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Assessing the relative importance of parameter and forcing uncertainty and their interactions in conceptual hydrological model simulations

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ABSTRACT

Predictions of river flow dynamics provide vital information for many aspects of water management including water resource planning, climate adaptation, and flood and drought assessments. Many of the subjective choices that modellers make including model and criteria selection can have a significant impact on the magnitude and distribution of the output uncertainty. Hydrological modellers are tasked with understanding and minimising the uncertainty surrounding streamflow predictions before communicating the overall uncertainty to decision makers. Parameter uncertainty in conceptual rainfall-runoff models has been widely investigated, and model structural uncertainty and forcing data have been receiving increasing attention. This study aimed to assess uncertainties in streamflow predictions due to forcing data and the identification of behavioural parameter sets in 31 Irish catchments. By combining stochastic rainfall ensembles and multiple parameter sets for three conceptual rainfall-runoff models, an analysis of variance model was used to decompose the total uncertainty in streamflow simulations into contributions from (i) forcing data, (ii) identification of model parameters and (iii) interactions between the two. The analysis illustrates that, for our subjective choices, hydrological model selection had a greater contribution to overall uncertainty, while performance criteria selection influenced the relative intra-annual uncertainties in streamflow predictions. Uncertainties in streamflow predictions due to the method of determining parameters were relatively lower for wetter catchments, and more evenly distributed throughout the year when the Nash-Sutcliffe Efficiency of logarithmic values of flow (lnNSE) was the evaluation criterion.

1. Introduction

The traditional understanding of water management is challenged by evidence of increasing nonstationarity in environmental systems (Milly et al., 2008). Modelling hydrological changes and their uncertainties is important for future water security (Wheater and Gober, 2013). Decision makers are increasingly interested in the uncertainty surrounding model predictions (Loucks et al., 2005), and so modellers are tasked with quantifying and communicating this uncertainty to inform water resources management and policy development (Willems and de Lange, 2007). However, details of the sources of uncertainty are typically not required by such end-users (Bruen et al., 2010). The onus is on modellers to understand the sources of uncertainty and therefore focus effort on reducing it, before communicating the overall uncertainty to end-users of streamflow predictions.

The uncertainties surrounding model outputs can have an aleatoric (e.g. measurement errors in forcing data) and/or epistemic character (e.g. omitted processes in model structures) and both are present in environmental modelling. In a model-based study, uncertainties can arise in (i) model context, (ii) model structure, (iii) forcing data and (iv) identification of parameter values (Walker et al., 2003). If the context of a study (including assumptions and boundary conditions) is defensible or justifiable, three dominant sources of uncertainty remain. The combination of these uncertainties in the modelling process produces its prediction error or predictive uncertainty (Todini, 2009). Understanding the three main sources of uncertainty and their interplay is necessary for an overall appreciation of the model prediction reliability. However, there are only a few studies that address all these facets (e.g. Butts et al., 2004).

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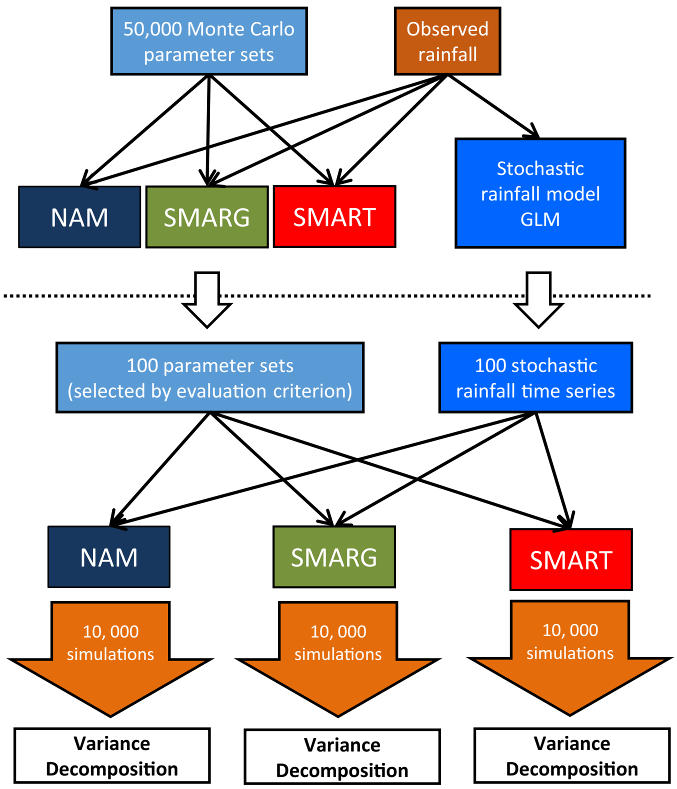

Fig. 1. Flow chart of methodology for variance decomposition.

Most studies have focused on one or two aspects of these uncertainty sources, for instance, uncertainty due to parameter estimation strategy has been widely studied in recent decades (Wheater et al., 1986; Wagener and Wheater, 2006; van Werkhoven et al., 2008; Sun et al., 2012; O'Loughlin et al., 2013). There is a growing body of literature investigating model structure uncertainty (Wagener et al., 2001; Clark et al., 2008; Breuer et al., 2009; Gupta et al., 2012), and more recent studies have investigated uncertainties in modelled streamflow due to both model structure parameter estimation strategy (Mendoza et al., 2015; Mockler et al., 2016), and model structure and forcing data (Renard et al., 2010).

Monte Carlo methods are frequently used to sample possible variations in forcing data and parameters using assumed probability distribution functions (e.g. GLUE methodology from Beven (2006)). Uncertainty assessments of forcing data has received relatively less attention than the effect of different model structures and parameters, and is mostly focused on precipitation as the dominant driving data (Kavetski et al., 2006; Chun et al., 2009; Younger, 2009; Sapriza-Azuri et al., 2013; Sapriza-Azuri et al., 2015), regardless of how estimated (Zappa et al., 2010), although there are some attempts to understand potential evapotranspiration (e.g. Chun et al., 2012). For this study, we have limited the investigation of forcing data to precipitation.

The objective of this study is to present an assessment of the relative importance of the sources of uncertainty in model predictions under a variety of plausible rainfall scenarios that may be used in studies, for example, of non-stationarity in hydrology. To do this, we combine stochastic rainfall ensembles (i.e. a collection of 100 rainfall time series simulations from specific weather states) and multiple parameter sets for three conceptual rainfall-runoff models (Fig. 1). In addition, we investigate the uncertainty interplay between the precipitation forcing and identification of hydrological model parameters by an analysis of variance model.

In summary, this framework is used to decompose uncertainty in simulated streamflow into three components:

(i) uncertainty in simulated flow due to uncertainty about the forcing data, here limited to the precipitation data (U-forcing),
(ii) uncertainties due to the method of determining model parameters (U-parameters), and
(iii) uncertainties due to the interactions between the above sources i.e. forcing data and model parameters (U-interactions).

The proposed uncertainty assessment approach is applied to monthly average simulations of 31 catchments in Ireland. Ireland is used in this study because of the availability of quality controlled climatological and hydrological data over an extended area. Moreover, the heterogeneity in soils, geology and topography in Ireland provides a diverse range of exemplars of partitioning of net precipitation between surface and groundwater flow paths contributing to streamflow. To quantify the uncertainty of the precipitation forcing, we use a Generalised Linear Model (GLM) framework (Chandler and Wheater, 2002) which has been applied in Australia, North and South America, Europe and Africa (Yang et al., 2005; Frost et al., 2011; Chun et al., 2013; Kigobe et al., 2014). Moreover, the adopted spatial GLM approach was tested in Ireland (Yang et al., 2005). It is extended here to include synoptic of the predominant atmospheric circulation pattern using Lamb weather type information (Jones et al., 2013) for generating spatial precipitation time series for all 31 Irish catchments.

To see how the choice of hydrological model may influence the uncertainty in each model's parameters, three conceptual rainfall models are used. Conceptual catchment models can be useful for investigating any possible changes in hydrological responses (Wheater et al., 1993) and they can be a learning tool for studying process dynamics (Dunn et al., 2008). Because of their simplicity, such models are computationally inexpensive to use for exploring uncertainties (e.g. Chun et al., 2009). The three rainfall-runoff models selected were (i) the Nedbør–Afstrømnings-Model (NAM), (ii) the Soil Moisture Accounting and Routing with Groundwater model (SMARG) and (iii) the Soil Moisture Accounting and Routing for Transport (SMART). The first two models were selected for this study as they have been widely applied in Irish catchments (Goswami et al., 2005; RPS, 2008; Bastola et al., 2011; Mockler and Bruen, 2013; O'Brien et al., 2013). The SMART model (Mockler et al., 2016; Mockler et al., 2014) was also included in the model comparison as it was recently developed for Irish catchments.

The structure of hydrological models, originally developed for flood forecasting and water resources analysis without climate change, have been identified as contributing significantly to the overall uncertainty envelope of future climate change impact scenarios in Ireland (Bastola et al., 2011). This study aimed to decompose the uncertainty in hydrological simulations for Irish catchments, in order to;

(i) identify the relative importance of uncertainty in streamflow due to U-forcing, U-parameters and U-interactions and,
(ii) compare this uncertainty for three different hydrological models and two performance criteria.

Following this introduction, Section 2 details the data, models and methods used to generate the model ensembles and variance decomposition. Results and discussion are presented in Section 3, followed by conclusions.

2. Data, models and methods

2.1. Irish catchment data

Ireland has an area of approximately 70,000 km^2 with gently undulating lowlands located in the centre with elevations generally