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Efficient uncertainty quantification for impact analysis of human interventions in rivers

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ABSTRACT

Human interventions to optimise river functions are often contentious, disruptive, and expensive. To analyse the expected impact of an intervention before implementation, decision makers rely on computations with complex physics-based hydraulic models. The outcome of these models is known to be sensitive to uncertain input parameters, but long model runtimes render full probabilistic assessment infeasible with standard computer resources. In this paper we propose an alternative, efficient method for uncertainty quantification for impact analysis that significantly reduces the required number of model runs by using a subsample of a full Monte Carlo ensemble to establish a probabilistic relationship between pre- and post-intervention model outcome. The efficiency of the method depends on the number of interventions, the initial Monte Carlo ensemble size and the desired level of accuracy. For the cases presented here, the computational cost was decreased by 65%.

1. Introduction

Human interventions in rivers, usually on the scale of a hundred meters to several kilometers, are carried out all over the world to improve various, sometimes competing, river functions. Motivations for such works include flood protection (Klijn et al., 2013; Warner and van Buuren, 2011; Rijke et al., 2012) and ecological restoration (Downs and Kondolf, 2002; Buijse et al., 2002; Stewardson and Rutherfurd, 2008). Detailed physics-based models are used to quantify the impact of interventions on river systems. Lammersen et al. (2002), Bronstert et al. (2007) and Te Linde et al. (2010) studied the effect of river training works on hydraulic variables along the River Rhine. Remo et al. (2009) did a similar study for more than 100 years of river engineering along the Middle and Lower Missisipi River, and Dierauer et al. (2012) assessed the effectiveness of dike relocation (termed 'levee set back' in that paper). In 'Room for the River', a recently finished large scale flood protection program in The Netherlands which consisted of 39 projects and had a projected budget of 2.0–2.4 billion euro, impact analyses with detailed physics-based models were a key ingredient in decision support (Rijke et al., 2012). In all reported studies model accuracy was increased and tested through a calibration-validation scheme, following good modelling practice (Rykiel, 1996; van Waveren et al., 1999; Jakeman et al., 2006).

However, the inherent problem with this deterministic approach for impact analysis is that models are used to provide predictions outside measured conditions. Not only are some interventions — especially those aimed at flood protection — aimed at impact under unobserved extreme conditions, but once calibrated for a pre-intervention river system, models cannot be assumed to retain their accuracy when applied to the modified post-intervention system. Nonetheless, uncertainty is not explicitly quantified, either because there is high confidence in the physical basis of the hydraulic model (Te Linde et al., 2010) or because of limited resources (Bronstert et al., 2007).

In environmental management, there is an increasing need for policy support that is realistic about uncertainties that may impact decisions (Uusitalo et al., 2015). In model-based decision support this requires identification of potential sources of uncertainty and methods to quantify uncertainty of model output. There are many ways to categorize sources of uncertainty. One way is to distinguish between uncertainty in parameters, model input and technical implementation (Draper, 1995; Walker et al., 2003; Warmink et al., 2010; Skinner et al., 2014). In river modelling, parameter uncertainty is considered to be dominated by hydraulic roughness (Horritt and Bates, 2002; Warmink et al., 2013b), and to a lesser extent boundary conditions derived from rating curves (Pappenberger and Beven, 2006; Di Baldassarre et al., 2010) and uncertainty in geometry (van Vuren et al., 2005; Neal et al., 2015). Quantification of model output in river modelling as a function of various sources of uncertainty is carried out using variations of

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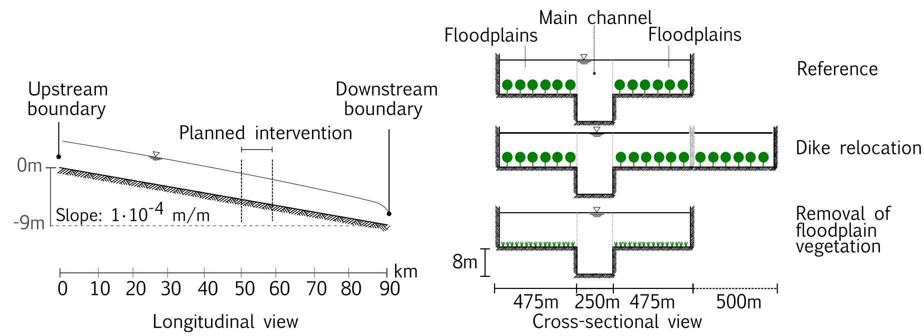

Fig. 1. The model is a straightened, idealised version of the River Waal, with a two-stage compound channel along the entire channel. The two intervention types are implemented between km 50 and km 60.

Monte Carlo simulation (Werner, 2004; Pappenberger et al., 2005, 2006; Warmink et al., 2013b; Straatsma et al., 2013; Neal et al., 2015). In catchment hydrology and climate change, probabilistic assessment of environmental impact is quantified using Monte Carlo simulation (Eckhardt et al., 2003; Breuer et al., 2006; McMichael and Hope, 2007) or multi-model approaches (Giorgi and Mearns, 2003; Tebaldi et al., 2005; Smith et al., 2009; Thirel et al., 2015). However, to our knowledge there is no literature on probabilistic impact analysis for physics-based models in the context of a changing environmental system, either due to human intervention or natural causes. A partial explanation for this knowledge gap is that long runtimes of a detailed river models render a fully probabilistic assessment with Monte Carlo simulation arduous with standard computer resources. It becomes infeasible in the context of river intervention modelling for decision support, where designs will go through various iterations and intermediate forms before a decision to implement it can be made. Therefore, to meet the growing demand to incorporate uncertainty in decision support, a more efficient uncertainty quantification method is required.

The central question in this paper is: how can we reduce the computational investment of uncertainty quantification for impact analysis of river interventions with physics-based models? We approach this challenge by combining a hypothesis of inter-model correlation between the various models involved in impact analysis with the rigorous Bayesian approach developed in the multi-fidelity framework of Koutsourelakis (2009). The new method is tested by comparing it against a classical Monte Carlo approach.

We introduce the framework of impact assessment, the case studies and the efficient uncertainty quantification method in section 2. Results showing the output probability distributions of both the classical Monte Carlo approach as the new, efficient method are presented in section 3. Section 4 discusses potential applications of the method for decision support in river management, sensitivities and possible extensions. In section 5 we briefly summarise the method and results, and draw conclusions.

2. Methodology

2.1. Definition of hydraulic river models and parameters

A hydraulic (alternatively termed 'hydrodynamic') river model is a predictive tool made with a modelling system using data and parameters specific for a natural river system at a certain period. An example of a model is a SOBEK hydraulic model (the modelling system) for the River Waal (the natural system) as it was in the summer of 2010 (the period). Since these models are physics-based, the parameters involved generally have a clear physical interpretation. Of all the parameters in a hydraulic model, roughness coefficients are generally considered the most sensitive and uncertain ones.

Various elements in a river system generate hydraulic resistance. In the following, we consider that each roughness element has its own set of parameters, specific to the roughnes formula, and that each instance of that element inherits the same parameter values. For example, in this paper we use the Manning formula to account for friction of the roughness element 'grass', which only has the Manning coefficient as a parameter. The roughness element 'grass' is used in many places throughout the model, but with the same value of the Manning coefficient for each instance it is used. The value of the friction coefficients can be determined in various ways. For many elements, values have been estimated with empirical research (Chow, 1959). In practice, roughness parameters are often calibrated for specific cases based on often limited measurement data. However, in both cases there remains significant uncertainty in those values, the effect of which will propagate to uncertainty in model outcomes.

The spatial distribution of roughness elements in natural rivers is generally heterogeneous. In channels, roughness often comes from bed material, bed forms or structural elements like groynes. Floodplains are generally more diverse, with various vegetation species, hedges, pools and other structural features. Human intervention in a river system may change the distribution of roughness elements by removal, addition or modification of structures and roughness elements. For that reason the collection of friction parameters pre-intervention is not necessarily equal to the collection of friction parameters post-intervention.

2.2. Case studies

We explore two different river interventions in a low-land river. In both cases the objective is to calculate the water levels along the river at a given high and steady discharge. We refer to this discharge as the design discharge and the water levels produced during this discharge as the design water level (DWL). The use of a steady instead of unsteady conditions leads to an over-prediction of water levels by nullifying diffusive attenuation, but avoids subjectivity related to the shape of an unsteady discharge wave. The two cases are both chosen to cause a significant lowering of the DWL, but by different processes.

The first case is relocation of a dike. Many low-land rivers frequently experience water levels at or above the general level of the surrounding hinterland. Dikes are embankments specifically built to protect the hinterland against floods, but in turn constrain the river system. In the Rhine River, this has led to a so called 'technological lock-in' which necessitates continuing strengthening and raising of the dikes (Wesselink, 2007). An expensive, but effective alternative is to relocate the dikes to increase the size of the floodplains. Real-world

Table 1
Overview of roughness parameters in the model.

Roughness element	symbol	Mean	Variance
Main channel	n_m	0.03	0.002^2
Brush	n_b	0.07	0.01^2
Grass	n_g	0.04	0.005^2