Water Security 3 (2018) 9–17

Contents lists available at ScienceDirect

Water Security

journal homepage: www.elsevier.com/locate/wasec

Paradigmatic changes required in water resources management to benefit from probabilistic forecasts

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ARTICLE INFO

Keywords:
Probabilistic forecasts
Predictive probability
Bayesian decision
Probabilistic thresholds

ABSTRACT

Water availability forecasting techniques, either in the form of mean, high and low flows on medium and long time horizons or as floods on shorter ones, are becoming more and more familiar and used by Water Resources Management decision makers. More recently probabilistic meteorological and hydrological forecasts have also been made available, but their potential benefits are far from being fully exploited. This work discusses the present misconceptions as well as the paradigmatic changes needed to reach the objective of convincing decision makers on the essential advantages descending from the correct and appropriate use of probabilistic forecasts within the frame of Bayesian informed decision approaches.

1. Introduction

In Water Resources Management (WRM), decision makers are frequently confronted with the need of taking the most appropriate decisions under the uncertainty of what may occur in the future. To support their decision making under uncertainty, Decision Theory [5,6,8] invokes Bayesian informed decision approaches, which find the most appropriate decision by maximizing (or minimizing) the expected value of a “utility function”, thus requiring its definition, together with the estimation of a “predictive probability” density [5]. The utility function is a function expressing, usually in economical terms, benefits arising from the decision to be maximized. In this work the concept of utility has also been extended to losses (negative benefits) to be minimized. The utility function may not necessarily be an “objective” function as it may also be used to express the “subjective” decision maker’s preferences or his risk propensity. The second requirement in Bayesian decision is the availability of a predictive probability density, providing an estimate of the probability of occurrence at a future time of a triggering variable, such as, when dealing with WRM, a discharge, a water stage or a water volume.

In the last two decades, meteorologists and hydrologists have more and more recognized the need for probabilistic forecasts instead of the classical deterministic ones, but their use has been mostly limited to assessing forecasting uncertainty with scant interest to decision makers. While Bayesian decision approaches based on probabilistic forecasts have been extensively used in economics [9], in WRM they were mostly used to drawing uncertainty bands around the forecasts rather than properly exploited for rational decision making. Although proper methodologies to issue and to use probabilistic forecasts in decision making are today widely available, water resource agencies and decision makers have rarely adopted them, partly due to conservatism of governmental agencies [19] and partly due to the lack of awareness on the potential benefits both in terms of robustness of the Bayesian decision making approach (reduced probability of taking the wrong decisions) and in terms of reduction of losses deriving from the taken decisions.

Proper uses of probabilistic forecasts seem to be at the early stages of the Diffusion of Innovations process described by Rogers [20], who points out the characteristics that make innovation successfully adopted such as: (i) the degree to which an innovation is perceived as better than the idea it supersedes; (ii) as being consistent with the existing values, past experiences, and needs of potential adopters; (iii) as being easy to understand and use; and (iv) the degree to which results of an innovation are visible to others.

Therefore, a number of clarifications are needed to reduce the “complexity” and explain the “relative advantages” of probabilistic forecasts to succeed at diffusing their use in informed decision making, together with paradigmatic changes in the interpretation and use of probabilistic forecasts to meet “compatibility”. Several aspects of the problem are in fact still misconceived or unclear, such as:

– Although not explicitly stated, deterministic forecasts are implicitly assumed as “exact”, frequently leading to wrong decisions;
– Probabilistic forecasts do not increase our uncertainty; on the contrary they can reduce our uncertainty if properly used within a Bayesian decision scheme;

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https://doi.org/10.1016/j.wasec.2018.08.001
Received 23 February 2018; Received in revised form 10 August 2018; Accepted 13 August 2018
2468-3124/

– Hydrological and meteorological ensembles generated by perturbing model parameters together with initial and boundary conditions are not a correct representation of predictive uncertainty;
– Utility functions must be derived in collaboration with the decision makers to express their subjective preferences. Alternatively, when utility functions are not defined, deterministic thresholds should be converted into probabilistic ones.
– Decision makers must be made aware of the potential benefits of informed decisions descending from incorporating the probabilistic forecasts into Bayesian decision schemes to fully exploiting all available information.

An overview of the required perception and understanding changes and their potential improvement on WRM effectiveness is here presented. Several examples in this article relate to real time flood forecasting and flood risk alleviation because most of the conceptual work was done in these domains, but the concepts can be easily extended to other water resources management areas such as optimization of reservoir management or the search for the most appropriate adaptation measures to climate change.

2. Main paradigmatic changes needed

2.1. Operational use of probabilistic predictions

Informed decision making requires selecting the appropriate action $a \in A$ among a set A of possible pre-determined actions to be taken when affected by a spread of the potential levels of magnitude of a future event, each of which appropriately weighted with its relevant probability of occurrence. From a Bayesian perspective, robust decision making can be obtained by maximizing a utility function $U[a, h]$, which can be objective, in terms of benefit or losses, or subjective expressing the decision maker's propensity at risk. Usually, the utility is a function of the chosen action a as well as of a decision triggering variable h (for instance the water level overtopping h_T a triggering value such as an alert threshold or the dykes elevation). The utility function U can also be a function of more than one triggering variable, but for the sake of simplicity without losing the generality, in this work we will limit the discussion to one triggering variable.

If the future value $h = h^*$ is known and sufficient time is available to implement the decision, the most appropriate action a^* among the set A of possible actions can be directly derived as:

$$a^* = \underset{a \in A}{argmax(min)}\, U[a, h^*] \tag{1}$$

But in the majority of situations decisions have to be taken in advance since waiting for a measure of h is not compatible with the time required to implement the selected decisions, which implies estimating the predictive probability density $f\{h\ |I\}$, which is defined as our best knowledge of h conditional to all the available information I. As can be noticed, the scope of prediction is not to produce a deterministic optimal value h^*, but rather to generate a probabilistic forecast $f\{h\ |I\}$ expressing our best knowledge on the future unknown value h.

As shown in Figs. 1 and 2, in the presence of significant uncertainty on a future value, for the reasons explained in the following section, Eq. (1) cannot be directly used because the most appropriate decision a^* must be found as a function of the expected benefit/losses $E\{U[a, h]|I\}$, which cannot be simply computed by setting $h^* = E\{h|I\}$ in Eq. (1) to give:

$$E\{U[a, h]|I\} = U[a, h^*] = U[a, E\{h|I\}] \tag{2}$$

because generally $E\{U[a, h]|I\}$ differs from $U[a, E\{h|I\}]$. In order to benefit from the probabilistic forecast one must then rewrite the decision equation as:

$$a^* = \underset{a \in A}{argmax(min)}\, E\{U[a, h]|I\} \tag{3}$$

where

$$E\{U[a, h]|I\} = \int_{\Omega_h} U[a, h] f\{h\ |I\} dh \tag{4}$$

is the expected value of the utility function and Ω_h the domain of existence of h.

In other words, one should not limit the assessment to the value of the utility at single points such as the mean, the median or the mode, but instead must evaluate all future possible occurrences, each of which attached with its probability of occurrence given by the predictive density, and "marginalize" the effect of uncertainty, which corresponds to taking the expected value as in Eq. (4).

Summarizing, the decision under uncertainty problem requires issuing a probabilistic prediction in the form of the predictive probability density, expressing our best knowledge on the future occurrence h, conditional on all the available information, which is usually encapsulated in a single model forecast $\hat{\boldsymbol{h}} = \hat{h}$ or in m models' forecasts $\hat{\boldsymbol{h}} = [\hat{h}_1, \hat{h}_2, \cdots, \hat{h}_m]$, namely:

$$f\{h\ |I\} = f\{h\ |\hat{\boldsymbol{h}}\} \tag{5}$$

The predictive probability density $f\{h\ |\hat{\boldsymbol{h}}\}$, which is generally referred to as a probabilistic forecast, is then the essential information required to estimate the expected benefits or damages descending from each decision action a, allowing to select the most appropriate action a^* as given by Eq. (3).

2.2. Probabilistic instead of deterministic predictions

As it appears from the previous section, the main paradigmatic change needed in order to adopt probabilistic instead of deterministic forecasts lies in the perception of the nature and meaning of models' forecasts.

In broad sense, taking rational decisions means finding in real time the most appropriate alternative within a pre-determined set of options established in the planning phase. The planning phase is essentially developed and tested in hindcast mode and decisions are mostly developed knowing what has happened, while in operation, a decision maker, being not aware of what will occur in the future, needs increasing his knowledge on the future outcomes, which is usually done through one or more models' forecasts.

On the contrary, in the case of WRM, as for instance reservoirs management or real time flood forecasting and warning, even today decisions are mostly taken by directly comparing models' predictions to pre-determined water volumes or water level thresholds. In particular, following the historical practice of comparing water level measurements to thresholds on large rivers, flood emergency warning and management is currently based on the comparison of water level forecasts to thresholds. But whereas water level measurements are affected by small and negligible measurement errors, which justify the approach, predictions of future water levels are affected by much larger prediction errors. By using "deterministic forecasts" such as model predictions we totally disregard the fact that predictions may be wrong and that the future actual occurrence may be far from what was predicted, with consequent important effects on the estimation of expected benefits or losses descending from our decision.

In order to understand this critical point let us consider the following simple flood warning problem.

As previously stated the objective of prediction is to allow for a correct and robust estimation of the expected benefits and/or losses descending from our decisions. Let us analyze the effects on the final decision arising from a prediction of the future water stage h either in the form of a single value, such as for instance the expected value (deterministic forecast), or in terms of a predictive probability density (probabilistic forecast).

A levee in a river has a height of h_T above the riverbed. If the water level overtops the levee damages occur, which can be described as: