

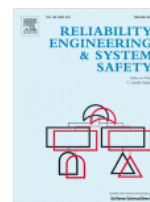
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## Estimation of a quantity of interest in uncertainty analysis: Some help from Bayesian decision theory

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### Abstract

In the context of risk analysis under uncertainty, we focus here on the problem of estimating a so-called quantity of interest of an uncertainty analysis problem, i.e. a given feature of the probability distribution function (pdf) of the output of a deterministic model with uncertain inputs. We will stay here in a fully probabilistic setting. A common problem is how to account for epistemic uncertainty tainting the parameter of the probability distribution of the inputs. In the standard practice, this uncertainty is often neglected (plug-in approach). When a specific uncertainty assessment is made, under the basis of the available information (expertise and/or data), a common solution consists in marginalizing the joint distribution of both observable inputs and parameters of the probabilistic model (i.e. computing the predictive pdf of the inputs), then propagating it through the deterministic model. We will reinterpret this approach in the light of Bayesian decision theory, and will put into evidence that this practice leads the analyst to adopt implicitly a specific loss function which may be inappropriate for the problem under investigation, and suboptimal from a decisional perspective. These concepts are illustrated on a simple numerical example, concerning a case of flood risk assessment.

### Keywords

Uncertainty analysis; Decision theory; Epistemic uncertainty; Bayes estimation; Predictive estimation

### Figures and tables from this article:

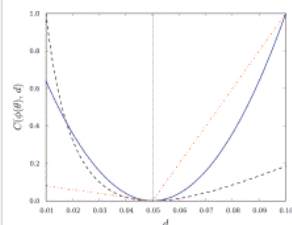


Fig. 1. Cost functions for the estimation of a tail probability. Continuous line, quadratic loss; dashed line, log-quadratic loss; dash-dotted line, weighted absolute loss, with  $C_2=10 \times C_1$ . The vertical line corresponds to the true value  $\varphi$ . Cost functions are normalized for viewing convenience.

[Figure options](#)

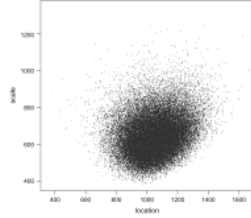


Fig. 2. The  $10^4$  draws from the posterior distribution of the maximal discharge density parameters  $(\eta, \beta)$ .

Figure options

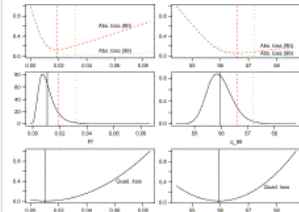


Fig. 3. Bayes estimates of dike failure probability  $P_f$  (left) and water level quantile  $q_{0.95}$  (right). Top: expected weighted absolute loss functions (dashed line corresponds to the 90-th quantile, dotted line to the 99-th quantile). Middle: posterior distributions of both quantities of interest. Bottom: Expected quadratic loss functions. Vertical lines indicate the Bayesian estimator values.

Figure options

Table 1. 30 discharge values, simulated from the  $Gu(1000, 600)$  distribution.



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