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Evaluation of uncertainty propagation into river water quality predictions to guide future monitoring campaigns

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Abstract

To evaluate the future state of river water in view of actual pollution loading or different management options, water quality models are a useful tool. However, the uncertainty on the model predictions is sometimes too high to draw proper conclusions. Because of the complexity of process based river water quality models, it is best to investigate this problem according to the origin of the uncertainty. If the uncertainty stems from input data or parameter uncertainty, more reliable results are obtained by performing specific measurement campaigns. The aim of the research reported in this paper is to guide these measurement campaigns based on an uncertainty analysis. The practical case study is the river Dender in Flanders, Belgium.

First an overview of different techniques that give valuable information for the reduction of input and parameter uncertainty is given. A global sensitivity analysis shows the importance of the different uncertainty sources. Further an analysis of the uncertainty bands is performed to find differences in uncertainty between certain periods or locations. This shows that the link between periods with high uncertainty and specific circumstances (climatological, eco-regional, etc.) can help in gathering data for the calibration of submodels (e.g. diffuse pollution vs. point pollution).

Keywords: Monitoring; Optimal experimental design; River water quality modelling; Uncertainty analysis; River basin management; Sensitivity analysis

1. Introduction

In the field of environmental modelling and assessment, uncertainty analysis (UA) is a necessary tool to provide, next to the simulation results, a quantitative expression of the reliability of those results. Next to the expression of uncertainty bounds on the results, uncertainty studies have mainly been used to provide insight into parameter uncertainty. However, uncertainty analysis can also be a means to prioritize uncertainties and focus research efforts on the most problematic points of a model. As such, it helps to prepare future measurement campaigns and to guide policy decisions. It also yields further insights into the model itself and can give hints for future model improvements (Uhlenbrook and Sieber, 2005).

In this study, the use of UA as an evaluation tool is assumed to be applied on an already calibrated model that can reproduce the measured data well but with an unacceptably high uncertainty. We only consider parameter and input uncertainty that can be minimised by gathering additional data. Model structure uncertainty and mathematical uncertainty are not taken into consideration. The aim of this research is to show how UA can be used to guide future monitoring campaigns to make model results more reliable by minimising the parameter and input data uncertainty of the model. The practical case study is the river Dender in Flanders, Belgium. The methods can be used for every variable under study and for all kinds of rivers but the conclusions made for the case study are only applicable for the Dender.

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2. Case study: the Dender basin

The Dender river, a tributary of the river Scheldt in Belgium, drains an area of 1384 km^2. The main channel is partly canalised and contains 14 sluices. The river is heavily polluted by domestic, industrial and agricultural pollution.

The software used to make a model for the river Dender, is ESWAT. It is an extension of SWAT, the Soil and Water Assessment Tool developed by the USDA (Arnold et al., 1996), that includes a dynamic QUAL2E based water quality model (van Griensven and Bauwens, 2000). Other changes to SWAT were also made to allow for integrated modelling of the water quantity and quality processes in river basins.

3. Methods

To reduce the overall uncertainty on the model results for a certain variable, the following steps are proposed:

1. Identify which sources contribute most to the overall uncertainty on the model results;
2. Estimate or calculate the uncertainty related to those main contributors;
3. Propagate the uncertainty through the model;
4. Analyse the model results to set up a future monitoring campaign;
5. Perform the new measurements;
6. Recalibrate the model with these new data;
7. Repeat steps 3–6 until satisfying results are obtained;

For every step of this process different techniques exist that can be chosen among according to the experience of the modeller. In the practical example the particular methods we used will be described.

3.1. Step 1: identification of the main uncertainty contributors, uncertainty characterisation

The objective of a sensitivity analysis of model output can be defined as 'to evaluate how a given model depends on its input factors' (Saltelli et al., 2000). It is often assumed that the numbers of important factors in a model is small compared to the total number of factors. A sensitivity analysis can reveal those most influential factors.

Two approaches exist: a global or local sensitivity analysis. In a local analysis, input variables or parameters are varied one at the time and their influence on the model outcome is investigated while holding the other parameters fixed to a central (nominal) value. In a global analysis the space of the input variables and parameters is explored within a finite (or even infinite) region and the variation of the output induced by a factor singly or in combination with each other is taken globally, that is averaged over the variation of all the factors. A global sensitivity analysis is more reliable but requires more calculation. Because it is assumed that an already calibrated model is available, a local sensitivity analysis will probably identify the most important parameters and data of the model. Indeed, local analysis is done around an a priori assumed value of a parameter and for a calibrated model the parameters are the best values obtained with the available data.

For a local sensitivity analysis the following methods exist: (a) finite difference method, (b) the direct differential method, (c) the Green's function method, (d) the polynomial approximation method and (e) automatic differentiation. For a detailed review of existing sensitivity techniques reference is made to the reviews of Turanyi (1990) and Rabitz et al. (1983). Global sensitivity techniques like Monte Carlo based methods, one factor at the time, GLUE and FAST are thoroughly discussed in Saltelli et al. (2000).

3.2. Step 2: estimation or calculation of uncertainty

Parameter uncertainty can be calculated using the covariance matrix obtained during the local sensitivity analysis or during the calibration process (Beck, 1987).

If no direct calculations of uncertainty are possible, e.g. for the uncertainty on the inputs, one can try to estimate the uncertainty. One can divide the parameters and data in uncertainty classes (accurately known, very poorly known and an intermediate class) and assign a percentage uncertainty to them. A similar approach was adopted by Reichert and Vanrolleghem (2001).

3.3. Step 3: propagate the uncertainty through the model

For this step Monte Carlo methods can be used, in which the input data or parameters are sampled between the uncertainty bounds that were determined in the previous step. Another option is to apply linear error propagation. The advantage of the latter is computational efficiency. However, if model non-linearities are significant within the uncertainty range, the results will be inaccurate. Monte Carlo simulation is a simple technique but requires a large number of model runs, which is computationally demanding. It is possible to use 'the Latin Hypercube sampling' which will need less runs and give the same accuracy of uncertainty results because it is a more effcient sampling method than 'ad random sampling' (McKay, 1988).

3.4. Step 4: analyse the model results to set up a future measurement campaign

Two different approaches can be used depending on the aim for which the additional measurements are collected. If it is the aim to reduce parameter uncertainty, an automated optimal experimental design method that is explained in Vandenberghe et al. (2002) can be used. It is based on maximisation of the determinant of the Fisher Information Matrix, which corresponds to the minimisation of the variance of the parameter estimates. This maximisation is done by varying the location, frequency, kind of variables measured and period of the year for measuring using a synthetic time-series generated by the simulator. From this optimisation one can find experimental designs that are giving parameter estimates with a desired degree of accuracy. Also, combinations of external circumstances that give data with low information content are detected during the optimisation. This method requires a lot of simulation runs but is totally automated and as such requires no additional information or knowledge from the modeller.

However, when only focussing on the input data uncertainty that leads to output uncertainty, expert-knowledge is required. It is then the aim to find a link between periods of high/low uncertainty and external circumstances (rain, discharge points, seasons, solar radiation, etc.). This information is then used to make decisions about location, period, frequency, etc. of future measurements. Further, with this link, the directions and magnitudes of change in relation to management interventions can be identified and one becomes able to differentiate between associated outcome sets (Jakeman and Letcher, 2003).

3.5. Step 5: perform the measurements

At this stage it is essential to ensure a good quality control on the measurements to minimise measurement errors. It is also important to carefully add information concerning time, location and depth of the water sample taken. This information is very important for highly dynamic models with a small time step where situations vary from hour to hour (e.g. algae blooms).

3.6. Step 6: recalibrate the model with new inputs

An important issue here is that the calibration method has to be able to find the optimal values. First, a choice is to be made between manual and automated optimisation methods. The former totally depends on the experience of the modeller. Automated methods can differ in their particular search method: global search methods scan the whole parameter space and are as

such able to find the global optimum, but do not provide uncertainty measures. Local search methods start on a certain point in parameter space and end when they find an optimum. However, there is no guarantee that this is the global optimum, so for those methods it is best if one can start in the neighbourhood of the optimum. With these methods often covariance matrices for the optimum parameter estimates are calculated, because most of the methods are derivative based.

3.7. Step 7: repeat steps 3–6 until satisfying results are obtained

The stop criterion for this trial and error method is dictated by an 'a priori' desired reliability of the model results. In practice, however, personnel, time and equipment issues will be the limiting factor and will indicate when this process stops.

4. Results and discussion

The seven steps are now demonstrated on a case study: simulations of the water quality of the river Dender, Flanders, Belgium for 1994. The evaluation of the uncertainty on model results is performed for nitrate concentration in the river water. The work was started with a model that could be considered well calibrated for the hydrological part because there was an extended data set for the calibration of the model. However, the model was not satisfying because calibration of the water quality part of the model was only done with a limited amount of instream measurements. Moreover, information about the point pollution and diffuse pollution inputs were very uncertain.

It can be seen from Figs. 1–3 that there is a large discrepancy between the measurements and the simulations around day 240 and time 340–350. There is a combination of reasons for this: the very low nitrate concentrations that are measured around day 240 are probably correct measurements because the river has a very low oxygen during that period and then the denitrification rate is very high. The fact that the model could not simulate this phenomenon is probably caused by the fact that the model is not performing well under those extreme circumstances. In that period there is probably a large model structure uncertainty. The measurements around time 340–350 lay almost all within the uncertainty bounds so input and parameter uncertainty can explain the difference between the model outcomes and measurements.

4.1. Step 1: identification of the main uncertainty contributors

In this study we focus on the variable nitrate. We will evaluate the sensitivity of the model result "the duration that NO_3 is higher than 3 mg/l at Denderbelle", a place near the mouth of the river, towards the parameters and inputs. For the diffuse pollution, a previous study for a similar nitrogen leaching model (implemented in SWIM) from arable land in large river basins (Krysanova and Haberlandt, 2001) showed that the relative importance of natural and anthropogenic factors affecting nitrogen leaching was as follows: (1) soil, (2) climate (3) fertilisation rate and (4) crop rotation. Reducing the uncertainty on inputs for soil and climate depends on better equipment to measure the different variables and proper use of sophisticated mathematical techniques to interpolate for locations that are not measured. A lot of studies on that subject already exist (Sevruk, 1986). So for diffuse pollution it was decided to only evaluate the data on management practices. The hydrological model parameters were profoundly calibrated for this model because there was no data scarcity for the water level and flow of the river Dender (van Griensven, 2002). When the hydrological data would have been scarce or of bad quality we should have to include the hydrological parameters in the sensitivity analysis as well because they will also contribute a lot to the final uncertainty. Finally we consider the parameters of the water quality model because this model was difficult to calibrate with the limited amount of data available.

Conducting sensitivity analysis for all input data and parameters in the ESWAT model is a too complex task for the program we use: UNCSAM (Janssen et al., 1992). This program cannot handle more than 50 parameters at a time. So we split the problem in three parts: global sensitivity to (1) model parameters (2) point pollution input and (3) diffuse pollution input. Solution of each subproblem results in a ranking of the parameters. We used the Standardised Regression

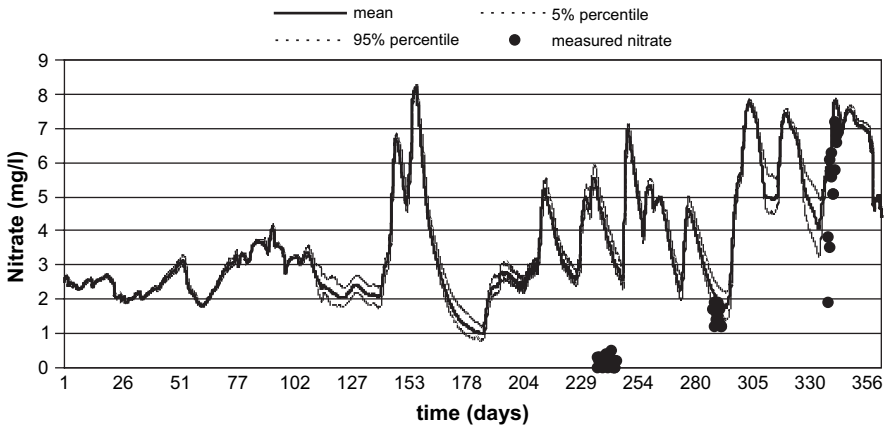

Fig. 1. Simulation of nitrate concentration at Denderbelle, 1994, with uncertainty ranges due to parameter uncertainty.

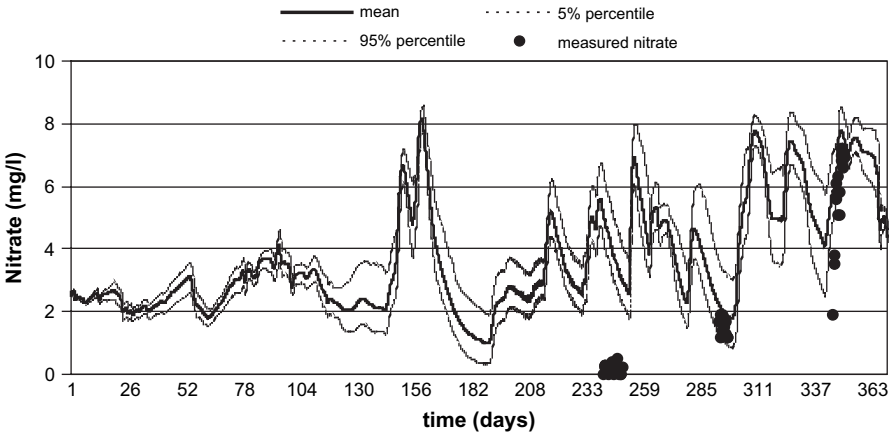

Fig. 2. Simulation of nitrate concentration at Denderbelle, 1994, with uncertainty ranges due to point pollution input uncertainty.

Coefficient (SRC), a measure often used for sensitivity analysis (Saltelli et al., 2000)

$$\mathrm{SRC}_i = \frac{\Delta y / S_y}{\Delta x_i / S_{x_i}}$$

with $\Delta y/\Delta x_i$ = change in output due to a change in an input factor and S_y, S_{x_i} the standard deviation of, respectively, the output and the input. The input standard deviation S_{x_i} is specified by the user.

The technique is explained in detail in Vandenberghe et al. (2001).

The parameters or input data that are found to contribute significantly to the output (5% level) in each of the three subproblems are then taken together in one overall global sensitivity analysis in order to compare the contribution of the different outputs. This subselection of parameters and inputs can now be handled by UNCSAM. In Table 1 this result is indicated with ''combined parameter-input''. Table 2 gives the used ranges for a uniform distribution and the nominal values for the water quality model parameters.

The ranges for the diffuse pollution inputs are given in Table 3 and the way they were determined is explained in Vandenberghe et al. (2003). For the point pollution inputs we sampled uniformly between half and double the values, as we decided that those inputs belong to the uncertainty class 'poorly known'. Indeed, the point pollution loads were only available as yearly averages.

The global sensitivity of the parameters and the inputs shows that some parameters, O_2 uptake per unit of NH_3 oxidation, O_2 uptake per unit of HNO_2 oxidation, denitrification rate, rate NO_2 to NO_3, O_2 uptake per unit of algae respiration and the reaeration rate are most influential. They are followed by the input data, planting date on farming land, amount of fertilisation on pasture in subbasin 12 and BOD loads from point 1 and 6. This result could not have been concluded from the separate analyses of inputs and parameters. Apparently the parameters can make the model to produce results that are not much influenced by the input data. This shows the importance of a well-calibrated model.

It can be argued that it is not safe to only take the most important factors from the three separate sensitivity analysis to study the combined parameter/input sensitivity. To address this an extra analysis was done and it was possible to deduce from an SA in which some non-statistically significant parameters (shown in Table 1) were added, that the approach that was followed was safe because the same parameters came out to be most important and the non-significant parameters

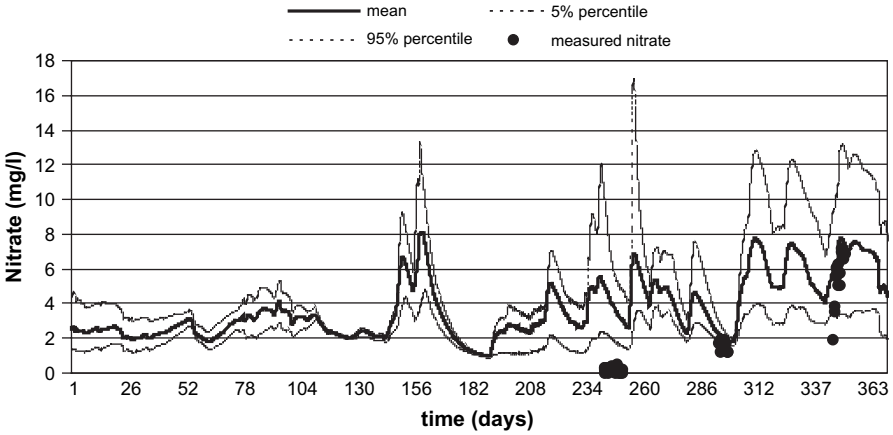

Fig. 3. Simulation of nitrate concentration at Denderbelle, 1994, with uncertainty ranges due to diffuse pollution input uncertainty.

Table 1
Results of the sensitivity analysis for the model output "hours $NO_3 > 3$ mg/l" at Denderbelle, 1994

Diffuse pollution input	SRC	Point pollution input	SRC	Parameter	SRC	Combined parameter-input	SRC
pa_{16} [a]	−0.30	BOD point 6	−0.61	a_{i5} [i]	−0.7	a_{i5}	−0.51
fa_4 [b]	0.23	NO_3 point 7	0.42	r_{k5} [j]	−0.34	a_{i6}	−0.50
gro_{pa} [c]	−0.18	BOD point 5	−0.38	r_{k2} [k]	0.32	r_{k5}	−0.40
pl_{fa} [d]	0.17	BOD point 8	−0.24	r_{k1} [l]	−0.21	b_{c2}	0.38
co_5 [e]	−0.17	NH_3 point 1	0.23	a_{i6} [m]	−0.2	a_{i4}	−0.31
co_{15} [f]	−0.16	BOD point 3	−0.23	b_{c2} [n]	0.17	r_{k2}	0.12
pa_{12} [g]	0.16	BOD point 7	−0.22	r_{k3} [o]	0.12	pl_{fa}	−0.08
co_{11} [h]	0.15	BOD point 1	−0.14	a_{i4} [p]	−0.09	BOD point 6	−0.07
		NO_3 point 5	0.11	r_{s3} [q]	0.07	BOD point 1	−0.07
		BOD point 4	−0.09	k_1 [*]		pa_{16}	0.07
		NH_3 point 2	0.09	b_{c1} [*]			
		BOD point 2	−0.08	a_{i1} [*]			
		NH_3 point 3	0.06	a_{i0} [*]			

[*] Parameters with SRC = not significant ($p = 0.9$) but also taken into the combined SA for a safety check.
[a] pa_{16} = Amount of fertilisation on pasture in subbasin 16.
[b] fa_4 = Amount of fertilisation on farming land in subbasin 4.
[c] gro_{pa} = Growth date of pasture.
[d] pl_{fa} = Plant date on farming land.
[e] co_5 = Amount of fertilisation on corn in subbasin 5.
[f] $co1_5$ = Amount of fertilisation on corn in subbasin 15.
[g] pa_{12} = Amount of fertilisation on pasture in subbasin 12.
[h] co_{11} = Amount of fertilisation on corn in subbasin 11.
[I] a_{i5} = O_2 uptake per unit of NH_3 oxidation.
[j] r_{k5} = Denitrification rate.
[k] r_{k2} = Oxygen reaeration rate.
[l] r_{k1} = Carbonaceous biological oxygen demand deoxygenation rate coefficient in the reach.
[m] a_{i6} = O_2 uptake per unit of HNO_2 oxidation.
[n] b_{c2} = Rate NO_2 to NO_3.
[o] r_{k3} = Rate of loss of BOD due to settling.
[p] a_{i4} = O_2 uptake per unit of algae respiration.
[q] R_{s3} = Benthic source rate for NH_4-N in the reach.

form the separate analysis did not show up in the top of the list.

4.2. Step 2: estimation or calculation of uncertainty

For both the point and diffuse pollution input identical uncertainties were taken for the sampling range. For the uncertainty to be applied to the parameters a recalibration with the selected parameters is best because this makes that uncertainty ranges can be calculated with the covariance matrix. However, this was not done in this study: uncertainties of 50% were assigned to each of the parameters. The norminal values were found with a calibration that was performed with a global effective search method (SCE-UA) (Duan et al., 1992) and uncertainties on these parameter values were not calculated during that calibration because in this method no covariance matrices are calculated.

4.3. Step 3: propagation of the uncertainty through the model

Here again the uncertainties are split: parameter uncertainty, diffuse pollution uncertainty and point pollution uncertainty. For each of these three subproblems an uncertainty analysis was performed in which all of the uncertainty sources are varied at the same time to see the effects of the uncertainty on parameters and inputs. The uncertainty bands (i.e. the 5% and 95% percentiles) were calculated for the modelled time series.

Figs. 1–3 shows the time series of nitrate concentrations in the river water at Denderbelle, situated near the mouth, with the 5% and 95% uncertainty bounds for uncertainty due to point input (Fig. 2) and diffuse pollution input (Fig. 3). Fig. 1 shows the uncertainty bounds for nitrate at the same location due to parameter uncertainty.

4.4. Step 4: analyse the model results to set up a future measurement campaign

To reduce parameter uncertainty, optimal experimental design based on the Fisher Information Matrix can be done (as explained in Section 3). This is the most objective method to find important measurement locations, times, conditions to better estimate the parameters. This design of new experiments is not presented here as we focus here on the uncertainty analysis and what information can be revealed from it.

Linking the results obtained in step 3 to the external circumstances, rainfall intensity and river flow (Fig. 4), it can be seen that diffuse pollution inputs are important during periods with intense rainfall and high flows. Under those conditions, the uncertainty on the nitrate concentration is mainly due to these factors. The small uncertainty bounds observed at the beginning of the year, even under high flows and

Table 2
Parameters and initial conditions used in the sensitivity analyses (*Arnold et al., 1996; **Bowie et al., 1985; ***calibrated)

Variable	Description	Units	Range	Nominal value
a_{i1}	Ration of chlorophyll to algae biomass	μg-chl *a*/mg algae	10–100*	10***
a_{i1}	Fraction of algae biomass that is nitrogen	mg N/mg algae	0.07–0.09*	0.09***
a_{i2}	Fraction of algae biomass that is phosphorus	mg P/mg algae	0.01–0.02*	0.02***
a_{i3}	O_2 production per unit algae growth	mg O_2/mg algae	1.4–2.6**	2.3**
a_{i4}	O_2 uptake per unit of algae respiration	mg O_2/mg algae	1.6–2.3*	2.0*
a_{i5}	O_2 uptake per unit of NH_3 oxidation	mg O_2/mg NH_3-N	3.0–4.0*	3.5*
a_{i6}	O_2 uptake per unit of HNO_2 oxidation	mg O_2/mg HNO_2-N	1.00–1.14*	1.07*
μ_{max}	Maximum algae growth rate	1/day	1.0–3.0*	2.2*
r_{hoq}	Algae respiration rate	1/day	0.05–0.5*	0.2*
k_l	Michaelis-Menten half-saturation constant for light	langley/hour	0.72–6.16**	5.226***
k_n	Michaelis-Menten half-saturation constant for nitrogen	mg N/l	0–10*	0.1*
k_p	Michaelis-Menten half-saturation constant for phosphorus	mg P/l	0–10*	0.014*
Λ_0	Minimum light intensity for algae bloom	J/m^2	1.5–7.5***	5.0***
Λ_1	Algae light self shading coefficient	g algae biomass/m^2	0.01–2.0***	0.3***
Λ_2	Sediment shading coefficient	mg/l	10–200***	100***
P_n	Algae preference factor for ammonia	mg/l	0–1*	0.3***
k_{dd}	Algae die-off rate	1/day	0.01–0.8***	0.2****
r_{s1}	Local algae settling rate in the reach.	m/day	0.01–1.85*	0.15*
r_{s2}	Benthic (sediment) source rate for dissolved phosphorus in the reach.	mg dissolved P/(m^2 day)	0.01–0.03**	0.01**
r_{s3}	Benthic source rate for NH_4-N in the reach.	mg NH_4-N/(m^2 day).	0.0004–1.8**	1.0**
r_{s4}	Rate coefficient for organic N settling in the reach.	m/day	0.001–3.0***	0.05*
r_{s5}	Organic phosphorus settling rate in the reach.	m/day	0.001–0.1*	0.03*
r_{k1}	Carbonaceous biological oxygen demand deoxygenation rate coefficient in the reach.	1/day	0.02–3.4*	0.87*
r_{k2}	Oxygen reaeration rate in accordance with Fickian diffusion in the reach.	m/day	0–100*	0.3***
r_{k3}	Rate of loss of carbonaceous biological oxygen demand due to settling in the reach.	m/day	0.1–3.0***	0.2***
r_{k4}	Benthic oxygen demand rate in the reach	g/m^2 day	0.02–12.8**	5**
r_{k5}	Coliform die-off rate in the reach.	Day	0.05–4.0*	0.9*
r_{k6}	Decay rate for arbitrary non-conservative constituent in the reach.	Day	0–10***	1***
b_{c1}	Rate constant for biological oxidation of NH_4 to NO_2 in the reach.	1/day	0.1–1*	0.1***
b_{c2}	Rate constant for biological oxidation of NO_2 to NO_3 in the reach.	1/day	0.2–2*	1.0*
b_{c3}	Rate constant for hydrolysis of organic N to NH_4 in the reach.	1/day	0.2–0.4*	0.4***
b_{c4}	Rate constant for mineralization of organic P to dissolved P in the reach.	1/day	0.01–0.7*	0.1*
r_{ktemp}	Rate constant for heat exchange	m/day	0.1–1***	0.35***

rainfall, are acceptable because during those months management practices are less important than in other periods of the year. During dry weather flow, the input uncertainty of the loads is strongly propagated. Hence this UA indicates that one can obtain a better calibration for the diffuse pollution part of the model with data taken during wet periods with high flows. If one focuses on calibrating the in-stream behaviour and point pollution then measurements during dry periods are needed, as in such conditions the model is not sensitive towards input of diffuse pollution.

Further it is seen on Fig. 1 that the 95% bounds show much higher peaks than the mean concentration time series. This means that some peak values of nitrate in the river water at Denderbelle may not be predicted properly due to an underestimation of the amount of fertiliser used. Those peaks (e.g. days 156 and 260) are significantly higher than the levels of nitrate for basic water quality.

It is also of interest to know how uncertainty is propagated from one location to the other. This analysis was done for the uncertainty propagation due to diffuse pollution inputs. The number of hours that NO_3 was above 3 mg/l was calculated. This was done for the time series of the mean, the 5% bound and the 95% bound (Fig. 5). The uncertainty bounds become larger when approaching the mouth due to the summation of the uncertainties on all diffuse pollution inputs that enter the river. However, it is interesting to see that with the available quality of input data no conclusions can be drawn concerning the question whether the diffuse pollution causes nitrate to exceed 3 mg/l longer downstream than upstream. More accurate data are needed to draw good conclusions from the model results.

Table 3
Uncertainty ranges for diffuse pollution input

Input	Uncertainty
Plant date for the crops	±1 month
Harvest date of the crops	±1 month
Amount of fertiliser applied per subbasin and per crop (kg/ha)	±25%

Step 5: Perform the measurements.
Step 6: Recalibrate the model with new inputs.
Step 7: Repeat step 3 till 6 until satisfying results are obtained.

The last three steps in the procedure are only relevant when a new measurement campaign is actually conducted. However,

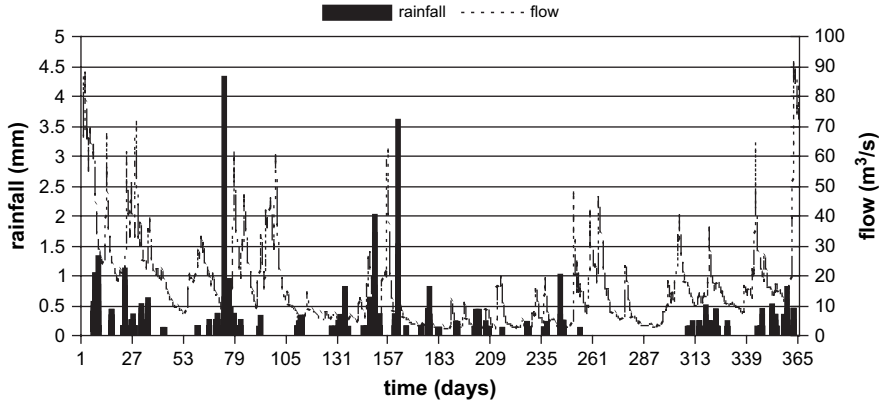

Fig. 4. Rainfall intensity and flow in 1994 at Denderbelle.

for budgetary reasons no additional measurements could be done.

5. Conclusions and recommendations

The results of an uncertainty analysis were here evaluated to guide future monitoring campaigns. The conclusions are not intended to be real guidelines for future measurement campaigns on the river Dender. Due to a too small set of available measurements a validation of the model was not possible which is a valuable and necessary step for the reliability of the predictions. However, the conclusions show the advantages of a guided measurement campaign and are more focussing on the techniques and the possibilities of the proposed seven-step approach, rather than giving results for the particular case used here.

Information of output sensitivity to the inputs was collected by considering diffuse and point pollution inputs separately. Measurements during dry periods can be used to better calibrate the model for point source pollution because the inputs of diffuse pollution are not important then. On the other hand, periods with intense rainfall and high flows are very interesting for the calibration of the model with respect to diffuse pollution impacts because the model output nitrate is then very sensitive towards the inputs related to farmer's practices.

When evaluating the influence of the uncertainty of the diffuse pollution inputs, the uncertainty bounds appeared to be too high to draw reliable conclusions from the model results. So, it showed the importance of accurate measurements and input data if the model results have to serve for decision support and river basin management.

It is obvious from the comparison between the global sensitivity analyses, for the subgroups of inputs and parameters and the combination parameters-input, that the parameters were most important. This shows that it is best to start with a good calibration of the model and then focus on collecting more accurate input data.

Too often a model is calibrated with only one comprehensive measurement campaign. This is mostly not the most efficient way. When for example only measurements during dry periods are made in such simple campaigns, the model cannot be well calibrated for the diffuse pollution part. So, it is better to perform two separate smaller measurement campaigns with the first one being an 'exploring' one, while the second campaign is guided by previous analysis of the model results. The combination of the two monitoring campaigns can assure that at least some measurements are performed at 'the right moment', making the calibration process easier and more reliable.

It is necessary to combine all previous uncertainty analyses to evaluate the total uncertainty on the model results and to

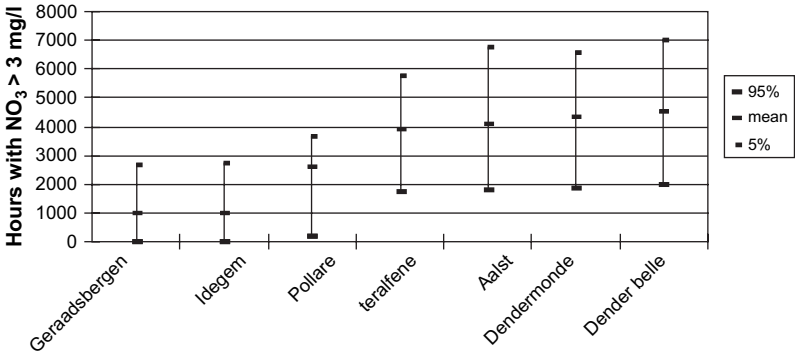

Fig. 5. Uncertainty on predicted hour of NO_3 exceeding 3 mg/l from upstream to the mouth of the Dender in 1994. Only diffuse pollution input uncertainty is considered.

compare them with the measurements. In this way, also model structure uncertainty can be quantified (Willems and Berlamont, 2002).

It needs to be mentioned that the seven steps approach as presented here can often not be followed completely (especially step 7) because of time and/or budget limitations. The continued repetition of the steps until satisfying results are obtained is an ideal situation but stopping after the first six steps, is surely acceptable. All depend on the aim of the model use and the desired degree of precision. Often, the aims of the modelling study are reconsidered after an evaluation of the precision of the model rather than to pursue a smaller uncertainty.

A shorter procedure does not seem useful because that would mean we leave out the idea of conducting of new measurements and we come again to the current practice of gathering inputs and measurements to build a model without knowing beforehand which inputs and measurements are most important (Van Waveren et al., 1999). So, large projects can for sure benefit from an additional measurement campaign, and a first measurement campaign can be kept limited.

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