Integrated methodological framework for assessing the risk of failure in water supply incorporating drought forecasts. Case study: Andean regulated river basin

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ABSTRACT

Hydroclimatic drought conditions can affect the hydrological services offered by mountain river basins causing severe impacts on the population, becoming a challenge for water resource managers in Andean river basins. This study proposes an integrated methodological framework for assessing the risk of failure in water supply, incorporating probabilistic drought forecasts, which assists in making decisions regarding the satisfaction of consumptive, non-consumptive and environmental requirements under water scarcity conditions. Monte Carlo simulation was used to assess the risk of failure in multiple stochastic scenarios, which incorporate probabilistic forecasts of drought events based on a Markov chains (MC) model using a recently developed drought index (DI). This methodology was tested in the Machángara river basin located in the south of Ecuador. Results were grouped in integrated satisfaction

indexes of the system (DSI_G). They demonstrated that the incorporation of probabilistic drought forecasts could better target the projections of simulation scenarios, with a view of obtaining realistic situations instead of optimistic projections that would lead to riskier decisions. Moreover, they contribute to more effective results in order to propose multiple alternatives for prevention and/or mitigation under drought conditions.

Keywords: Risk assessment, probabilistic drought forecasts, simulation of stochastic scenarios, water resource systems management

1 Introduction

In Andean river basins, drought events are affecting water availability for the multiple uses of lowland residents, causing harmful social, economic and ecological impacts. The development of methodologies for the characterization and forecasting of drought events provides a good support for water managers with a view to make appropriate decisions for a reliable water supply and adverse to the risk of failure (Avilés et al. 2016).

In order to improve the ability to characterize and predict drought events, water managers use information expressed in index form (Svoboda et al. 2004; Shukla and Wood 2008). Different hydrological and climatic conditions in a river basin discourage the use of some indexes, given the specific information and calculation process to develop these indicators (Mishra and Singh 2010; Barua et al. 2012). In fact, the characterization of droughts requires indicators that are generally applicable, but also indicators specific for a region in order to capture the type of droughts with the available information (Staudinger et al. 2014). Moreover, these indicators must reflect the succession of several events of water scarcity during different time periods (Kao and

Govindaraju 2010). Consequently, this study uses the drought index (DI) developed by Avilés et al (2015), which presents the advantage of grouping available information on variables related to water including different time scales in a single index that identifies the frequency and severity of several drought events.

On the other hand, reliable and timely drought events forecasts play an important role in decision-making in order to reduce the impacts of this phenomenon on water resource systems (Madadgar and Moradkhani 2013; Madadgar and Moradkhani 2014). A large number of models provide a prediction of drought states without considering the uncertainty associated with forecasting (Hwang and Carbone 2009). This aspect can be handled with probabilistic forecasts, which offer a prediction associated with its uncertainty quantitatively (Hwang and Carbone 2009; Avilés et al. 2016). Several authors have developed probabilistic drought forecast models, but few of them are able to predict probabilistically future droughts given the information of previous events (for instance, using the conditional probability). Such is the case of the large majority of common models based on MC (Ochola and Kerkides 2003; Paulo and Pereira 2007; Cancelliere et al. 2007; Nalbantis and Tsakiris 2009; Avilés et al. 2015; Avilés et al. 2016; Khadr 2016; Mahmoudzadeh et al. 2016) and the most sophisticated models based on Bayesian networks (BN) (Madadgar and Moradkhani 2013; Madadgar and Moradkhani 2014; Avilés et al. 2016; Chen et al. 2016; Phan et al. 2016). These two approaches were compared recently by Avilés et al. (2016) through the ranked probability skill score (Wilks 2011) , who concluded that models based on MC proved to be equally efficient to predict probabilistically drought events as models based on BN. Nevertheless these authors highlight the best performance of the first order MC model (MCFO) with a view to predict wet and dry periods. For this reason, this study uses the MCFO model in order to predict probabilistically drought events, which have the advantage of being one of the most used models in stochastic processes of discrete time series, highlighting its simple calculation approach and lower computational costs.

The characterization and forecasting of drought events could improve the management and operation of water resource systems. However, obtaining indicators that quantify the risk of failure and the satisfaction of a set of demands could represent a reliable option to improve the information for decision-making, which aims to minimize or mitigate the effects of drought on water resources systems in regulated river basins (Haro et al. 2014). For this purpose Monte Carlo simulation is perhaps the most widely employed method to evaluate the risk of failure and to quantify the deficit in water supply. This approach has been exposed in several studies (Sánchez et al. 2001; Cancelliere et al. 2009; Rossi et al. 2012; Andreu et al. 2013; Avilés and Solera 2013; Rossi and Cancelliere 2013; Haro et al. 2014; Haro-Monteagudo et al. 2017; Vogel 2017), which consists of the generation of multiple probable scenarios by using synthetic generation models. In this study we chose the first-order multivariate periodic autoregressive models (MPAR1) to generate multiple hydrological synthetic series. These models offer the advantage of representing adequately the temporal (autocorrelation) and spatial correlation (cross-correlation) of time series, and they can also be characterized by different dependency structures for each season of the year (Sveinsson et al. 2007; Cancelliere et al. 2009).

Some water managers generally prefer not to deviate from their usual practices (Gong et al. 2010). This may result in decisions towards the average conditions and a distancing from extreme conditions, with the consequent decrease in effectiveness of decision-making. In this sense, managers sometimes prefer to incorporate forecasts of hydrometeorological variables within their management tools. The purpose of this approach is to understand the sensitivity of the water resource system with respect to the satisfaction of demands and to improve the evaluation of the possible risks of shortages, achieving more certainty in their decisions (Brown et al. 2010; Gong et al. 2010). The forecasts combined with multiple simulation tools could condition and limit future scenarios, facilitating water availability prediction and the simulation of water supply to different demands (Brown et al. 2010). Therefore, the purpose of this study is to develop an integrated methodological framework for assessing the risk of failure in water supply through the incorporation of probabilistic drought predictions. This approach could help to address possible scenarios and to analyze more realistic situations of risk of failure in water resource allocation for the different uses. Moreover, this methodology may provide support to water managers and reduces uncertainty in decision-making to enhancing measures to prevent or mitigate the impacts of water scarcity.

2 Methods

Following the methodology based on Montecarlo simulation, the assessment of the risk of failure was developed by analyzing multiple situations of water resources management. For the application of this methodology AQUATOOL Decision Support System (DSS) (Andreu et al. 1996) was employed and, more specifically the module for the simulation of water resources systems management (SIMGES) (Andreu et al. 2007) and the module for risk management evaluation (SIMRISK) (Sánchez et al. 2001). The simulation process in SIMGES consists of a conservative flow network that is optimized monthly by linear programming with the Out-of-Kilter algorithm (Bazaraa et al. 2011), to maximize a target function (satisfaction of demands and storage of reservoirs) subject to restrictions of mass conservation and physical limits of flow transport in channels and reservoir capacities. This simulation process for several scenarios is done by running SIMRISK model. It is based on the Monte Carlo simulation and assesses the risk of failure in water supply. The outputs of this model are probabilistic information that allows analyzing the number of failures in the system and their severity. Through this information, decision makers are able to formulate prevention and/or mitigation measures to address risk and maximize system performance (Cancelliere et al. 2009; Haro et al. 2014). This methodology is presented in the Figure 1 by the non-shadowed forms and it consists of the following steps:

i) Using a stochastic model of monthly river flow time series, a synthetic hydrological generation is completed conditioned to the previous observations, which generates multiple scenarios of possible future river flows;

ii) With the multiple generated scenarios, the current features of the water exploitation system and the management rules of the system, multiple simulations of future management are performed;

iii) The results of the multiple simulation are analyzed statistically in order to obtain the probabilities of failure of the demands;

iv) The information provided in the previous step determines the state of the system and supports the decision-making process about the admissibility or not of the risk;

v) When the risk is not accepted, then new alternatives of management are formulated, which feedback the multiple simulation model (step 2). The following steps are repeated until making a new decision about whether the risk is acceptable or not. This process is replicated repeatedly until the risk associated with the decision is appropriate.

This study proposes an integrated methodological framework that is shown in Figure 1 by the non-shadowed and shadowed forms, the latter are described below:

i) The generation of probabilistic drought forecasts is performed by the development of a drought index (DI) and the previous drought states using a drought forecast model.

ii) The probabilistic drought predictions are introduced in the synthetic generation of hydrological time series.

iii) The previous drought states are also introduced in the simulation of the future management of multiple scenarios;

iv) The results of the multiple simulations provide several indicators of risk of failure in water supplies through a statistical analysis. These indicators are grouped to build integrated demand satisfaction indexes, which will serve to make decisions on the management of the system;

v) When satisfaction index is not acceptable, management alternatives are re-formulated and the simulation of future management with multiple scenarios is run again (step 3);

vi) This process is repeated until an acceptable satisfaction index is achieved.

Each step of the methodology is detailed below.

2.1 Drought index

For the construction of the DI, a similar calculation exposed by Keyantash and Dracup (2004) is used, where the available information of the r water-related variables are subjected to a Principal Component Analysis (PCA). The PCA-derived eigenvectors establish the relationship between the principal components (PCs) and the original data:

$$S = D * E \quad (1)$$

where S is the matrix (w x r) of the PCs (where w is the number of observations), D is the matrix (w x r) of the original standardized information, and E is the matrix (r x r) of the eigenvectors. The DI is the first major component (PC1), normalized by its standard deviation:

$$DI_{i,k} = \frac{S_{i,1,k}}{\sigma_k} \quad (2)$$

where $DI_{i,k}$ is the value of the DI for month k in year i, $S_{i,1,k}$ is the PC1 during year i, for month k, and σ_k is the standard deviation of the sample of $S_{i,1,k}$. Once the DI values are calculated for each year and each month, they are rearranged in chronological order in a single time series.

The DI is a standardized index capable of capturing the anomalies of the average moisture conditions in a river basin based on the available information of water related variables (Kao and Govindaraju 2010; Madadgar and Moradkhani 2013). Any phenomenon that can be continually quantified, such as the drought index, can be treated as a discrete variable by categorizing the time series considering the thresholds for each drought state (Avilés et al. 2016). Therefore, the DI, as a standardized variable, is divided into categories to characterize the drought states, using the same thresholds as the World Meteorological Organization (2012). Regarding this latter reference, the categories considered are the following: $DI > 0$ = category 0 (not drought); $-1 < DI \leq 0$ = category 1 (mild drought); $DI \leq -1$ = Category 2 (moderate, severe and extreme drought). The three states of category 2 are taken as a single state called drought. This monthly time series of categorical values is the input of the MC model.

2.2 Markov chain model

The behavior of MC models is governed by a set of transition matrices that indicate the probabilities of occurrence of the states of a system for a future time interval given the current status information and/or past interval states, depending on the order of the model. The Markovian property of the m^{th} order MC model is:

$$P\left(Y_{tn}\middle|Y_{tn-1}, Y_{tn-2,}Y_{tn-3,} \dots, Y_1\right) = P\left(Y_{tn}\middle|Y_{tn-1}, Y_{tn-2,} \dots, Y_{tn-m}\right) \quad (3)$$

Considering a MCFO model, that is, m = 1, the transition probabilities provide the probabilistic state forecast one step forward based on the current state, applying the following formula:

$$p_{ij} = P(Y_{tn} = j|Y_{tn-1} = i) \quad (4)$$

where p_{ij} represents the transition probability that Y_{tn} is equal to category j given that Y_{tn-1} equals category i. The estimated transition probability $\hat{p}_{ij}$ can be calculated by taking into account the conditional relative frequencies of the transitions (f_{ij}):

$$\hat{p}_{ij} = \frac{f_{ij}}{\sum_j f_{ij}} \quad i, j = 1, \dots, s \quad (5)$$

where f_{ij} is the frequency that Y is equal to category i at time t_{n-1} and equal to category j at time t_n. The value of s is the number of states of the system. The numerator presents the number of transitions from category i to category j and the denominator represents the sum of the number of transitions from category i to any other category.

2.3 Incorporation of probabilistic drought forecasts in the generation of hydrological synthetic series

The MPAR1 model is used to generate multiple hydrological synthetic series. These models can be expressed as:

$$\mathbb{Z}_{\upsilon,\tau} = \phi_{1,\tau}\,\mathbb{Z}_{\upsilon,\tau-1} + \mathcal{E}_{\upsilon,\tau} \tag{6}$$

where, $\mathbb{Z}_{\upsilon,\tau}$ is a column vector [q x 1] of the q inflows (normalized and standardized) to the reservoirs in the water exploitation system with zero mean and unit variance for year ν and month τ. $\phi_{1,\tau}$, are the matrices [q x q] of periodic autoregressive parameters of order 1 for each month, and $\mathcal{E}_{\upsilon,\tau}$ is the column vector [q x 1] of the normally distributed independent noise terms with mean zero and matrices [q x q] of variance-covariance $\mathbb{G}_{\tau}$. The MPAR1 model is adjusted (parameter estimation) through the method of moments. In order to ensure the collection of a normally distributed independent noise, a large number of random numbers must be generated, so that the statistics of the probability distribution are fulfilled. Therefore, ten thousand random numbers for $\mathcal{E}_{\upsilon,\tau}$ are generated by a truncated multivariate normal distribution with mean zero and variance-covariance matrices $\mathbb{G}_{\tau}$ in three intervals: 1) From the maximum value of $Z_{\upsilon,\tau}$ of each monthly time series to the value of $Z_{\upsilon,\tau} = 0$; 2) From the value of $Z_{\upsilon,\tau} = 0$ to the value of $Z_{\upsilon,\tau} = -1$; and 3) From the value of $Z_{\upsilon,\tau} = -1$ to the minimum value of $Z_{\upsilon,\tau}$ of each monthly series. These intervals are analogous to the non-drought, mild drought and drought states, respectively, on the DI scale. Each interval corresponds a fraction of the 10000 random numbers, which is equal to the probabilistic predictions of each drought state (in other words, the probabilistic forecast of the states: non-drought, mild drought and drought become a percentages of the 10000 random numbers for the first, second and third interval, respectively).

For the previous values (τ-1) we assume the following: 1) Value of $\mathbb{Z}_{\upsilon,\tau-1} = 0$, equal to the average value of each monthly time series; 2) Value of $\mathbb{Z}_{\upsilon,\tau-1} = -1$; and 3) Minimum value of $\mathbb{Z}_{\upsilon,\tau-1}$ of each monthly time series (analogous to the lower limits of each drought states on the DI scale). Using Equation 6 a prediction of the distribution function of the possible values of $\mathbb{Z}_{\tau}$ conditioned to the previous values $\mathbb{Z}_{\tau-1}$ is obtained. This procedure is carried out twelve times ahead to obtain 10000 synthetic series of 12 months each. This considerable amount of generated series is able to capture all, or a large part, of the variability of water inflows to reservoirs, addressing a large part of the uncertainty of these variables. The multiple time series are the input information for the simulation model.

2.4 Multiple simulation model for failure risk assessment

The simulation period is 12 months with the purpose of operating and managing the system within a year. The simulation scenarios for the risk of failure assessment model are built considering the simulation starting month, initial storage volume of the reservoirs, previous drought states and the previous hydrological conditions. The latter two conditions are also used in the generation of synthetic series.

During each month of the simulation period for each scenario, demands may receive a supply higher or equal to the value required (satisfaction status), or a lower value (dissatisfaction status). In the latter case, there will have a supply failure with a deficit (D) equal to the demand value minus the quantity of water supplied. The severity level of the deficit D will depend on the amount of water supplied with respect to the quantity required; therefore the supply is divided into different levels representing the fraction of the quantity of water required by a demand. Level 1 (n1) is the most serious situation, it means that the deficit exceeds 75% of the demand, this is, the supply is between 0 and 25% of the value required; level 2 (n2) means that the supply represents between 25 and 50% of the value of the demand; level 3 (n3) means that supply is between 50 and 75%; and level 4 (n4) is the less serious state, which means that the supply is between 75 and 100%.

The tolerance to the risk of failure of several demands can become a subjective task. However, as a support for objectivity, this information can be represented in a single demand satisfaction index (DSI). The DSI is the result of the number of failures in the supply of the demands through a reliability index (RI) and the severity of these failures through a severity index (SI). Following in a similar way as Hashimoto et al. (1982) and Sandoval-Solis et al. (2011) propose, these indices for a particular demand and for each month in the simulation period can be calculated as follows:

$$\mathrm{RI} = \frac{(\text{total number of simulations} - \text{number of failures})}{\text{total number of simulations}} \tag{7}$$

$$\mathrm{SI} = \frac{\sum_{j=1}^{n}(D_j)}{\text{total number of simulations} * \text{demand value}} \tag{8}$$

$$\mathrm{DSI} = \mathrm{RI} * (1 - \mathrm{SI}) \tag{9}$$

where n is equal to the number of supply levels and D_j is the deficit at each level of supply. If there are several demands the DSI can be calculated as a satisfaction index of a group of demands DSI_G by a weighted sum of the particular DSI as follows:

$$\mathrm{DSI_G} = \left(\sum_{i=1}^{k} \frac{\text{Demand i}}{\sum_{i=1}^{k} \text{Demand i}} * \mathrm{DSI_i}\right) * 100 \tag{10}$$

where i is the counter of the individual demands and k is the total number of demands in the water resource system.

The DSI_G could be used to make decisions every month of the year in an operational context. The value of this index can vary from 0% to 100%, the higher the value of the DSI_G index, the greater the satisfaction of the system.

3 Case study

The approach proposed in this study was applied to the Machángara river basin (325 km^2) located in the southern Ecuadorian Andes at an altitude of 2440 - 4398 m.a.s.l (Figure 2). This river basin is particular important because it has one of the few multipurpose water resource systems in southern Ecuador for the benefit of the local and regional economy and ecology. In the upper part, Chanlud (16 hm^3) and El Labrado (6 hm^3) reservoirs are located, which supply water for different uses. The first one is located in the Machángara Alto river sub-basin and the last one is located in the Chulco river sub-basin. The competition for the different water uses is caused by an increasing pressure on water resources due to population growth at an average annual rate of 2% and an increase in irrigated areas. On the other hand, the future climate analysis in the river basin shows an intensification of rainfall seasonality (wetter rainy periods followed by extreme dry seasons) for 2020-2050. These results, point to less water resources availability during several seasons in the future.

For the development of the DI, we use monthly time series data (1971 - 2010) of average precipitation and reservoir inflows. This information derives from the National Institute of Meteorology and Hydrology of Ecuador (INAMHI) and the Machángara River Basin Council (CBRM). This methodology includes five time windows (1, 3, 6, 9 and 12 months) for each variable in order to capture the short and medium term of drought events. In other words, five precipitation time series (PR1, PR3, PR6, PR9 and PR12) are generated for the two sub-basins and five more for the reservoir inflows (VS1 VS3, VS6, VS9 and VS12). For the purpose of considering the monthly seasonality, each time series is divided according to each month of the hydrologic year; in addition, all the information was standardized.

The information required for the quantification of water demands is provided by the CBRM. Data reproduce the three most important water uses in the river basin, taking as a priority use the human consumption in the city of Cuenca (240000 inhabitants); in the second place, the water for irrigation (1300 Ha) and finally the hydropower generation (40 MW). An ecological flow equivalent to 10% of monthly average streamflows is also considered. A scheme of the water resources system of the Machángara river basin is shown in Figure 2.

4 Results and Discussion

4.1 DI calculation

Eigenvalues and eigenvectors are obtained by using PCA for each month and for each sub-basin (Machángara Alto and Chulco rivers), and the correlation matrices of the ten time series (PR1, PR3, PR6, PR9, PR12, VS1, VS3, VS6, VS9 and VS12) for each sub-basin. From equations 1 and 2 we obtain the twelve sets of DI values, which are rearranged chronologically in order to obtain a single time series for each sub-basin (1971- 2010). Figure 3 shows the DI values for each sub-basin and the drought severity thresholds, where the frequency and duration of each drought event (non-drought, mild drought and drought) can be observed.

4.2 Probabilistic drought forecasts using the MCFO model

Taking into account the seasonality and using Equation 5, twelve transition probability matrices are built for each sub-basin. These matrices allow us to obtain the probabilistic forecast of the following month j given the status category of the current month i (Equation 4). Table 1 shows the probabilistic drought forecasts in the sub-basins of the Machángara Alto and Chulco rivers.

4.3 Generation of hydrological synthetic series with the incorporation of probabilistic drought forecasts

The MPAR1 model (Equation 6) is able to preserve some statistics of the historical time series of normalized and standardized reservoir inflows. Table 2 presents the monthly thresholds of the intervals for the generation of random numbers (Ɛ) and the previous values $\mathbb{Z}_{\tau-1}$ for the generation of synthetic series.

For instance, for the generation of ten thousand random numbers for the month of August (the least rainy month), with a category 2 drought state (drought); during the month of July, and with the information of the Tables 1b and 2, we would have in the El Labrado reservoir: 0 random numbers (equal to 0% of 10000, since the percentage is equal to the probabilistic forecasts of non-drought state in August) in the interval [0, 3.23], 3300 random numbers (equal to 33% of 10000, as the percentage is equal the probabilistic predictions of mild drought state in August) in the interval [-1, 0] and 6700 random numbers (equal to 67% of 10000, considering the probabilistic forecasts of drought state in August) in the interval [-1.66, -1]; adding 10000 random numbers. A similar analysis can be performed for the Chanlud reservoir. Therefore, through the two sets of random numbers, the parameters of MPAR1 model for August, the previous hydrological conditions of July for both reservoirs (assuming a similarity with the drought states of the two sub-basins, the previous values of July would be $\mathbb{Z}_{\tau-1}$= -1.68 for the reservoir of Chanlud and $\mathbb{Z}_{\tau-1}$= -1.65 for the reservoir of El Labrado, see Table 2) and by using Equation 6; 10000 hydrological synthetic series are generated with a twelve-month length (simulation period).

4.4 Failure risk assessment

The simulation process is performed with 1728 scenarios built on the modification of 12 options for the simulation starting month (January to December), 16 combinations of initial storage volumes of the reservoirs (Chanlud with 4, 8, 12 and 16 hm^3 and El Labrado with 1.5, 3, 4.5 and 6 hm^3) and 9 combinations of monthly previous hydrological conditions for each reservoir (Table 2). These scenarios are the inputs for the failure risk assessment model. Taking the most unfavorable scenario as an example: August as the simulation starting month, minimum values of the previous hydrological conditions for the reservoir inflows in the month of July, category 2 (drought) in the month of July as previous drought status for both sub-basins and the initial storage volumes for Chanlud equal to 4 hm^3 and 1.5 hm^3 for El Labrado.

The results obtained are presented in the Figure 4a, which shows the probabilities of failure of water demands at the four levels of supply (n1, n2, n3 and n4) and for each month of the simulation period. It can be observed that there is a significant probability of failure for the irrigation demands in the month of September (probability of n1 equal to 60% and total probability equal to 80% approximately). Likewise, in this month urban demand has a moderate probability of failure (total probability equals approximately 34%). In October, the probability of irrigation demands falls slightly (total probability equal to approximately 60%), and there is zero probability of failure for the urban demand. In November and December irrigation demands have a low probability of failure (total probability less than 10%) and there is still zero probability of failure for urban demand. This information could be considered as sufficient evidence for the identification of severe prevention and/or mitigation measures to reduce the risk of failure of supplies in the months of September and October and other less severe measures for the months of November and December. The tolerance to the risk of failure will depend on the subjectivity of decision-makers, however for get a more objective decision-making DSI_G was used in order to concentrate the results of all demands. Using the Equations 7, 8, 9 and 10, the DSI_G is calculated for each scenario and for each month of the simulation period.

Figure 4b shows the DSI_G of the scenario described above with different initial storage volumes. For initial storage volumes equal to 4 hm^3 for Chanlud and 1.5 hm^3 for El Labrado, we can see that the DSI_G is equal to 30% in the month of September and 60% in the month of October and in the rest of the months it is greater than 90%. Therefore, the information in this figure shows, in a more integrative and comprehensible way, that for the months of September and October some preventive and/or mitigation measures will need to be formulated in order to operate and manage the system in such a way that the risk of failure is reduced. In order to show the advantages of the incorporation of drought forecasts, the failure risk assessment was also performed without the incorporation of drought predictions (Figure 4c), where it can be seen that the DSI_G values were substantially increased. Therefore, the incorporation of probabilistic drought forecasts could better target the projections of simulation scenarios and contribute to more effective decision-making results in drought conditions.

This improvement of the resulting information for the decision-making discussed above coincides with some studies that are detailed below: Sankarasubramanian et al. (2009) showed that there was an improvement in the seasonal and intra-seasonal allocation of water when the predictions of the climatological probabilities in the reservoir inflows were used. On the other hand, Pouget et al. (2015) showed improved decision-making when seasonal climate forecasts were integrated into management tools. Likewise, the results of Gong et al. (2010) also showed an improvement in water management practices when forecasts of climate-based flows were incorporated into reservoir operation tools, reducing the number of drought emergency days.

5 Conclusions

This study proposes an integrated methodological framework for assessing the risk of failure to the supply of demands in a water resource system by improving traditional methodologies through the incorporation of probabilistic drought forecasts and by providing information to support decision-making in the water management during periods of scarcity. The simulation process was performed for 12 months through the analysis of 1728 scenarios developed from the variation of the water supply and the current water demand. Each scenario comprises 10000 synthetic series of water inflows to reservoirs (incorporing probabilistic drought forecasts), the main features of the water resources system, the monthly previous hydrological conditions and the simulation starting month. This approach was applied to the Machángara river basin, achieving an ensemble of water resources system satisfaction indexes. These results showed that the incorporation of drought probabilistic predictions in water management simulation could better target the projections of possible scenarios, also allowing the analysis of more realistic situations of risk of failure in water resource allocation for the different demands. This approach could be applied with the purpose of building a portfolio of prevention or mitigation options in order to reduce the risk of failure during water scarcity conditions.

Acknowledgements

This study was part of the doctoral thesis of Avilés A. at the Technical University of Valencia. This research was funded by the University of Cuenca through its Research

Department (DIUC) and the Municipal public enterprise of telecommunications, drinking water, sewage and sanitation of Cuenca (ETAPA) through the projects: "Identificación de los procesos hidrometeorológicos que desencadenan inundaciones en la ciudad de Cuenca usando un radar de precipitación" and "Ciclos meteorológicos y evapotranspiración a lo largo de una gradiente altitudinal del Parque Nacional Cajas". The authors also thank INAMHI and the CBRM for providing the information for this study. The authors wish to thank the Spanish Ministry of Economy and Competitiveness for its financial support through the ERAS project (CTM2016-77804-P). We thank Ángel Vázquez, who helped in the programming of the multiple simulations. Also we thank to the TropiSeca project.

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FIGURES

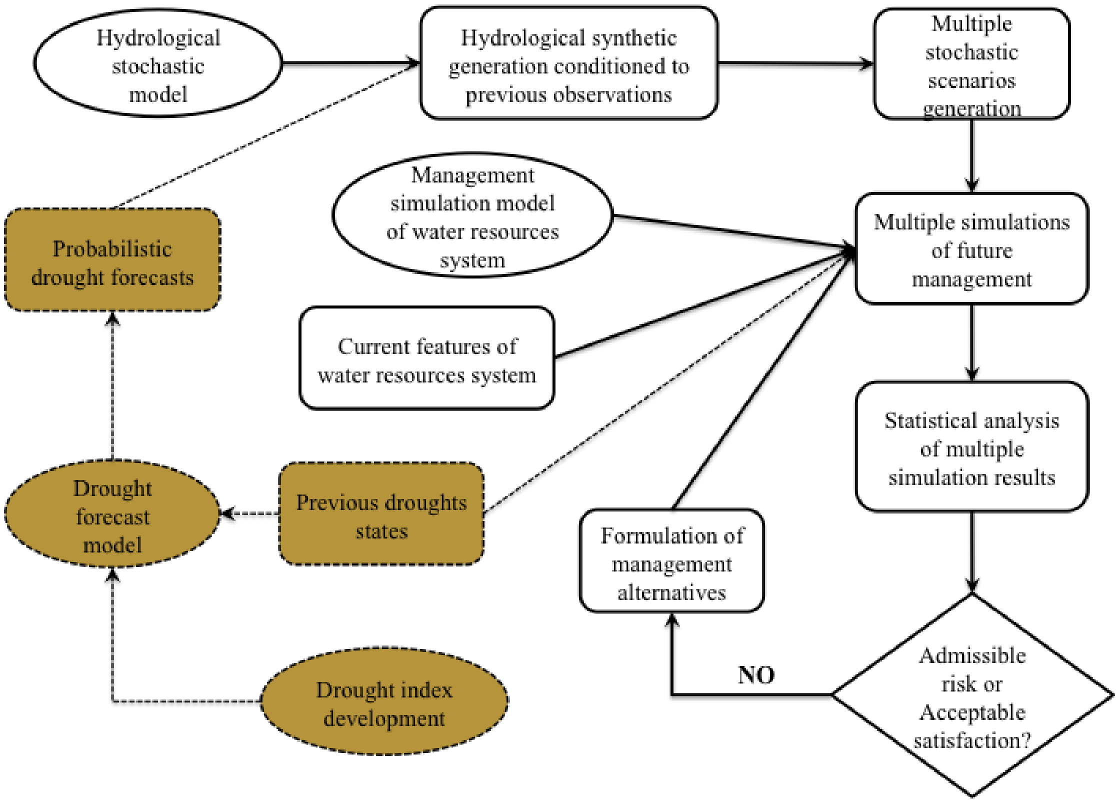

Fig 1 Integrated methodological framework for assessing the risk of failure in water resource systems

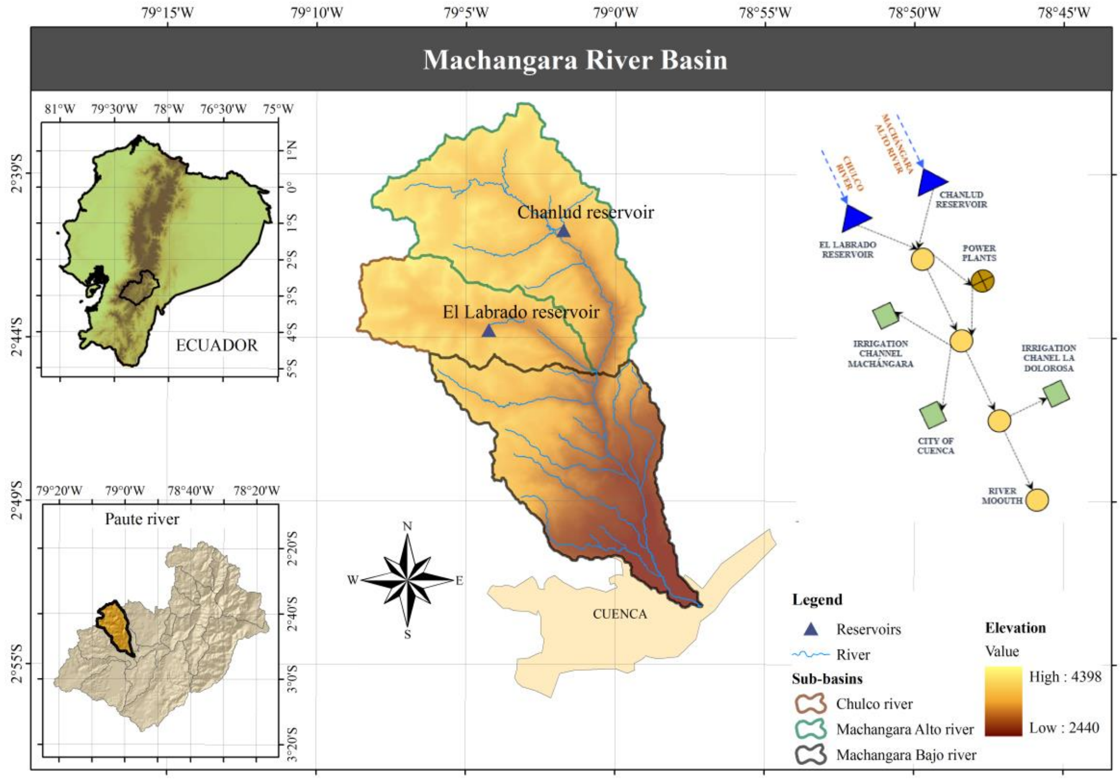

Fig 2 Location and scheme of the water resources system of Machángara River Basin

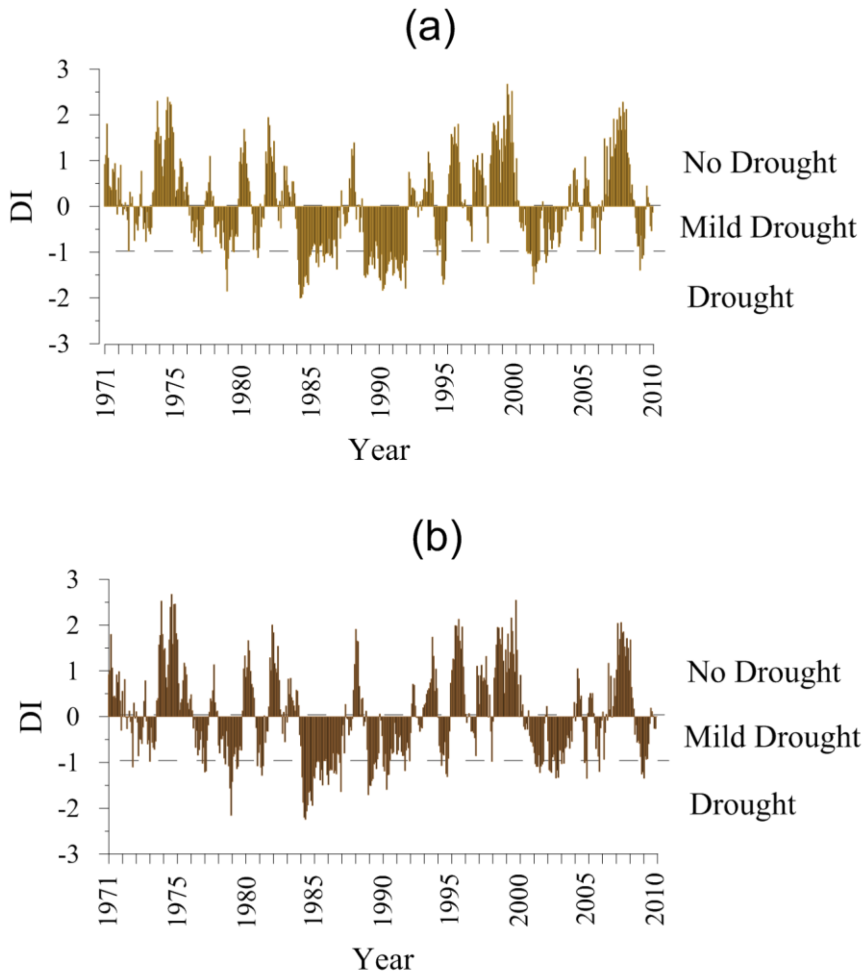

Fig 3 Time series of the DI (1971 - 2010) in the sub-basins of the rivers: (a) Machángara Alto and (b) Chulco

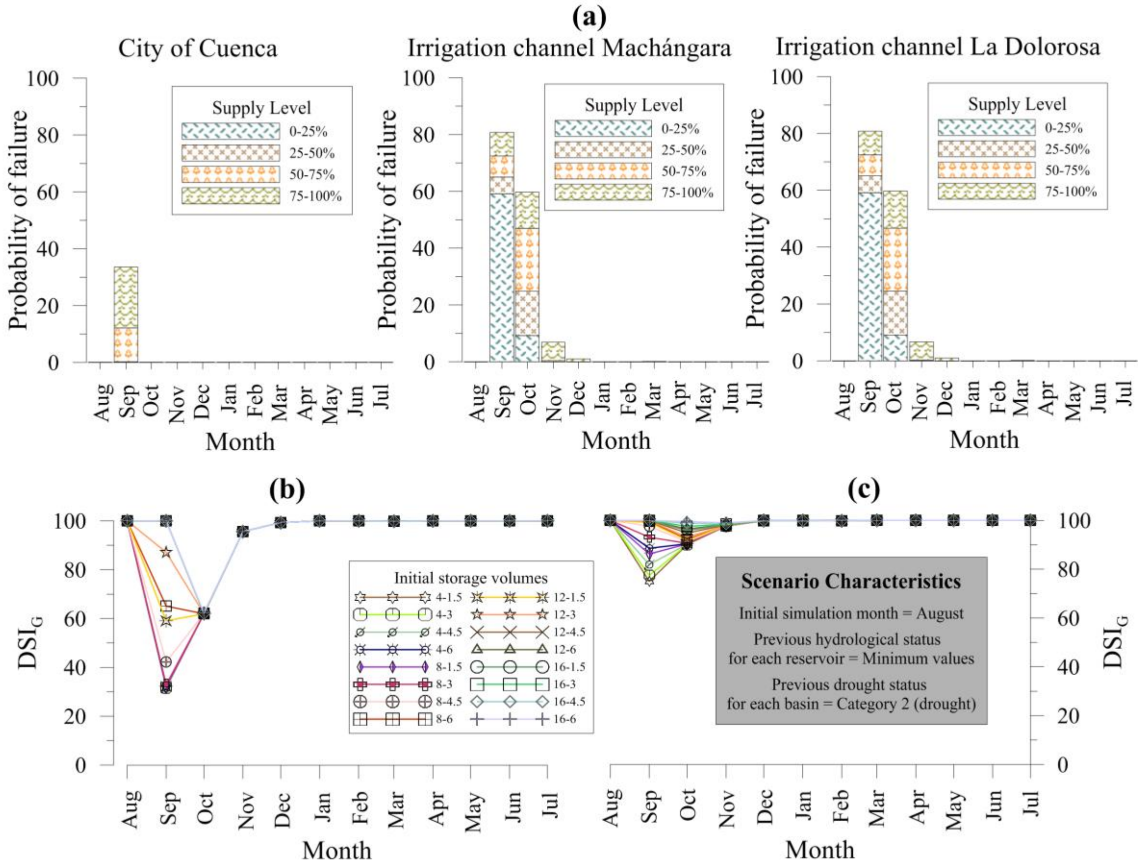

Fig 4 (a) Probability of failure of the water demands and DSI_G of the water resource system of the Machángara River Basin for the most unfavorable scenario. With different initial storage volumes applying the methodology: (b) with the incorporation of drought forecasts and (c) without the incorporation of drought forecasts

TABLES

Table 1 Probabilistic forecasts of drought for: (a) Machángara Alto river sub-basin and (b) Chulco river sub-basin

(a)

Category current month i	**Category next month j**	**Probabilistic forecasts for the next month j**											
		jan	**feb**	**mar**	**apr**	**may**	**jun**	**jul**	**aug**	**sep**	**oct**	**nov**	**dec**
0	**0**	0.75	0.80	0.94	0.95	0.86	0.80	1.00	0.86	0.84	0.82	0.78	0.89
	1	0.25	0.15	0.06	0.05	0.14	0.20	0.00	0.14	0.16	0.18	0.22	0.11
	2	0.00	0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	**0**	0.45	0.18	0.21	0.18	0.20	0.13	0.19	0.08	0.08	0.24	0.22	0.24
	1	0.45	0.55	0.58	0.73	0.80	0.74	0.75	0.84	0.92	0.76	0.67	0.47
	2	0.10	0.27	0.21	0.09	0.00	0.13	0.06	0.08	0.00	0.00	0.11	0.29
2	**0**	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	1	0.11	0.56	0.25	0.11	0.44	0.20	0.00	0.00	0.25	0.33	0.25	0.20
	2	0.89	0.44	0.75	0.89	0.56	0.80	1.00	1.00	0.75	0.67	0.75	0.80

(b)

Category current month i	Category next month j	Probabilistic forecasts for the next month j											
		jan	**feb**	**mar**	**apr**	**may**	**jun**	**jul**	**aug**	**sep**	**oct**	**nov**	**dec**
0	**0**	0.75	0.79	0.95	0.89	0.85	0.79	0.94	0.89	0.72	0.86	0.78	0.78
	1	0.25	0.21	0.05	0.11	0.15	0.21	0.06	0.11	0.28	0.14	0.22	0.22
	2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
1	**0**	0.29	0.31	0.08	0.21	0.08	0.06	0.17	0.13	0.07	0.27	0.18	0.33
	1	0.50	0.38	0.84	0.65	0.84	0.76	0.72	0.68	0.86	0.59	0.53	0.54
	2	0.21	0.31	0.08	0.14	0.08	0.18	0.11	0.19	0.07	0.14	0.29	0.13
2	**0**	0.00	0.00	0.00	0.00	0.12	0.00	0.00	0.00	0.00	0.00	0.20	0.14
	1	0.17	0.38	0.33	0.14	0.50	0.25	0.33	0.33	0.57	0.50	0.40	0.29
	2	0.83	0.62	0.67	0.86	0.38	0.75	0.67	0.67	0.43	0.50	0.40	0.57

Table 2 Thresholds of the historical series of normalized and standardized streamflows in Chanlud and El Labrado reservoirs

Threshold	jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec
	Chanlud reservoir											
Max	2.28	1.72	1.68	1.88	2.25	2.15	2.79	3.24	2.23	2.35	1.97	1.69
Mean	0	0	0	0	0	0	0	0	0	0	0	0
Level -1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Min	-1.60	-1.71	-2.40	-3.01	-2.55	-1.77	-1.68	-1.69	-1.76	-1.68	-1.68	-1.94
	El Labrado reservoir											
Max	2.34	1.71	1.71	1.91	2.22	2.14	2.84	3.23	2.33	2.28	1.97	1.61
Mean	0	0	0	0	0	0	0	0	0	0	0	0
Level -1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
Min	-1.47	-1.78	-2.45	-3.00	-2.37	-1.60	-1.65	-1.66	-1.84	-1.66	-1.74	-2.09