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Application of a decision sensitivity measure for the cost-benefit analysis of a flood polder at the Bavarian Danube

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ABSTRACT: We use a decision sensitivity measure to evaluate the influence of model parameter uncertainty on the result of a cost-benefit analysis for a flood risk mitigation measure. The sensitivity measure is the expected value of partial perfect information (EVPPI), which quantifies the monetary value of eliminating the uncertainty of an input parameter considering the expected improvement in the final decision to be taken. We present a flood risk model assessing the benefit of the flood protection measure and quantify selected input parameter uncertainties. On this basis, we evaluate the EVPPI through a mere post-processing of the Monte Carlo samples generated in the uncertainty analysis. The application demonstrates the advantages of the EVPPI compared to the more commonly used variance-based sensitivity measures.

1. INTRODUCTION

Taking or supporting a decision is typically the main motivation for a risk analysis. While sensitivity analyses traditionally serve to make a statement about the relative influence of uncertain input parameters on the uncertainty of the model output (Saltelli et al., 2008), in the face of a decision it seems rather natural to assess the absolute influence of the uncertainty of input factors on the actual decision to be made, i.e., by means of a decision sensitivity measure (Felli and Hazen, 1998; Straub et al., 2022).

Felli and Hazen (1998) first proposed using the expected value of partial perfect information ($EVPPI$) as a decision sensitivity measure in the field of medical decision making, and **?** proposed its use for sensitivity analysis in the context of probabilistic safety assessment. The EVPPI quantifies the value of reducing uncertainty in model inputs considering the improved decision making. It is thus a natural sensitivity measure for factor prioritization, i.e., for determining which input uncertainties should be reduced first to improve decision making. However, the EVPPI has rarely been used in environmental engineering applications and not – to our knowledge – for flood risk assessment.

Flood risk management has changed significantly over the last decades towards more integrated risk-based approaches that explicitly account for uncertainties of both aleatory as well as epistemic nature (Hall and Solomatine, 2008). Making decisions in the field of flood risk management should be supported by a proper uncertainty and sensitivity analysis, utilizing an informative sensitivity measure that is related to the respective decision.

A series of flood detention basins (so called flood polders) are planned along the Bavarian Danube. Their aim is to reduce the risk of downstream flooding in case of extreme flood events by reducing the peak discharge. To assess the economic efficiency of these measures and support decision making, a flood risk model is set up and incorporated into a cost-benefit analysis. The flood risk model is inevitably subject to epistemic uncertainty, whose effect is quantified in an uncertainty analysis. As part of this analysis, we employ a decision sensitivity measure to evaluate the influence of model uncertainties on the net benefit of the flood polder. In this paper, we showcase this analysis for the case of a single flood polder location. We present a simple algorithm that evaluates the EVPPI decision sensitivity measure as a by-product of the Monte-Carlo based uncertainty analysis without significant computational efforts. Exemplary results are presented to illustrate the approach and to demonstrate the advantages of this measure compared to the first-order variance-based (Sobol') sensitivity measure.

2. DECISION-ORIENTED SENSITIVITY ANALYSIS

Global sensitivity analyses often serve to identify those input factors on which more information should be collected to reduce the uncertainty of the model output. This task is known as *Factor Prioritization* (Saltelli et al., 2008; Pianosi et al., 2016). Probably the most well known sensitivity measure for this task is the first-order Sobol' index. An alternative to this relative measure is the EVPPI, which quantifies the value of information that knowing a parameter has for improved decision making. The advantage of this decision sensitivity measure is that, in the context of a specific decision, it provides not only a relative ranking of the different uncertain input parameters, but also information on the absolute importance of a specific uncertainty in the decision making process. The following section briefly summarizes the EVPPI in the context of a cost-benefit analysis and presents a simple but effective algorithm for its calculation.

2.1. *Expected value of partial perfect information*

Here we consider the use of the EVPPI for a cost-benefit analysis, in which a decision is taken to implement a measure M if its benefit exceeds its cost. Hence, the cost-benefit analysis of the measure M requires the estimation of the expected monetarized risk reduction $r_M - r_0$, i.e., the benefit of the measure, where r_M is the risk when the measure is implemented and r_0 is the risk without M, as well as the quantification of the costs c_M for implementing the measure. All quantities are discounted to their present value by means of an annually compounded discount rate d. The net benefit of the flood polder is $r_0 - r_M - c_M$.

Risks and costs are a function of uncertain input parameters $\mathbf{X} = [X_1, X_2, \ldots, X_n]$. Ultimately, the decision is taken based on the expected values of risks and costs with respect to the probability distributions of $\mathbf{X}$. The conditional value of partial perfect information ($CVPPI$) of a single uncertain input parameter X_i quantifies the potential gains due to changing the optimal decision after learning that a specific random input variable takes a value $X_i = x_i$. The optimal a-priori decision without knowledge of X_i is a_{opt} and the optimal posterior decision conditional on $X_i = x_i$ is $a_{opt|x_i}$. In this binary decision context, the CVPPI is then evaluated as:

$$CVPPI_{X_i}(x_i) = \begin{cases} |r_0(x_i) - r_M(x_i) - c_M(x_i)| & a_{opt|x_i} \neq a_{opt} \\ 0 & else \end{cases} \tag{1}$$

Computing the expected value of the $CVPPI_{X_i}(x_i)$ with respect to the prior distribution of X_i yields the expected value of partial perfect information on X_i:

$$EVPPI_i = \int_{x_i} CVPPI(x_i) \cdot f_{X_i}(x_i)\, dx_i \tag{2}$$

This $EVPPI_i$ is the expected gain in the difference of risk reduction and cost when eliminating the uncertainty on X_i. The higher the EVPPI, the more beneficial a reduction of the uncertainty in X_i. The EVPPI also provides an upper bound on how much one should spend to reduce uncertainty in X_i.

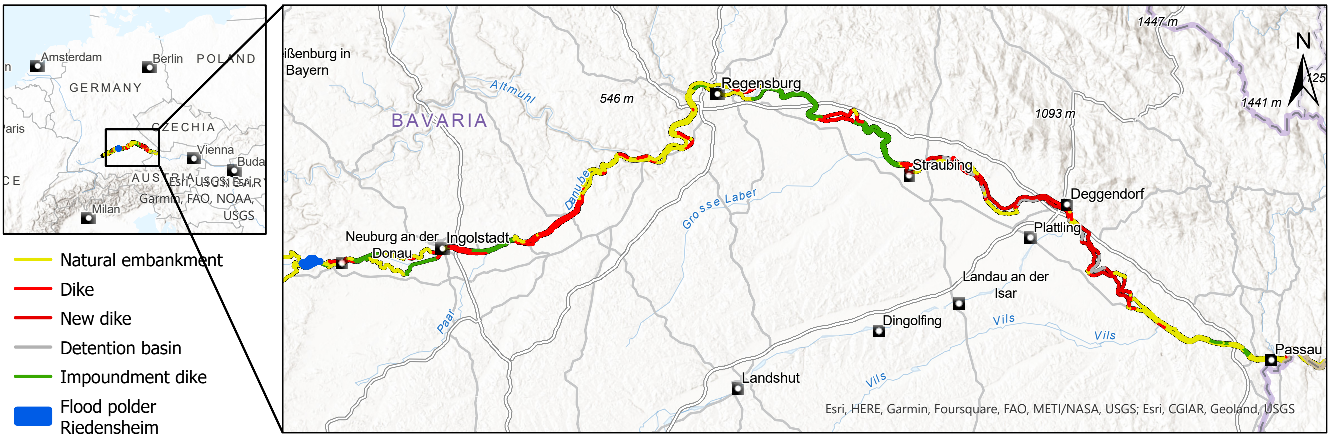

Figure 1: Overview of the project area.

2.2. *Evaluation of the EVPPI via Monte Carlo analysis*

The flood risk with and without M is evaluated by means of a Monte Carlo based uncertainty analysis with $n_{MCS} = 95'000$ samples. On this basis, the expected net benefit of the flood polder is estimated. The same samples can be utilized to approximate the CVPPI of Eq. (1). To this end, the n_{MCS} model evaluation pairs (X_i, Y), where Y denotes the net benefit, are ordered according to their value of x_i. $E_{X_i}[Y(\mathbf{X})|x_i]$ is then approximated by a running mean smoothing approach (Storlie and Helton, 2006), adapted using a constant block sample size $n_b = 2 \cdot 10^4$. For all values of X_i that lead to a value of $E_{X_i}[Y(\mathbf{X})|x_i]$ whose sign differs from the a-priori net benefit have a positive CVPPI according to Eq. (1). The EVPPI is then obtained by solving the integral of Eq. (2) numerically.

3. APPLICATION TO THE COST-BENEFIT ANALYSIS OF A FLOOD POLDER

The specific decision under consideration is the one of implementing a flood polder at the Danube close to the city of Riedensheim, Germany. The polder provides a retention volume of 8 million m^3 with an expected life-time of 100 years. Since a flood polder activation takes effect downstream of the polder location, the study area comprises the river stretch between Riedensheim and Engelhartszell, where the Danube crosses the border to Austria. An overview of the study area is shown in Figure 1. The activation of the flood polder is planned for flood events exceeding a 100-year flood in the Danube close to Riedensheim, which corresponds to a discharge of 2200 m^3/s at the location of the polder.

3.1. *Overview of the flood risk model*

To estimate the expected benefit of the flood polder, a probabilistic flood risk model is developed, whereof an intermediate model version is presented in the following. To this end, the Bavarian Danube is discretized on both river sides into segments of varying length, roughly between 300 and 600 meters, based on their embankment structure. Every segment side is characterized as being either natural embankment, dike, detention basin or impoundment dike. All dike segments are considered as potential locations for overtopping and breaching.

The probabilistic flood risk model includes the following modules, which are embedded in a Monte Carlo framework with a temporal resolution of one hour and shown in blue in Figure 2.

1. *Hydrological load module*. The input of the flood risk model are deterministic flood scenarios originating from the project ClimEx (Ludwig et al., 2019), from which 3500 model years are utilized. They result from 50 transient climate simulations, each modeling extreme events between 1980 and 2050 in Bavaria based on meteorological and hydrological simulations under RCP8.5 (IPCC, 2013). 38 events exceed the 100-year

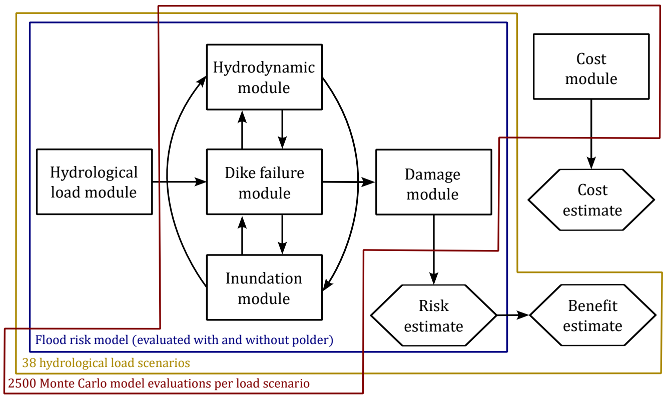

Figure 2: Modules of benefit-cost-analysis.

flood close to Riedensheim and were implemented in the one-dimensional hydraulic model SOBEK to derive hydrological load scenarios described by discretized hydrographs at every segment of the river. To each load scenario we assign an occurrence probability $p_o = \frac{1}{50 \cdot 70 \text{ years}}$.

2. *Dike failure module*. For each hydrological load scenario, the response of the river system is simulated 2500 times with and without the flood polder (resulting in a total of $38 \cdot 2500 = 95'000$ Monte Carlo samples). In each model evaluation, all dike segments are quasi-randomly tested against breaching using a generic fragility function shown in blue in Figure 3. This fragility function $F(w)$ describes the probability of breaching in function of the water level w relative to the crest level. It was derived by applying a set of limit state functions for different sub-breaching mechanisms (Vorogushyn, 2008) on the river dikes at the Danube. Additionally, a breach width is quasi-randomly sampled from the distribution proposed by Vorogushyn (2008) for every dike segment.
3. *Hydrodynamic module*. In case of dike failure or overtopping, the discharge through the breach or over the dike is calculated using the formula of Poleni, modified by a dike breakage parameter μ^* (Kamrath et al., 2006), which was set to the constant value $\mu^* = 0.7$. By multiplying the discretized discharge values with the temporal resolution of $\Delta t = 3600$ s, the corresponding inundation volumes are obtained. The inundation volume is limited through a coupling with the inundation module to ensure that the water level in the inundation area neither exceeds the water level in the river at the breach location, nor the height of adjacent downstream located dike segments. The reduction of the discharge in the river is propagated downstream using a simple routing approach derived specifically for this flood risk model.
4. *Inundation module*. The relationship between inundation volume and inundation height was derived for every dike segment using a static geographic information system (GIS) analysis.
5. *Damage module*. In a second GIS-analysis, the relationship between inundation height and direct tangible damage was derived for every dike segment by intersecting the inundation areas generated in Module 4, a digital elevation model and the Basic European Assets Map (Assmann et al., 2018), and multiplying the resulting damage potential with land-use specific damage functions. Indirect and intangible damages are not incorporated in the current model version.

3.2. *Quantified uncertainties*

In the scope of this work, the uncertainty of five selected input parameters is quantified using derived probability distributions, which are listed in Table 1.

- *Fragility function $F(w)$*: An upper and a lower bounding fragility function $F_U(w)$ and $F_L(w)$, shown in Figure 3, are derived based on a combination of the reviewed literature (Vorogushyn, 2008; Apel et al., 2014), expert judgment and the awareness of the uncertainties accompanied by the underlying pre-processing method. Therewith, random fragility functions $F_R(w)$ are obtained through Eq. (3), where X_F is a model uncertainty factor.

$$F_R(w) = X_F \cdot F_U(w) + (1 - X_F) \cdot F_L(w) \quad (3)$$

- *Dike breakage parameter μ^**: To account for the uncertainty accompanied by fixing μ^*, an

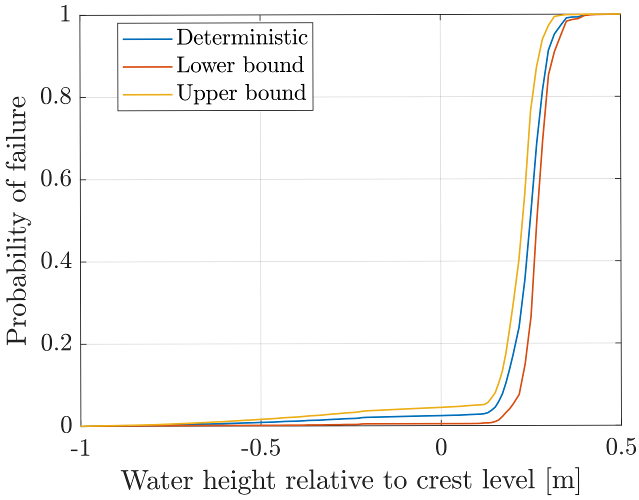

Figure 3: Fragility function and uncertainty bounds.

additive constant X_{μ^*} is introduced based on the results of Kamrath et al. (2006), extended for non-straight river sections.

- *Limit volume V*: A maximal flood volume V is attributed to each dike segment, which takes backflow processes over downstream located adjacent dike segments into account. The uncertainty of this parameter is quantified by a single multiplicative factor X_V on the limit volume V to represent the limitations of the underlying static GIS-approach.
- *Damage D*: Both the input data as well as the implementation of the different steps of the damage module are subject to various uncertainties. These uncertainties are modeled by a single multiplicative factor X_D on the damages.
- *Costs C*: Only the costs for reinvestment, operating costs and some additional minor expenses are subject to uncertainty, which is modeled by a single multiplicative factor X_C on these costs.

The quasi-randomly sampled realizations of each considered uncertain input parameter are propagated through the model in the scope of a conducted uncertainty analysis based on the Monte Carlo framework; thus, both the aleatory uncertainties inherent in the probabilistic flood risk model as well as the five considered epistemic uncertainties are sampled all-at-a-time.

Table 1: Parametrization of uncertain inputs.

Parameter	Parametrization of uncertainty (**U**:Uniform pdf, **T**:Triangular pdf)
X_F	**U**(0,1)
X_{μ^*}	**U**(-0.3,0.3)
X_V	**T**(0.9,1,1.5)
X_D	**T**(0.5,1,1.5)
X_C	**U**(0.9,1.1)

4. RESULTS

Note: The following results were manipulated by adding fixed arbitrary values to the resulting risks and costs, since the study is still ongoing and the model is not yet in its final version.

Table 2 shows the expected net benefit of the flood polder in function of the discount rate d. Because of the long life-time of the system, the choice of the discount rate has a significant influence on the resulting net benefit. For discount rates $d = 1.5\%$ and $d = 2\%$, the optimal prior decision with respect to the net benefit using the current model version and manipulated results is to build the flood polder. By contrast, for a discount rate $d = 2.5\%$, the net benefit is negative and thus the manipulated current model results suggest not to build it.

Table 2: Expected net benefit (NB) [€] for different discount rates d.

	$d = 0.015$	$d = 0.02$	$d = 0.025$
NB	$10.2 \cdot 10^6$	$2.2 \cdot 10^6$	$-3.9 \cdot 10^6$

Table 3 summarizes the results of the decision-oriented sensitivity analysis. The effect of a varying discount rate demonstrates the direct connection of the EVPPI to the decision under study: The further away the expected net benefit is from zero, the less likely it is that knowing the parameters will lead to a change of the decision, hence the lower the absolute influence of the uncertainties and the EVPPI.

Table 4 shows for comparison purposes the computed first-order Sobol' sensitivity indices. Overall, all investigated input parameters have low first-order Sobol' indices, which is due to dominating aleatory uncertainties.

While factor prioritization can be observed to

Table 3: Resulting decision-sensitivity measure on the net benefit [€] for different discount rates d.

X_i	$EVPPI(x_i)$		
	$d = 0.015$	$d = 0.02$	$d = 0.025$
X_F	0	$6.0 \cdot 10^5$	$2.5 \cdot 10^5$
X_{μ^*}	0	$1.0 \cdot 10^5$	0
X_V	0	0	$0.3 \cdot 10^5$
X_D	0	$7.9 \cdot 10^5$	$1.4 \cdot 10^5$
X_C	0	0	0

Table 4: Resulting first-order Sobol' sensitivity indices.

X_i	S_i
X_F	$0.9 \cdot 10^{-3}$
X_{μ^*}	$0.5 \cdot 10^{-3}$
X_V	$0.3 \cdot 10^{-3}$
X_D	$1.5 \cdot 10^{-3}$
X_C	$0.4 \cdot 10^{-3}$

change for different discount rates using the EVPPI, the relative Sobol' indices remain quasi-constant for all discount rates d.

5. DISCUSSION

Uncertainty and sensitivity analysis has received increasing attention in the field of flood risk management over the last two decades and a variety of sensitivity measures are employed (Pianosi et al., 2016). However, interpreting these measures and their implication on the decision under study is not always straightforward. By contrast, decision-oriented sensitivity measures are easier to interpret, because they directly relate the input parameter uncertainty to the optimality of the risk management decision under consideration.

In this work, we estimate the expected value of partial perfect information of five input parameters of a flood model that supports the decision of whether or not to implement a flood polder in Riedensheim at the Bavarian Danube. We evaluate the EVPPI as a side-product of a conducted uncertainty analysis, without requiring additional model evaluations. The estimated EVPPI values indicate that gathering more information on the input parameters, especially on the fragility function F and on the depth-damage relationship D, can potentially improve decision making.

As intuitively expected, an increasing discount rate decreases the expected net benefit of the flood polder. Given the current model version and manipulated results, for a discount rate of $d = 2\%$, the expected net benefit is closest to zero. For this case, the EVPPI values are highest, since learning more about the input parameters is more likely to change the decision. By contrast, for a lower discount rate of $d = 1.5\%$ it is unlikely that the decision changes and the EVPPI's of all input uncertainties are estimated as zero.

The corresponding first-order Sobol' sensitivity indices show the same ordering of the input uncertainties as the EVPPI for the case $d = 2\%$, but different for the other values of the discount rate. The Sobol' indices do not consider the decision but just provide a relative measure of the effect of the input uncertainties on the variance of the model output. Hence they do not account for the importance of the uncertainties on the optimality of the decision. They can also not be interpreted in an absolute sense like the EVPPI, which corresponds to the amount of money that should maximally be invested to reduce the uncertainty in a specific input. Therefore, in this specific decision context, the decision-related sensitivity measure provides beneficial information about the absolute influence of the uncertainty of model inputs and thus on which model input more data should be collected to reduce the uncertainty involved in decision-making.

6. CONCLUSIONS

We show that the expected value of partial perfect information is an informative and intuitively interpretable sensitivity measure directly related to the decision that is to be supported by the model. The application to a flood risk mitigation decision demonstrates the advantages of the measure while being computationally equally expensive as comparable variance-based first-order sensitivity measures. By varying the discount rate, we highlight how the decision-related sensitivity measure is affected by the specific decision context and the probability with which an uncertainty can affect the optimality of the decision to be made.

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