	0.13	0.18	0.28	0.39	0.46	0.48	0.53
AMCII									
0mm	0	0	0	0	0	0.03	0.09	0.17	0.26
20mm	0	0	0.04	0.09	0.17	0.23	0.43	0.52	0.70
40mm	0.07	0.10	0.20	0.26	0.41	0.61	0.96	1	1
60mm	0.16	0.26	0.48	0.50	0.67	0.67	1	1	1
AMCIII									
0mm	0	0.01	0.01	0.07	0.18	0.26	0.41	0.61	0.74
20mm	0.14	0.19	0.28	0.49	0.60	0.75	0.93	0.98	1
40mm	0.48	0.55	0.64	0.79	0.81	0.93	1	1	1
60mm	0.64	0.68	0.68	0.81	0.81	0.93	1	1	1

As the flood causative rainfall episode (mm/6 hours) usually occurs in the middle of rainfall event of a longer duration (more than 12 hours) at the Posina basin, temporal discretization for precipitation forecasts is required to calculate probabilistic FFG for a specified time duration. In our example, we used two 6-hourly steps to illustrate the proposed approach. With Figs. 2 (a)-(d), we are able to estimate probability of threshold runoffs, given forecasted or observed values of the preceding 6 hourly rainfall episode.

We can also see that the maximum probabilistic value without AMC and under AMCI is less than one. This is resulted by the fact that some flood events required excessive rainfall amounts which are beyond the probability area or the 16.5 mm to 60 mm probability zone. Therefore simulated events or evidence beyond this zone would not be included in Bayes' computation, considering the fundamentals of Bayesian theorem.

The current FFG system produces FFG values that are just enough to exceed the flood threshold under a given soil moisture condition. It does not provide information on., for example, to what certainty we shall expect flooding if forecasted rainfall is higher than the FFG value. However, with the approach presented in this work, we are able to make relevant assessments with numerical expression of risk, based on which an operator or a decision maker may or may not issue a flood warning/alert. It is also worth to mention that the approach to managing low-probability/high-consequence as opposed to high-probability/low-consequence events, even though the 'calculated' risk would be the same, may be (and is likely to be) different [19]. Therefore, it is expected that the responsible person or organization shall perform considerate risk assessment at a regional or local level.

Bayesian inferences depend on prior and likelihood of observed data and not on other data that might have been observed. However, since limited data could not provide sufficient estimates, we demonstrated a justified solution to use simulated data in a Bayesian model. As a result, we estimated Bayesian probability of flash flood occurrences, based on observed rainfall and varying antecedent soil moisture condition, which allows reducing uncertainty by adding probabilistic value to FFG. The methodology aims at increasing the confidence level of the decision maker in issuing or not issuing flash flood alert.

Theoretically, if we had expended Bayes' computation with additional input parameters, such as: Seasonality, leaf stage, wind speed, wind direction etc., we would further narrow our probability area based on the expert judgment and the data available. However, it would be reasonable to recommend that explanatory power of each selected input parameter is considered, to avoid overloading the Bayes computations with variables of less significance. It is also worthy to mention that land use and land cover changes may eventually modify the rainfall-runoff pattern in time, therefore as in any other deterministic approach, care shall be taken when selecting and applying measured data periods for building the hydrologic and Bayesian models. Furthermore, in the measured dataset, we may also observe the influence of climate changes (e.g. increased frequencies of rainfalls with certain magnitude) which may on the other hand allow extrapolating expected frequencies of high intensity rainfalls for the projected period. Thus, since we often may not be given an opportunity to work with the ideal dataset for their direct applications, we may introduce external or expert knowledge in the Bayesian model viable for application. As we have already demonstrated in this work, application of simulated data is possible, without contradicting the fundamentals of Bayesian theorem.

In this study, we did not discuss the continuous assessment of risk in the proposed Bayesian model but only demonstrated its application with two consecutive rainfall episodes. However, in practice, the model needs to be updated continuously, which is beyond the scope of this work.

The proposed methodology has an advantage in that it does not intend to substitute the conventional FFG system but rather it is a complementary tool to the existing systems. Moreover, the proposed methodology can be applicable as a ready tool, separate from deterministic models wherever the former is inconsistent or non-existent.

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