INVESTIGATION OF THE EFFECT OF INTERCEPTION AND EVAPOTRANSPIRATION ON THE RAINFALL-RUNOFF RELATIONSHIP USING BAYESIAN NETWORKS

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ABSTRACT

In recent years Bayesian networks have been often used to model and analyze complex relationships between input and output data. In the hydrological sciences, such a relationship is the one describing one of the complex natural phenomena, the rainfall-runoff process. Because of the highly nonlinear nature of this relationship, it is not easy at all to account for any kind of inherent uncertainty. The present study contributes in confronting the uncertainties in streamflow predictions and in better understanding the spatial variability of this hydrological phenomenon, which is quite important in hydro-climatological time series analyses and equally significant in water resources management approaches.

A Bayesian network is a kind of decision support system based on probability theory and inference making using the Bayes rule. This rule describes mathematically how existing beliefs can be modified with the input introduction of new evidence. This property makes Bayesian Networks a powerful and widespread tool in many areas of artificial intelligence and statistics because of efficient algorithms that make probabilistic inference effective in highly-structured problem domains. The significant contribution of the Bayesian method is the uncertainty estimation of the outputs in the form of confidence intervals, which are particularly needed in practical water resources applications.

The objective of this paper is to illustrate how Bayesian models could be developed to provide a formal framework for estimating the uncertainty in hydrologic scaling relationships, such as the rainfall-runoff relationship. More analytically, in the present study a Bayesian network is introduced to simulate the relationship between rainfall and runoff in a mountainous watershed in North California. The model is tested using daily rainfall and streamflow data series from the drainage basin. It is shown that the model can successfully approximate the rainfall-runoff relationship and efficiently estimate the resulting streamflow.

Keywords
Bayesian networks, rainfall, runoff, watershed, uncertainty

1. INTRODUCTION

Precipitation, snow, interception and evapotranspiration are the dominating factors affecting the water flow on any mountainous watershed surface. Precipitation and snow is water delivered to Earth from the atmosphere and they are the major water sources in a mountainous system in addition to streams, springs, soil moisture, groundwater, and vegetation. Before reaching the ground, part of precipitation and snow will be intercepted and retained by the forest canopy and ground litter (Chang, 2006). The amount of precipitation intercepted by the forest canopy has been determined indirectly from the difference between the measured precipitation and the amount reaching the ground as throughfall rain and stemflow (Johnson, 1990). A similar way of defining rainfall interception is commonly determined by comparing rain amounts measured above a forest canopy or in an open site against throughfall measured below a forest canopy (Ward and Trimble 2003). From this process a portion of the rainfall and snow water never reaches the ground because it vaporizes back to the air and the amount of interception loss is determined by storm and forest characteristics (Chang, 2006).

The intercepted amounts of rainfall vary considerably between 10% and 30% (Landsberg et al, 1997) and depend on forest composition, tree geometrical characteristics and seasonal changes in foliage cover. In snow-affected zones, like the watershed of the present case-study area, canopy interception of snowfall can become as high as 30% of precipitation in dense forests and as important as rainfall interception during the winter period (Lundberg and Koivusalo, 2003). Canopy interception of precipitation and snow by forest stands is significant, particularly in coniferous forests like the pine forest of our research area. The main process responsible for changes in water yield as a result of alterations in vegetation at the mean annual scale is evapotranspiration (Zhang et al, 2001). Changes in forest composition, structure, or density that reduce evapotranspiration rates generally increase water yield from mountainous watersheds. A number of studies have shown that annual water yield can increase between 15 and 500 mm with forest removal, although these changes often last for only a few years and depend on many parameters like climate, soil characteristics, and percentage and type of vegetation removal (Brown et al, 2005).

A large number of models have been developed to simulate the relationship of rainfall-runoff. These models are categorized as empirical, black-box, conceptual and physically-based models. Among them, this particular physical phenomenon has been simulated with two feed-forward neural networks trained with the backpropagation algorithm. The first was a simple three-layer network with one hidden layer while the second one was more complicate with four layers (two hidden layers). Results show that the simple feedforward neural network produced better prediction performance efficiencies than the multiple neural network with two hidden layers (Botsis and Latinopoulos, 2010). In addition, the application of neural networks in rainfall-runoff relationship was investigated with one simple feed-forward neural network, the results of which show that the neural networks are usually capable of representing either normal or extreme flow conditions (Triantafyllou et al, 2011). Moreover, an application of a support vector regression (SVR) model for the simulation of the rainfall-runoff relationship depicted some important issues of nonlinear models applying in runoff forecasting. Next, a comparison was made between support vector regression and neural networks models, which showed that SVR can replace some of the neural network models for weather prediction applications (Botsis et al, 2011). These models are of the black-box type and it is important to compare them with more sophisticated models like Bayesian networks. These can estimate the parameters of the water-balance system with probabilities. This is a unique advantage, especially in cases where some parameters are difficult to measure, like interception and evapotranspiration. Herr and Krzysztofowicz (2010) present how the analytic-numerical Bayesian forecasting system can be used as a generator of the Bayesian ensemble forecast of river stages and investigate the sample size requirements for ensemble forecasts. Reggiani and Weerts (2008) presented an application of a Bayesian processor to asses the predictive uncertainty on water level predictions in the river Rhine flood forecasting system.

In the present paper a Bayesian approach to estimate the effects of interception and evapotranspiration in runoff prediction is introduced. The research work described herein focuses on in the rainfall-runoff relationship and aims at confronting the uncertainties in streamflow predictions. The success of this approach depends on the accuracy of the input data of Bayesian network (rainfall-snow and streamflow measurements) and on the accuracy estimation of the conditional probability table (CPT) of two variables, namely interception and evapotranspiration. The developed Bayesian network model is applied to a time series of daily rainfall and runoff measurements in a mountainous forested watershed.

2. METHODOLOGY

2.1 Bayesian networks

A Bayesian network (BN) is a decision support system that is successfully used for many years in numerous and diverse research fields, such as hydrology and artificial intelligence. Bayesian networks simulate the operation of natural systems, and are most effective when designed and set up with data and measurements of some field variables. In this work the water balance of a mountainous forested watershed is studied. More specifically, the relationship of rainfall-runoff, which is one of the most complicate hydrologic phenomena, is thoroughly investigated. It should be noted that the water balance of the watershed and the ultimate rate of runoff depend directly on interception and evapotranspiration. Bayesian networks are a type of decision support system based on a theory of probability using Bayes' rule, which describes mathematically how existing beliefs can be modified with the introduction of new evidence. The two fundamental rules of probability theory have the form of equations (1) and (2).

$$sum\ rule\ p(X) = \sum_Y p(X,Y) \tag{1}$$

$$product\ rule\ p(X,Y) = p(Y|X) \cdot p(X) \tag{2}$$

The probability that X will take the value x_i *and* Y will take the value y_j is written as $p(X=x_i, Y=y_j)$ and it is called the joint probability of $X=x_i$ and $Y=y_j$. The sum rule of probability $p(X=x_i)$ is sometimes called the marginal probability, because it is obtained by marginalizing, or summing out, the other variables (in this case Y):

$$p(X = x_i) = \sum_{j=1} p(X = x_i, Y = y_i) \tag{3}$$

If considering only those instances for which $X = x_i$, then the fraction of such instances for which $Y = y_j$ is called the conditional probability of $Y=y_j$ given $X=x_i$ and it is written as $p(Y=y_j|X=x_i)$. Here p(X,Y) is a joint probability and is verbalized as "the probability of X and Y". Similarly, the quantity p(Y|X) is a conditional probability and is verbalized as "the probability of Y given X", whereas the quantity p(X) is a marginal probability and is simply "the probability of X". From the product rule, together with the symmetry property p(X,Y) = p(Y,X), one can immediately produce the following relationship between conditional probabilities, which is called Bayes' theorem (Bishop, 2006).

$$p(Y|X) = \frac{p(X|Y) \cdot p(Y)}{p(X)} \tag{4}$$

Equation (4) constitutes the relationship between the probabilities p(X) and p(Y) and the conditional probability of X given Y. If the joint distribution of two variables factorizes into the product of the marginals, so that p(X,Y) = p(X)p(Y), then X and Y are said to be independent. From the product rule, it follows that p(Y|X) = p(Y), and so the conditional distribution of Y given X is indeed independent of the value of X. In the Bayesian approach, neither a real distinction between "knowns" and "unknowns" nor a distinction between "variables" and "parameters" is made. The distinction is rather between "a priori" variables and parameters (values for parameters and variables that were measured, estimated, or taken from the literature), and "posterior" values (most likely values for parameters and variables, taking into account all a priori values and their uncertainty and using the model) (Van der Tol et al, 2009). Bayesian networks have been used to model a variety of environmental systems (Kragt, 2009). This paper describes a BN developed in the context of catchment water resources management. The focus of this application is in the generation of a model for better understanding of the catchment processes and especially the effect of interception and evapotranspiration in the rainfall runoff relationship. Moreover, this study aims in methodically dealing with the uncertainties in streamflow predictions and in appreciating the spatial variability of this hydrological phenomenon, which is important for hydro-climatological time series analyses and for water resources management applications. Finally, it is shown how BNs can be used to support catchment decision making.

2.2 Data preparation

The precipitation data from four meteorological stations and the streamflow data in the catchment area of the case study are used as inputs in the BN. Precipitation data were obtained from the California Data Exchange Center (Department of Water Resources), while streamflow data were taken from the U.S. Geological Survey. Precipitation measurements are the aggregate of daily rainfall and daily water content of snow for 21 years in the period from 31-01-1989 to 31-01-2011.

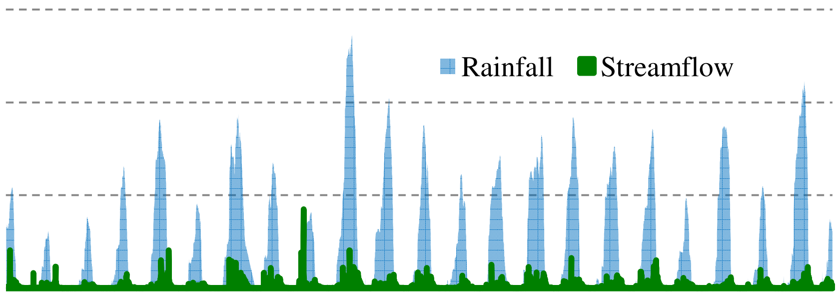

Figure 1: Time series of rainfall and streamflow data

The daily streamflow measurements for the same period are those of the Trinity River in Northern California. The data were first preprocessed by using interpolation to correct measurement errors with exceptionally extreme values and for completing missing data in the time series. Then, for the rainfall measurements, we used the method of arithmetic mean is used to calculate the average value of daily rainfall from the values of four meteorological stations. The Bayesian approach is applied using the preprocessed time series of rainfall and streamflow as model inputs. Figure 1 shows the preprocessed time series for rainfall and streamflow data.

2.3 Rainfall-runoff model

In the BN model developed in this study, the state of the factor *streamflow* depends on the states of three other factors: *rainfall*, *interception* and *evapotranspiration*. This means that if the rainfall, interception, and evapotranspiration alltogether, or just any one of them is changed then the streamflow will also change. Consequently, streamflow is considered conditionally dependent on the states of these factors. In Figure 2 the dependence between the problem's critical factors (variables) is indicated by a simple graph, where the factors are represented by nodes and their mutual dependences by arrows. Note that the directions of arrows indicate the cause-effect processes and their feasibility. Referring to the graph in Figure 2, it is clear that, while changes in rainfall, interception and/or evapotranspiration values can all affect streamflow rates, a reverse process is not feasible.

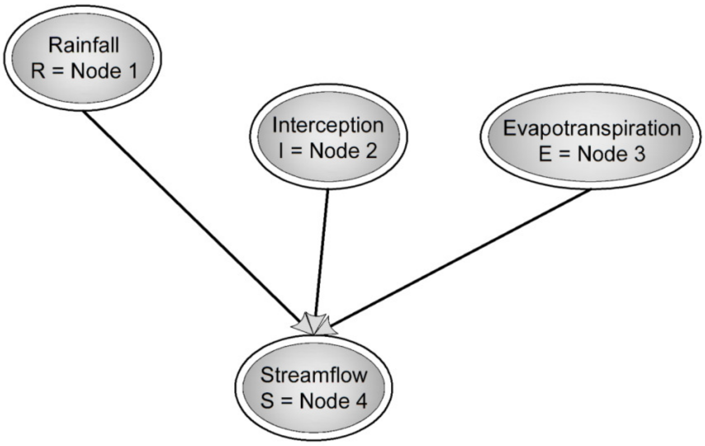

Figure 2: Bayesian Network

The BN model comprises three components: (a) a set of variables that represent the factors relevant to watershed water balance, (b) the links between these variables and (c) the CPTs behind each node that are used to calculate the state of the node. Where two nodes are linked the destination node is termed the *'child'*, the node from which the link originates is known as the *'parent'* (Bromley, 2005). In our application the variables *rainfall (R)*, *interception (I)* and *evapotranspiration (E)* are the *parents* and the variable streamflow is the *child*. Moreover, the links represent a possible action or an observed condition between the *parents* and the *child* that is the effect of water balance variables in the streamflow. The links represent different scenarios that might arise between the variables. All network nodes have three possible states: low, medium and high. The time series for *rainfall* and *streamflow (S)* were quantized into low, medium and high levels using appropriate limits based on the available data measurements. Rainfall (and snow) data were divided into three subfields using the following limits.

$$\left(0, \tfrac{1}{3} maxR\right), \left(\tfrac{1}{3} maxR, \tfrac{2}{3} maxR\right), \left(\tfrac{2}{3} maxR, maxR\right) \qquad (5)$$

The streamflow measurement data were divided into three groups of equal size in order to avoid having very few data in any group. For the interception and evapotranspiration variables there are no measured data, so they were quantized and the corresponding conditional probability tables were constructed by using appropriate limits drawn from the literature. The data of the literature that supported the formation of the conditional probability tables were based on observations of the effect of interception and evapotranspiration in streamflow. The key to constructing a good network is to have the best available data with which to construct the CPTs, although the best data available may be imperfect and not fully reliable. A particular strength of Bayesian networks is that they will accommodate any type of data, but of course the less reliable the information the more uncertain will be the result and the wider the distribution of probabilities. In some instances the data for a variable are non-existent and in these cases it may be necessary to rely on expert opinion (Bromley, 2005). It is known that changing the evapotranspiration or interception will have an impact on the runoff potential. But to quantify 'potential' is difficult, and relevant data is unlikely to exist. In this study, data and information from observations of forested mountainous watersheds from a number of studies used to complete the CPTs of $P(S|I)$ and $P(S|E)$. With this type of subjective input the degree of uncertainty is likely to be greater than that obtained from measured data, but the ability to use this type of input enables the Bayesian networks to overcome potential problems of data scarcity.

Table 1 shows the probability of S (streamflow) being in any particular state (s_1, s_2, s_3) given a state of I (interception - i_1, i_2, i_3) and it can be written as P(S│I). For example if interception is in state i_3 (high), the probability of streamflow being in state s_1 (low) is 0.6 (60%), s_2 (medium) is 0.3 (30%) and s_3 (high) is 0.1 (10%). In the same way Table 2 depicts the probability of S being in any particular state (s_1, s_2, s_3) given a state of E (evapotranspiration - e_1, e_2, e_3) and it can be written as P(S│E). For example if evapotranspiration is in state e_2 (medium), the probability of streamflow being in state s_1 (low) is 0.35 (35%), s_2 (medium) is 0.5 (50%) and s_3 (high) is 0.15 (15%). Note that each column must add up to 1 and the probabilities given are based on the fact that variables I and E have a 100% probability of being in state i_1, i_2 or i_3 and e_1, e_2 or e_3. But in reality it is unlikely to be certain of the state of interception and evapotranspiration and especially in all the surface of the mountainous forested catchment. There will always be some uncertainty in the determination of parameters which are affecting in the water balance of a basin. Applying Bayes theorem in the present case study leads equation 4 to the following form:

$$p(S|R,I,E) = \frac{p(R,I,E|S) \cdot p(S)}{p(R,I,E)} \quad (6)$$

Equation (6) provides the conditional probability of S given R, I, E.

Table 1: Conditional probability table P(S│I)

CPT - Conditional Probability Table - P(S│I)		Interception (Variable I)		
		Low (i_1)	Medium (i_2)	High (i_3)
Streamflow (Variable S)	Low (s_1)	0.1	0.3	0.6
	Medium (s_2)	0.3	0.5	0.3
	High (s_3)	0.6	0.2	0.1

Table 2: Conditional probability table P(S│E)

CPT - Conditional Probability Table - P(S│E)		Evapotranspiration (Variable E)		
		Low (e_1)	Medium (e_2)	High (e_3)
Streamflow (Variable S)	Low (s_1)	0.05	0.35	0.65
	Medium (s_2)	0.3	0.5	0.3
	High (s_3)	0.65	0.15	0.05

Interception and evapotranspiration fluxes between the land surface, the forest canopy and the atmosphere are important components of the water balance in mountainous watersheds.

Figure 3: The case study watershed in Northern California

Our model network is applied to the study of the affect of interception and evapotranspiration in the rainfall-runoff relationship in a mountainous forested watershed which is located in Northern California (Figure 3). This region has the same geographic latitude as Northern Greece. The watershed size is about 385.9 km^2 and the larger part of the catchment surface is covered by pine forest.

3. RESULTS

The initial plan of this study was to design a BN in order to investigate the water balance of mountainous forested watersheds and, in addition to that, to focus in the uncertainty inherent in this complex hydrological phenomenon. The developed BN model is indeed able to calculate the effect of interception and evapotranspiration in rainfall-runoff relationship and in streamflow prediction.

Table 3: Results of Bayesian network

P(S│R,I,E)										
	R=1	R=2	R=3	R=1	R=2	R=3	R=1	R=2	R=3	
I=1	0.0179	0.0000	0.0000	0.2857	0.0584	0.0225	0.6964	0.9416	0.9775	
I=2	0.0705	0.0000	0.0000	0.6248	0.2367	0.1032	0.3046	0.7633	0.8968	E=1
I=3	0.2111	0.0000	0.0000	0.5610	0.2712	0.1214	0.2279	0.7288	0.8786	
	S=1			S=2			S=3			
	R=1	R=2	R=3	R=1	R=2	R=3	R=1	R=2	R=3	
I=1	0.1645	0.0000	0.0000	0.6246	0.3094	0.0370	0.2108	0.6906	0.9630	
I=2	0.3075	0.0000	0.0000	0.6487	0.6914	0.4540	0.0438	0.3086	0.5460	E=2
I=3	0.5994	0.0000	0.0000	0.3793	0.7289	0.4994	0.0213	0.2711	0.5006	
	S=1			S=2			S=3			
	R=1	R=2	R=3	R=1	R=2	R=3	R=1	R=2	R=3	
I=1	0.4071	0.0000	0.0000	0.4993	0.4464	0.2304	0.0936	0.5536	0.7696	
I=2	0.5858	0.0000	0.0000	0.3992	0.8013	0.5995	0.0150	0.1987	0.4005	E=3
I=3	0.8259	0.0000	0.0000	0.1688	0.8287	0.6423	0.0053	0.1713	0.3577	
	S=1			S=2			S=3			

In Table 3, the posterior probability of low (S=1), medium (S=2) and high (S=3) streamflow is produced by different scenarios of possible states of the other three parameters: rainfall, interception and evapotranspiration. For the case of high streamflow results show that when the interception and evapotranspiration are increased, the streamflow is decreased, but in the state of high rainfall the effect of water balance parameters is sensibly lower. The BN results show also that the probability of generating low streamflow is zero when rainfall values range from medium to high. When rainfall is low the probability of generating low streamflow values varies, depending on the states of both interception and evapotranspiration. Specifically, when the interception and evapotranspiration change (from low to medium and to high range) the probability of low streamflow increases. More balanced seem to be the results in the case of medium streamflow, a fact showing more clearly the effect of interception and evapotranspiration. In Figure 4 the results of the model for the case of high rainfall, expressed as percentages, are presented.

Table 4 presents the percentage change of probabilities of high streamflow for all combinations of interception and evapotranspiration, when the state of rainfall changes first from low to medium and secondly from medium to high. For example for low interception and low evapotranspiration the probability increase of high streamflow is 35.21% from low to medium rainfall. For the same state of interception and evapotranspiration the probability increase of high streamflow is 3.81% from medium to high rainfall.

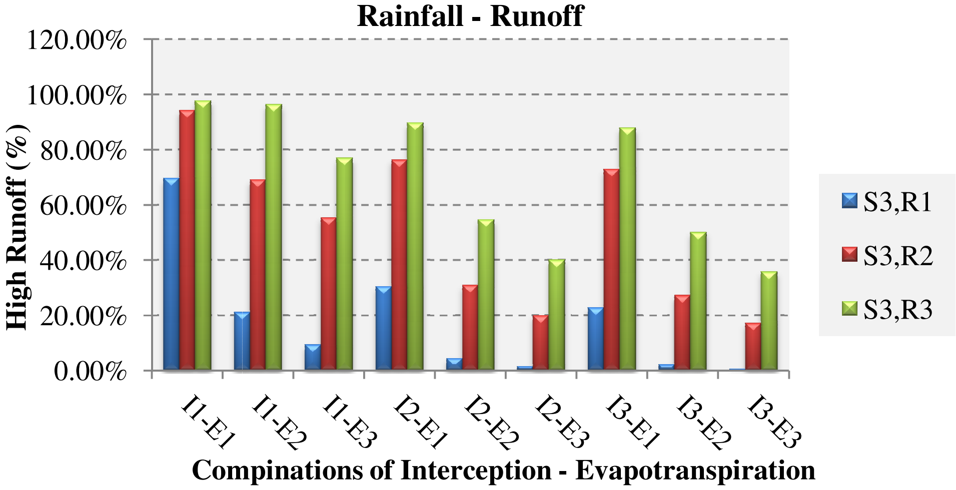

Figure 4: Results of Bayesian Network for high rainfall

From this result we conclude that, as long as the storm events are more rapid, the effect of interception in the final runoff is lower. On the other hand when the state of rainfall changes from medium to high, the percentage change of high rainfall probability is extremely lower. The second result is probably due to small differences between low and high ranges of rainfall. Figure 5 presents the results of table 4. It should be also noted the great difference in high streamflow between the rainfall states low-medium and medium-high.

Table 4: Comparison between different states of rainfall

	R=1 – R=2	R=2 – R=3	
I=1	35.21%	3.81%	
I=2	227.61%	39.44%	E=1
I=3	491.45%	39.02%	
	S=3		
	R=1 – R=2	R=2 – R=3	
I=1	150.59%	17.49%	
I=2	604.57%	76.93%	E=2
I=3	1224.67%	101.56%	
	S=3		
	R=1 – R=2	R=2 – R=3	
I=1	219.79%	20.55%	
I=2	1172.77%	84.66%	E=3
I=3	3132.08%	108.81%	
	S=3		

Coupé and van der Gaag (2002) propose an empirical approach to sensitivity analysis, based on changing each of the parameters and observing the related changes in the posterior probabilities. In their study the sensitivity analysis was used to identify the most ‘sensitive set’ of variables in the Bayesian network. So the values of CPTs of evapotranspiration and interception were change into a particular percentage and the variations of the model's output were examined for every evidence. The variations in parameters in a percentage of 10% did not significantly affect the model's behavior.

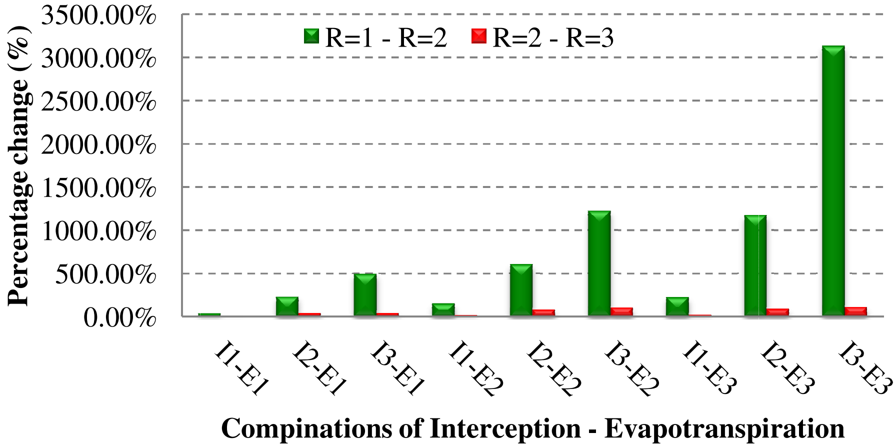

Figure 5: Streamflow compare between different states of rainfall

4. CONCLUSIONS

The presented BN efficiently models the effects of interception and evapotranspiration in the rainfall-runoff relationship. The advantage of the proposed methodology is its very simple operational procedure, based solely on rainfall-runoff measurements and two conditional probability tables, those for the interception and evapotranspiration variables. Moreover the Bayesian approach has the advantage of identifying hydrological variables that are very difficult or impossible to measure accurately over the entire surface of the basin.

The results from the BN application follow the reasonable rule of physical hydrological phenomena that the storm events generate floods. Moreover it is predictable that the effect of interception and evapotranspiration reduce the final amount of runoff. The most remarkable results of the BN model are the probabilities of generating high streamflow, because the high runoff in a water basin creates floods. Probably, the most important aspect of this work is that we focus in the uncertainty of the complex hydrological phenomenon of water balance in forested mountainous watersheds. The study tries to determine the percentage of effect of interception and evapotranspiration in streamflow and to calculate the likelihood of generating the streamflow. The results show that the values of interception and evapotranspiration are decisive in final streamflow generation. Yet, in storm events the effect of these hydrological variables is less than the cases of customary rainfalls.

The Bayesian technique for estimating the probabilities of generating low, medium and especially high streamflow in watersheds is open to a wide range of possible applications. It is particularly useful in flood forecasting applications, where reliability and reduction of uncertainty in the results are the major requirements. The test on measurement data of rainfall and streamflow has demonstrated the efficiency of the technique and application to measurements data has giver qualitative confirmation of the improvements that can be obtained by its application. Todini (2001) arrives at the same conclusion by combining, in a Bayesian sense, weather radar-based rainfall estimates with rain-gauge measurements. The assessment of the effects of time variations in the rainfall spatial co-variance structure as a function of the different weather types and the application of the model in a variety of watersheds with different characteristics will contribute to the improvement of the BN in rainfall-runoff modeling.

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