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Technical Note

Application of Bayesian and cost benefit risk analysis in water resources management

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SUMMARY

Decision making is a significant tool in water resources management applications. This technical note approaches a decision dilemma that has not yet been considered for the water resources management of a watershed. A common cost-benefit analysis approach, which is novel in the risk analysis of hydrologic/hydraulic applications, and a Bayesian decision analysis are applied to aid the decision making on whether or not to construct a water reservoir for irrigation purposes. The alternative option examined is a scaled parabolic fine variation in terms of over-pumping violations in contrast to common practices that usually consider short-term fines. The methodological steps are analytically presented associated with originally developed code. Such an application, and in such detail, represents new feedback. The results indicate that the probability uncertainty is the driving issue that determines the optimal decision with each methodology, and depending on the unknown probability handling, each methodology may lead to a different optimal decision. Thus, the proposed tool can help decision makers to examine and compare different scenarios using two different approaches before making a decision considering the cost of a hydrologic/hydraulic project and the varied economic charges that water table limit violations can cause inside an audit interval. In contrast to practices that assess the effect of each proposed action separately considering only current knowledge of the examined issue, this tool aids decision making by considering prior information and the sampling distribution of future successful audits.

1. Introduction

Bayesian decision analysis is usually employed to make decisions in the presence of uncertainty. Therefore, it was primarily developed to utilize additional information to reduce the risk of uncertain decisions. Bayesian decision theory quantifies the yield of various decisions using probabilities and costs that accompany such decisions. The basic aim is to choose the class for which the expected loss is smallest. The problem is posed in probabilistic terms, and it is assumed that all relevant probabilities are unknown. The probabilistic approach is powerful if the probability distributions are indeed known, but this is often not the case. A common way to overcome this difficulty is to apply Bayesian decision theory by establishing a prior distribution (Berger, 1985; O'Malley and Vesselinov, 2014).

An initial application of Bayesian decision theory in hydrology was to assess the costs of overdesign of a flood levee in the face of flood frequency uncertainty (Davis et al., 1972). Since then, it has been used in many applications. For example, it has been used to determine optimal groundwater sampling frequencies (Grosser and Goodman, 1985) and in decision analyses to engineer design projects, groundwater flow and transport, and monitoring networks in which the hydrogeological environment plays an important role (Freeze et al., 1990). It has been used to address the problem of permitting waste sites under conditions of imperfect information (Marin et al., 1989; Medina et al., 1989) and for the engineering design of a groundwater interception well used to capture a contaminant plume (Wijedasa and Kemblowski, 1993). Moreover, it has been used for selecting the best experimental design for groundwater modeling and management design under parameter uncertainty (McPhee and Yeh, 2006) and for investigating the value of collecting hydraulic conductivity data for optimal groundwater resources management (Feyen and Gorelick, 2005).

Since the early 1990s, in most decision analysis studies, it was assumed that decisions would be made by a rational, financially driven decision maker who might be risk averse but who would otherwise make decisions that maximized his or her economic position. However, the decisions are strongly influenced by the profile of

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the decision maker. Thus, water resources management experts need to be aware of the complexity of the decision process, the close relationship that exists between the technical input and the risk term in a decision analysis, and the widely differing views toward the methodology and value of risk calculations (Freeze, 2015).

The decision-making process, according to the Bayesian risk, is a methodology that combines the expected loss of a specific decision with the probability, θ, the loss will occur. The methodology is based on statistical knowledge that is produced after sampling and using prior knowledge information. The latter is known as "soft information" (Czado and Brechmann, 2014; Lerche and Paleologos, 2001; Parent and Bernier, 2003). The basic characteristics of the Bayesian decision theory are the state parameters θ_i ($i = 0...n$) that correspond to the number of stated decisions, the state of the possible decisions or actions $A(i)$, and the state of the expected loss function that corresponds to each decision, $L(A(i), \theta_i)$. The set Θ that considers all the possible state parameters, θ_i, is known as the parametric space. Set A contains all possible actions $A(i)$. A loss function $L(A(i), \theta_i)$ is defined for all $A(i)$, θ_i that belong to $[\Theta \times \mathrm{A}]$.

The Bayesian decision method is applied herein to address the dilemma of whether to construct a water reservoir for irrigation purposes or to apply a groundwater resources management policy in terms of scaled set fines when the aquifer is depleted over a certain limit. The work was inspired by an actual case at the Mires Aquifer of the Messara Valley on the Island of Crete, Greece, where the sustainable aquifer level limit was set by the local authorities at 38 m above sea level. This value was based on a physically based approach that involves physical characteristics of the basin. The local authorities considered that the high aquifer capacities of the 80s can not be met nowadays, while the recent are quite low. Therefore, in order to promote environmental policy and awareness they set an aquifer level limit considering the feasible medium aquifer capacities during the 90s, which were on average determined equal to 65 Mm^3. The aquifer effective area is equal to 20 km^2 and the porosity equal to 0.085 (Varouchakis, 2015). Dividing the first two figures and then their result with the porosity the aquifer level was calculated equal to 38 m.

This work provides a tool (coded process, Appendix A) that considers, except from the Bayesian decision method, a cost-benefit analysis approach to assess the stated dilemma and to help decision makers to compare techniques for testing potential strategies for decision dilemmas in hydrological applications.

2. Methodology

2.1. Decision-making process

The decision-making process involves two stages: state estimation and decision making. For state estimation, firstly, all the state parameters θ_i are defined. However, in the Bayesian approach, a state parameter is an unknown quantity and is considered a random variable that must be determined. The procedure of estimating each θ_i involves previous knowledge on the examined issue and the use of the subjective prior distribution $\pi(\theta_i)$ that expresses the prior information for each state parameter. Next, the Bayesian risk function is obtained to estimate the optimal decision or the decision with the minimum expected risk (Berger, 1985; Lerche and Paleologos, 2001; Wolfson et al., 1996). The latter also applies in terms of a cost-benefit analysis procedure and denotes the preferable action. The Bayesian decision-making process follows these four steps:

1. Set up the decision-making problem by introducing the possible actions set A and the parametric space Θ.
2. Establish the expected loss function for each decision $A(i)$, and provide the state of the goal function. If, at this step, the parameters θ_i are considered known, then the decision process is called a cost-benefit analysis, and Step 4 is directly applied. If not, then both Steps 3 and 4 apply.
3. Develop the subjective prior distributions for each θ_i quantifying the previous information.
4. Combine Steps 1, 2, and 3 via the risk function. The decision with the minimum expected risk is the optimal decision.

Fig. 1 presents a flowchart that describes the methodological steps of Bayesian and cost-benefit risk analysis.

2.2. Reservoir construction dilemma: case study

The decision-making problem considers two possible decisions. The first is to continue the same irrigation practice that causes the aquifer over-pumping, with a probability of paying fines to the authorities (related to the number Y of over-pumping violations). The second is to stop that practice and use a reservoir that will supply the area with irrigated water. Therefore, the authorities must examine an environmental policy based on over-pumping penalties while considering the construction of a reservoir. Thus, the dilemma in this case is whether to continue the irrigation practice and pay the potential fines or to construct a reservoir. The answer is firstly given in terms of Bayesian decision theory considering a fixed cost for the reservoir construction and an environmental policy regarding the irrigation groundwater that considers a varied penalty policy for over-pumping. The following approach presents the mathematical procedure that is applicable with any penalty policy and construction cost.

Action $A(0)$: Do not construct the reservoir

The goal function is the expected value of the loss function for action $A(0)$. Thus, the goal function is expressed as follows:

$$G(A(0), \theta_0) = E[L(A(0), Y)]. \tag{1}$$

The penalty policy can consider a range of loss functions order. Usually in environmental problems, a linear or a parabolic loss function is applied. In addition, a combination of scaled loss functions is often applied to express first soft and then harsh penalty policies. Herein, a scaled parabolic function is assumed to express the penalty policy variation because of the importance of the problem. Its expression is given below:

$$L(A(0), Y) = \begin{cases} K_1 Y^2, & 0 \leqslant Y \leqslant n_1 \\ K_2 Y^2, & n_1 < Y \leqslant n_2 \\ K_3 Y^2, & Y > n_2 \end{cases}, \; K_1 < K_2 < K_3, \tag{2}$$

where K_v are the fines to be paid ($v = 1, 2, 3$), n_j is the audit interval limit ($j = 1, 2$), and Y denotes the unknown number of over-pumping violations. The loss function implies the fines to be paid to the local authorities. The expected value of the loss function is provided by the following equation similar to Eq. (1):

$$G(A(0), \theta_0) = \sum_{Y=0}^{N} L(A(0), Y) f(Y). \tag{3}$$

In the previous equation, $f(Y)$ denotes the discrete probability density function of Y violations in an interval of N audits, and $L(A(0), Y)$ denotes the loss function for decision $A(0)$. Combining Eqs. (2) and (3), the analytical mathematical expression of the goal function for action $A(0)$ is obtained:

$$G(A(0), \theta_0) = \sum_{Y=0}^{n_1} K_1 Y^2 f(Y) + \sum_{n_1+1}^{n_2} K_2 Y^2 f(Y) + \sum_{n_2+1}^{N} K_3 Y^2 f(Y). \tag{4}$$