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Sensitivity analysis for hydrology and pesticide supply towards the river in SWAT

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Abstract

The dynamic behaviour of pesticides in river systems strongly depends on varying climatological conditions and agricultural management practices. To describe this behaviour at the river-basin scale, integrated hydrological and water quality models are needed. A crucial step in understanding the various processes determining pesticide fate is to perform a sensitivity analysis. Sensitivity analysis for hydrology and pesticide supply in SWAT (Soil and Water Assessment Tool) will provide useful support for the development of a reliable hydrological model and will give insight in which parameters are most sensitive concerning pesticide supply towards rivers. The study was performed on the Nil catchment in Belgium.

In this study we utilised an LH-OAT sensitivity analysis. The LH-OAT method combines the One-factor-At-a-Time (OAT) design and Latin Hypercube (LH) sampling by taking the Latin Hypercube samples as initial points for an OAT design. By means of the LH-OAT sensitivity analysis, the dominant hydrological parameters were determined and a reduction of the number of model parameters was performed. Dominant hydrological parameters were the curve number (CN2), the surface runoff lag (surlag), the recharge to deep aquifer (rchrg_dp) and the threshold depth of water in the shallow aquifer (GWQMN). Next, the selected parameters were estimated by manual calibration. Hereby, the Nash–Sutcliffe coefficient of efficiency improved from an initial value of −22.4 to +0.53.

In the second part, sensitivity analyses were performed to provide insight in which parameters or model inputs contribute most to variance in pesticide output. The results of this study show that for the Nil catchment, hydrologic parameters are dominant in controlling pesticide predictions. The other parameter that affects pesticide concentrations in surface water is 'apfp_pest', which meaning was changed into a parameter that controls direct losses to the river system (e.g., through the clean up of spray equipment, leaking tools, processing of spray waste on paved surfaces). As a consequence, it is of utmost importance that hydrology is well calibrated while—in this case—a correct estimation of the direct losses is of importance as well. Besides, a study of only the pesticide related parameters, i.e. application rate (kg/ha), application time (day), etc., reveals that the application time has much more impact than the application rate, which has itself a higher impact than errors in the daily rainfall observations.

Keywords: SWAT; Sensitivity analysis; Water quality modelling; River-basin management

1. Introduction

Dynamic models form suitable instruments for risk assessment of toxic components in natural river systems (Deksissa et al., 2004). By using exposure models under time-varying conditions, risks can be determined more

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realistically as compared to a steady state or a static approach (Verdonck et al., 2002). Advantages consist in better predictions of impacts of accidental discharges, of effects of specific climatological or seasonal variations and of evolutions in water quality. A prominent example is the dynamic modelling of pesticides.

The first step in the development of a dynamic exposure model for pesticides is to build a reliable hydrological model (Novotny and Olem, 1994). The hydrology of a river catchment will determine to a great extent the transport of solutes, suspended sediments and colloids in the water system. SWAT was found to be a suitable tool for modelling non-point source pollution on catchment scale. A SWAT model not only allows hydrological predictions but also predictions of pesticide loads at different locations along the river as function of time.

Pesticide modelling is much more complex than hydrologic modelling. As mentioned by Rickert (1993) and Ongley (1996), the modelling of pesticides is situated on a high level of scientific complexity and a lot of processes are not yet completely understood (Warren et al., 2003). They require a lot of additional input data that are often unavailable, incomplete or uncertain. Nevertheless, they are of great importance for a correct representation of the pesticide fate (Neitsch et al., 2002b). Examples are the application rates and dates of a particular pesticide, which depend on the farmer and vary from year to year (Beernaerts et al., 2002). Correct and detailed information is generally not available and lumped assessments for the entire catchment do not give reliable results, especially when spatial and temporal dynamics at small scales are of interest.

The objectives of this study are twofold: first, to determine the most influential model parameters, which results in a reduced set of parameters for model calibration and second, to gain insight into the important processes determining the fate of pesticides. Moreover, knowledge of the most important sources of uncertainty for the modelling of pesticide fate is useful in anticipation of oriented data collection for future pesticide modelling.

2. Methods

2.1. Catchment area

In this study we focus on the Nil, a small, hilly basin situated in the central part of Belgium, southeast of the capital city Brussels (Fig. 1). The average elevation measures 151 m a.s.l., with the highest top reaching 167 m a.s.l. and the watershed outlet lying at 110 m a.s.l. The Nil-catchment drains an area of 32 km^2, is 14 km long and has a retention time of about 1 day. Seven percent of the area is inhabited and the main crops grown are winter wheat (22% of the catchment area), corn (15%) and sugar beet (10%). Eighteen percent of the catchment consists of pasture. The predominant soil type is loam.

Further, the catchment is characterised by a low baseflow which results from its specific geological structure. Highly permeable Brusselian sands, showing hydraulic conductivities between 10^{-3} and 10^{-5} m/s, lay above a less permeable socle (Abdeslam, 1998). Hereby, an

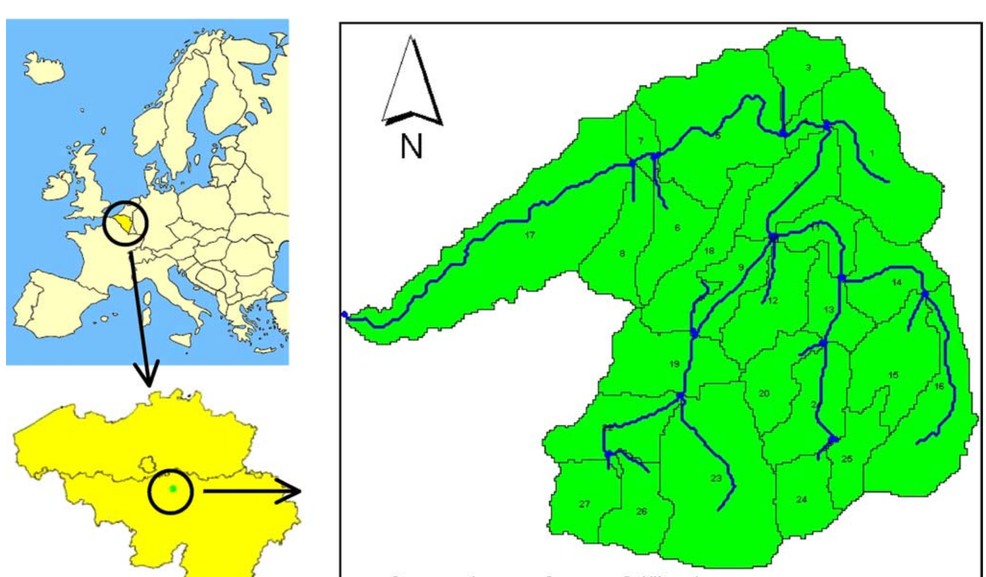

Fig. 1. Situation of the Nil-catchment and sub-basin delineation automated by means of a DEM.

important part of the groundwater of the Nil-catchment is drained to the adjacent river 'Train'.

The Nil-catchment was selected because it is a well-documented basin, studied in detail in terms of pesticide application (Beernaerts et al., 2002).

2.2. Model description

SWAT2000—the Soil and Water Assessment Tool—was developed by the USDA (Arnold et al., 1998) to predict the impact of land management practices on water, sediment and amount of chemicals originating from agriculture, in large complex river basins with varying soils, land use and management conditions over a long period of time. It is a partly physically based and partly distributed, continuous model with a daily calculation time step.

The water quantity processes simulated by SWAT include precipitation, evapotranspiration, surface run-off, lateral subsurface flow, ground water flow and river flow. The pesticide component of SWAT simulates pesticide losses in surface runoff, sediments and percolation below the root zone. The movement of the pesticide is controlled by its solubility, degradation half-life, and soil organic carbon adsorption coefficient. Pesticides on plant foliage and in the soil degrade exponentially according to the appropriate half-life coefficient (Neitsch et al., 2002a).

This research focuses on the pesticide atrazine. Since the monitoring of in-stream atrazine concentrations showed clear peaks during non-rainy periods and even non-windy days, it was concluded that significant direct losses occur during the pesticides application dates (e.g. through the clean up of spray equipment, leaking tools, processing of spray waste etc.) (Beernaerts et al., 2002). Therefore, the SWAT codes were slightly modified in order to consider these direct losses by changing the meaning of the parameter 'apfp_pest' (application efficiency coefficient) from indicating the process whereby a fraction of the applied rate is lost from the system towards the process by which a fraction of the applied pesticide is diverted directly to the river system. This modification is allowed in this case, in which pesticides are not applied by airplanes but directly on the fields by spray equipments and where losses outside the system are not expected to be significant. The direct losses are considered to be lower than 5%, but their impact is nevertheless significant since these losses are directly ending up in the river system.

We used the AVSWAT2000 version of the model, where the simulator is integrated in a GIS by an ArcView pre-processor (Di Luzio et al., 2002). It uses gridded DEM data, polygon/grid coverages of soils and land use, and point coverages of weather stations as basic input to the model.

Within SWAT, a catchment is partitioned into a number of sub-basins (Fig. 1), based on the threshold area which defines the minimum drainage area required to form the origin of a stream. Within the sub-basins, hydrologic response units (HRUs) are defined, which are lumped land areas consisting of unique combinations of land cover, soil and management (Neitsch et al., 2002a).

2.3. Input data

For the Nil-catchment, weather data from 1998 to 2002 were obtained from the Belgian Royal Meteorological Institute for the stations of Chastre and Ernage. These data include daily precipitation and daily maximum and minimum temperatures.

Because the quality of the performed calculations will strongly be influenced by the detail of the maps used, special attention was given to utilise high resolution maps. A 30 m resolution DEM created by local government authorities was added to the AVSWAT model-interface.

The 1999 land use map with a spatial resolution of 30 m, was obtained from Romanowicz et al. (2003). They combined Landsat TM satellite images with the SIGEC dataset. The SIGEC dataset includes information of crop distribution over a catchment area and is based on the claims of farmers for EU subsidies. A standard classification resulted in 50 classes, which was reduced to 23 land use classes which can be handled by the SWAT model.

A detailed soil map was created by digitizing the required parts of the maps 117E, 130E and 130W; all at scale 1:25,000 (IRSIA, 1961). The basic soil properties (percentage of sand, clay and silt, the texture class, the percentage of carbon and the horizon thickness) were obtained from the analytical database AARDEWERK (Van Orshoven and Vandenbroucke, 1993). In order to calculate the hydraulic conductivity (K_{sat}), pedotransfer functions from the HYPRES database were used (Wösten et al., 1999). The available water capacity (AWC) was estimated from water contents at pF 4.2 and 2.5 using the RETC program (van Genuchten et al., 1991).

Pesticide data were collected by CODA (2003). To this end, inquiries were conducted during springs of 1998 until 2001. The farmers were asked to give as detailed information as possible concerning the amount of pesticide they applied, the application dates, the kinds of pesticides they utilised for their different crops and the treated surface. Forty two percent of the farmers could give detailed information. In this study, we focus on the use of atrazine on corn during the growth season of 1999, when the application rate amounted to 0.783 kg/ha. All applications occurred in the month of May.

For the simulation, the Nil was divided into 27 sub-basins and reaches. The sub-basins are further divided into 227 HRUs, as defined by land use and soil type.

2.4. Sensitivity analysis for the model parameters

2.4.1. Sensitivity analysis and parameter reduction

A complex hydrologic model is generally characterised by a multitude of parameters. Due to spatial variability, measurement error, incompleteness in description of both the elements and processes present in the system, etc., the values of many of these parameters will not be exactly known. Therefore, to achieve a good fit between simulated and measured data, models need to be conditioned to match reality by optimising their internal parameters. This model calibration procedure can be either manual or automated. In both cases, it is advisable to be supported by techniques such as sensitivity analysis. A parameter sensitivity analysis provides insights on which parameters contribute most to the output variance due to input variability. Based on this information, a calibration can be performed for a limited number of influential parameters. The performance of the calibration may then be evaluated by performance criteria such as e.g. the Nash–Sutcliffe coefficient of efficiency (Nash and Sutcliffe, 1970).

2.4.2. The LH-OAT sensitivity analysis

In this study, we performed an LH-OAT sensitivity analysis. The LH-OAT method combines the One-factor-At-a-Time (OAT) design and Latin Hypercube (LH) sampling by taking the Latin Hypercube samples as initial points for an OAT design (Fig. 2) (van Griensven and Meixner, 2003).

Latin Hypercube sampling (McKay, 1988) is a sophisticated way to perform random sampling such as Monte-Carlo sampling, resulting in a robust analysis requiring not too many runs (Saltelli et al., 2000). It subdivides the distribution of each parameter into m ranges, each with a probability of occurrence equal to $1/m$. Random values of the parameters are generated, such that each range is sampled only once. For each of the m random combinations of the parameters an OAT loop is performed.

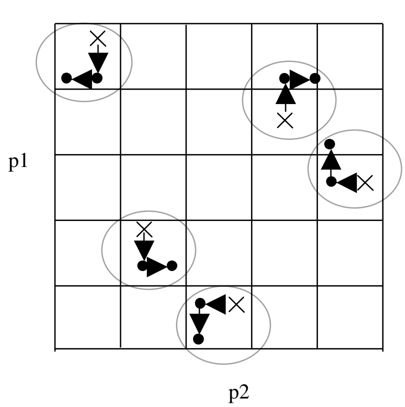

Fig. 2. Illustration of LH-OAT sampling of values for a two parameters model where X represent the Monte-Carlo points and ●, the OAT points (van Griensven and Meixner, 2003).

In the OAT design (Morris, 1991), only one input parameter is modified between two successive runs of the model. Therefore, the change in model output (e.g. SSE of the surface runoff) can then be unambiguously attributed to such a parameter modification by means of an elementary partial effect $S_{i,j}$ defined by Eq. (1).

$$S_{i,j} = \left[\frac{\mathrm{SSE}(\Phi_1,\ldots,\Phi_i*(1+f),\ldots,\Phi_p) - \mathrm{SSE}(\Phi_1,\ldots,\Phi_i,\ldots,\Phi_p)}{f}\right] \tag{1}$$

where $S_{i,j}$ is a partial effect for parameter Φ_i around an LH point j, f is the fraction by which the parameter Φ_i is changed (a predefined constant) and SSE is the sum of squared errors. In Eq. (1), the parameter is randomly increased or decreased with the fraction f. Considering p parameters, one loop involves performing $p+1$ model runs to obtain one partial effect for each parameter. As the influence of a parameter may depend on the values chosen for the remaining parameters, the experiment is repeated for all the m LH samples. The final effect will then be calculated as the average of a set of the m partial effects.

As a result, the LH-OAT sensitivity analysis method is a robust and efficient method: for m intervals in the LH method, a total of $m\times(p+1)$ runs is required. The LH-OAT provides ranking of parameter sensitivity based on the final effects. Using the LH and One-factor-At-a-Time techniques in unison means that the sensitivity of model output to a given parameter is assessed across the entire feasible range for that parameter and across a number of different values for other parameters in the model, thus incorporating a limited amount of parameter interaction.

2.4.3. Parameter sensitivity for hydrology

The sensitivity analysis was performed for 27 parameters that may have a potential to influence river flow (Table 1). The ranges of variation of these parameters are based on a listing provided in the SWAT manual (Neitsch et al., 2002a) and are sampled by considering a uniform distribution. The distributed parameters are changed in a lumped way by sampling a relative change (in percentage), whereby they are restricted to their physical range. The analysis was carried out using simulations for hydrology at the mouth of the river, for the period between 1998 and 2001.

2.4.4. Parameter sensitivity for atrazine modelling

In addition to the hydrological parameters of Table 1, the pesticide parameters of Table 2 were also included in the sensitivity analysis. The ranges of variation are defined based on the extensive literature review for atrazine that was performed by Liu et al. (1998). Only for

Table 1
Parameters and parameter ranges used in the sensitivity analysis + sensitivity ranking (with Gw. = groundwater, Evap. = evaporation, Geom. = Geomorphology)

Name	Min	Max	Definition	Process
ALPHA_BF	0	1	Baseflow alpha factor (days)	Gw.
BIOMIX	0	1	Biological mixing efficiency	Soil
blai	−50	50	Leaf area index for crop*	Crop
canmx	0	10	Maximum canopy index	Runoff
CH_K2	0	150	Effective hydraulic conductivity in main channel alluvium (mm/hr)	Channel
ch_n	−20	20	Manning coefficient for channel	Channel
CN2	−50	50	SCS runoff curve number for moisture condition II*	Runoff
epco	−50	50	Plant evaporation compensation factor*	Evap.
ESCO	0	1	Plant evaporation compensation factor	Evap.
GW_DELAY	0	100	Groundwater delay (days)	Gw.
GW_REVAP	0.02	0.2	Groundwater "revap" coefficient	Gw.
GWQMN	0	1000	Threshold depth of water in the shallow aquifer required for return flow to occur (mm)	Soil
rchrg_dp	0	1	Groundwater recharge to deep aquifer (fract)	
REVAPMN	0	500	Threshold depth of water in the shallow aquifer for "revap" to occur (mm)	Gw.
SFTMP	−2	2	Snowfall temperature (°C)	Snow
SLOPE	−50	50	Average slope steepness (m/m)*	Geom.
SLSUBBSN	−50	50	Average slope length (m/m)*	Geom.
SMFMN	0	10	Min. melt rate for snow (mm/°C/day)	Snow
SMFMX	0	10	Maximum melt rate for snow (mm/°C/day)	Snow
SMTMP	−2	2	Snow melt base temperature (°C)	Snow
sol_alb	0	1	Moist soil albedo	Soil
SOL_AWC	−50	50	Available water capacity (mm/mm soil)	Soil
sol_k	−50	50	Soil conductivity (mm/h)*	Soil
sol_z	−50	50	Soil depth*	Soil
surlag	0	10	Surface runoff lag coefficient	Runoff
TIMP	0.01	1	Snow pack temperature lag factor	Snow
TLAPS	−50	50	Temperature laps rate (°C/km)*	Geom.

*Relative percent change.
Italicised: parameters that were optimised in the manual calibration.

Table 2
Pesticide parameters and parameter ranges used in the sensitivity analysis + sensitivity ranking

Name	Default	Min	Max	Definition	Process
apfp_pest	–	0.95	1	Application efficiency when considering direct losses	Pesticide
hlff_pest	5	4	7	Degradation half-life of the chemical on the foliage (days)	Pesticide
hlfs_pest	60	8	170	Degradation half-life of the chemical in the soil (days)	Pesticide
Koc_pest	100	64	135	Soil adsorption coefficient	Pesticide
pwsol_pest	33	28	70	Solubility of the chemical in water (mg/l)	Pesticide
wofp_pest	0.45	0.36	0.45	Wash-off fraction	Pesticide

*Relative percent change.

the parameter 'wofp_pest' (wash off fraction), no information was found, and an arbitrary range of ±20% was taken. The parameter sensitivities for the pesticide sub-model focus on the variation of the daily average pesticide concentrations and the daily average pesticide loads for the period 1998–2001 at the mouth of the river.

2.5. Sensitivity analysis for the model inputs

Compared to water quantity modelling, pesticide modelling is confronted with many more uncertainties related to the model inputs. This may even cause a parameter calibration to be impossible. For instance, correct information on the amount and date of pesticide application does often not exist while it is expected that such information is crucial for a correct modelling (Neitsch et al., 2002b). A proper calibration then requires some inverse modelling techniques to tackle this problem. A sensitivity analysis of these model inputs can help to get insights in what the major input factors are that affect the model output and that hence need special attention.

To perform a sensitivity analysis, the model inputs cannot be dealt with in the same way as the model parameters since they cannot be represented by a single value: for each run, a series of error values needs to be sampled to consider the spatial or temporal variation of the system. It is, for instance, not likely that the error in rainfall input is the same for each rain gauge or for each day. It is neither likely that all farmers apply pesticides on the same day or that the error on application rate is the same within the entire catchment. Therefore, another procedure must be used to evaluate the sensitivity of model outputs to uncertainties that are inherent to the model inputs.

A new module "CANOPI" (Confidence ANalysis Of Physical Inputs) was developed within the SWAT codes that allows for a random variation on model inputs for each day (for the climate data) or for each HRU within the model (for both the pesticide application data) according to a uniform or normal distribution. For each input factor, N runs are performed whereby that particular input factor is randomly varied in time and/or space according to the provided error range. The average and variation of a model output are calculated for each input. The corresponding coefficient of variation provides insights in the relative importance of the uncertainty of these input factors.

Both the influence of climatic inputs (such as daily rainfall and temperature data) and atrazine application data (such as atrazine application rate and dates) are analysed. For both, a uniform distribution is considered over the ranges of variation that are listed in Table 3.

3. Results and discussion

3.1. Parameter sensitivity for hydrology

Fig. 3 summarizes the sensitivity ranking for the performance for flow, which is determined by calculating the sum of squared errors (SSE) between daily simulated flows and daily flow observations. When we focus on the spring periods (March–June), the same parameters appear to be important.

In both cases the curve number (CN2) is the most important parameter, followed by the parameters surlag, rchrg_dp and GWQMN. The importance of the groundwater parameters is not surprising, due to the fact that drainage to deeper groundwater is high which has its origin in the geological structure of the catchment. Through the permeable Brusselian sands, groundwater of the Nil-catchment passes towards the adjacent river 'Train' (Abdeslam, 1998).

Table 3
Ranges of variation for the input data

Type of input data	Range	Variability
Rainfall	±10%	Temporal: daily
Temperature	±1 °C	Temporal: daily
Atrazine application rate	±20%	Spatial: for each HRU with CORN
Dates	*±20 days (from May 15)*	*Spatial: for each HRU with CORN*

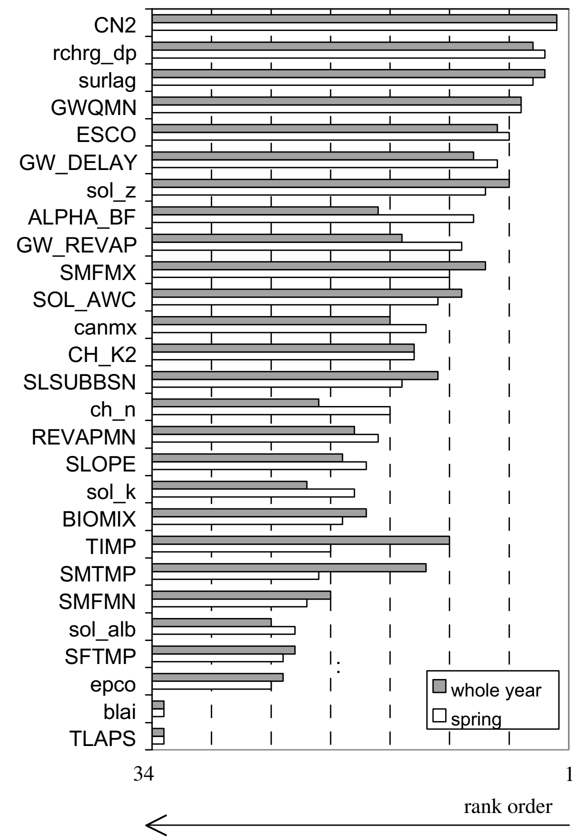

Fig. 3. Graphical representation of the sensitivity ranking for hydrology over the whole year and during spring, for a subset of parameters. The definition of the different parameters can be found in Table 1.

The sensitivity of the curve number is consistent with results determined in other studies (e.g. Lenhart et al., 2002; Cryer and Havens, 1999).

3.2. Calibration of the hydrological parameters

In the manual calibration, parameters influencing baseflow and surface flow are optimised. To reduce the number of parameters that will be calibrated, the above-mentioned ranking of sensitive parameters is used. Only the most influential parameters are eligible for calibration. As the parameters SOL_AWC and sol_z are supposed to be determined precisely, no optimisation was performed for them. The parameters that are given priority in the manual calibration are italicised in Table 1.

The results of the manual calibration are given in Fig. 4b. By way of comparison, cold simulation results are presented in Fig. 4a. Cold simulation results are produced by the model before any calibration is performed.

As shown in Fig. 4b, a reasonable fit was obtained for the manually calibrated flows. Nevertheless, better calibration is possible if seasonally dependent parameters could be adjusted throughout the year. For example, different values for the ESCO parameter during winter

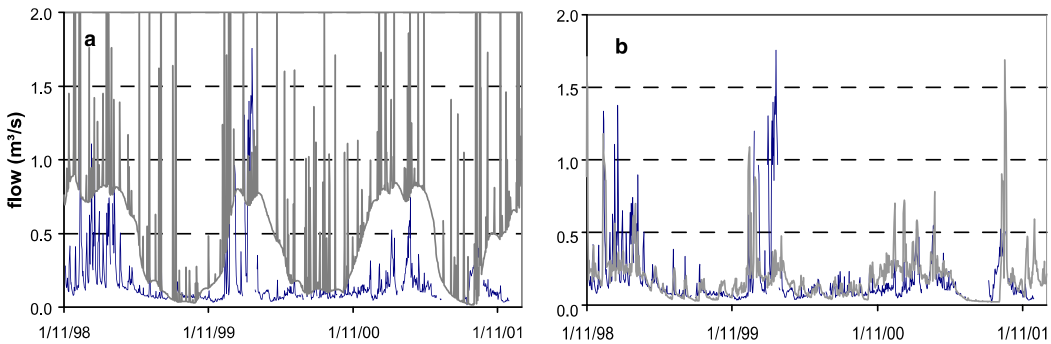

Fig. 4. (a) Comparison of measured (—) and cold simulation (—) flow data. (b) Comparison of measured (—) and manually calibrated (—) flow data.

and summer would permit more realistic simulations of water evaporation during both seasons and thereby increase model efficiency. As herbicides are applied during the spring period from begin March to the end of June, we focused on good prediction performance in that period and we optimised the selected parameters specific for spring. As shown in Fig. 5, a good fit is obtained between measured and simulated flows during spring. The Nash–Sutcliffe coefficient improved from an initial value of −22.4 for the cold simulation, to +0.53 after calibration specific for spring.

3.3. Parameter sensitivity for atrazine modelling

As presented in Fig. 6, the only parameter that is in competition with the hydrological parameters is 'apfp_pest'. In this case, this parameter controls the direct losses to the river system (see above). The importance of direct losses in the Nil-catchment was already mentioned by Beernaerts et al. (2002) and was also found to be important in certain catchments in Germany (Neumann et al., 2002) and Greece (Albanis et al., 1998).

In summary, for making reliable predictions of atrazine towards the river, it is highly important that the hydrology, especially the curve number, is well calibrated while a correct estimation of the direct losses is of importance as well.

3.4. Input sensitivity for atrazine modelling

This sensitivity analysis is performed with the previously described manually calibrated model, but a recalibration might be needed when pesticides are also considered. However, since this may require better assessments for the model inputs, it is first aimed to define the most important input factors.

For each input factor, 100 runs were performed. The results for the average concentrations and average loads (Table 4) show that the date of application is much more important than errors that may occur in the application rate or rainfall errors. Errors in temperatures are the least important. The importance of the application date can be explained twofold: first, the contribution of direct losses (through the clean up of spray equipment, leaking tools, processing of spray waste etc.) to total amount of pesticides found in the river is estimated to be 50–70% in the studied catchment. Consequently, errors in application date will result in significant errors in predictions of the direct losses in this catchment. Secondly, the percentage of pesticides that eventually will reach the river

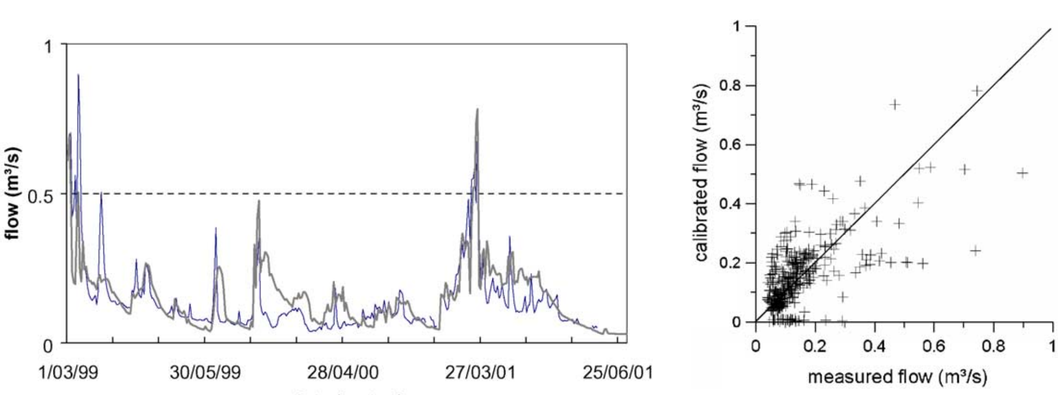

Fig. 5. Comparison of measured (—) and manually calibrated (—) flow data for the spring periods shown sequentially from 1999 up to 2001.

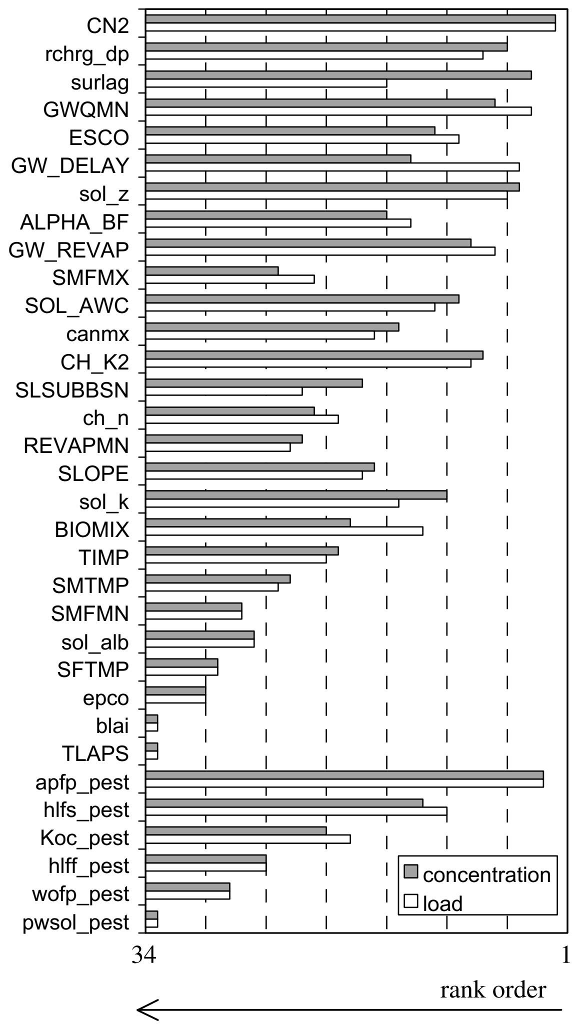

Fig. 6. Graphical representation of the sensitivity ranking for atrazine modelling for a subset of parameters. The definition of the different parameters can be found in Tables 1 and 2.

Table 4
Coefficient of variation for the CANOPI results

Type of input data	Average atrazine concentration	Average atrazine load
Rainfall	0.0434	0.0512
Temperature	0.0029	0.0031
Atrazine application rate	0.0321	0.0324
Dates	*0.3024*	*0.3233*

through surface run-off depends highly on the period between the application and the next rain event. In Belgium, a randomly defined application date may easily coincide with a rainy day. In reality, farmers will not apply pesticides on rainy days. Therefore, it is important to consider the weather pattern while setting up the management files for pesticide applications. If we would consider this also in the sensitivity analysis, we may expect a somewhat smaller influence of the application date on the losses originating from surface runoff.

4. Conclusions

A methodology to achieve information about sensitive parameters and model inputs for hydrology and pesticide supply in SWAT, was presented. First, an intensive data collection, the digitisation of soil maps and the calculation of related soil parameters was performed for the Nil catchment.

An LH-OAT sensitivity analysis for hydrology allowed for the screening of the large set of input parameters. The selected subset of parameters was then used for model calibration. The manual calibration resulted in good fits to the observed flows. Better results would be possible if seasonally dependent parameters could be adjusted to the current season.

By including pesticide parameters in the sensitivity analysis, it appears that besides a good calibration of the hydrology also a correct estimation of the direct losses is important. The importance of these direct losses for this catchment was already proven by an experiment during the years 1998–2002. Measurements of pesticide concentrations at the mouth of the river Nil (1998–1999) showed high peaks even during non-rainy wind still days. Consequently, these high peaks can only originate from direct losses due to the clean up of spray equipment, leaking tools, etc. During the years 2000–2001, sensitization of farmers regarding this issue resulted in a significant decrease of pesticide loads in the river. When this sensitization campaign was finished in 2002, pesticide loads in the river immediately increased (Beernaerts et al., 2002). This proves the importance of direct losses, which were estimated to be 50–75% of the total amount of pesticides found in the river 'Nil'.

Finally, the sensitivity analysis for the input factors reveals that the date of application is much more important than errors that may occur in the application rate or rainfall errors. Consequently, the application date can be an important source of uncertainty and needs special attention for data collection. As the management files were not adapted to the weather pattern, we can expect that such a sensitivity analysis will result in a smaller influence of the application date on the losses originating from surface runoff.

The importance of hydrology and of the reduction of uncertainties in inputs for modelling pesticide fate were also mentioned by Dubus et al. (2003).

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