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An application of the GLUE methodology for estimating the parameters of the INCA-N model

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Abstract

The conceptual and parameter uncertainty of the semi-distributed INCA-N (Integrated Nutrients in Catchments—Nitrogen) model was studied using the GLUE (Generalized Likelihood Uncertainty Estimation) methodology combined with quantitative experimental knowledge, the concept known as 'soft data'. Cumulative inorganic N leaching, annual plant N uptake and annual mineralization proved to be useful soft data to constrain the parameter space. The INCA-N model was able to simulate the seasonal and inter-annual variations in the stream-water nitrate concentrations, although the lowest concentrations during the growing season were not reproduced. This suggested that there were some retention processes or losses either in peatland/wetland areas or in the river which were not included in the INCA-N model. The results of the study suggested that soft data was a way to reduce parameter equifinality, and that the calibration and testing of distributed hydrological and nutrient leaching models should be based both on runoff and/or nutrient concentration data and the qualitative knowledge of experimentalist.

Keywords: GLUE; INCA; Soft data; Uncertainty analysis; Nitrogen; Fuzzy rule

1. Introduction

Improved computational resources have made it possible to develop and apply complex distributed models to evaluate hydrological and nutrient processes on a catchment scale (2006-this volume). As catchment scale systems are heterogeneous and hydro-biogeochemical processes are non-linear, the use of these models has raised several questions concerning parameterization and calibration, such as equifinality and over-parameterization (e.g. Beven, 2002).

The parameters in equations established for relatively small-scale systems studied in the laboratory or at the plot-scale are not necessarily valid in grid-based representations of heterogeneous catchments: there is no general method to derive model parameters by up-scaling point measurements to fluxes averaged over space or time and, in practice, it is impossible to measure all the parameters required for each grid cell (Beven, 1989, 2001; Blöschl and Grayson, 2002). According to Beven (2006), several empirical studies have shown that many models and many parameter combinations give equally good fits to data, indicating that it is impossible to find an optimal model or an optimal parameter set in hydrological modelling: a problem termed equifinality. Problems caused by heterogeneity and non-linearity in parameterizing a

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hydrological model have been demonstrated for example by Durand et al. (2002).

The type and spatial resolution of a catchment-scale model define the input data needed for calibration. A model with a simple structure often does not make the best use of the available data. Conversely, the model structure and the model parameters cannot be identified properly if there are too many model parameters and insufficient data to test the model performance. The latter is known as over-parameterization of a model (Refsgaard, 1997; Beven, 2001; Blöschl and Grayson, 2002). To avoid over-parameterization Refsgaard (1997) and Perrin et al. (2001) have suggested limiting the number of parameters subject to adjustment during calibration.

In hydrological modelling additional data or experimental knowledge of system behaviour are often used to assess the reliability of stream flow simulations. According to Refsgaard (1997) and Blöschl and Grayson (2002) calibration of distributed hydrological models should be based not only on discharge, but also on spatial patterns of other hydrological variables in catchment. In multi-criteria calibration, the model is calibrated using other complementary data in addition to discharge at the basin outlet (Vrugt et al., 2003b). Uhlenbrook and Sieber (2005) found that the incorporation of additional data, i.e. sub-basin runoff and observed tracer concentrations, reduced the prediction uncertainty of discharge. The same outcome was concluded by Khadam and Kaluarachchi (2004), who presented a method to incorporate soft information to describe the relative accuracy of calibration data.

Seibert and McDonnell (2002) presented a method where ‘soft data,’ defined as the qualitative knowledge of an experimentalist, were made useful through fuzzy-measures of model simulation acceptance. Soft data include high degree of uncertainty due to the spatial or temporal variation in the measurements, and may also include some expert knowledge. They conclude that even though a hydrological model calibrated using the concept of soft data in addition to calibration against observed runoff and groundwater levels gave lower runoff-efficiency values, it gave a more realistic description of the catchment behaviour in their perception.

In order to evaluate how well the system is described the model performance should be tested by comparing model predictions with independent data: data not used for calibration (Klemes, 1986). Even if a model shows in validation tests that it can perform the kind of task for which it is specifically intended, the model may perform well for the wrong reasons. For example, errors in model structure can be compensated by errors in parameter values. Refsgaard and Henriksen (2004) and Refsgaard et al. (in press) recommended the inclusion of an uncertainty assessment of model structure and parameter values in modelling studies, especially in cases when predictions are made beyond the range of available observations, e.g. to study the effects of future climate or land management changes.

Sensitivity and uncertainty analyses are primarily concerned with the question of how model outputs are affected by the variability of the model parameters and input values, and provide useful information when these components are not completely known. Sensitivity analysis is the determination of which parameters predominately control the model behaviour (Hamby, 1994), whereas uncertainty analysis is the estimation of error in the model output due to uncertainty in the model structure, parameters and data inputs (Thiemann et al., 2001; Vrugt et al., 2005). The Generalized Likelihood Uncertainty Estimation (GLUE) (Beven and Binley, 1992) approach defines the performance of possible parameter sets in terms of likelihood measures. Different uncertainty analysis methods in hydrological modelling are compared by Yu et al. (2001), Beven and Young (2003), Gupta et al. (2003), Mailhot and Villeneuve (2003) and Balakrishnan et al. (2005).

In recent years different sensitivity and uncertainty analyses have been applied to distributed, or semi-distributed, hydrological and nutrient leaching models. In this study, the main aim was to assess the structural and parameter uncertainty of the INCA-N (Integrated Nutrients in Catchments—Nitrogen) model (Whitehead et al., 1998; Wade et al., 2002a) using automatic calibration and the GLUE methodology (Beven and Binley, 1992) combined with the concept of soft data (Seibert and McDonnell, 2002). INCA-N is a widely used model of flow and nitrogen transport in river-systems covering a range of spatial scales (1–4400 km^2; Wade et al., 2002b). Even though Monte-Carlo based methods, such as GLUE, are computationally not the most effective ones, they have been applied successfully to several different hydrological and water quality models (Yu et al., 2001; Mailhot and Villeneuve, 2003; Balakrishnan et al., 2005; Muleta and Nicklow, 2005; Pastres and Ciavatta, 2005).

Raat et al. (2004) assessed measurement uncertainty by using INCA-N model and the Shuffled Complex Evolution Metropolis algorithm (SCEM-UA, Vrugt et al., 2003a) in a virtual catchment. The authors concluded that none of the synthesised data sets contained sufficient information to identify the model