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A two-step approach to investigate the effect of rating curve uncertainty in the Elbe decision support system*

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Abstract: For river basin management, the reliability of the rating curves mainly depends on the accuracy and time period of the observed discharge and water level data. In the Elbe decision support system (DSS), the rating curves are combined with the HEC-6 model to investigate the effects of river engineering measures on the Elbe River system. In such situations, the uncertainty originating from the HEC-6 model is of significant importance for the reliability of the rating curves and the corresponding DSS results. This paper proposes a two-step approach to analyze the uncertainty in the rating curves and propagate it into the Elbe DSS: analytic method and Latin Hypercube simulation. Via this approach the uncertainty and sensitivity of model outputs to input parameters are successfully investigated. The results show that the proposed approach is very efficient in investigating the effect of uncertainty and can play an important role in improving decision-making under uncertainty.

Key words: Elbe decision support system (DSS), Two-step approach, Uncertainty, HEC-6 model
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INTRODUCTION

Integrated river basin management (IRBM) involves conflicting issues like water quality, water supply, hydropower, flood risk and ecology. In recent years, IRBM has become more complicated because of these conflicting issues, large amounts of information, and ever-changing environmental conditions, like climate. Decision support systems (DSSs) are one of the possible solutions to aid decision-makers in dealing with such complicated management issues (Loucks and da Costa, 1991; Jamieson and Fedra, 1996; Salewicz and Nakayama, 2004; Giupponi, 2007; Sojda, 2007). To make a sound decision, decision-makers need to be aware of the existence of uncertainty in the evaluation of river engineering measures (European Commission, 2000; UN/WWAP, 2003; Walker *et al.*, 2003). It is therefore proposed that the modellers provide model outputs together with uncertainty information to decision-makers, which will surely add more reliability to decision-making in practice. Uncertainty assessment is regarded as one of the most important issues in a DSS (Mowrer, 2000). However, in most DSSs for river basin management, the uncertainty has not been taken into account because decision-makers believe that considering uncertainty adds more complexity to the already complicated decision-making. In recent decades, consideration of uncertainty in decision-making has been a popular and important research area (de Kort and Booij, 2007; Schlüter and Rüger, 2007). Uncertainty analysis is also regarded as one of the crucial steps in environmental model development (Jakeman *et al.*, 2006; Giupponi, 2007).

To investigate the effect of uncertainty in decision-making, a lot of methods are available, including an error propagation equation, Monte Carlo (MC)

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methods, response surface (RS) method and Bayesian uncertainty analysis. Table 1 summarizes the advantages and disadvantages of some of these uncertainty analysis methods, with some examples of applications. Besides the methods introduced in Table 1, other methods can be used for uncertainty propagation as well, for example Rosenblueth's point estimation method and Harr's point estimation method (Yu *et al.*, 2001). There are general rules for choosing an appropriate uncertainty propagation method, including linearity or non-linearity of models, monotony of models, efficiency of methods, and research or practical requirements (Saltelli *et al.*, 2000; Booij, 2002). For complicated systems a combination of methods is needed, which is the case in this paper.

A DSS has been designed for the Elbe River, located in Central Europe. As an integrated and complicated DSS, many models are included, in which the rating curves are one of the most important components. The rating curves are used to produce hydrological data needed for the Elbe River system analysis. The reliability of the rating curves is therefore essential for the DSS. In this paper the uncertainties in the rating curves are identified and a two-step uncertainty analysis approach is designed to propagate these uncertainties into the Elbe DSS. This approach is mainly proposed for a complicated decision-making situation and regarded as novel and efficient in investigating the effect of rating curve uncertainty. To demonstrate the efficiency and validity of the proposed approach, one of the main components of the Elbe DSS, the vegetation model which uses the rating curves as inputs, is therefore selected as an example.

STUDY AREA AND MODELS

Study area

The Elbe DSS focuses on the German part of the Elbe River (Fig.1). The DSS integrates important issues like water quality, flood risk, navigation and ecology (de Kok *et al.*, 2000). To cope with these different issues, several models have been used, such as 1D hydraulic models, a hydrological model HBV (Hydrologiska Byråns Vattenbalansavdelning) (Bergström, 1995), a flood risk model, a shipping model and a vegetation model. Among these models, the rating curves are one of the substantial components of the Elbe DSS. They serve as inputs into other models, such as the shipping and vegetation models in the Elbe DSS. Due to practical reasons, the vegetation model is used as an example.

Model

Two 1D hydraulic models are used to provide inputs to the vegetation model: the rating curves and Hydrologic Engineering Center (HEC)-6 model (U.S. Army Corps of Engineers, 1993). The rating curves describe the relationships between the discharge (Q) and water level (H) along the river, based on measurements at gauge stations. Though simple and useful, the disadvantage is that the rating curves based on measurements cannot model the effects of river engineering measures on the water levels. One such measure is channel dredging, which changes the geometry of the river channel and may change the rating curves along the river after implementation. The rating curves in the Elbe DSS are represented

Table 1 Advantages and disadvantages of different uncertainty propagation methods

Method	Characteristic	Advantage	Disadvantage	Application
Error propagation method	Analytical	Easy; preliminary results; time dependable	No interactions; local and linear approximation	McIntyre and Wheater (2004); Xu and Booij (2005)
Monte Carlo methods	Sampling method	Arbitrary level of accuracy; easily implemented; non-linear model	Time consuming; results difficult to analyze	Kuczera and Parent (1998); Thorsen *et al.*(2001); Yu *et al.*(2001)
Response surface method	Construction of response surface	Fast; transparent view of global sensitivity	Necessity of a lot of insight and expertise; not dynamic; complex	Janssen *et al.*(1990); Bauer *et al.*(1999)
Bayesian uncertainty analysis	Model averaging	Able to consider model structure and quantities uncertainty together	Lack of robustness of the probability of correctness for new models; irrelevance of the probability to the decision process	Draper (1995); Zio and Apostolakis (1996); Wasserman (2000)

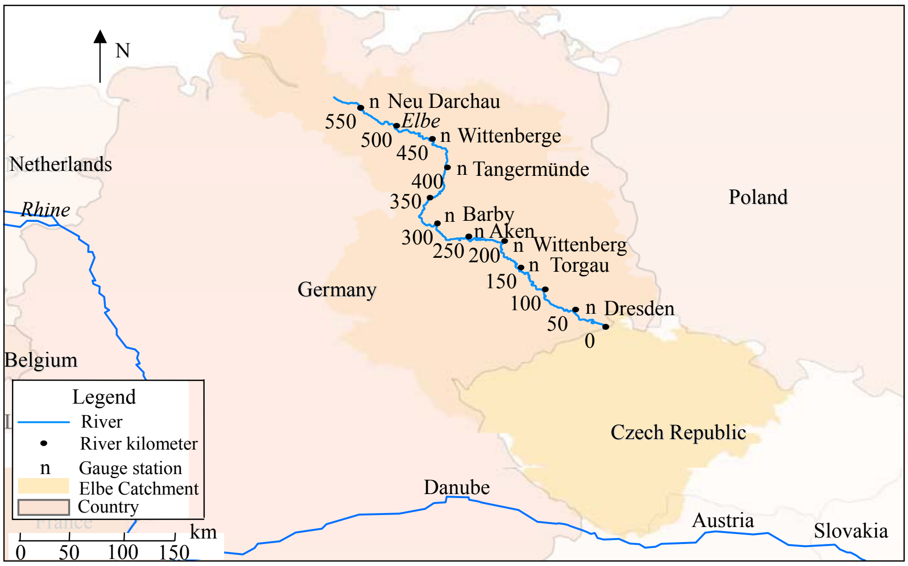


Fig.1 Part of the Elbe River in Germany

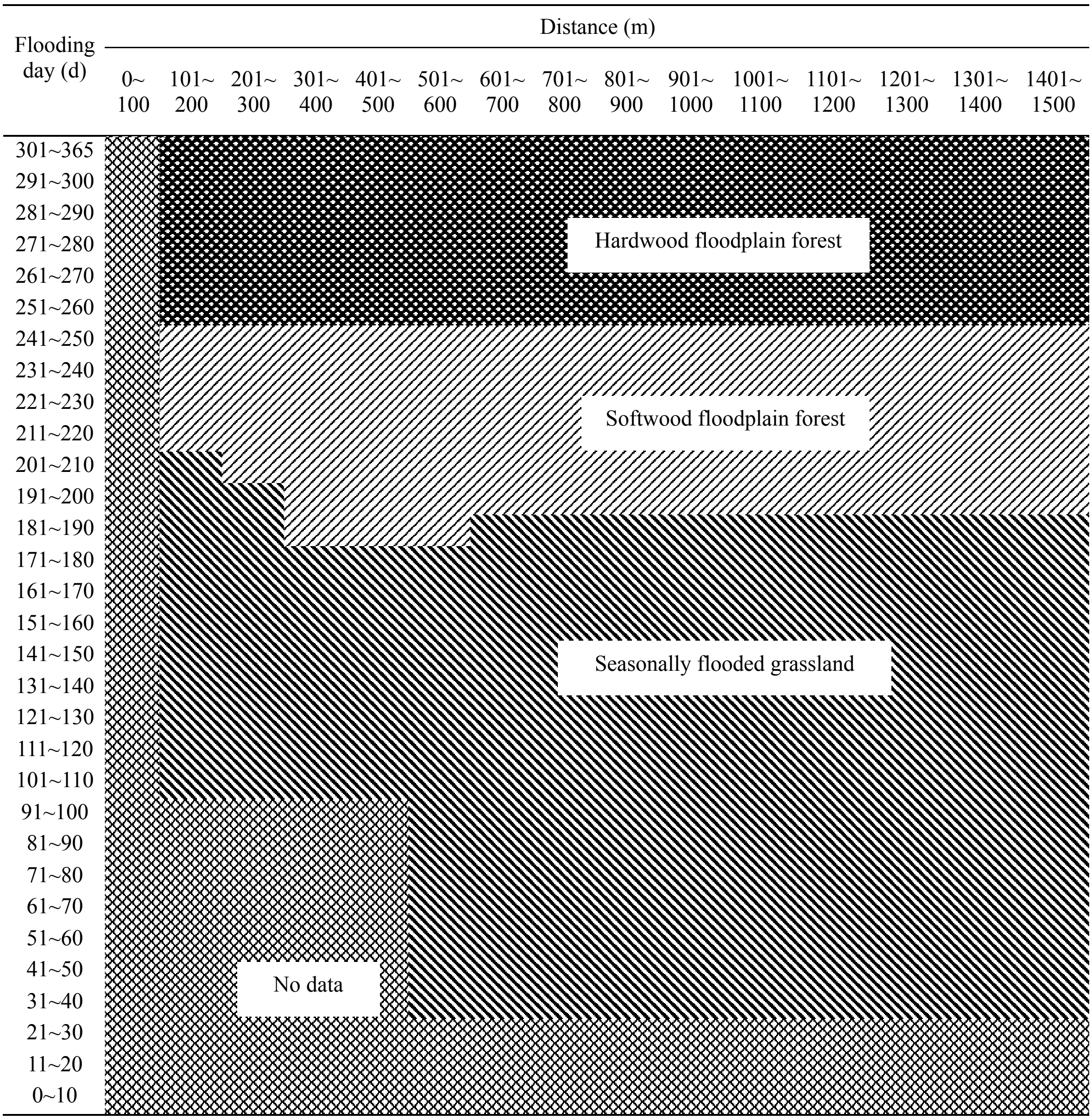
by: $H=a\times Q^b$, where Q is the discharge (m^3/s), H is the water level (m), and a and b are location-dependent parameters which can be found by least-square fitting. The main function of the HEC-6 model is to compute the water levels for river flow in the main channel. It is a 1D open channel flow model. The advantage of HEC-6 is its capability to take into account the effects of river engineering measures. One disadvantage is that this model cannot be used directly to compute the flood duration which is one dominant component for the vegetation model. In order to investigate the effects of different measures, the two models are combined in the Elbe DSS. First the HEC-6 model is used to produce the discharge and water level for different measures for each location along the Elbe River. Then these data are analyzed to derive the rating curves along the river by regression analysis. By doing this, new rating curves can be obtained to account for the possible measures that affect the geometry of channel and floodplains. 2D models are not yet used due to data availability and their high computational requirements.

The vegetation model is a simplified version of the rules from MOVER (Model for Vegetation Response), which is a vegetation sub-model of INFORM (Integrated Floodplain Response Model) from the German Federal Institute. This model is mainly used to produce maps for the dominant groups of vegetation (biotypes) in the floodplain area along the Elbe River (Fuchs *et al.*, 2002). It uses the flood duration (i.e., the total number of flooding days per year), the distance to the main channel, and land use, to determine the presence or absence of biotypes. In this model, a specification of the most expected biotype is determined on the basis of a set of rules. The rules consist of three matrices, one matrix for each land use type. The matrix provides specific ranges for the distance to the main channel and ranges for the number of flooding days of a biotype. One such matrix for agriculture is shown in Table 2. In this model, there are 11 dominant biotypes in total (Table 3). One important concept in this vegetation model is the flood duration. The lognormal distribution is used to model the daily discharge statistics. The number of flooding days based on the critical discharge in the floodplain area is calculated for each cell (x, y) in the area using the approximation of error function:

$$N_{\text{flood}}(x,y)=\frac{365}{2}\left(1-\text{erf}\left[\frac{\log(Q_{\text{crit}}(x,y))-\mu(x)}{\sqrt{2}\sigma(x)}\right]\right),\quad(1)$$

where the discharge parameters μ and σ are location-dependent and given by the daily discharge range; erf is the error function; Q_{crit} is the critical discharge; N_{flood} is the number of flooding days. The critical discharge Q_{crit} is defined as the discharge at which a certain piece of land (x, y) starts to flood. In order to determine

Table 2 Example rule matrix for agriculture (Fuchs *et al.*, 2002)



this critical discharge, the elevation of the land $z(x, y)$ and the rating curves are needed. The error function erf is given as

$$\mathrm{erf}(z)=\frac{2}{\sqrt{\pi}}\int_0^z \mathrm{e}^{-x^2}\,\mathrm{d}x. \tag{2}$$

The decision variables are the frequencies of 11 biotypes to characterize the biotype diversity in the floodplains along the Elbe River. They are calculated as the individual number of cells of each biotype divided by the total number of cells of all biotypes in the floodplain:

$$P_i = N_i / N_{\mathrm{total}}, \tag{3}$$

where P_i is the frequency of ith biotype; N_i is the number of cells of ith biotype in the floodplains and N_{total} is the total number of cells of all biotypes.

TWO-STEP APPROACH

In order to investigate the effect of the

Table 3 Biotypes in the floodplains along the Elbe River

Biotype number	Biotype description
0	No data
1	Seasonally flooded grassland
2	Softwood floodplain forest
3	Hardwood floodplain forest
4	Reed
5	Herb fringes and herb meadows
6	Grassland of wet to moist sites
7	Intensively used, species-poor, moist grassland
8	Other reeds
9	Herby flood banks and plains near the water
10	Dry and warm ruderal sites with dense vegetation
11	Moist ruderal sites

uncertainty in the rating curves on the vegetation model, a two-step approach is proposed in this paper. This approach is designed in two steps, mainly taking into consideration its efficiency for a complex DSS. The first step in this approach is analytical uncertainty propagation, which is efficient in the sense of its analytical characteristics, time-saving and high accuracy for modeling a linear system (Bevington and Robinson, 1992; also see references in Table 1) while simulation methods are often more time-consuming and the results are difficult to analyze. This is particularly designed to add more reliability to the rating curve uncertainty analysis results, since the rating curve equation can be transformed to a linear one, as described later. The second step is Latin Hypercube simulation, which is well known as needing less simulation time compared to other Monte Carlo methods and is more precise in producing random samples (Saltelli *et al.*, 2000). Besides its efficiency, this approach is also novel because usually uncertainty analysis is implemented in one single step by utilizing either analytical or simulation methods.

Analytical uncertainty propagation

The analytical approach is the first step, mainly used to investigate the uncertainties in the rating curve parameters a and b and propagate them into the parameters in the second regression analysis. The error in the water levels is normally distributed and the standard deviation is estimated to be σ_H=5 cm. To apply an analytical method, the equation of the rating curves is transformed to

$$\log H = \log a + b\log Q. \tag{4}$$

Let x=log$Q$ and y=log$H$. Then $\sigma_y=\sqrt{\sigma_H^2(\partial y/\partial H)^2}=\sigma_H/H$. Furthermore, let A=log$a$ and B=b. The estimations of A and B are respectively

$$A=\frac{1}{\Delta}\left(\sum_i\frac{x_i^2}{\sigma_{Hi}^2}\sum_i\frac{y_i}{\sigma_{Hi}^2}-\sum_i\frac{x_i}{\sigma_{Hi}^2}\sum_i\frac{x_iy_i}{\sigma_{Hi}^2}\right); \tag{5a}$$

$$B=\frac{1}{\Delta}\left(\sum_i\frac{1}{\sigma_{Hi}^2}\sum_i\frac{x_iy_i}{\sigma_{Hi}^2}-\sum_i\frac{x_i}{\sigma_{Hi}^2}\sum_i\frac{y_i}{\sigma_{Hi}^2}\right); \tag{5b}$$

where $\Delta=\sum_i\frac{1}{\sigma_{Hi}^2}\sum_i\frac{x_i^2}{\sigma_{Hi}^2}-\left(\sum_i\frac{x_i}{\sigma_{Hi}^2}\right)^2.$

A first-order error propagation equation is used to propagate the error originated from the HEC-6 model into the uncertainties in A and B. Based on the first-order error propagation equation, the standard deviations of A and B are computed as

$$\sigma_A=\sqrt{\frac{1}{\Delta}\sum_i\frac{x_i^2}{\sigma_{Hi}^2}};\ \sigma_B=\sqrt{\frac{1}{\Delta}\sum_i\frac{1}{\sigma_{Hi}^2}}. \tag{6}$$

So the uncertainties in the original parameters a and b are

$$\sigma_a=\sigma_A\mathrm{e}^A;\ \sigma_b=\sqrt{\frac{1}{\Delta}\sum_i\frac{1}{\sigma_{Hi}^2}}. \tag{7}$$

The second linear regression analysis is used to model the dependence of a and b at different river sections. The equations to model the dependency are:

$$\begin{cases} y=f_1+e_1x, \text{ for } a,\\ y=f_2+e_2x, \text{ for } b. \end{cases} \tag{8}$$

The uncertainties in a and b calculated by Eq.(7) are propagated into the regression parameters e_1, f_1, e_2, and f_2 in Eq.(8). The method for calculating the uncertainty in regression parameters can be found in (Sabatelli *et al.*, 2002).

As described above, this analytical approach is easy to implement and can provide accurate results for a linear system.

Latin Hypercube simulation

The second step is mainly to propagate the uncertainties in the regression parameters e_1, f_1, e_2 and f_2 into the vegetation model by Latin Hypercube simulation (Saltelli *et al.*, 2000). This sampling scheme first segments the assumed probability distributions into a number of intervals, each having equal probability. Then, from each interval, a value is selected at random according to the probability distributions within the interval. Latin Hypercube sampling is generally more precise for producing random samples than conventional Monte Carlo sampling, because the full range of the probability distribution is sampled more evenly. As mentioned before, this sampling scheme is also more efficient, since it needs far less simulation runs than normal Monte Carlo sampling, in achieving the same accuracy. Fig.2 shows a brief schematic graph of Latin Hypercube simulation to generate a sample of size 5 from input and parameter vector $\boldsymbol{X}=[x_1\ x_2]$, with x_1 normal on [−1 1] and x_2 triangular on [1 4].

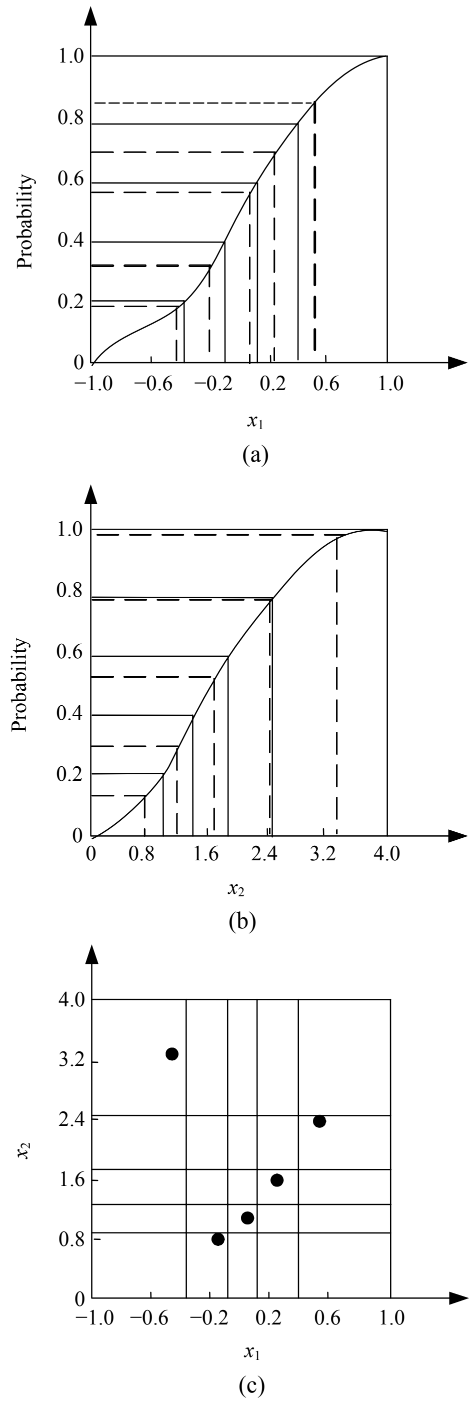


Fig.2 Illustration of Latin Hypercube simulation. (a) Random sample from x_1; (b) Random sample from x_2; (c) Random pairing (x_1 x_2). x_1: normal on [−1 1]; x_2: triangular on [1 4]

UNCERTAINTY SOURCES

In this paper, due to data availability, the authors focus on the analysis of uncertainty in the hydrological and hydraulic models. Therefore the uncertainty in the vegetation model is not considered, due to lack of information. Based on sensitivity analysis (Xu, 2005), the uncertainty in the rating curves is found to be the most dominant source. Therefore, in the following, only the uncertainty in the rating curves will be described.

Two linear regression analyses are involved in estimating the uncertainty in the rating curves. As stated before, the rating curves along the Elbe main channel are fitted from the discharge and water level data calculated from the HEC-6 model by linear regression analysis. This is the first linear regression analysis. In addition, the water levels upstream and downstream are highly dependent on each other. This is represented by a high dependence of the parameter a/b upstream and downstream. The dependence is modelled by another linear regression analysis in order to estimate the final uncertainty in the rating curves. This is the second regression analysis. The reliability of the rating curves depends greatly on the accuracy of the water levels calculated by the HEC-6 model. One source of uncertainty in the rating curves is therefore the error in the computed water levels. In the Elbe DSS, the HEC-6 model calculates the water levels for 10 different discharges for every 100 m. These 10 values correspond to the discharges of different return periods, which represent a whole range of the river flows in the Elbe River. A rough estimation of the error is obtained from the calibration of the HEC-6 model along the Elbe River sections 252~272 km, 291~299 km and 332~343 km. According to (Nestman and Buchele, 2002), the differences between the measured and calculated water levels are from 4 cm to 10 cm. A maximum value of 10 cm is adopted in this paper as the error in the calculated water levels in the river section concerned. This error will be propagated into the parameters a and b for each river location. It is assumed that there is no correlation between the parameters a and b.

RESULTS

Uncertainties in regression parameters

The uncertainties in the rating curves are propagated into parameters e_1, f_1, e_2 and f_2 using the analytical method. Table 4 shows the computed mean values and corresponding uncertainties (expressed by standard deviations) of the regression parameters. The numbers in these four regression parameters have quite different orders of magnitude. The order of magnitude of the uncertainty in f_1 is relatively high compared to those of other parameters, so are the mean values.

Table 4 Uncertainty in e_1, f_1, e_2 and f_2

Regression parameter	Mean	Standard deviation
e_1	-1.51×10^{-1}	1.16×10^{-3}
f_1	79.81	0.46
e_2	2.18×10^{-4}	7.26×10^{-6}
f_2	-2.41×10^{-2}	2.78×10^{-3}

Uncertainty and sensitivity analysis results

The uncertainties in the regression parameters shown in Table 4 are then propagated into the vegetation model by Latin Hypercube simulation. It is assumed that these four parameters are normally distributed. 100 Latin Hypercube simulations are generated. Figs.3a and 3b show examples of the scatter plots expressing the relationships between the four regression parameters and the frequencies of Biotypes 3 and 4 based on the simulation results, which indicate the sensitivity of the frequencies of Biotypes 3 and 4 to regression parameters. The effects of the regression parameters are different for these two biotypes. For Biotype 3, the scatter plots show a highly complex relationship between the four parameters and the vegetation model outputs. Most model outputs center around the mean value of 0.04. The frequency of Biotype 3 decreases monotonously with the parameter f_1. For Biotype 4, the model outputs distribute almost evenly and a monotonous increase with f_1 can be observed. These graphs show that the effect of regression parameter f_1 on the model outputs and its uncertainty is more important than those of other parameters. As expressed in Eq.(8), f_1 is the regression parameter related to the parameter a, which indicates that a may be more important than the parameter b. Fig.3b shows how sensitive are the model outputs to the parameters in the regression analysis and provide implications as to how to improve the vegetation model if necessary.

Fig.4 shows the uncertainties in the frequencies of 11 biotypes in the floodplains along the Elbe River. 'Bio 0' indicates the situation with no data available. The error bars show the mean values, 10th, and 90th percentiles of the model outputs. The 10th percentile of the model outputs indicates the value that is greater than 10% of the values in the frequencies of biotypes along the concerned river section. The 10th and 90th percentiles indicate the amount of uncertainty in the frequencies of 11 biotypes. From Fig.5 high uncertainties can be observed in the model out puts of this vegetation model. For example, for Biotype 4, the mean value is around 0.06; the 10th and 90th percentiles are 0.02 and 0.13, respectively, which shows high variability in the value of the frequency of Biotype 4.

Some facts can be figured out from the uncertainty results shown in Fig.4. For example, the error bar of Biotype 2 shows that Biotype 2 is likely to disappear in the future. If more diverse biotypes in the floodplains are expected, measures need to be identified by relevant decision-makers for increasing the frequency of Biotype 2. As shown in Table 3, Biotype 2 is soft wood. Therefore, re-forestation in the floodplains might be a good alternative to increase the biotype diversity. The error bars shown in Fig.4 can actually provide very useful information about the uncertainty in the biotype diversity in the floodplains along the Elbe River in the future, and enable decision-makers to make better decisions.

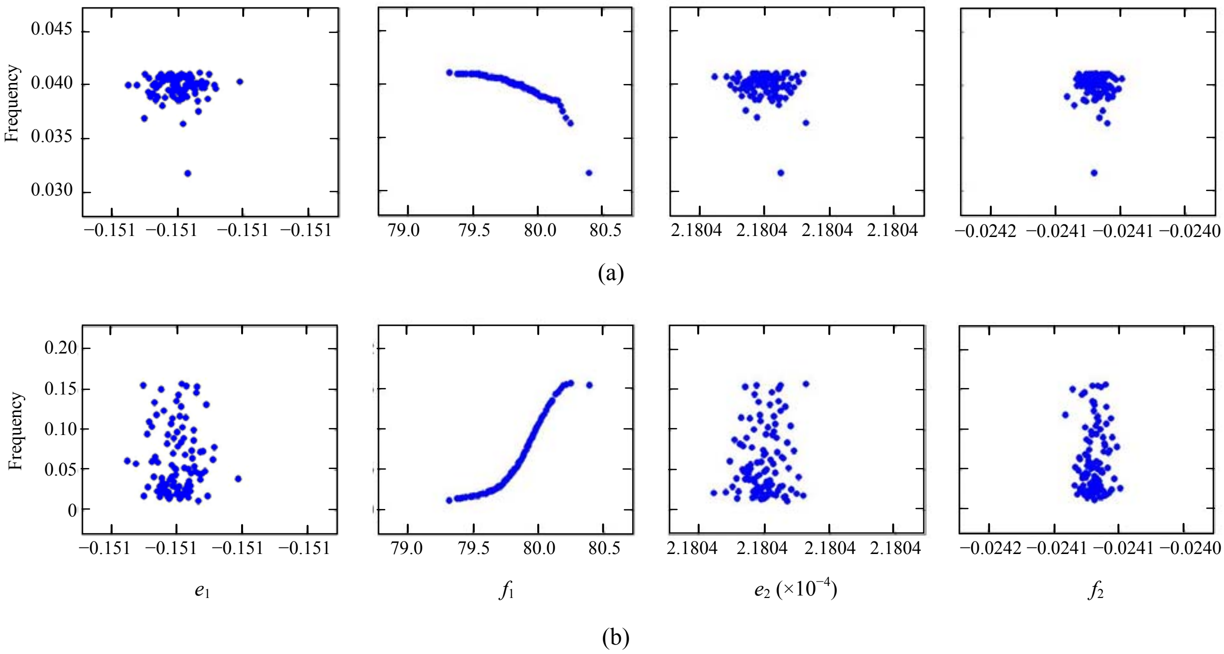


Fig.3 Four regression parameters (e_1, f_1, e_2, f_2) vs model outputs for (a) Biotype 3 and (b) Biotype 4

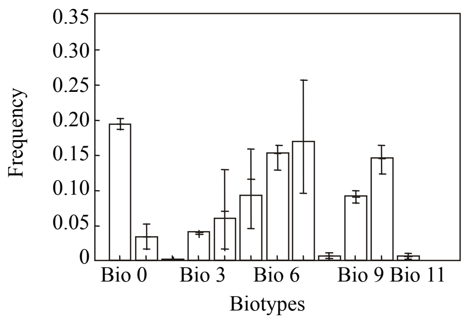


Fig.4 Error bars for the frequencies of 11 dominant biotypes in the Elbe floodplains ('Bio 0' is the situation without data, 'Bio 1'~'Bio 11' are the 11 dominant biotypes in the Elbe floodplains)

DISCUSSION

The two-step approach proposed in this paper is a quantitative method to propagate the uncertainty into model outputs. The example of the vegetation model shows a successful demonstration of applying the proposed approach. The two-step approach is demonstrated to be very efficient in both time and accuracy. First, the analytical characteristics of the first step can save much time and give accurate uncertainty analysis results. This is particularly suitable in the case of the rating curve, which can be transformed to a linear equation, and therefore a first-order error propagation method can be applied. The analytical approach is also easy to implement and has high computational efficiency. The high accuracy of uncertainty analysis results obtained by the first step adds more reliability to the rating curve uncertainty estimation and therefore the corresponding decision-making. Secondly, the choice of Latin Hypercube simulation in the second step is made because not only can it deal with a complicated non-linear system, which is the case in this paper (for the vegetation model), but can provide also more precise results than other simulation methods and need smaller simulation size. Therefore, a combination of such two steps can suit in particular the need of uncertainty analysis for a complicated DSS. Besides its high efficiency, the proposed approach is also novel because of the combination of an analytical method and a simulation method, which is seldom seen in the literature.

CONCLUSION

This paper introduces a two-step approach to analyze the effect of rating curve uncertainty in an Elbe DSS. The rating curves are a vital component of the Elbe DSS in modelling the effects of river engineering measures (combined with other hydraulic models). The example of the vegetation model in the Elbe DSS demonstrated the time and accuracy efficiency of a two-step uncertainty analysis approach by successfully propagating uncertainty originating from the rating curves into the model outputs. Although the uncertainties propagated into the frequencies of 11 biotypes are high, the complete results provide very useful insights into uncertainty information for further decision-making in river basin management.

As is well known, models are never perfect. Knowing about the uncertainty can help decision-makers understand the gaps in current knowledge. The approach proposed in this paper is demonstrated to be capable of propagating uncertainty in a complicated system in an efficient way and can therefore provide substantial support to decision- making under uncertainty. Besides, as shown in this paper, this approach provides the possibility to analyze the sensitivity of model outputs to model parameters and provides qualitative information about the importance of parameters. Based on such information, additional work can be done to improve the models so as to reduce the uncertainty if necessary. The approach therefore can play an important role in decision-making under uncertainty.

The extended application of the proposed two-step approach can be a full analysis of uncertainty in the data and models in the whole decision support system, especially the vegetation model itself. This approach is general since no special requirements for its application have ever been needed. This approach is therefore recommended to be applied to a more complicated management problem, which could include more components like flood damage assessment and water quality management, because of its high efficiency and generality.

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