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Integrated Catchment Studies*

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Acronyms and Abbreviations

AGU	American Geophysical Union
BSM2	Benchmark Simulation Model 2
EGU	European Geophysical Union
EIF	Effective Impervious Factor
EQI	Effluent Quality Index
EVI	Extreme Value distribution type I
GLUE	Generalized Likelihood Uncertainty Estimation
GSA	Global Sensitivity Analysis
ICM	Integrated Catchment Modelling
IF	Impact Factor
IWA	International Water Association
MUSLE	Modified Universal Soil Loss Equation
OCI	Operation Cost Index
TC	Time of Concentration
TSS	Total Suspended Solids
USLE	Universal Soil Loss Equation
WWTP	Waste Water Treatment Plant

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Executive Summary

The aim of this report is to provide an evidence base and a guide to further reading for QUICS report D4.4, titled 'Good Practice Guidance: Incorporating Uncertainty in the Integrated Catchment Studies'.

In this report, a short description of each journal paper used to demonstrate examples of quantifying uncertainties in modelling is made. Additionally, the list of the journals and the impact of them in the scientific community, in which these papers are published is provided.

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1 Introduction

In this report, an evidence base is given for the examples used in order to demonstrate how a modeller can quantify uncertainty in the context of Integrated Catchment Modelling (ICM). The scientific peer review journals used for this work are of great importance in the scientific field in which they are affiliated and their impact in the scientific community is high. Specifically, the journals used are the following:

- 1) Water Quality Research Journal of Canada, published by IWA (International Water Association), with an Impact Factor (IF) equal to 0.444
- 2) Water Science and Technology published by IWA, with an Impact Factor (IF) equal to 1.197
- 3) Hydrological Processes, published by Wiley, with an IF equal to 3.014
- 4) Journal of Hydrology, published by Elsevier, with an IF equal to 3.483
- 5) Water Resources Research, published by Wiley and American Geophysical Union (AGU), with an IF equal to 4.397
- 6) Hydrology and Earth System Science, published by European Geophysical Union (EGU), with an IF equal to 4.437
- 7) Journal of Environmental Engineering, published by American Society of Civil Engineers (ASCE), with an IF equal to 1.541

The list of the papers used is the following. In the next chapters, a short description for each paper will be provided.

- 1) Benedetti, L., Batstone, J.D., De Baets, B., Nopens, I., Vanrolleghem, A.P., 2012. Uncertainty Analysis of WWTP control strategies made feasible. *Water Quality Research Journal of Canada*, 47(1), 14-29.
- 2) Benedetti, L., Belia, E., Cierkens, K., Flameling, T., De Baets, B., Nopens, I., Weijers, S., 2013. The incorporation of variability and uncertainty evaluations in WWTP design by means of stochastic dynamic modeling: the case of the Eindhoven WWTP upgrade. *Water Science and Technology*, 67(8), 1841-1850.
- 3) Brandimarte, L. and Woldeyes, M.K., 2013. Uncertainty in the estimation of backwater effects at bridge crossings. *Hydrological Processes*, 27, 1292-1300.
- 4) Dimitriadis, P., Tegos, A., Oikonomou, A., Pagana, V., Koukouvinos, A., Mamassis, N., Koutsoyiannis, D., Efstratiadis, A., 2016. Comparative evaluation of 1D and quasi-2D hydraulic models based on benchmark and real-world applications for uncertainty assessment in flood mapping. *Journal of Hydrology*, 534, 478-492.
- 5) Dotto C.B.S., Mannina, G., Kleidorfer, M., Vezzaro, L., Henrichs, M., McCarthy D.T., Freni, G., Rauch, W., Deletic, A., 2012. Comparison of different uncertainty techniques in urban stormwater quantity and quality modelling. *Water Resources Research*, 46, 2545-2558.
- 6) Fu, C., James, L.A., Yao, H., 2015. Investigations of uncertainty in SWAT hydrological simulations: a case study of a Canadian Shield catchment. *Hydrological Processes*, 29, 4000-4017.

- 7) Muthusamy, M., Schellart, A., Tait, S., Heuvelink, B.M.G., 2017. Geostatistical upscaling of rain gauge data to support uncertainty analysis of lumped urban hydrological models. *Hydrology and Earth System Science*, 1077-1091.
- 8) Shen, Z.Y., Chen, L., Chen, T., 2012. Analysis of parameter uncertainty in hydrological and sediment modelling using GLUE method: a case study of SWAT model applied to Three Gorges Reservoir Region, China. *Hydrology and Earth System Science*, 16, 121-132.
- 9) Sriwastava, A., Tait, S., Schellart, A., Kroll, S., Van Dorpe, M., Van Assel, J., Shucksmith, J., 2017. Quantifying uncertainty in the simulation of sewer overflow volume. *Journal of Environmental Engineering*, accepted for publication.

Table 1 summarises which model outputs are examined under which type of uncertainty sources (model structure, parametric, input data).

Readers will find this report useful as an accompaniment to Report 4.4 and as a guide to further reading and exploration on this topic.

Table 1. Outputs and uncertainty source

Model output	Model structure uncertainty	Model parameters uncertainty	Input Data uncertainty
Discharge		xxx	
Sediment yield		x	
Snow Water Equivalent		x	
Combined Sewer Overflow volume		x	x
Total Suspended Solids concentration		x	
Effluent Quality Index		x	
Operation Cost Index		x	
Effluent time period to exceed the limit of 4 mg NH ₄ -N/L (% of the whole evaluation period)		x	
NH ₄ effluent		x	
Water surface elevation		xx	xx

2 Analysis of parameter uncertainty in hydrological and sediment modelling using GLUE method: a case study of SWAT model applied to Three Gorges Reservoir Region, China

In this paper, the source of uncertainty which is examined is the uncertainty due to model parameters. The case study is selected from an actual application; the Three Gorges Reservoir Region in China. The method used for the uncertainty analysis is the Generalized Likelihood Uncertainty Estimation (GLUE) method. In order to simulate the runoff process, the runoff curve number method was used, whereas for the infiltration phenomenon, the Green-Ampt method was implemented. For the sediment yield estimation, the Modified Universal Soil Loss Equation (MUSLE) was used.

The software used was the SWAT software, for 10,000 simulations. 20 parameters were chosen for the uncertainty analysis after a sensitivity analysis performed in the first step based on Morris screening method.

The parameters which are investigated for the uncertainty to the output results are: the SCS runoff curve number for moisture condition II (ranges from -0.25 to 0.15), the base flow alpha factor (ranges from 0 to 1), the groundwater delay time (ranges from 1 to 45), the Manning's n value for overland flow (ranges from 0 to 0.5), the effective hydraulic conductivity in main channel alluvium (ranges from 0 to 150), the base flow alpha factor for bank storage (ranges from 0 to 1), the available water capacity factor (ranges from 0 to 1), the saturated hydraulic conductivity (ranges from -0.2 to 300), the soil bulk density (ranges from 0.1 to 0.6), the snowfall temperature (ranges from -5 to 5), the maximum amount of water that can be trapped in the canopy when it is fully developed (ranges from 0 to 100), the soil evaporation compensation factor (ranges from 0.01 to 1), the threshold water level in shallow aquifer for baseflow (ranges from 0 to 5000), the threshold water level in shallow aquifer (ranges from 0 to 500), the Universal Soil Loss Equation (USLE) support practice factor (ranges from 0.1 to 1), the channel cover factor (ranges from 0 to 1), the channel erodibility factor (ranges from 0 to 1), the channel sediment routing parameter (ranges from 0 to 0.05), the exponent parameter for calculating sediment re-entrained in channel (ranges from 1 to 1.5), the average slope length (ranges from -0.1 to 0.1). The input data consists of a real rainfall time series for the period 2004-2007.

For the GLUE method, the likelihood function is the Nash-Sutcliffe coefficient, whereas for the sampling phase of the parameters, the Latin Hypercube Sampling was used. The likelihood function threshold which distinguishes the behavioral and non-behavioral set of parameters was set 0.5. The output results consist of a quantity variable (water flow) and a quality variable (sediment yield).

It seems that during the drier periods, the uncertainty band is relatively small (about 30 m³/s), whereas in the peak periods the uncertainty band reaches more than 150 m³/s. As far as the sediment yield is concerned, the uncertainty range is larger: during the dry periods the uncertainty band is about 50 x 10⁴ tonnes, whereas in peak periods can reach about 600 x 10⁴ tonnes of sediments.

3 Investigations of uncertainty in SWAT hydrological simulations: a case study of a Canadian Shield catchment

In this paper, the sources of uncertainty which are examined is the uncertainty due to model parameters. The case study is selected from an actual application: the Canadian Shield catchment in Canada. The method used for the uncertainty analysis is the GLUE method. The software used was the SWAT software, whereas two model structures were tested: SWAT and SWAT-CS (a version for Canadian catchments).

For the uncertainty analysis, 12000 combinations of 22 parameters sampled by uniform distribution were implemented. The parameters are required to describe:

- 1) Interception
- 2) Snowmelt
- 3) Evapotranspiration
- 4) Overland flow
- 5) River routing
- 6) Infiltration
- 7) Interflow
- 8) Bedrock percolation
- 9) Groundwater flow
- 10) Reservoir

The model first calibrated and validated against observed data. The input data consists of a real rainfall time series for the period 1978-1982. The output of the model is the Snow Water Equivalent and the Streamflow (quantity variables), in the sub-catchment HP4. For the GLUE method, the likelihood function is the Nash-Sutcliffe coefficient. The likelihood function threshold which distinguishes the behavioral and non-behavioral set of parameters was set at 0.45 for the Snow Water equivalent and 0.30 for the Streamflow.

4 Quantifying uncertainty in the simulation of sewer overflow volume

In this paper, the source of uncertainty which is examined is the input data and the model parameters, using the Monte Carlo technique. The case study is selected from an actual application: a small urban catchment located in Herent (Belgium). The model structure used is the InfoWorks-CS model. The input data which is examined is the weir crest level, whereas the parameters which are examined is the roughness height used in the Colebrook-White friction equation. For the Monte Carlo simulations, 1000 runs of the model were implemented. The weir crest level values randomly draw from a normal distribution, whereas the roughness height from a Log-logistic distribution and the fixed runoff coefficient from a truncated normal distribution correspondingly. The output variable is the Combined Sewer Overflow (CSO) discharge volume in one location of the catchment. It seems that the CSO volume ranges about 130 m³ of water for the 90% confidence interval.

5 Comparison of different uncertainty techniques in urban stormwater quantity and quality modelling

In this paper, the source of uncertainty which is examined is the model parameters, using four uncertainty analysis techniques:

- 1) the Generalized Likelihood Uncertainty Estimation (GLUE)
- 2) the Shuffled Complex Evolution Metropolis algorithm (SCEM-UA)
- 3) the multialgorithm, genetically adaptive multi-objective method (AMALGAM)
- 4) the classical Bayesian approach based on a Markov Chain Monte Carlo method and the Metropolis Hastings sampler (MICA)

The case study is selected from an actual application: an urban catchment located in Melbourne (Australia). The model structure used is the simplified model SIMPLE KAREN. As far as the quantity part of the study, four parameters are examined: the Effective Impervious Factor (EIF), the time of concentration (TC), the initial loss (li) and the evapotranspiration (ev). As far as the water quality part of the study, two parameters are examined: the water quality scale coefficient (W) and : the water quality shape coefficient (b). It seems that during the more dry periods, the uncertainty interval is relatively small (about 0.1-0.2 m³/s for all the uncertainty analysis methods), whereas in the peak periods the uncertainty band reaches about 0.7-1.0 m³/s. As far as the Total Suspended Solids (TSS) concentration range is concerned, the uncertainty band ranges from 20 to 100 mg/L for all the uncertainty analysis methods.

6 Uncertainty Analysis of WWTP control strategies made feasible

In this paper, the uncertainty source which is investigated is due to model parameters. The case study selected is the Benchmark Simulation Model 2 (BSM2), which is a protocol for evaluating the control strategy of a Waste Water Treatment Plant (WWTP) model. The sources of uncertainty examined are the model parameters, using the Monte Carlo technique. The model structure used is the WEST software. The output of the model is the three evaluation criteria as determined in the BSM2:

- 1) the Effluent Quality Index (EQI)
- 2) the Operation Cost Index (OCI)
- 3) the period of time in which the effluent exceeds the limit of 4 mg NH₄-N/L, expressed as a percentage of the whole evaluation period)

It is noted that as a preliminary step, a Global Sensitivity Analysis (GSA) is performed in order to rank the parameters according to the influence on the output.

7 The incorporation of variability and uncertainty evaluations in WWTP design by means of stochastic dynamic modeling: the case of the Eindhoven WWTP upgrade

The case study selected is the WWTP upgrade in Eindhoven. The sources of uncertainty which are examined are the model parameters, using the Monte Carlo technique. Specifically the parameters examined are: removal efficiency, certainty factor, peak factor. For the removal efficiency, the sample drawn by a uniform distribution, whereas for the certainty and peak factors from normal distribution.

The model structure used is the WEST software. The output of the model is the NH_4 effluent. Before the uncertainty analysis, a sensitivity analysis is performed in order to select which parameters affect more the results. With this procedure, the parameters mentioned before, were selected for a further uncertainty analysis.

8 Comparative evaluation of 1D and quasi-2D hydraulic models based on benchmark and real-world applications for uncertainty assessment in flood mapping

In this paper, the sources of uncertainty which are examined are the input data and the model parameters, using the Monte Carlo technique. The case study is selected from an actual application: Rafina stream, which is located north-east of Athens (Greece). The model structures used are the HEC-RAS software (1D model), the LISFLOOD software (2D-) and the FLO-2D software (2D) for 300 simulations each.

The input data consists of a steady flow, for which the Monte Carlo simulations randomly draw from a uniform distribution with range $250 \text{ m}^3/\text{s}$ to $1000 \text{ m}^3/\text{s}$. The examined parameter is the Manning's roughness coefficient, for which the Monte Carlo simulations randomly draw from a uniform distribution with range $0.01 \text{ s/m}^{1/3}$ to $0.1 \text{ s/m}^{1/3}$.

The output variables are the water depths in the upstream and the downstream cross-sections correspondingly. It is found that the distributions of the water depths approximate a normal distribution. It seems that the water depths range about 4 m using the HEC-RAS model, about 8-12 m using the LISFLOOD-FP model and about 2 m using the FLO-2D model, for the 95% confidence interval.

9 Uncertainty in the estimation of backwater effects at bridge crossings

In this paper, the sources of uncertainty which are examined are the input data and the model parameters, using the Monte Carlo technique and the GLUE method. The case study is selected from an actual application: Tallahala Creek, near Waldrup, Mississippi, USA.. The combined uncertainty due to these two sources is also quantified as well.

The model structures used is the 1D HEC-RAS software, using the steady flow mode. The input data consists of a steady flow, for which the 100 Monte Carlo simulations randomly draw from a normal distribution with a mean value equal to the flood peak with a return period $T=100$ years, estimated applying the Extreme Value distribution type I (EVI) and a standard deviation equal to the standard error of estimate for the EVI distribution, evaluated using the Kite formula. The examined parameter is the Manning's roughness coefficient for the main channel and for the floodplains, using the GLUE method: 48 behavioral models were selected, using as a criterion that the Mean Absolute Error compared with the corresponding observed data should be less than 0.5 m. Finally, each of the 48 behavioral scenarios was run using as an input the 100 runs derived previously, in order to quantify the combined uncertainty due to the input data and the model parameters. It seems that the water surface elevation ranges from about 0.5 m in the worst case, to 0.2 m in the best case, for the 95% confidence interval, investigating the input data uncertainty. Investigating the parameters data uncertainty, these intervals are ranging from about 1.0 m to 0.3 m, whereas investigating both input data and parameter uncertainty, these intervals are ranging from about 1.5 m to 1.0 m correspondingly.

10 Geostatistical upscaling of rain gauge data to support uncertainty analysis of lumped urban hydrological models

In this paper, the uncertainty source which is investigated is due to input data. The case study is selected from an actual application: a catchment located at Bradford, West Yorkshire, UK. Rainfall data collected from a cluster in an urban catchment are used in combination with spatial stochastic simulation to obtain optimal predictions of the spatially averaged rainfall intensity at any point in time within the urban catchment. The uncertainty in the prediction of catchment average rainfall intensity is obtained for multiple combinations of intensity ranges and temporal averaging intervals. Scarcity of measurement points is dealt with by pooling sample variograms of repeated rainfall measurements with similar characteristics. Normality of rainfall data is achieved through the use of normal score transformation. Geostatistical models in the form of variograms are derived for transformed rainfall intensity. Next, spatial stochastic simulation is applied to produce realisations of rainfall fields. These realisations in transformed space are first back-transformed and next spatially aggregated to derive a random sample of the spatially averaged rainfall intensity. Results show that the prediction uncertainty comes mainly from two sources: spatial variability of rainfall and measurement error. At smaller temporal averaging intervals both these effects are high, resulting in a relatively high uncertainty in prediction. With longer temporal averaging intervals the uncertainty becomes lower due to stronger spatial correlation of rainfall data and relatively smaller measurement error. Results also show that the measurement error increases with decreasing rainfall intensity resulting in a higher uncertainty at lower intensities.