Katholieke Universiteit Leuven
Faculteit Bio-ingenieurswetenschappen

DISSERTATIONES DE AGRICULTURA

Doctoraatsproefschrift nr. 676 aan de faculteit Bio-ingenieurswetenschappen
van de K.U.Leuven

Catchment scale water quantity impact analysis related to life cycle assessment for forestry and agriculture

Proefschrift voorgedragen tot het
behalen van de graad van
Doctor in de
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door

Griet Heuvelmans

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Beste lezer,

Eerst en vooral: dankjewel voor je interesse in dit boekje. Voor mij persoonlijk waren de jaren dat ik hieraan gespendeerd heb erg inspirerend en leerrijk. Via dit boekje wil ik deze ervaring graag met je delen. Moest je onderweg iets tegenkomen waarvan je zegt: daar wil ik meer van weten, of ben je geïnteresseerd in de gebruikte data en scripts, dan mag je me altijd contacteren.

Hoe het allemaal begon? Zo'n vijf en een half jaar geleden, ik zat destijds in het tweede ingenieursjaar, kregen we een lijst met mogelijke thesisonderwerpen voorgelegd. Op dat moment had ik nooit gedacht dat het onderwerp dat ik aanvinkte me nu nog altijd zou bezig houden. Een volledig jaar aan één thema werken was een nieuw gegeven en het leek een zee van tijd. Het thesiswerk viel bijzonder in de smaak. Ik maakte ook kennis met één van de raadselachtige aspecten van de wetenschap: hoe meer ideeën je uitwerkt, des te meer nieuwe ideeën er opduiken. Nog stof genoeg dus voor een doctoraat. Het IWT was zo vriendelijk mij financieel te steunen. De begeleiding door prof. Bart Muys en prof. Jan Feyen vond ik zeer waardevol, zowel in de beginperiode van mijn ingenieursthesis als bij de laatste - niet eens zo zware – loodjes van dit doctoraat.

Als je dit doctoraat leest, dan lijkt het misschien alsof alles naadloos op elkaar aansluit, alsof ik van de ene interessante ontdekking in de andere ben getuimeld. Helaas, een boekje over de dingen die misliepen of achteraf minder interessant bleken dan op het eerste zicht, zou veel lijviger zijn dan dit. Gelukkig waren er op de mindere momenten de collega's binnen en buiten het ILWB om mij terug op het goede spoor te zetten, en - zeker even belangrijk - kon ik altijd rekenen op de emotionele steun van het thuisfront.

A few words to the non-Dutch-speaking readers: thanks for your interest in my work. The years that I've been working on this topic were very inspiring to me, and I would like to share this experience with you via this thesis. I hope you enjoy it!

Met vriendelijke groet,

Griet

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Samenvatting

Levenscyclusanalyse (LCA) is een methode om het milieuprofiel van productiesystemen op te stellen. LCA werd ontwikkeld voor industriële productieprocessen, maar het aantal toepassingen in de land- en bosbouw groeit gestaag. Standaard LCA databanken bevatten momenteel onvoldoende gegevens voor een precieze berekening van de milieu-impact van landgebruiksystemen. Daarnaast vertoont landgebruik, in tegenstelling tot industriële systemen, een aanzienlijke tijdruimtelijke dynamiek wat noopt tot een uitbreiding van de bestaande LCA methodiek. Het onderzoek beperkte zich tot de impact van landgebruik op waterkwantiteit. De impactcategorie 'regionale waterbalans' werd ingevoerd om de temporele variatie in waterafvoer in rekening te brengen. Percentielen van afvoertijdreeksen werden als indicatoren gebruikt voor droogte- en overstromingsrisico en stroomafwaartse waterbeschikbaarheid. In de praktijk zijn afvoertijdreeksen vaak niet voor handen. Het SWAT model werd daarom gebruikt om deze te simuleren. SWAT brengt de ruimtelijke variatie in hydrologische impact in rekening door een stroombekken onder te verdelen in eenheden die uniform zijn qua abiotiek en landgebruik. De parameters van het SWAT model werden gerelateerd aan locatie en gebiedseigenschappen om betrouwbare simulaties van niet-bemonsterde bekkens mogelijk te maken. De onzekerheid op het voorspelde afvoerregime, die inherent is aan het modelleren, werd berekend met de 'General Likelihood Uncertainty Estimation' procedure. Deze onzekerheid bleek aanzienlijk groter te zijn dan de onzekerheid t.g.v. onnauwkeurige informatie over het toekomstige landgebruik voor een gevalstudie over bebossing in het Zwalmbekken. Het verlagen van de onzekerheid kan de bruikbaarheid van SWAT voor LCA vergroten, en vormt daarom een aandachtspunt voor verder onderzoek. Daarnaast moet nagegaan worden in hoeverre de hier voorgestelde methode voor de generatie van ontbrekende gegevens en het omgaan met tijdruimtelijke variatie overdraagbaar is naar andere landgebruik gerelateerde milieuthema's zoals bodemkwaliteit en biodiversiteit.

Abstract

Life cycle assessment (LCA) is a method to construct the environmental profile of production systems. It was initially developed for industrial production; however, the number of applications to agriculture and forestry is growing. Standard LCA databases do not include all aspects typical for land use systems. Moreover, contrary to industrial systems, land use systems and their environmental impact show a considerable spatio-temporal variability necessitating an extension of the existing LCA methodology. This research focuses on the definition and the calculation of land use related water quantity impacts. A new impact category 'regional water balance' was introduced to account for environmental problems related to the temporal variability of water flows using percentiles of stream flow time series as indicators for downstream water availability, flood and drought risk. But stream flow records are often missing in practice. Therefore, the hydrological model SWAT was used to generate these. SWAT considers the spatial variability in hydrological impact by subdividing catchments in units with homogeneous site and land use characteristics. The parameters of SWAT were linked to location and catchment attributes to enable reliable simulations in ungauged basins. The General Likelihood Uncertainty Estimation procedure was used to calculate the uncertainty on the predicted stream flow regime inherent in the use of a hydrological model. This uncertainty proved to be considerably larger than the uncertainty due to imprecise information about the future land use, as demonstrated for a case-study on afforestation in the Zwalm catchment, Flanders, Belgium. Future work should try to reduce predictive uncertainty to increase the usefulness of SWAT for LCA. Besides, it should be evaluated whether the proposed method for dealing with data gaps and spatio-temporal variability is applicable to other land use related environmental issues such as soil quality and biodiversity.

Chapter I: Introduction

At first sight, hydrological modelling and life cycle assessment (LCA) are two disciplines with little or no overlap. The first one is concerned with the mathematical description of water flow paths through a watershed, the second deals with the construction of environmental profiles of production systems for the purpose of eco-labelling, product comparisons, etc. It might therefore be somewhat strange that these two subjects come together in this research.

Life cycle assessment

According to ISO 14040-14044, life cycle assessment (LCA) is a technique for assessing the environmental aspects and potential impacts associated with a product (CEN, 1997). It consists of four stages (**Fig. 1**):

1. Goal and scope definition, including the identification of system boundaries and the choice of a functional unit in which all impacts will be expressed. This generally is one unit of the end product e.g. one bread in the case of cereal production. For LCAs in the agricultural and forestry sector, it is also common to select a reference system for expressing the environmental impact in relative terms.
2. Inventory of all material flows into and out of the production system that take place during the life cycle of the product.
3. Impact assessment: assessing the impact of the inventoried flows on the environment. To this end, the inventory data are attributed to impact categories representing major environmental issues like eutrophication, acidification etc. More specific environmental problem(s) (e.g. aquatic and terrestrial eutrophication) are identified for each theme and for every problem, an indicator is proposed that quantifies the contribution of the production system to that problem.
4. Interpretation of the results including a critical review of the method and the results and the formulation of conclusions and recommendations.

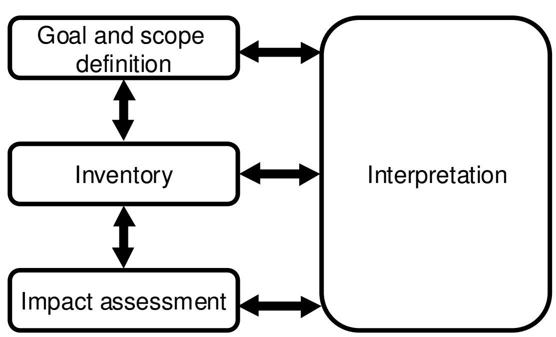

Fig. 1: Structure of an LCA study

Hydrological impact in LCA

Hydrological impact had never been a great concern to LCA practitioners, probably because LCA has its roots in the industrial sector, and these production systems indeed have little influence on watershed hydrology. Water quantity was absent in early LCAs or was treated solely as a resource: the less water consumed, the better. Since the beginning of the nineties, more and more LCA applications in the agri- and silvicultural sector are reported (Frühwald and Solberg, 1995; Ceuterick, 1996). Several authors have noticed that the LCA methodology needed to be revised to include the environmental impacts that are typical for these sectors (Frühwald, 1995; Audsley et al., 1997). Initially, the main focus of these revisions was on land: in contrast to industrial production systems, agri- and silvicultural systems occupy vast amounts of land, and may initiate land degradation. Land use was introduced as a new theme - or 'impact category' in LCA terminology - in the existing LCA methods to account for the impact of a production system on land availability and quality (Lindeijer, 2000). The 'land quality' component of this new impact category covered amongst others changes in hydrological properties of the (agro-)ecosystem. Several variables were proposed as indicators for the water part of the land use impact category: evapotranspiration, groundwater recharge, surface runoff volume (e.g. Baitz et al., 2000; Schweinle, 2000). The main problem was the calculation of the indicators for a given production system. Among LCA practitioners it was generally assumed that there is no universally applicable model available (Weidema and Lindeijer, 2001). Some authors therefore relied on locally valid empirical relationships (e.g. Schweinle, 2000), others assumed that the hydrological impact was linearly related to the amount of vegetation using e.g. above-ground biomass or primary productivity as a preliminary rough indicator (Weidema and Lindeijer, 2001).

In contrast with the ideas in the LCA world, hydrological model developers sometimes claim that their models are universally applicable. Some models are even specifically designed for simulating the impact of land management. Can these models be of use to LCA? It is difficult to answer this question right away because hardly any study applied one of these hydrological models in the context of an LCA. One exception to this is a preliminary case-study that was set-up for comparing and assessing the impact of forestry scenarios for reducing carbon dioxide emissions (Muys et al., 2002; Heuvelmans, 2001; Heuvelmans et al., 2005). A hydrological model was used in this study to make an inventory of all water flows into an out of the considered production systems. Based on this, the water indicators that were being used in the impact category 'land use' in LCA i.e. surface runoff and evapotranspiration were calculated and interpreted. Whereas LCAs are usually performed as site-generic desktop studies, the use of the model allowed making a site-specific assessment of water quantity impacts starting from generally available data about land use, soil, weather and topography. The use of a hydrological model for inventorying water flows is promising, but it still requires further research. In particular, we need to gain insight in the uncertainty and reliability of the model predictions and how this may affect the reliability of the LCA. Next to this, the preliminary study revealed some shortcomings of the existing approaches to water quantity in LCA, i.e. the considered indicators did not fully match with the environmental concerns perceived by the society. In the following paragraph, the problems encountered in the preliminary case-study are discussed in more detail as they form the starting point of this thesis.

Problem setting

Impact description

At present, two impact categories describe water quantity related problems: the land use impact category and the impact category abiotic resource depletion. The abiotic resource depletion impact category assesses the impact of production systems on resource availability with emphasis on future resource needs. Water quantity indicators commonly used in the impact category land use are evapotranspiration and surface runoff. Both indicators are considered as measures of the health of ecosystems: evapotranspiration should be as high as possible and surface runoff as low as possible.

Available methods always use temporally and spatially averaged evapotranspiration, runoff and resource use to calculate indicators (Karjalainen et al., 2001). The question is whether these variables really reflect the environmental concerns of the society (Owens, 2002). In reality, many hydrological impacts are due to the occurrence of extreme events, flood flows and dry periods. These problems are not well reflected by the indicators of the currently used LCA methods. One could argue that the amount of surface runoff is proportional to the risk of flooding, however, surface runoff is also variable in time and the environmental impact can be expected to depend on this temporal variability. So there is a need to revise the current approach to water quantity in LCA so that indicator scores better correspond with the perceived environmental problems. A general framework for the definition and interpretation of indicators is also required to avoid conflicting interpretations. For example, the indicator 'evapotranspiration' which is positively related to ecosystem health conflicts with the resource depletion indicators. The first encourages high water consumption rates, whereas following the second, evapotranspiration should be minimised to maximise water availability for future generations.

Impact calculation

The use of a hydrological model enabled the calculation of hydrological impact in a more direct way as compared to earlier approaches that used e.g. biomass production as approximate indicator. However, to be useful for LCA, the model should be able to deliver reliable predictions in data poor cases. In the preliminary case-study, it was not possible to perform a site-specific calibration or validation because measurements of hydrological variables were not available for the studied region. Because of a lack of data, the question whether simulation results are realistic is often left unanswered in LCA applications. This is due to the nature of the LCA approach: it has to be a quick and easy-to-use environmental impact assessment tool. Since proper parameterisation of the applied equations and validation of the model outcome are very time-consuming, these aspects are often left aside. Nowadays, there is a growing awareness among LCA practitioners that such simplifications undermine the credibility of LCA.

To solve the calibration and validation problem, one ought to have a method for estimating parameters at ungauged sites, i.e. sites without stream flow gauges, and for hypothetical environmental settings. The validity of default model parameters is questionable in this case. More advanced techniques for estimating model parameters in ungauged areas and for hypothetical environmental conditions may be needed. Parameter ranges derived with these techniques can be included in the inventory of a LCA study, which feeds the impact assessment modelling.

Impact evaluation

It is well-known that the predictions of hydrological models are uncertain because of simplifications in the model structure and problems with the identification of model parameters and inputs. Consequently, the indicators that are used in an LCA and calculated with a hydrological model also carry some degree of uncertainty. In the early days of life cycle research, uncertainty was of little concern. As with the model calibration and validation problem, uncertainty was often ignored because LCA is meant to be easy-to-use. Today, however, most LCA practitioners are aware that an uncertainty assessment is essential for a correct evaluation of the results of the impact assessment. For example, in the preliminary case-study, the difference in evapotranspiration and surface runoff indicator scores between the studied forest scenarios is relatively small. If the uncertainty on the model output is taken into account, this difference might become insignificant. In the case-study, the difference in hydrological response for a given forest type between the soil textural classes was quite large. As a consequence, a site-generic approach, which is most commonly used in LCA, would lead to a larger uncertainty on the model output than a site-specific approach. Future research should try to quantify the uncertainty on the model predictions and assess how this output propagates to uncertainty on the indicator scores. This should also reveal whether a site-specific approach could increase the reliability of the impact assessment compared to a site-generic approach.

Research objectives

In response to the problems outlined in previous paragraph, the following research objectives are identified (**Fig. 2**):

- Impact description
  - Extend the currently available method proposals with indicators reflecting the importance of spatio-temporal variability of water flows
  - Develop a unifying framework facilitating the joint interpretation of different water quantity indicators
- Impact calculation:
  - Develop parameterisation schemes for a hydrological model so that it can be applied in ungauged areas and/or for hypothetical scenarios
- Impact evaluation:
  - Calculate the uncertainty on the water balance indicators and compare this uncertainty with the impact caused by land use change

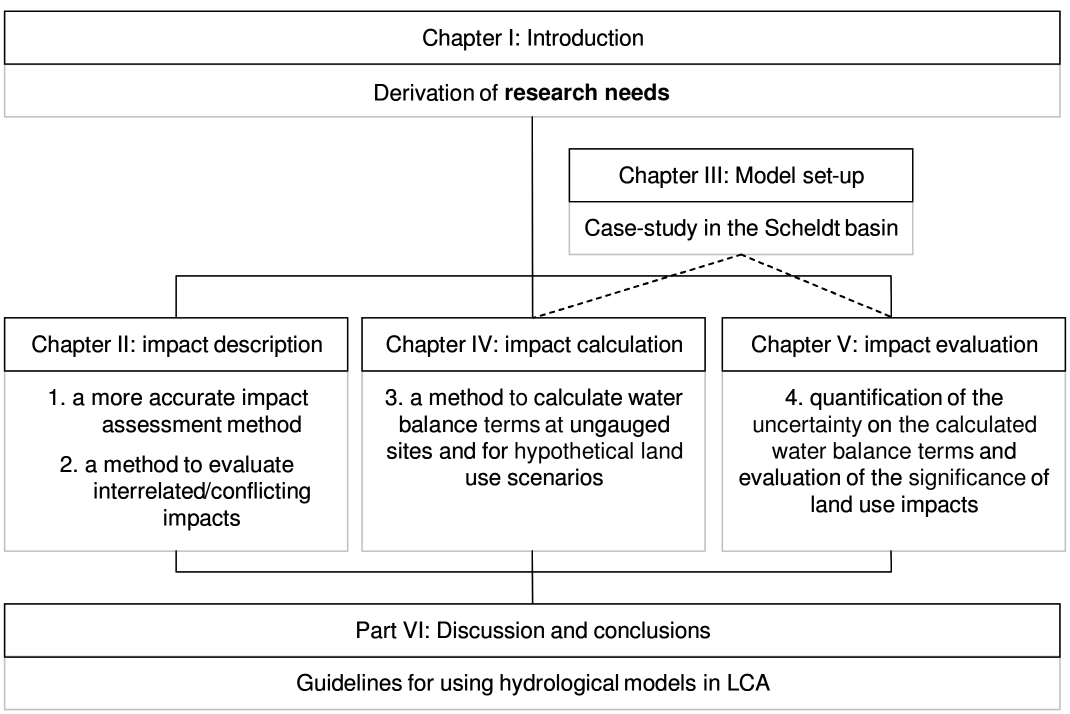

Fig. 2: Research questions and structure of this work

The questions with respect to the description of the hydrological impact in LCAs of land-intensive systems are addressed in chapter II of this work. This chapter gives an overview of the current impact assessment methodology to reveal the water quantity related environmental issues that are overlooked in available method proposals. In particular, a framework for the joint interpretation of the newly introduced hydrological indicators and already existing land use impact indicators is discussed. The questions about impact calculation and evaluation are dealt with by means of a case-study for agricultural and forestry scenarios in Flanders. Chapter III introduces this case-study with a description of study sites, model structure and set-up and data sources. Chapter IV focuses on impact calculation, with particular attention for the estimation of model parameters in ungauged areas or for hypothetical environmental settings. Chapter V builds further on these simulations with an extensive uncertainty analysis. Finally, all results are brought together in chapter VI, providing guidelines for using a hydrological model in LCAs of land-intensive production systems.

Chapter II: Impact description*

The impact description focuses on the definition and interpretation of indicators i.e., relatively easily quantifiable variables reflecting the impact of a land use system on the environment. First, the presently available indicators relevant to our working field are reviewed. Shortcomings are identified and the existing method is extended in order to integrate all possible impacts of land use systems on the water balance. After this, the interpretation of the indicators of the extended LCA method is discussed using exergy analysis as a general framework.

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*Chapter II is adapted from:
Heuvelmans, G., Muys, B., Feyen, J. 2005. Extending the life cycle methodology to cover impacts of land use on the water balance. Int. J. Life Cycle Assess. 10, 113-119.
Heuvelmans, G., Muys, B., Feyen, J. Towards a holistic land use impact assessment: The case of water related ecosystem services. Submitted.

II.1 Extending the LCA methodology to cover impacts of land use system on the water balance

Introduction

Earlier research in life cycle impact assessment resulted in a diversity of impact categories and related indicators. Udo de Haes et al. (1999) synthesised the best available practice and proposed a structured list of impact categories to be used as a baseline (**Table 1**). In their overview, a discrepancy exists between the environmental importance of an issue and the detail it is dealt with in the impact assessment. One of the problems, as highlighted by Weidema (2000), is that the representation of some life cycle stages is out of proportion, while others do not get the attention they deserve. This trend is especially visible in sectors (food, wood, fibre) that entail agricultural or silvicultural production systems. The majority of LCAs is restricted to the industrial part of the production chain notwithstanding the potential environmental impact of land intensive systems. This incited an ongoing revision of the existing methodology (Audsley et al., 1997, Mattsson et al., 2000, Schweinle, 2002) for incorporation of the impacts of agricultural or forestry practices.

Table 1: Overview of impact categories as presented by Udo de Haes et al. (1999). Categories that contain water quantity issues are marked in bold

Input related impact categories	Output related impact categories
Extraction of abiotic resources	Climate change
Extraction of biotic resources	Stratospheric ozone depletion
Land use	Human toxicity
	Eco-toxicity
	Photo-oxidant formation
	Acidification
	Nutrification

The overall aim of this chapter is to outline methodological improvements of available methods for water quantity issues, making a case for a spatio-temporally explicit approach. First, the system boundaries needed to define the water flows between the production system and the environment are discussed. These flows are then attributed to impact categories, linked to potential environmental burdens and to one of the four areas of protection (natural resources, ecosystem health, human health and man-made environment). Appropriate indicators are selected for each potential burden. The set of indicators can be used to make the impact modelling more realistic. This is of particular importance when a major part of the environmental impact is due to agriculture or forestry practices. Such activities have a significant influence on the regional water balance and, thus, on the risk of floods and droughts, two issues that are overlooked in the current practice.

Setting the system boundaries

Hofstetter (1998) conceives the life cycle approach to environmental impact assessments as studying the interactions between three concentric spheres (**Fig. 3**). The inner sphere or technosphere contains the product system. It is embedded in the ecosphere on which it exerts a certain environmental pressure due to emissions, waste disposal, etc. Overall, two kinds of interactions between the technosphere and the ecosphere can be distinguished: (I) extraction of inputs needed by the production system which are attributed to the input related impact group and (II) disposal of outputs produced by the system which are evaluated in the output related impact group. The outer sphere or valuesphere judges whether the environmental pressure caused by the production system holds an environmental threat. Bengtsson et al. (1998) propose a data model with a similar structure covering a technical, an environmental, a social and a geographical entity that mutually interact.

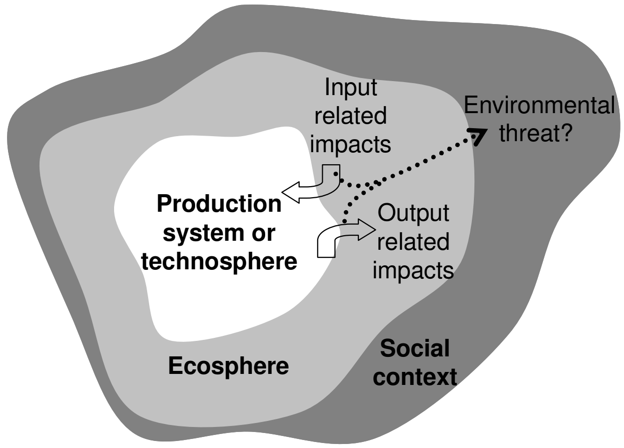

Fig. 3: Environmental impact as conceived in LCA

The boundary between the eco- and technosphere needs special attention in case of location-specific assessments of agricultural and silvicultural production systems, because these systems are spatially and temporally dynamic (Ritter et al., 2001). For LCAs of industrial production, both spheres used to be considered as abstract static entities having no spatial and temporal scale (Karjalainen et al., 2001). In our case, however, the technosphere is a piece of land occupied for a certain time and surrounded (conceptually as well as physically) by the ecosphere, which is the subject of the impact assessment. So, the considered (land intensive) production begins and ends at a certain point in time. Within this period, temporal fluctuations in site properties that are evaluated in the input related impact group might occur. But these fluctuations are of no interest to the life cycle assessment as these belong to the internal management of the technosphere. At the end of the considered time span, the technosphere dissolves yet it may still have long-lasting environmental effects. Input related on-site impacts are no longer trapped inside the technosphere so that the shift in site properties might be understood as an environmental impact. The magnitude of this impact depends on how the system boundaries are defined in time, i.e. the onset and the end of the production system. For example, the traditional approach evaluates the impact on water table height as the difference between the height at planting date and at harvesting date. So life cycles are assessed at the product level, for instance 1 kg of barley. The production of barley may not stand on its own, but may be part of a crop rotation system in which a negative impact during one phase might be compensated later on. For example, lowering of the water table during a heavily irrigated phase can partly be compensated by less water use during a fallow period. To account for such fluctuations of the environmental impact, it has been proposed to compare biological production systems in the perspective of one full crop rotation (Cowell and Clift, 2000). Input related impacts compare resource availability or site properties at the same phase within the cyclic production scheme, e.g. at the beginning of the rotation. Output related indicators address average impacts over one or several rotation periods (Karjalainen et al., 2001). Typically the quantity of emissions is not constant but varies according to land management practices such as ploughing or clear cutting, and to external (climatic) conditions. The perception of environmental pressure by the valuesphere sometimes depends on this temporal variability of emissions crossing the system boundaries. As a consequence, these impacts cannot be represented adequately by average indicators over a rotation period. This clearly is the case for water outputs: If all water is emitted at once, the flood risk will be higher than when water is released slowly. In addition to the extension of system boundaries, this notion should be kept in mind when proposing an impact assessment method.

Input related impacts – The impact category abiotic resources

As depicted in **Table 1**, the abiotic resource and land use impact categories both handle input related impacts (Heijungs et al., 1997). The category 'abiotic resource extraction' emphasises the reduced availability of the resource to present and future generations (Penington et al., 2004). In the case of water, the impact of the production system on the freshwater reserves is assessed. The land use impact category can contain quantitative aspects of land use (how much land is used for how long? cfr. Spitzley and Tolle, 2004) as well as qualitative aspects (Lindeijer, 2000). Depending on the method, water issues may be part of the qualitative aspects of the land use impact category. Qualitative aspects constitute the so-called functional approach to land use impacts addressing changes in the regulative functions of the land (Baitz et al., 2000). Land use systems may affect the hydrological functioning of a land area and this way water enters the land use impact category. Because land use systems regulate the outflow of water, the ecosystem functions to be evaluated will be linked to output related water impacts. Therefore, the integration of water in the land use impact category will be discussed later on in this chapter after the section on output related impacts. Land use will still be considered as an input related impact though we first need to clarify a few concepts before elaborating water related land use impacts. The remainder of this paragraph will focus on abiotic resource depletion.

For the environmental impact of abiotic resource depletion, several approaches have been developed. The basic approaches (summarised by Heijungs et al., 1997 and Lindfors et al., 1995) simply value the depletion according to the remaining reserves. The more sophisticated ones (summarised by Audsley et al., 1997) account for the pathway the resource follows after being released from the technosphere. One of the simplest indicator proposals of Lindfors et al. (1995), the static reserve life, will be used as a starting point for assessing the depletion of water resources. This indicator is defined as the ratio between the global reserve of the resource to the amount of the resource that is consumed. The reciprocal of this indicator may also be used, cfr. the depletion index of Herendeen and Wildermuth (2002), but the original form is easier to interpret: it estimates the number of years that the activity can go on until the reserve is exhausted. Next to its simplicity, the major reason for selecting this indicator is that the depletion risk of all resources is expressed in the same unit, i.e. years, allowing one to rank all resources according to their risk to get exhausted. To become fully operational for water resources, the static reserve life concept needs two small modifications. The first problem is that resource reserves are estimated at a global scale. Cowell and Clift (2000) argue that such an approach, whilst useful for easily transportable resources, makes little sense for soil because soil losses in a certain region cannot be compensated by a reserve in another region. Since a similar objection can be made, at least partly, for water resources, estimating the available reserves at a smaller scale is proposed, i.e. a field or landscape unit. Doing so, spatial variability is included in the resource depletion assessment. The second problem is the reserve life needs to be dynamic instead of static in time. The indicator of Lindfors et al. (1995) is static in the sense that it neglects new formation of the resource. For soil – or more general for fund resources - this makes sense because soil formation occurs at slow rates and the fertile upper layer of the soil that is prone to erosion is of a main concern. Since freshwater reserves are consumed and replenished much quicker than soil, assessing the sustainability of water use – or, more generally, assessing the consumption of flow resources - requires balancing water consumption with inflow. This results in the following equation:

$$\mathrm{Ind}_A = \frac{R}{U - P} \qquad \textit{Eq. 1}$$

Where:

Ind_A : indicator of dynamic water reserve life (years)
R : freshwater reserves (mm)
U : water use (mm)
P : precipitation (mm)

When water use exceeds precipitation, the dynamic reserve life span will indicate the number of years until the freshwater reserves will be depleted, assuming that water inflow and outflow remain the same. This situation does occur for example in dry areas with heavily irrigated agricultural production like in the Middle East and Mediterranean countries (Yang and Zehnder, 2002). The average annual rainfall in these regions varies between 0 and 340 mm per year, insufficient to meet crop water requirements. Another example are eucalypt plantations in southern India that transpire almost all water to be reached by their roots: These can consume more than 1000 mm of water per year, exceeding the average annual rainfall that amounts to 700 mm (Calder et al., 1997). If precipitation equals water use, the reserve life span becomes infinite, i.e. water use will never deplete the freshwater reserves. In case precipitation exceeds water use, the reserve life will be a negative value representing the number of years to get a precipitation surplus that equals the freshwater reserves available today. Note that a variable proportion of the water will reach the aquifer system while the remaining excess fraction leaves the catchment as runoff.

At first sight, temporal aspects could be a point of discussion in the assessment of the depletion of flow resources like water, because these resources can be temporally depleted depending on the timing of the resource use. The abiotic resource category is pointed towards the area of protection 'natural resources'. The environmental burden connected with this impact category is the availability of resources for future generations, not the competition for resources in the present generation, justifying the disregard of temporal variability.

Output related impacts

None of the output related categories in **Table 1** deals with impacts on the water balance, although the potential burdens connected to water outputs are commonly acknowledged. To cover these burdens, a new impact category is introduced here, called 'regional water balance'. This impact category is oriented towards the areas of protection ecosystem health and human health, with flood risk, drought risk and average water availability downstream as main environmental burdens. A complicating factor, for the proper assessment of these impacts, is that one needs to consider the spatial organisation of the land use scheme as well as the timing of the emissions. The following sections explain how this can be accomplished and discuss the practical implications and the feasibility of the proposed method.

Spatial Variability

Among LCA practitioners, there is a growing awareness of the value of site-specific data, at least for some output related impact categories (Ross and Evans, 2002). For impacts on the regional water balance, spatial differentiation can be of great value since the control of water flows in an (agro-)ecosystem is site-dependent. For example, the evapotranspiration of a forest will be different in southern Europe compared to Belgium, within Belgium in the loam belt versus the sandy region, within one region in the valley versus on the plateau. So it is evident that the impact of land use on water outflows cannot be judged without considering the spatial pattern of the land use scheme. The best way to account for spatial variability in an LCA methodology depends on the decision-making context. Two cases can be distinguished: LCAs serve either as a guide for optimising a certain production process or as a means of selecting the most environmentally friendly option amongst different production scenarios. Similar divisions can be found in Hofstetter (1998), who distinguishes a static attribution case and a dynamic change oriented case, and Tillman (2000) who differentiates between a retrospective or accounting perspective and a prospective one. Both authors mention that the two approaches might lead to different scope definitions, inventory models and impact assessment methods. Tillman (2000) elaborated the implications of such a goal-oriented grouping for the inventory and so created a setting that was applied to our working field.

Identification of the critical subprocesses, i.e. the processes that contribute the most to the environmental damage, is the main task in accounting LCAs. Take for example the eco-labelling of agricultural products. Certain standards must be reached in order to get an eco-label. A life cycle assessment can in this case help to demarcate the critical areas or parcels that have an extreme value for one or more indicators (high surface runoff rates, high soil erosion rates, etc.). Maps or GIS layers representing the spatial variability in indicator scores may satisfy the needs here as they indicate where the management should be adopted (by introducing zero tillage, etc…). The impact assessment is cause oriented, i.e. the main question is which spatial unit is causing which fraction of the impact. Indicator scores are rarely spatially aggregated and if so they are just area-weighed. Such an approach assumes that the total environmental impact is simply the sum of all the subunits – called ‘additivity’ by Tillman (2000), which is generally incorrect as complex interactions between subunits may raise or lower the total impact.

While useful for studying one particular scheme, the latter procedure is not suited to compare scenarios. In this so called change oriented case, the outcome of the impact assessment should be effect oriented, i.e. give an idea of the total effect per scenario. Assume that one wants to compare the environmental impact of traditional and organic farming to support the agricultural funding policy. The main question here is which scenario is the best, rather than which subprocess or spatial unit is causing the difference in impact. Indicators must therefore be represented in another way: one global score per scenario is needed instead of the GIS layers or maps. Applied to the impact category regional water balance, scenario optimisations ask for the contribution of each spatial unit to stream flow, whereas scenario comparisons are mainly interested in the total stream flow per scenario.

Temporal variability

There is no doubt that making the temporal aspect explicit enhances the transparency of a methodology. This calls for multiple values for every variable of the indicator set, which can be gathered through long-term experiments or approximated with time series produced with a continuous model. Next, the time series must be aggregated into one or a few indicators reflecting the environmental burdens mentioned above. For average downstream water availability and drought risk, stream flow records averaged over a month seem appropriate because this is the highest level of aggregation where these impacts can still be detected. Then a quantile plot - showing the accumulated frequency of the observed or simulated monthly stream flow – can be constructed and a probability density function (PDF) can be fitted to the plot. Using the probability density function, the 5th and 50th percentile can be calculated (left part of **Fig. 4**). The 50% quantile, or median, will replace the annual average score used earlier representing the average amount of water available downstream. This indicator has environmental as well as social importance, since it controls downstream ecosystem processes and the amount of water available for other human activities. The same remark applies to the fifth percentile, i.e. the monthly stream flow with an exceedance probability of 95%, which represents the risk of droughts. Peak flows cannot be derived from monthly aggregated flows; a daily or even smaller time step is needed in this case. The 95th percentile or the daily stream flow with an exceedance probability of 5% can be used as an indicator for flood risk (right part of **Fig. 4**).

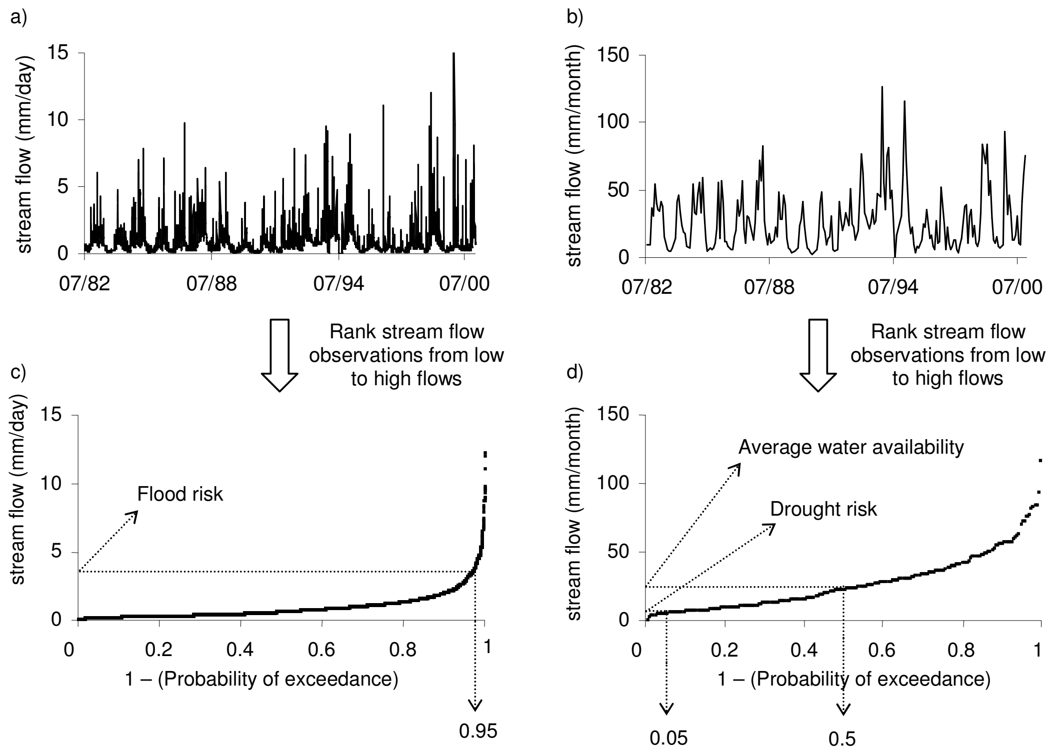

Fig. 4: Calculation of indicators for flood risk, drought risk and average water availability downstream. Theoretical example for the Maarkebeek catchment. Data are collected by the Flemish environmental administration (AMINAL)

Practical implications and feasibility

To calculate the proposed regional water balance indicators, stream flow records must be available. These data are not always accessible, so one could question the feasibility and universality of the proposed method. However, many hydrological models exist for estimating stream flow for a given land use scenario from more easily available data about climate, topography, soil properties and land use characteristics. Some models, e.g. the SWAT model (Soil and Water Assessment Tool) (Arnold et al., 1998), even include databases of crop characteristics needed to run the model. Because of this, data for a basic model application are available for almost every case-study, though the accuracy of the modelling will depend on the quality and representativeness of the input data.

Only a limited post-processing of the output of a hydrological model is necessary to calculate the regional water balance indicators: it involves sorting stream flow observations from low to high flow values, eventually after rescaling the data to the appropriate time step, to calculate the median and the 5th and 95th quantile. The resulting indicators cannot directly be averaged into one single score because of a difference in magnitude – the drought risk indicator is always smaller than the indicator for average water availability downstream – and a difference in meaning – drought risk and average water availability indicators should be maximised, whereas flood risk indicators should be minimised. Moreover, the comparison of the indicators for different climatic zones may be difficult because of differences in the precipitation regime. The precipitation regime as well as other climatic factors constrain the flow regime and so affect the possible values of the regional water balance indicators. It is proposed to use the potential natural vegetation, which is site (climate and soil) dependent, as a reference system for making the indicator scores comparable. This gives us the following, normalised indicator formulas for average downstream water availability and drought risk:

$$\mathrm{Ind}_B = \frac{\mathrm{Ind}_{B_{ref}} - \mathrm{Ind}_{B_{act}}}{\mathrm{Ind}_{B_{ref}}} \qquad \textit{Eq. 2}$$

Where :

Ind_B : Normalised indicator of average downstream water availability and drought risk

$\mathrm{Ind}_{B_{ref}}$: (non - normalised) indicator for the reference system

$\mathrm{Ind}_{B_{act}}$: (non - normalised) indicator for the system under study

The normalised indicator for flood risk can be formulated as follows:

$$\mathrm{Ind}_C = \frac{\mathrm{Ind}_{C_{act}} - \mathrm{Ind}_{C_{ref}}}{\mathrm{Ind}_{C_{ref}}} \qquad \textit{Eq. 3}$$

Where :

Ind_C : Normalised indicator of flood risk

$\mathrm{Ind}_{C_{ref}}$: (non - normalised) indicator for the reference system

$\mathrm{Ind}_{C_{act}}$: (non - normalised) indicator for the system under study

Contrary to the non-normalised versions, this flood risk indicator has the same meaning as the drought risk and downstream water availability indicator, in the sense that positive scores indicate unwanted impacts and negative scores indicate desired effects. The normalised indicators can simply be averaged to get an overall score for the impact on the regional water balance.

Input related impacts revisited – The impact category land use

Now that the method for assessing output related water impacts is established, let us revisit the qualitative part of the land use impact category. Several methodologies of varying complexity have been developed for assessing land qualities. The simplest ones are land use classifications that are too rough to assess the impact of land management. The more complex ones are functional approaches that reflect the impact of human activities on the functioning or the regulating capacity of the ecosystem (Lindeijer, 2000). Some functional methodologies use one global indicator that summarises the total impact on ecosystem functions in a rather indirect way, e.g. the biodiversity indicator of Müller-Wenk (1998). Multiple indicators (e.g. Giegrich and Sturm, 1998) may be preferable, however, for an intuitively more direct representation of environmental system complexity. It is with these 'multiple indicator' functional approaches that we meet water issues in the land use impact category.

Giegrich and Sturm (1998) used such a 'multiple indicators' approach reflecting the degree of naturalness of the land under the planned activities. Water resource indicators were chosen to represent water balance disturbances, e.g. artificial drainage, irrigation. Following their methodology, a negative impact is attributed to every human intervention so that an optimisation of land management is not feasible. Schweinle (2000) and Baitz et al. (2000) overcome this problem by evaluating the physical impact itself instead of the non-natural activities and structures that might cause it. Both authors describe the impact on water quantity with the variable groundwater supply, defined as precipitation minus surface runoff and evapotranspiration. Baitz et al. (2000) use one additional water quantity indicator called 'rainwater drain' that describes the ability of the land use to hold surface water. Schweinle (2000) mentions that all water balance terms are potentially useful indicators, apart from quantification difficulties.

As stated earlier, the 'function' of the land use with respect to water flows can be conceived as the way a land use system affects output related impacts, i.e. average water availability, flood and drought risks. The indicator 'groundwater recharge' of the available method proposals can be coupled more or less to drought risk, and 'rainwater drain' to flood risk. Overall, land use affects the water balance through two mechanisms: by consuming a certain amount of water and by controlling how excess water runs off. Water consumption lowers water availability downstream and therefore influences local as well as regional ecosystem processes. It is proposed to quantify this environmental impact of land use with the indicator precipitation surplus that equals precipitation minus evapotranspiration. A part of the excess water infiltrates in the soil, possibly percolates to groundwater reserves, before it joins stream flow. The remainder forms surface runoff that reaches the channel quickly increasing the risk of high peak flows and floods. From an environmental impact point of view, distinction between these two flows is obviously necessary. This is achieved by adding a second land use indicator: surface runoff. The amount of water that infiltrates the soil, diminished with the amount of water withdrawn by vegetation, can be used as an indicator associated with drought risk. For all three indicators, spatial variability should be handled in the same way as outlined for output related impacts.

Whereas the water balance impact category evaluates the regional water balance during the activities – as a consequence of the outflow of water from the system, the environmental mechanism examined in the land use impact category is slightly different. This category analyses how the land use change and the land occupation that are part of the production system have altered the site properties so that the hydrological behaviour of the land changed. This change in land quality is evaluated as the change in water outputs of the land use system after one rotation compared to situation at the beginning of that rotation. As explained in the first paragraph on system boundaries, temporal fluctuations in land qualities during the production belong to the internal affairs of the technosphere. Consequently, they do not need to be evaluated in the land use impact category of a life cycle assessment.

Conclusions

Whereas earlier method improvements for LCA of land use systems focused on the extension of system boundaries leading to a better inventory, this chapter dealt with the spatio-temporal dynamics of flows passing the system boundaries, resulting in a more realistic impact assessment.

Table 2 shows an overview of the methodology constructed throughout this chapter. Two input related impact categories are proposed, the abiotic resource category dealing with future freshwater reserves, and the land use impact category that is concerned with changes in the hydrological response of the land. For both categories, indicators are defined at a smaller scale compared to current method proposals in order to account for the spatial variability of water reserves and flows. The main step forward compared to existing method proposals is the introduction of a new impact category ‘regional water balance’ covering a previously unexplored terrain: the output related water impacts, i.e. drought and flood risk and average downstream water availability.

Table 2: Scheme of an LCA methodology for assessing impacts on water quantity

Impact category	Indicator	Environmental threat
Input related		
Abiotic resource depletion	Water dynamic reserve life	Future freshwater reserves
Land use	Change in surface runoff	Flood mitigating capacity
	Change in (infiltration minus evapotranspiration)	Drought mitigating capacity
	Change in precipitation surplus	Control on water flows
Output related		
Regional water balance	Daily stream flow with an exceedance probability of 5%	Flooding of human properties, disturbance of ecosystems by floods
	Monthly stream flow with an exceedance probability of 50%	Average water availability for other ecosystem processes and human activities e.g. hydropower generation
	Monthly stream flow with an exceedance probability of 95%	Drought risk, drying of wetlands

Depending on the social context in which the life cycle assessment is performed, the indicators from **Table 2** might receive variable weighting. Although the methodology can undoubtedly increase the credibility of the impact assessment, the main drawbacks are the increasing data requirements that might hinder the feasibility of the method. Chapters III to V of this work will look for solutions to this problem, by applying a numerical model to calculate the indicator scores from more easily accessible data.

II.2 Joint interpretation of aquatic and terrestrial impacts based on the exergy concept

Introduction

In chapter II.1, a set of indicators was identified that can be used to assess the impact of land use systems on water flows for the aquatic (regional water balance impact category) and the terrestrial (land use impact category) environment. The approach is bottom-up, i.e. combines (existing) methods for aquatic and terrestrial water fluxes. A bottom-up approach typically starts with listing all human interventions and then climbs up the impact chain towards a multitude of environmental problems that can be represented by a limited number of indicators (**Fig. 5**). For example, the approach of Gottfried (1992), that views ecosystems as multi-product factories, is constructed using bottom-up reasoning.

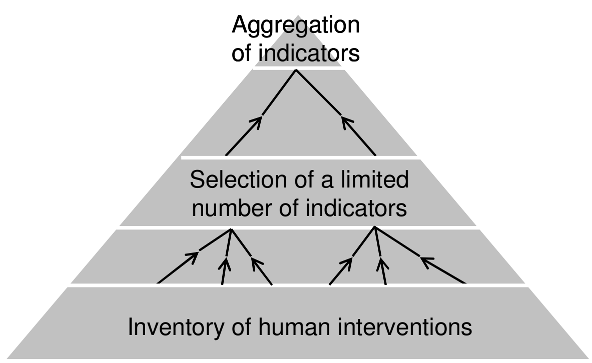

Fig. 5: Bottom-up approach for environmental impact assessments

The main difficulty in the bottom-up approach is the valuation and aggregation of indicators that is often needed for decision-making. Indicators do not share a common background so that the interpretation of aggregated scores is not straightforward. In our method proposal, downstream water interests (as represented by the regional water balance impact category) and upstream water requirements (represented by the land use impact category) might conflict because the first requires a minimal stream flow volume whereas the second aims at improving site productivity, that is often accompanied by an increase in water consumption.

The alternative to the bottom-up approach is a top-down impact assessment that starts at the end of the impact chain, with the major environmental concerns of the society, called areas of protection or safeguard subjects. Four areas of protection are distinguished (Udo de Haes et al., 1999): ecosystem health or natural environment, human health, man-made environment and resource availability. The major difficulty here lies in quantifying the contribution of the system under study to these areas of protection in a comprehensive manner. One usually defines indicators a few steps down the impact chain, this means that the area of protection is split up in a few sub-problems with an easily quantifiable indicator variable for every of these sub-problems. To enable the aggregation of indicator values for the different sub-problems into one meaningful overall score, all indicators should relate to the same general understanding and goal function of the area of protection.

Our aim was to develop an impact assessment method, with focus on ecosystem health, being the sum of the health of the aquatic and the terrestrial ecosystem. This led to the definition of indicators representing conflicting interests, as discussed in previous section. The joint interpretation of these indicators requires a general measure of ecosystem health that applies to the aquatic as well as the terrestrial system (**Fig. 6**).

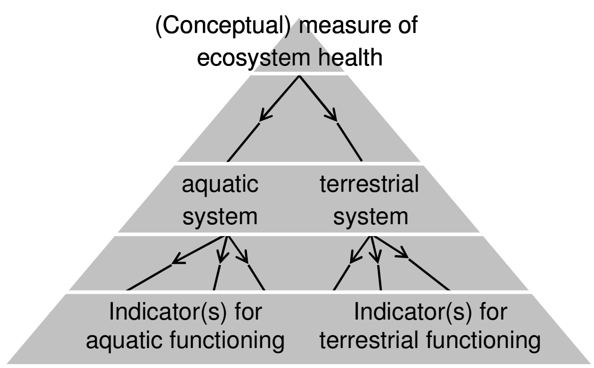

Fig. 6: A top-down approach for environmental impact assessment

Exergy maximisation as a goal function for impact assessments of the joint aquatic-terrestrial environment

Since the 60s a number of goal functions have been proposed that can be used as a measure of ecosystem functioning. The use of a goal function as a universally valid driving force behind the development of natural systems is controversial (Pueyo Punti, 2003). Nevertheless, goal functions may be useful to describe ecosystem development and functioning at a well-defined spatial and temporal scale (Wilhelm and Brüggemann, 2000). Jorgensen (1994) provides an overview and intercomparison of goal functions for ecosystem functioning. The author concludes that exergy analysis is preferred over other concepts (biomass-based, entropy based, etc.) because, amongst others, it has a high correlation with other goal functions. Exergy analysis has since then been applied to assess the health of freshwater ecosystems (e.g. Xu et al., 1999) and terrestrial systems (e.g. Aerts et al., 2004), but applications to the joint terrestrial-aquatic environment are rare.

In this work, the exergy concept will be used as a unifying concept, to enable the joint interpretation of water quantity indicators. All figures and ideas presented in this chapter must be considered as hypotheses that build on the findings of other researchers.

Exergy is defined as that part of the system's energy that is available to do work. It expresses the useful work potential of a system at some specified state i.e. the upper limit on the amount of work a system can deliver without violating any thermodynamic law. Due to the limitations of the first and the second law of thermodynamics, the exergy of a system depends on the surrounding environment. The first law of thermodynamics states that energy is always conserved, whereas the second law states that energy can flow spontaneously to a less-ordered state, or a state with a lower exergy level like heat. So exergy is not conserved and can be considered as a (scarce) resource according to Ayres (1998).

Incoming solar energy has high exergy content. Ecosystems developing over time in absence of large perturbations from state 1 to state 2 use part of the incoming exergy S (mainly from the sun, also from wind, precipitation etc.) to increase their internal exergy level (**Fig. 7**):

$$L_2 > L_1 \qquad \textit{Eq. 4}$$

Where L_1 and L_2 represent the exergy level of the ecosystem in state 1 and state 2. The remainder of the incoming exergy is converted to 'useless' energy like heat with an exergy level close to zero. Following the second law of thermodynamics, the total energy content is conserved:

$$l_1 + s = l_2 + u \qquad \textit{Eq. 5}$$

Where l_1 and l_2 are the energy contents of the ecosystem in state 1 and state 2, s the incoming (solar and other) energy, u the amount of 'useless' energy production. Unlike the energy content, the exergy content is not conserved but decreases:

$$L_2 < L_1 + S \qquad \textit{Eq. 6}$$

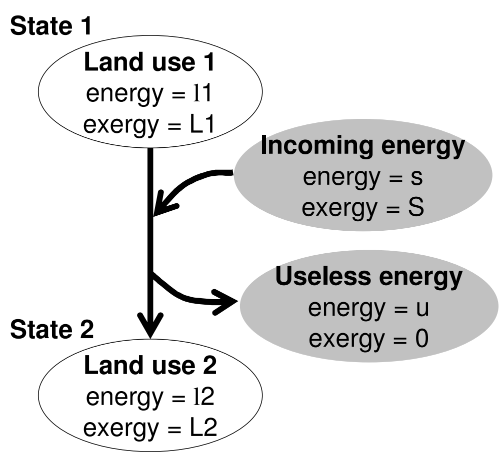

Fig. 7: Energy and exergy flows during ecosystem development in absence of large perturbations

The internal exergy level of an ecosystem is proportional to the amount of biomass, the complexity of trophical networks and genetic information (Muys et al., 2003). Biomass can be combusted and so produces work, explaining why it can be considered as a form of exergy. The contribution of the complexity of trophical networks and genetic information to the exergy level is rather indirect: this complexity is amongst others required to recover after natural disturbances and so warrants the production of biomass in the future. According to the Carnot cycle, the internal exergy level of an (eco)system is a prerequisite for the execution of work. Applied to terrestrial ecosystems, this 'work' refers to the capacity of the ecosystem to dissipate external wind, radiation, water and matter flows. The magnitude of the dissipative capacity (i.e. the exergy buffering capacity) is proportional to the evapotranspiration rate of an ecosystem (Aerts et al., 2004; Katul et al., 2001). Consequently, evapotranspiration is a measure of exergy buffering, which is in turn proportional to the internal exergy level of an ecosystem.

A high exergy content points out a good ecosystem health so that exergy maximisation can be considered as a driving force behind ecosystem functioning (Bendoricchio and Jorgensen, 1995). Degraded ecosystems reflect most of the incoming solar exergy whereas well functioning ecosystems utilise relatively more incoming exergy for biomass production and the build-up of complexity and buffering capacity. The exergy level of a land use system can therefore be considered as a measure for the impact of that land use system on terrestrial ecosystem health (Wagendorp et al., 2006), the exergy of the associated aquatic system can be seen as a measure for the impact on aquatic ecosystem health (Silow and In-Hye, 2004).

Because exergy cannot always be measured in a direct way, it is usually evaluated with proxy indicators, which are assumed to be proportional to biomass, complexity and buffering capacity. Peters et al. (2004) proposed such a set of proxies for the terrestrial exergy level.

This chapter tries to interpret the land use and regional water balance indicators of previous chapter as exergy proxies to enable the evaluation of trade-offs between upstream and downstream interests.

As discussed above, the internal exergy level of a terrestrial system defines its dissipative capacity, which in turn is proportional to the amount of evapotranspiration. The exergy level of an aquatic system on the other hand requires a minimal stream flow volume to ensure habitat conditions etc. Maximisation of the terrestrial exergy level will increase evapotranspiration. In extreme cases, if ecosystems are forced by human interventions (irrigation, fertilisation, use of exotic species) to surpass the maximal productivity of natural systems, this could lower stream flow volumes and so endanger the functioning of the aquatic ecosystem, see for example Scott and Lesch (1997) for forest plantations and Berndes (2002) for bioenergy production and thus lower the exergy level downstream.

In the past, exergy analysis was most of time applied to either the aquatic or the terrestrial environment. But as demonstrated above, for cases where water is a limiting resource, it is more needed to consider the joint terrestrial-aquatic environment to enable making trade-offs between upstream and downstream water use.

An exergy-based impact assessment method

From previous paragraph, it is clear that balancing upstream and downstream water conflicts is a major element of an exergy based impact assessment approach. Previous chapter proposed land use and regional water balance indicators reflecting terrestrial and aquatic impacts (or exergy levels) respectively. Because these variables have a different order of magnitude, direct aggregation of these indicators into one overall score of environmental performance is not possible. Next to this, the comparison of these indicators for land use scenarios under different climatic regimes is only meaningful if local conditions restricting the potential values of the indicators are accounted for. Both problems were handled by expressing the indicator scores relative to a reference system, the potential natural vegetation, which reflects site conditions. The normalised indicators can then be aggregated into one overall indicator score by calculating a weighted average of the proposed indicators, where the weights depend on the decision-making context.

The main reason for selecting the potential natural vegetation as a reference is that it is the state with the highest exergy level for a given site. According to Muys (2002b), the state with the highest exergy level is preferred over other references (the thermodynamic equilibrium or using no reference system, the state with zero impact, the state before intervention) because it can unambiguously be assessed and because it correlates well with the abiotic factors constraining the magnitude of environmental, in particular hydrological, variables.

The state with the highest exergy level i.e. the natural climax vegetation and the associated stream flow regime, is not static in time and space. It rather is a mosaic of different successional stages (Bormann and Likens, 1992). Starting from scratch after a large-scale perturbation, the exergy level of the pioneer ecosystem first increases up to a certain maximum, and after that a 'steady state' is attained with exergy levels fluctuating between a lower and an upper threshold value T_2 and T_1 (**Fig. 8**).

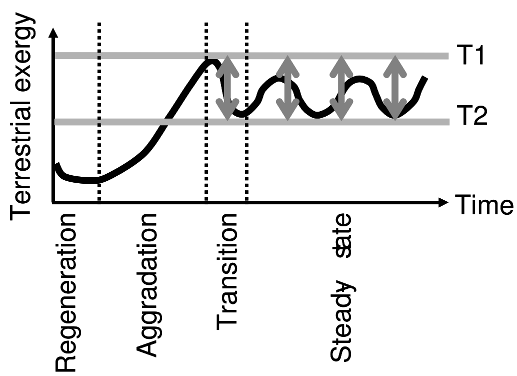

Fig. 8: Expected fluctuations of the terrestrial exergy level of a natural ecosystem throughout natural succession (modified after Bormann and Likens, 1992)

As depicted in **Fig. 8**, not every patch of this mosaic contains the highest possible exergy level at every moment. Though on the long-term, the spatially averaged total exergy level of the reference system (= collection of patches) cannot be surpassed. A similar line of reasoning can be followed with respect to aquatic exergy levels, leading to the recognition of two threshold values in between which the aquatic exergy level of natural river systems is situated.

Fig. 9 pictures the expected fluctuations of terrestrial and aquatic exergy levels throughout the different successional stages compared to two other generic land use systems: a degraded ecosystem (e.g. overgrazed pasture) which has a lower terrestrial and aquatic exergy level compared to the reference, and a forced ecosystem (a system yielding more than natural productivity, because of a large degree of human intervention e.g. irrigation, pesticides etc.), that has a higher terrestrial exergy level but a lower total and aquatic exergy content.

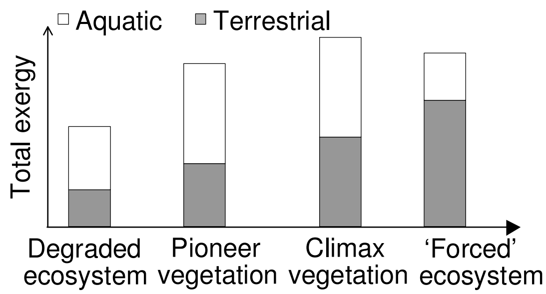

Fig. 9: Hypothetical aquatic and terrestrial exergy level of degraded and forced ecosystems compared to the variation in exergy levels occurring in natural succession

Because of the spatio-temporal variability of the reference system, the indicators theoretically refer to spatially and temporally averaged water fluxes. So the calculation of indicator scores would require a clear insight in the hydrology of all successional stages. In most places, this knowledge is not readily available. However, for most regions, the extreme cases of the successional chain are known i.e. the final stage (T_1 in **Fig. 8**) and the first vegetation development and hydrological response after disturbances like fire. Usually, for the sake of simplicity and to keep the method operational the final stage T_1 is used.

Threshold effects

In a first approximation, the environmental impact is often supposed to be linearly related to the deviation of the indicator score from the score for the final stage T_1. However, slight deviations from this reference may not cause a significant impact, whereas after a certain threshold, the environmental impact may increase exponentially. For example, Eiswerth and Haney (2001) showed that, for indicators of biodiversity conservation, ignoring threshold effects might bias the results of the impact assessment and so alter the resulting decisions. It can be expected that a similar problem arises for hydrological impact assessments. The main reason for such a non-linearity is the dynamic nature of the reference system and its resilience. The resilience of an ecosystem is the ecosystem's potential for restoring its structure and the functioning after a perturbation (Holling, 1973). Cropp and Gabric (2002) argued that the natural climax system is the state the most resilient to perturbation. Human interventions tend to simplify ecosystems in function of one single target resource. Such practices diminish the system's resilience, so that even a small perturbation might transform the system irreversibly to a less desirable state (Folke, 2003)(**Fig. 10**). In general, two different non-sustainable situations can be distinguished: degraded ecosystems with an exergy content much lower than the reference point T_2 in **Fig. 8** and forced ecosystems with a terrestrial exergy level significantly higher than the reference T_1 in **Fig. 8**.

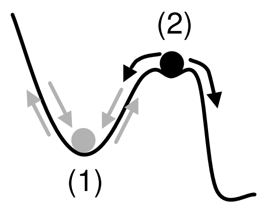

Fig. 10: Expected changes in the exergy level of resilient (1) and non-resilient (2) systems after external perturbations (modified after Holling (1973) and Folke (2003))

One typical example of degraded ecosystems is an over-grazed pasture. Bremer et al. (2001) demonstrated that grazing can reduce the evapotranspiration rate of grassland. This decrease in green water flow points out a decrease of the terrestrial exergy level and can eventually endanger the system's resilience and the sustained delivery of ecosystem services. This negative trend can be avoided by an increase in green water flows (Rockström, 2003), for example by adopting grazing density and frequency.

Typical examples of forced ecosystems are forestry plantations with exotic tree species. The terrestrial exergy level of these systems surpasses the exergy of the natural climax vegetation. The high water consumption causes a lowering of the stream flow volumes hindering a good functioning of the aquatic ecosystem. These land uses are characterised by a high degree of human intervention or inputs. Because of the interventions, these systems become resistant i.e. they will not react on certain small perturbations. Although these systems might look healthy at first sight, they lack resilience and can therefore not be considered as sustainable. As demonstrated in **Fig. 11**, if a perturbation occurs or if the intensity of the human interventions diminishes, their (terrestrial) exergy can fall below the lower threshold value T_2 i.e. the minimal amount of terrestrial exergy present in every patch of the natural succession mosaic. Natural succession is seriously delayed or even made impossible because site conditions are altered e.g. lowering of water table.

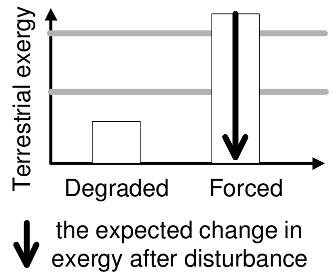

Fig. 11: The expected change in the terrestrial exergy level of degraded and forced ecosystems after a disturbance. T_1 and T_2 represent the maximum and minimum terrestrial exergy level of the different stages during natural succession

Previous two examples indicate that a linear approximation of the environmental impact is not adequate and that threshold effects should be taken into account. Identification of these threshold values is not straightforward, but although hard data about this issue are lacking, one can expect these values to be site-specific. Besides, one can also assume that threshold values lay outside the range of conditions encountered in natural succession. Therefore it is proposed to use the highest and the lowest of the exergy levels of the different successional stages (T_1 and T_2) as approximate threshold values, if no further information is available. T_1 can represent the state with the highest possible terrestrial exergy, without harming downstream ecosystems and so poses the upper limit for the terrestrial exergy level whereas the associated stream flow regime corresponds with the lowest aquatic exergy threshold. Additionally, the first successional stage T_2 and the associated stream flow volumes indicate the lower threshold for the terrestrial and the upper for the aquatic exergy level. A land use system with an exergy level within this range may be named sustainable. Close-to-nature silvicultural systems for example often mimic natural succession leading to uneven-aged forests. Exergy levels can be expected to fall within the proposed interval indicating that such a system is sustainable. Agricultural systems do not include equivalents to the latest successional stages. A first prerequisite for sustainability is in this case that the terrestrial/aquatic exergy levels never get lower/higher than the level of the first successional stage. Moreover, these systems should be embedded in a mosaic with more advanced successional stages so that the relative proportion of every stage is comparable to the proportions present in a natural mosaic (the areas covered by every successional stage should have the same order of magnitude). If these two conditions are fulfilled, then agricultural systems may be considered sustainable. This view on sustainability of water flows is parallel to the ideas presented by Bengtsson et al. (2003) with respect to biodiversity management. The authors of this study emphasise that the management of nature reserves must be part of a landscape level (10-100 km^2 or more) land management towards a mosaic of land use types of different successional stages to ensure continued ecosystem functioning after disturbances. This way, resilient landscapes are built consisting of nature reserves embedded in a matrix of sustainably managed agricultural and silvicultural lands.

Conclusions

Regional water balance and land use indicators were interpreted jointly following a top-down approach, starting with the specification of an overall goal function of ecosystem development: maximisation of the exergy level of the joint aquatic-terrestrial environment. For the sake of simplicity, the environmental impact was measured as a linear function of the deviation of the water fluxes from the reference system i.e. the state with the highest total exergy level. In combination with these linear indicators, the exergy levels of the different successional stages and the associated stream flow conditions defined the range wherein a system may be considered sustainable. Outside this range, the sustainability of a land use system is questionable because of a potential loss of resilience.

Chapter III: Model set-up

LCA studies often demand the simulation of ungauged areas and/or catchments under an altered environmental setting. Such model applications require a thorough understanding of model structure and parameters. Besides, the more basic question regarding the applicability of the model to present-day conditions needs to be addressed prior to the simulation of more complex cases. Therefore, chapter III describes the model structure used for all simulations in this thesis and discusses the sensitivity analysis and model calibration and validation procedures. The Flemish part of the Scheldt river basin is selected as a study site representative for north-western European conditions. The data and findings presented in this chapter form the starting point for subsequent chapters on impact calculation and evaluation, that present more advanced parameter estimation and evaluation schemes needed for modelling ungauged catchments or impacts of environmental change.

Materials and methods

Selecting an appropriate model structure

To enable the simulation of land use impact, Bronstert (2004) and Ott and Uhlenbrook (2004) state that a model must include a physically based description of all relevant hydrological processes. In practice, however, high data requirements limit the usefulness of highly complex physically based models. There exists an optimal model complexity for every case-study depending on the quantity and quality of the available input data and the objective of the study, as demonstrated by Jakeman and Hornberger (1993) for rainfall-runoff modelling and Van Rompaey and Govers (2002) for erosion modelling. Sivapalan (2003) proposed using a downward approach for selecting a suitable model structure. This downward reasoning can be applied in a hierarchical manner starting with the exploration of first-order controls of the hydrological response and further increasing the complexity of the model to improve the match between predicted and observed hydrological variables at different levels. Calder (1998) provides an example of this downward paradigm for plot-scale land use impact simulation. Water consumption of different forest types was assessed by evaluating restrictive factors for evapotranspiration in different climates. For catchment scale simulation, the approaches of Jothityangkoon et al. (2001) and Wooldridge and Kalma (2001) can be considered as a hierarchical downward approach. These studies concluded that the spatial variability in soil depth and vegetation (forest versus non-forest) were among the most important factors controlling the hydrological response. In line with the findings of Ott and Uhlenbrook (2004) and Bronstert (2004), it is emphasised that this spatial variability should be incorporated in the model structure to reflect the differences in hydrological response mechanisms between different regions or land use types. Lumped models or point models that are commonly used in the context of LCAs do not take into account this spatial variability in hydrological response. Therefore, a (semi-) distributed modelling approach is needed. Semi-distributed models are models that subdivide a catchment in units with a uniform hydrological response. These units, called hydrological response units (HRUs), hydrotopes or hydrological simulation units, are usually derived from soil maps, land use maps, digital terrain models or a combination of these.

In this case-study, the semi-distributed SWAT model (Arnold et al., 1998) is used. This model combines a physical backbone with conceptual simplifications and offers flexibility with respect to the method to calculate the reference evapotranspiration, the possibility to use local weather data or to generate with the in-built weather generator the necessary climatic data, and the availability of a crop characteristics database. Thanks to these facilities, the amount of data required to run the SWAT model is relatively small compared to other models with the same level of complexity. Data for a basic model application are available for almost every case-study, though the accuracy of the modelling will depend on the quality and representativeness of the input data. Because of this, the SWAT proved to be a useful model structure for land use impact simulation (Arnold and Fohrer, 2005).

This thesis only considers the water quantity module of the SWAT. Detailed information about the theoretical background of all modules can be found in Arnold et al. (1998) and Neitsch et al. (2002). The remainder of this paragraph gives a short overview of the model structure to make the thesis understandable for readers who are not familiar with the SWAT.

The SWAT model can be applied with different spatial discretisation schemes, but most users apply it in a semi-distributed way, that is supported by a user friendly ArcView GIS interface (DiLuzio et al., 2002; DiLuzio et al., 2004). The semi-distributed discretisation that was also used for our simulations splits a catchment in different subcatchments as defined by the hydrological structure (river network) and/or topography. Every subcatchment is further subdivided into several hydrological response units having a uniform soil and land use. The land phase of the hydrological cycle is modelled independently for every response unit.

For every HRU, the volume of quick flow[*], calculated with a modified version of the Curve Number (CN) technique (USDA SCS, 1972), is subtracted from the precipitation volume to assess the amount of water that enters the soil profile. Potential evapotranspiration (Epot) is estimated with a modified Penman-Monteith method (Monteith, 1965). Together with the plant growth subroutine that is a simplified version of the EPIC model (Williams et al., 1984), these Epot estimates allow computing the actual plant transpiration. Actual soil transpiration and the redistribution of water over the different soil layers depend on the water content of these layers and their hydraulic properties. Inter flow is computed as a function of

[*] In the SWAT, total stream flow is the sum of three simulated water flows. These are conceptual representations of surface runoff, lateral flow in the unsaturated zone and groundwater or base flow. In this thesis, the terms ‘quick flow’, ‘inter flow’ and ‘slow flow’ refer to the flow conceptualizations and predictions of SWAT. The terms ‘surface runoff’, ‘lateral flow’ and ‘groundwater flow’ or ‘base flow’ are only used to refer to real-world phenomena.

topographical and soil hydraulic features. Water percolating from the bottom of the soil profile can join the shallow or the deep aquifer. Seepage to the deep aquifer is considered as a loss so only the water from the shallow aquifer can bring forth slow flow or re-enter the soil profile through capillary forces. The volumes of slow, inter and quick flow generated by the HRUs are aggregated per subbasin, and routed through the stream network to the outlet of the catchment.

Site description

The Flemish part of the Scheldt river basin is selected as a representative for north-western Europe. In total, 25 catchments were simulated within this region (**Fig. 12**). Besides, some preliminary model runs and sensitivity tests were carried out for Meerdaal, a forested area in the Dijle basin (See Heuvelmans et al., 2005 for a detailed site description).

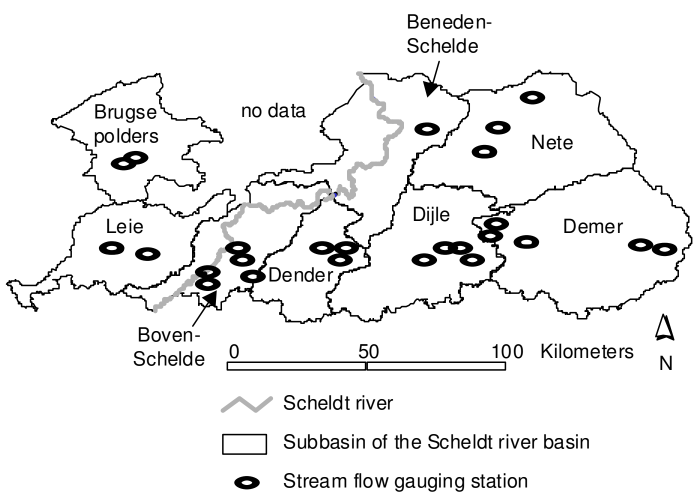

Fig. 12 : Location of the 25 studied catchments

The area has a temperate climate, with a mean July temperature between 16.2°C and 17.8°C and a mean January temperature between 1.7°C and 3.2°C depending on the catchment considered. Average yearly rainfall amounts between 722 and 855 mm per year with shorter and more intensive storms in the summer months and more frequent and generally less intensive storms during the winter. Despite the limited size of the study area, there is a wide variation in environmental characteristics. The southern part has an undulating relief, and is covered with fine-textured fertile soils. Agriculture is the dominant land use in most catchments in the southern part, with winter grains and maize as most cultivated crops. A few forests occur on less fertile soils or near river courses. In the northern part, the relief is flat, soils are sandier and have a higher infiltration capacity, so that runoff generating processes are different from the south. In the west, soils have a slightly higher clay content resulting in better conditions for agricultural activities. Towards the east, only the most fertile soils in the valleys are under agriculture, most are planted with maize, and the remainder is afforested. Scattered built-up areas occur in all study catchments, but none of them contains a large urban centre.

Table 3 : Area, slope, height and dominant soil texture and land use of the study areas

ID	Scheldt river subbasin	Area (km²)	Slope (%)	Height (m.a.s.l.)	Dominant land use*	Dominant soil**
1	Benedenschelde	107.98	0.18	10 - 31	F	S
2	Bovenschelde	2.68	2.65	32 - 91	AL	SL
3	Bovenschelde	31.00	2.56	31 – 132	AL	L
4	Bovenschelde	111.81	2.12	11 - 131	AL	L
5	Bovenschelde	47.86	2.81	17 – 150	AL	L
6	Bovenschelde	2.24	2.35	29 - 93	AL	L
7	Brugse polders	67.63	0.40	10 - 47	P	S
8	Brugse polders	73.93	0.33	11 – 42	P	S
9	Demer	64.00	1.62	13 - 103	AL	SL
10	Demer	37.74	1.80	35 - 100	AL	SL
11	Demer	15.02	2.04	15 - 70	AL	SL
12	Demer	99.87	1.33	43 - 125	AL	L
13	Demer	27.38	0.97	48 - 120	F	S
14	Dender	21.23	1.82	18 – 91	AL	L
15	Dender	87.43	1.74	12 – 95	AL	L
16	Dender	25.90	1.63	19 - 90	AL	L
17	Dijle	50.71	2.02	39 - 118	AL	L
18	Dijle	39.32	2.01	27 - 121	AL	L
19	Dijle	48.22	1.60	22 - 101	AL	SL
20	Dijle	35.08	1.71	32 - 103	AL	SL
21	Leie	73.71	0.65	20 - 55	AL	SL
22	Leie	92.18	0.63	14 - 55	AL	SL
23	Nete	89.18	0.18	11 - 31	AL	S
24	Nete	56.54	0.22	19 - 35	F	S
25	Nete	209.93	0.19	13 - 33	F	S

*Land use codes: AL: arable land, P: pasture, F: forest
**Soil codes: S: sand, SL: sandy loam, L: loam

Data

The geographical scope of this study is relatively small, so that data sources and providers were the same for all studied catchments. Daily discharge was registered by the Environmental Administration (AMINAL). For most gauging stations, data for the 6-year period 1990-1995 were used for calibration, and 1996-2001 data for validation. If data from other time periods were used, this is specified. Else, the reader can assume that the above mentioned splitting scheme (1990-1995 / 1996-2001) was employed. For Meerdaal, stream flow data were not available, therefore these simulations were only used for explorative purposes (see chapter I) and sensitivity tests (see below).

Climatic data were obtained from the Royal Meteorological Institute (KMI). Digital soil and land use maps were distributed by Flemish Land Agency (VLM). Basic soil attributes were derived from the AARDEWERK database (Van Orshoven et al., 1993), and served as input for pedo-transferfunctions (Vereecken et al., 1990) to calculate soil hydraulic properties. Land use attributes were taken from the crop database of the SWAT model and adapted to local practice. Digital elevation models were interpolated using elevation data from the National Geographical Institute (NGI).

Sensitivity of stream flow predictions to model structural aspects

The sensitivity of the SWAT for changes in model structural aspects was tested for Meerdaal. An extensive discussion can be found in Heuvelmans (2001) and Heuvelmans et al. (2005). The following gives an overview of the findings that are relevant for this work.

The digital elevation model, the land use and the soil map were used to delineate subbasins and HRUs. The threshold values for subbasin and HRU delineation determine how much terrain information is taken into consideration in the hydrologic analysis. Whereas it can be assumed that more terrain information provides better simulation results, the computation time can increase exponentially with the amount of detail (Mamillapalli et al., 1996; Thieken et al., 1999). Based on preliminary model runs for Meerdaal, the threshold values for the subdivision of the study areas in subbasins and HRUs were chosen such that the change in simulated average daily stream flow volume after a further refinement of the terrain representation was negligible (<5% change compared to a reference situation). This procedure gave a threshold of 50 ha for subbasin delineation, and 10% for soil and 15% for land use in the HRU definition (**Fig. 13**). The thresholds for soil and land use were used for all further simulations. The threshold for subbasin delineation was adjusted for each catchment to obtain the best visual match with the river network registered in the Vlaamse Hydrologische Atlas.

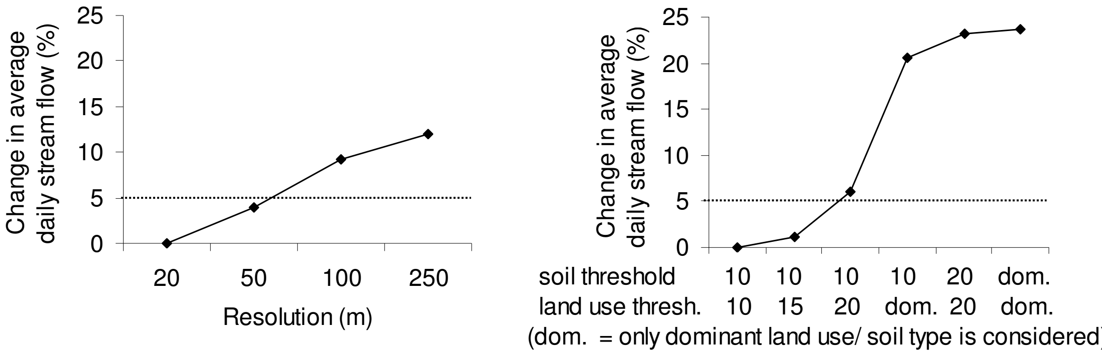

Fig. 13: Change in simulated average daily stream flow when increasing the complexity of terrain representation for Meerdaal. Left: impact of map resoltion (reference: 20m). Right: impact of HRU delineation (reference thresholds: 10% for soil and 10% for land use)

Besides the threshold values, the choice of pixel resolution for the DEM, land use and soil maps may affect the output in several ways (Romanowicz et al., 2005). The resolution of the DEM influences the model output by changing the boundaries of the (sub)basins. This results in a shift in the HRU distribution which can affect the stream flow volumes simulated at the (sub)basin scale. Furthermore, altering the DEM-resolution might change topographical characteristics: a lower resolution delivers a flatter and more simple terrain (Thieken et al., 1999). This can change the model output, in particular quick flow. To evaluate the impact of map resolution, several model pre-runs were made for Meerdaal testing different resolutions. This procedure led to an optimal resolution of 50 m that is used in all further simulations (**Fig. 13**).

Finally, the sensitivity of the average daily stream flow predictions was evaluated for weather generator input, for the calculation method of evapotranspiration and for the length of the simulation period. The weather generator was not used in any further simulation, but it might be useful for LCA applications in data poor regions. Therefore, we should gain insight in the sensitivity of the model output for weather generator parameters.

The sensitivity analysis for weather generator inputs was restricted to precipitation because this is by far the most determining weather factor of the water balance (McKay, 1988). Tested precipitation parameters were rainfall pattern, rainfall intensity and rainfall quantity. To generate the rainfall pattern, the SWAT option that describes the temporal rainfall pattern with the probability of a wet day after a dry day and after a wet day was chosen as the reference. When these probabilities are unknown, a second option is available that uses the number of wet days in a month. For the generation of rainfall intensity, the maximum 0.5 hour rainfall in the entire period of record was estimated in two ways: as the maximum of the simulated rainfall (used as reference) and as the half hour rainfall with a return period of 10 years. In the sensitivity analysis the effect of rainfall intensity was evaluated using the monthly maxima of the simulated precipitation for Brasschaat and the monthly values with a return period of 10 years, as derived for Ukkel. Finally, to evaluate the usefulness of the simulated rainfall quantities for the prediction of long-term average daily stream flow, one run was made with observed precipitation data as input.

The SWAT model offers three methods to calculate evapotranspiration: Penman-Monteith, Hargreaves or Priestley-Taylor. Penman-Monteith is usually considered the best but has high data requirements. Hargreaves or Priestley-Taylor need less information and can be used when some of the weather data are missing. Comparison of the result of these three methods allows selecting the most suitable method for calculating evapotranspiration for a given level of data availability.

The simulation period was initially set at five years. Extending the simulation period seems advantageous because a longer time series better represents the total climatic variation. On the other hand, in the presence of a systematic error, a longer simulation period increases the risk that the error on the model output is no longer negligible. To test this hypothesis, simulations lasting for 25, 50 and 100 years were evaluated.

Sensitivity of stream flow predictions to model inputs

In the model calibration, parameters were adjusted to obtain the best possible agreement between observed and simulated stream flow time series. However, the SWAT model contains many parameters. Optimising all of them would offer the modeller too many degrees of freedom compared to the information content of the available stream flow data, and this could possibly lead to over-parameterisation (Perrin et al., 2001). The calibration procedure was therefore preceded by a one-way sensitivity analysis for identifying the main controlling model parameters. This sensitivity analysis was performed for the Maarkebeek catchment (ID=5 in **Table 3**). Only the most sensitive parameters were adjusted in the calibration.

First, a minimum and a maximum were defined for every relevant input variable based on literature data or based on the recommendations in the manual of the SWAT. Two model runs were performed for every parameter, one with the maximum and one with the minimum parameter value.

Model calibration

The parameters were manually optimised by trial-and-error. The quality of each set of parameters for which the SWAT model was run was tested according to the following two criteria: (1) the accuracy of daily simulated stream flow data, and (2) the accuracy of the annual totals of the flow components. Comparison of the simulated and observed daily stream flow is based on the model efficiency (EF) (Nash & Sutcliffe, 1970), which was calculated as follows, with $\overline{O}$ the mean observed daily stream flow; O_i and P_i the observed and simulated stream flow at day i, and n the number of days:

$$EF = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \qquad \textit{Eq. 7}$$

The optimal value of the model efficiency is 1.

For evaluating the correctness of the simulated annual flow components, observed stream flow time series were split into their components with the algorithm presented by Arnold et al. (1995). In this procedure, the quick flow component q_t at time step t is calculated from the total flow Q_t with the following filter equation:

$$q_t = \beta * q_{t-1} + \frac{1+\beta}{2} * (Q_t - Q_{t-1}) \qquad \textit{Eq. 8}$$

$$\text{with } q_t > 0 \text{ and filter parameter } \beta = 0.925$$

The filter was applied three times with the total flow Q_t for the second and third pass equal to the slow flow component (Q_t - q_t) resulting from respectively the first and second pass. The slow flow component (Q_t - q_t) after the third pass gives a good approximation for slow flow.

The correctness of the simulated annual flow components was evaluated as the percent deviation of the predicted average annual slow flow and quick flow compared to the volume of these components obtained by filtering. This deviation should not solely be ascribed to the error on the SWAT simulations, because the filtering algorithm itself is some kind of model bearing some degree of uncertainty. Nonetheless, it has been demonstrated that filtered flow components can be useful for assessing the performance of a physically based model like the SWAT (Arnold and Allen, 1999). The filter results were used as a general guideline for evaluating which part of the hydrological cycle is more realistically modelled (quick or slow flow generation) given an increase in model performance for daily stream flow simulation after adjusting a certain parameter. The final identification of the ‘optimal’ parameter set was solely based on the model efficiency for daily stream flow simulation.

The model evaluation was based on the same criteria i.e. on daily flows and average annual flow components. The stream flow time series of calibration and validation period are similar: both periods contain a representative set of high and low flow periods.

Results and discussion

Sensitivity analysis: model structural aspects

Table 4 presents the results of the sensitivity analysis for model structural aspects. The sensitivity of simulated stream flow for rainfall pattern and intensity is small, and is mainly due to changes in quick flow volumes. Replacing the weather generator with observed rainfall only slightly affects stream flow simulation. The rainfall simulator can thus be useful if one is interested in average long-term effects, as in LCA.

Stream flow predictions obtained when using Hargreaves or Priestley-Taylor methods to calculate reference evapotranspiration, deviate clearly from the simulations with the Penman-Monteith formula. If data availability allows it, the Penman-Monteith method should be used.

Accumulation of systematic errors does not seem to happen for the considered time spans: the % change of average daily stream flow does not really increase when the simulation period is prolonged.

Table 4: Sensitivity of simulated average daily stream flow to model structural aspect

Variable	Sensitivity
Rainfall	
Pattern	-
Intensity	-
Quantity	+
Evapotranspiration	
Priestley-Taylor	+
Hargreaves	++
Time span	
25 years	-
50 years	+
100 years	+

-: < 5% change; +: 5-15% change; ++: 15-30% change; +++: > 30% change

Sensitivity to input variables - implications for model calibration

The sensitivity of average daily stream flow predictions to changes in input variables is presented in **Table 5**. Based on sensitivity runs for the Maarkebeek, it was decided to optimise seven parameters in the model calibration (**Table 6**). As indicated by Lenhart et al. (2002), the model output is very sensitive to changes in soil parameters like the AWC (Available Water Capacity) and the saturated hydraulic conductivity. These parameters were estimated indirectly with pedo-transferfunctions (Vereecken et al., 1990) using soil texture and organic matter as input. It is well known that the use of transferfunctions only yields a rough approximation of the soil hydraulic properties. Therefore the estimates of AWC and conductivity were optimised during calibration. The percent change in soil parameter values was forced to be equal for all soil types and soil horizons in order to simplify the parameter optimisation process. The same approach was used for the optimisation of the curve numbers, with the tabulated curve number for a given soil/land use combination as a first approximation.

*Table 5: Sensitivity of simulated average daily stream flow to model inputs. Parameter definitions can be found in the SWAT manual for all parameters, and in **Table 6** for the parameters adjusted in the calibration*

Variable	Sensitivity	Variable	Sensitivity	Variable	Sensitivity
ALPHA_BF	++	GSI	+	SAND	+
BIO_E	-	GW_DELAY	++	SILT	+
BLAI	+	GW_REVAP	+++	SOL_ALB	-
CANMX	-	GWQMIN	+	SOL_AWC	+++
CHTMX	+	HVSTI	-	SOL_BD	++
CH_N	-	LAIMX1	-	SOL_K	+++
CLAY	++	LAIMX2	-	SOL_ZMX	++
CN2	+++	RCHRG_DP	-	SURLAG	-
DLAI	-	RDMX	+	T_BASE	+
EPCO	-	REVAPMN	+++	T_OPT	+
ESCO	+				

-: < 5% change; +: 5-15% change; ++: 15-30% change; +++: > 30% change

Table 6: Definition of model parameters adjusted in the calibration

Parameter:	Definition:
ALPHA_BF	Recession constant: indicates the response of base flow to changes in shallow aquifer recharge (days)
GW_REVAP	Coefficient controlling water movement between root zone and shallow aquifer (dimensionless)
REVAPMN	Threshold value: Amount of water in the shallow aquifer before water movement to the unsaturated zone or the deep aquifer can occur (mm)
GW_DELAY	Groundwater delay (days)
SOL_AWC	Available water capacity (AWC) (mm water/mm soil)
SOL_K	Hydraulic conductivity (mm/hr)
CN2	SCS curve number (dimensionless)

Besides the soil parameters, SWAT is very sensitive to four groundwater related parameters that mainly control the simulation of slow flow. GW_REVAP and REVAPMN control the (capillary) rise of water out of the shallow aquifer to the soil profile (**Fig. 14**): GW_REVAP controls the rate of capillary rise, whereas REVAPMN indicates the minimum volume of water that needs to be present in the shallow aquifer before water can re-enter the soil profile. GW_DELAY and ALFA_BF control the transfer of water from the soil profile to the shallow aquifer and stream network: the first represents a lag between the time that water exits the soil profile and enters the aquifer, the second is a measure of the steepness of the base flow recession. All groundwater parameters were assumed uniform over the whole catchment.

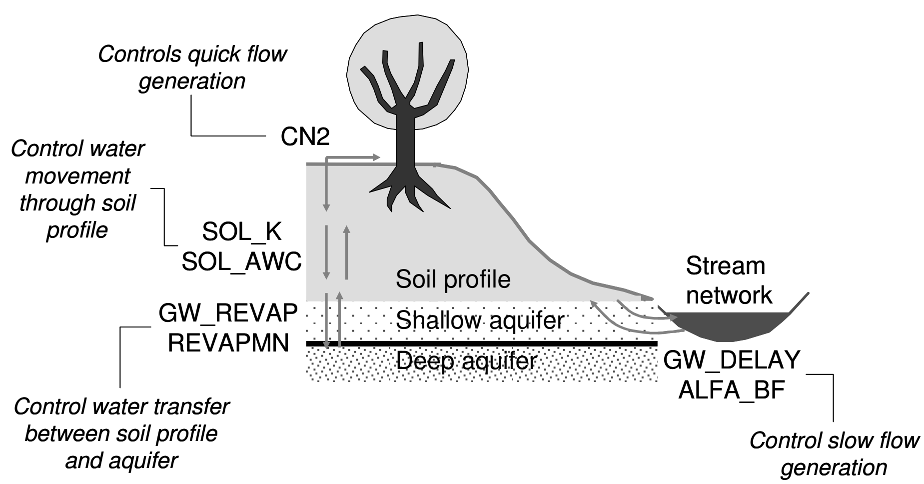

*Fig. 14: General overview of the processes simulated by SWAT, and of the parameters that control these processes (processes are indicated by grey arrows). Parameter definitions can be found in **Table 6**.*

Evaluation of the performance of the SWAT for Flemish catchments

The model performance for daily flows, evaluated as the model efficiency of Nash and Sutcliffe (1970), varies between 0.95 and 0.70 for the calibration period and between 0.92 and 0.67 in the validation period, which can be considered as acceptable according to Qi and Grunwald (2005). As all model simulations rely on the same data sources, a lower model performance for a certain catchment can only be explained by a less adequate parameterisation or a higher model error i.e. a discrepancy between the physical backbone of the model and the hydrological processes prevalent in that catchment. To avoid a misunderstanding of the impact of model parameterisation on model performance, one should bear in mind the differences in model error between the 25 catchments. Differences in model error are estimated as differences in model performance between the 25 catchments when using a locally optimal parameterisation.

The lowest model performances and hence the highest model errors occur in the northern part of the study area. This part of the study area has a less pronounced relief. Several large artificial channels cross the catchments under study in this region, so that parts of these catchments drain to the artificial channels instead of the natural river network. Discharge measurements of artificial channels are not available. The combination of the flat terrain and the presence of the artificial channels complicates the delineation of the area that actually drains to the stream network, explaining why the model error is larger in the northern part. But the model efficiency in this part of the study area is still acceptable and, even more important, the loss in model performance after the transfer of model parameters from the calibration to the validation period is small: around 5% (**Fig. 15**). This suggests that the parameters capture the hydrological response mechanisms of the study sites.

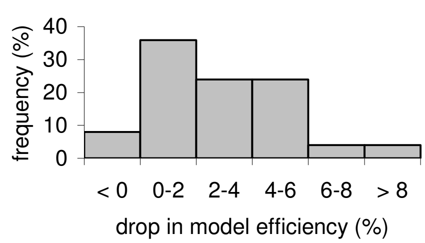

Fig. 15 : Loss in model efficiency for daily stream flow simulation after transfer of parameters from the calibration (1990-1995) to the validation (1996-2001) period for the 25 study catchments

Conclusion

Based on earlier research, the most cost-effective model settings were identified: map resolutions were set to 50m, thresholds for HRU delineation were set to 10% for soil and 15% for land use, the Penman-Monteith method is used to calculate reference evapotranspiration and the calibration was restricted to the seven model parameters of **Table 6**. These settings were used in all further analyses. With these settings, acceptable model performances were attained for the 25 study catchments. However, model performance in the northern part (Nete region) was relatively low, due to the flat terrain and presence of artificial canals that complicate the delineation of drainage areas.

Chapter IV: Impact calculation*

Chapter IV deals with the simulation of stream flow time series needed to calculate the indicators proposed in chapter II. Because the geographical scope of a life cycle assessment only rarely coincides with the boundaries of a gauged catchment i.e. a catchment for which stream flow data are available, there is a need to develop a method for parameterising the SWAT for ungauged areas. This chapter discusses the necessity of parameter regionalisation and presents some regionalisation techniques that can be useful in LCAs of agri- and silvicultural systems. The proposed techniques are illustrated with a case-study in the Flemish part of the Scheldt river basin.

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*Chapter IV is adapted from:
Heuvelmans, G., Muys, B., Feyen, J. 2004. Evaluation of hydrological model parameter transferability for simulating the impact of land use on catchment hydrology. Phys. Chem. Earth 29, 739-747.
Heuvelmans, G., Muys, B., Feyen ,J. 2004. Analysis of the spatial variation in the parameters of the SWAT model with application in Flanders, Northern Belgium. Hydrol. Earth Syst. Sci. 8, 931-939.
Heuvelmans, G. , Muys, B., Feyen, J. 2005. A comparison of parameter regionalisation strategies for the water quantity module of the SWAT with application in the Scheldt river basin. Proceedings of the 3rd International SWAT conference, Zürich, Switzerland, in press.
Heuvelmans, G., Muys B., Feyen, J. Regionalisation of the parameters of a hydrological model: comparison of linear regression with artificial neural nets. J. Hydrol., in press.

IV.1 Problem setting: parameterising SWAT for problem oriented modelling

Hydrological models can be applied in two different contexts: models can either be used 'inside' hydrology as research tools to increase our knowledge about hydrological processes or 'outside' hydrology to support operational decisions (Klemes, 1986). In the first case, study areas can be selected in function of data availability. For problem oriented modelling, study areas are generally predefined and consequently data for a site-specific optimisation of model parameters are often not available. When modelling the impact of hypothetical scenarios of land use or climate change, parameters for post-change conditions can never be obtained with a case-specific model calibration. Since SWAT is used for operational modelling in this work, i.e. for the simulation of land use impact in LCA, the question arises how the parameters of the SWAT can be quantified in ungauged catchments or under an altered environmental setting. Do default parameter values deliver a reliable model output in this case? Or does one need a more advanced parameter regionalisation strategy?

A split-sample validation is the most basic test for evaluating the predictive capacity of a (hydrological) model for problem oriented modelling. Parameter values are optimised with respect to half of the available stream flow time series for one gauging station and validated against the second half of the series. It has often been suggested that such a validation – as applied in chapter III of this work – is insufficient for testing the capacity of a model for simulating the impact of environmental change (Refsgaard and Knudsen, 1996; Mroczkowski et al., 1997). Ewen and Parkin (1996) for example, stated that, for this purpose, calibration and validation should use stream flow time series from time periods with different environmental characteristics. Bathurst et al. (2004) even suggested a more powerful validation considering internal catchment conditions as well as stream flow observations at the catchment outlet.

Chapter IV tries to assess the most cost-effective way for estimating model parameters for applications of the SWAT in Flanders. Therefore, the usefulness of SWAT defaults for modelling Flemish conditions was first evaluated. Next, the possibility to improve the performance of the model with more advanced parameter regionalisation strategies was explored.

Parameter regionalisation is a procedure for deriving parameter estimates for ungauged catchments from previous model applications to gauged catchments. Although this technique was already applied a few decades ago (e.g., Magette et al., 1976, James, 1972), it is still an actual topic in applied hydrological modelling (e.g., Parajka et al., 2005; Croke et al., 2004; Kokkonen et al., 2003, Mwakalila, 2003; Wooldridge et al., 2001). There exists a wide variety of regionalisation techniques. Some techniques predict parameter values based on the location of a catchment, others link model parameters to catchment attributes like average slope, area and shape of the catchment. For each of these 2 categories, the regionalisation scheme can either be continuous (can be obtained by kriging or by establishing regression equations with catchment attributes as inputs) or discontinuous (delineating validity ranges for parameter values or parameter sets either as spatial zones or as intervals of a certain catchment attribute).

Both location-based and attribute-based parameter regionalisation were considered in this work. The use of defaults and average parameter values for the entire study region was evaluated to demonstrate the potential advantages of these advanced parameter estimation techniques.

IV.2 Are SWAT defaults applicable in Flemish conditions?

Method

The SWAT model was applied to the 25 studied catchments with default parameter values and with site-specific parameter optima. The performance of the model with and without calibration was assessed. If calibration considerably increases the performance of the model, then default parameters do not really fit Flemish catchments. In that case, a more advanced parameter regionalisation strategy must be developed to enable a reliable simulation of ungauged areas.

Results

The upper part of **Fig. 16** shows the model efficiency obtained for Flemish catchments with default parameters. The resulting model efficiencies vary significantly. In the central part of Belgium, SWAT defaults give an acceptable model behaviour for some of the simulated catchments, with model efficiencies for daily and monthly stream flow simulation slightly higher than 0.6. In the north, west and east, the model performance is unacceptable for all catchments (lower than 0.4). The simulation of slow flow is more problematic than the simulation of quick flow; slow flow volumes are generally overestimated (**Fig. 17**).

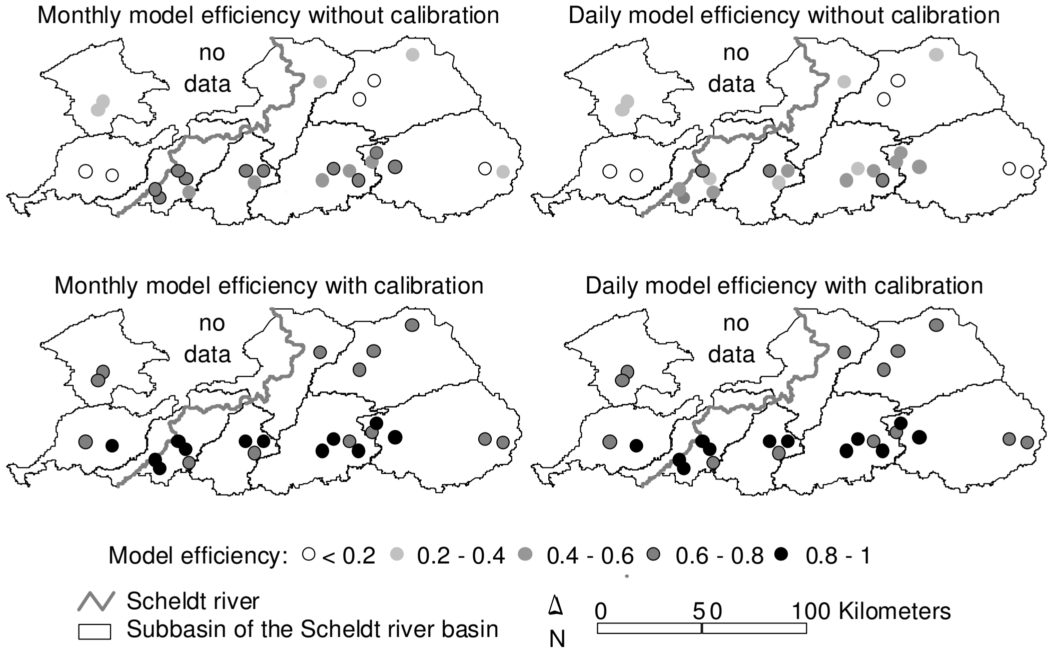


Fig. 16: Model efficiency for daily and monthly stream flow simulation using default parameter values and site-specific parameter optima

The spatial pattern of model efficiencies obtained with site-specific parameter optima (lower part of **Fig. 16**) resembles the pattern obtained with the default parameters: catchments in the central part generally have higher model efficiencies. However, after calibration, an acceptable model fit is attained for all catchments. In average, the increase in model efficiency due to the use of local parameter optima amounts about 0.3 for monthly flows and about 0.4 for daily flows. For the catchments in central Belgium, the increase in model performance after calibration is larger for daily than for monthly flows.

Discussion and conclusion

Although acceptable model efficiencies were attained for some catchment areas, the default parameter values provided by the SWAT do not really suit Flemish catchments. A site-specific model calibration or a regionalisation of parameter estimates is therefore desired. For the northern part of our study area, the overestimation of base flow with default settings (left part of **Fig. 17**) is mainly due to an inadequate parameterisation of the revap process i.e. the transfer of water between shallow aquifer and root zone. The amount of revap is underestimated with default parameter values, hence evapotranspiration volumes are underestimated and too much water is diverted to the river network as slow flow.

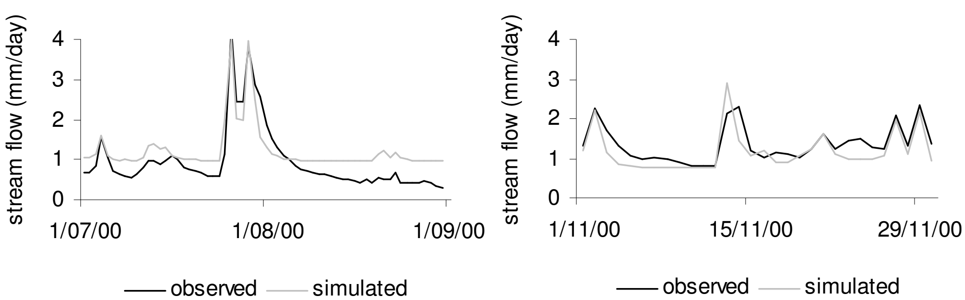


Fig. 17: Typical simulation results when using default model settings in the northern part of the study region (left figure) and in central Belgium (right figure)

Using the default settings, the total flow volumes are well predicted for catchments in central Belgium, but the timing and the steepness of slow flow recessions is incorrect (right part of **Fig. 17**). As a consequence, the efficiency for yearly stream flow prediction is acceptable but the efficiency for daily stream flow prediction is rather poor.

IV.3 Temporal and spatial transferability of parameter sets: potential implications for land use impact simulation

Introduction

Previous chapter demonstrated that using one world-wide applicable model and parameter set is not recommended. This chapter tries to assess whether all catchments in Flanders can be modelled with one single parameter set. In such case, parameter sets could be exchanged between different catchments without a significant loss of predictive capacity.

The transfer of calibrated model parameters from a (nearby) gauged catchment to the catchment under study can be regarded as a special case of a 'geographical regionalisation' (Vandewiele and Elias, 1995) that estimates parameters based on optimal parameter sets in neighbouring catchments. When simulating the impact of land use change on catchment hydrology, the optimal parameter set before the change is usually transferred to post-change conditions, except for the crop and management characteristics. This approach can also be considered as regionalisation, i.e., the transfer of parameter values from the actual land use scenario to a hypothetical catchment. Like for the spatial transfer of parameter sets, the transfer to other land use scenarios might decrease the performance of the model.

The objective of this chapter is to assess the influence of parameter transfers within Flanders on the performance of the SWAT. Transferability is evaluated stepwise: transfers in time, within the catchment, between adjacent catchments and between catchments with different environmental conditions. Comparing the impact of parameter transfers and the impact of land use change on the simulated stream flow regime allows assessing the model's capacity to predict accurately the impact of land use change.

Method

Study Areas

The test areas were chosen such that a stepwise evaluation of parameter transferability was feasible. Two test catchments, the Maarkebeek and Zwalm river basins, having comparable environmental and hydrological conditions, and a third basin, the Aa catchment being different of topography, soil, land use and hydrological properties, were selected (**Table 7**).

Table 7: Characteristics of the study catchments

	Maarkebeek	**Zwalm**	**Aa**
Surface	51 km²	114 km²	204 km²
Topography	Rolling (10m-150m.a.s.l.)	Rolling (9m-154m.a.s.l.)	Flat (9m-35m.a.s.l.)
Hydrology			
Specific yield[1]	0.50	0.55	0.35
Slow/Inter/Quick[2]	50/20/30	50/20/30	60/20/20
Land Use			
Arable Land	**50%**	**45%**	20%
Forest	2%	5%	**35%**
Pasture	**30%**	**30%**	**25%**
Urban	15%	20%	20%
Soil	Loam – Sandy loam	Loam	Sand

[1] Ratio between stream flow and precipitation
[2] % contribution to total stream flow of slow flow/inter flow/quick flow

Because model parameters are expected to reflect the hydrological properties mentioned in **Table 7**, optimal parameter values will most probably be similar for the Zwalm and the Maarkebeek catchment and significantly different for the Aa. As a consequence, it is likely that the exchange of parameters between the Zwalm and Maarkebeek catchment will have less effect on the model performance, than a transfer of model parameters between the Maarkebeek or Zwalm and the Aa catchment.

Model calibration and evaluation

For testing the temporal transferability of parameter sets, the SWAT model was calibrated manually for the seven gauging stations, resulting into seven 'optimal' parameter sets. The first half of the available time series was used for model calibration (**Table 8**). The second half was set aside for testing the temporal transferability of the model parameters, i.e. the traditional split sample test.

Table 8: Stream flow gauging stations

Code	Catchment	Main/Internal*	Drainage area (km²)	Time period
A.0	Aa	main	204	1985-2000
A.1	Aa	internal	37	1986-2000
Z.0	Zwalm	main	114	1985-2000
Z.1	Zwalm	internal	31	1991-1996
Z.2	Zwalm	internal	2	1995-1996
M.0	Maarkebeek	main	51	1985-2000
M.1	Maarkebeek	internal	3	2000

* main: station is located at the catchment outlet
internal: station is located upstream from the catchment outlet

The evaluation of spatial transferability, i.e. the exchange of the optimal parameter sets within and between catchments, consisted of three steps: transfers within the catchment, between neighbouring catchments and between catchments under a different environmental setting. For the transfers within a catchment, the available time spans of the internal stations are shorter than those of the main stations. To avoid the mixing up of the effects of temporal and spatial transfers of parameter estimates, the SWAT model was recalibrated at the main outlet using only the overlapping part of the internal and main time series. The impact of transfers between neighbouring catchments was examined by exchanging parameter sets of the main stations of the Zwalm and Maarkebeek catchment. For the evaluation of parameter transfers between catchments under a different environmental setting, parameter sets of the main stations of the Maarkebeek and the Aa catchment were exchanged, as well as the parameter sets of the main stations of the Zwalm and the Aa catchment. The quality of each set of parameters for which the SWAT model was run was tested according to the two criteria discussed in Chapter III: (1) the accuracy of daily simulated stream flow data, and (2) the accuracy of the annual totals of the flow components. The same two criteria were used for model evaluation, i.e. to assess the effect of the transfer of the optimal set of parameters on model performance. To explore the implications for the prediction of land use impact, SWAT was applied to the Maarkebeek catchment for the actual and a virtual land use scenario. In the virtual scenario, the entire catchment was converted to pasture. Such a drastic land use change is expected to cause large changes in parameter optima and a large decrease in model performance when transferring parameters from the actual to the virtual land use scenario. As such, the case-study can be regarded as the worst possible impact that parameter transfers might have on the capacity of a model to simulate land use impact.

The model was applied three times for every scenario, each time with a different 'optimal' set of parameters, i.e. the optimal sets for the main stations of the Maarkebeek, the Zwalm and the Aa river basin. From the results of these model runs, the variation in model output per land use scenario and per parameter set could be estimated. Comparison of the variation in model output due to the use of different parameter sets and due to a change in land use gives an estimate of the potential impact of parameter transfers on the capability of the model to predict the impact of land use change on catchment hydrology.

Results and Discussion

Evaluation of parameter transferability

For all catchments, the model performance for daily stream flow predictions is the highest after model calibration (**Fig. 18**). When parameters are transferred in time (traditional split sample test), the model efficiency does not decrease significantly, even the exchange of parameters between Maarkebeek and Zwalm only slightly affects the model performance. As mentioned before, those catchments are hydrologically very similar in contrast to the Aa catchment, which has a totally different hydrology, topography, soil and land use.

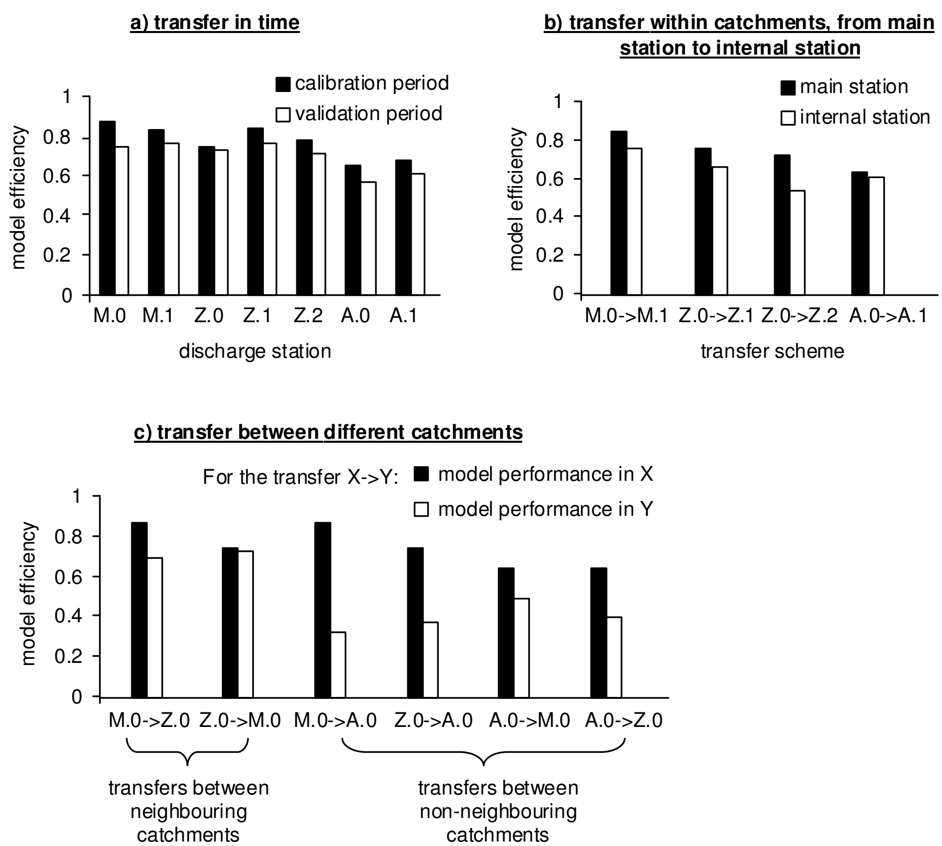


Fig. 18: Impact of parameter transfers in time and space on model efficiency. Black bars indicate the performance in the catchment and in the time span wherefore parameters are optimised. White bars indicate the model performance in the catchment and in the time span whereto parameters are transferred. Codes of discharge stations are explained in ***Table 8****.*

In general, the SWAT model performs considerably less on the Aa catchment, probably because the model was initially developed for agricultural catchments with an undulating relief. One can expect that that the quick flow module of the SWAT model is more elaborated than the slow flow module. This might also explain the relative large percent deviation in slow flow caused by transferring in time and space the model parameters of the Aa catchment (**Fig. 19**).

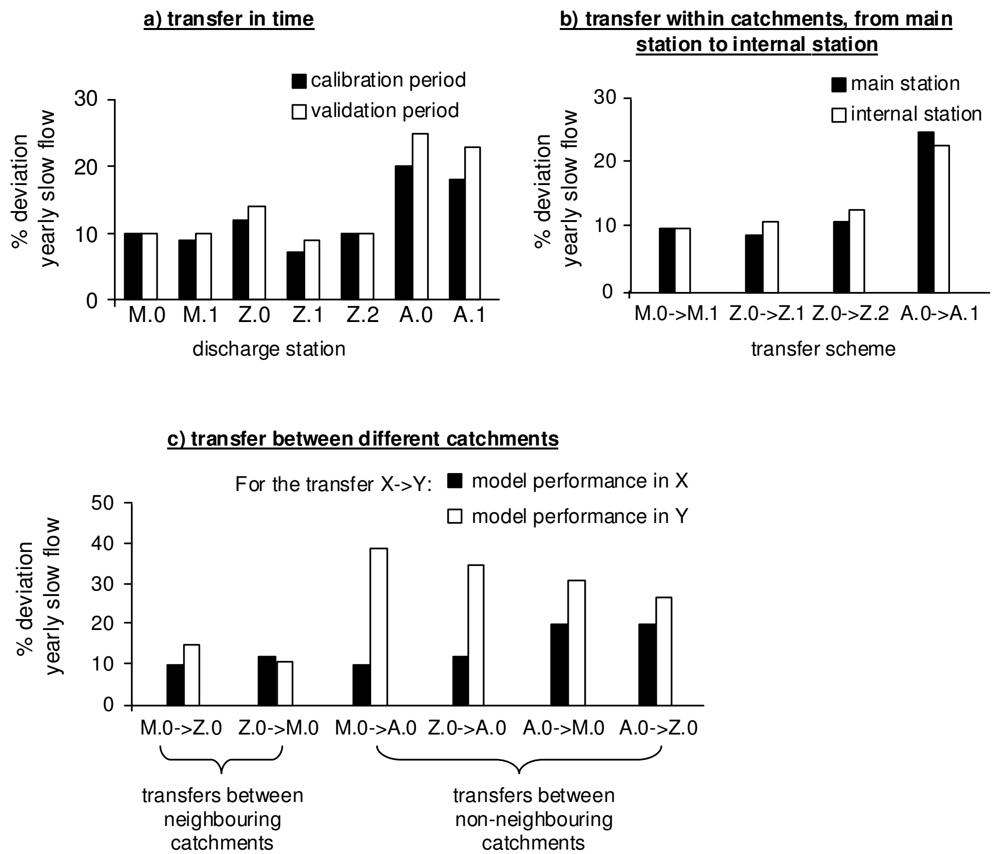


*Fig. 19: Impact of parameter transfers in time and space on the deviation of simulated yearly slow flow from the slow flow volume obtained by filtering observed stream flow time series. Black bars indicate the deviation in the catchment and in the time span wherefore parameters are optimised. White bars indicate the deviation in the catchment and in the time span whereto parameters are transferred. Codes of discharge stations are explained in **Table 8**.*

The deviation of quick flow (**Fig. 20**) as well as slow flow is acceptable for the exchange of parameters between Zwalm and Maarkebeek. Even after parameter exchange between Zwalm/Maarkebeek and Aa, the deviation of the simulated slow flow remains acceptable. This can be explained by the fact that the parameters that control quick flow were transferred as relative values, with the tabulated curve numbers and the outcomes of transferfunctions as reference. These parameters were actually regionalised in some sense, i.e. they were adapted to the local land use and soil. This was not the case for the groundwater parameters. Those parameters were transferred as absolute values without any modification resulting in a larger deviation of the slow flow simulation after the transfer of parameters from Maarkebeek or Zwalm to Aa.

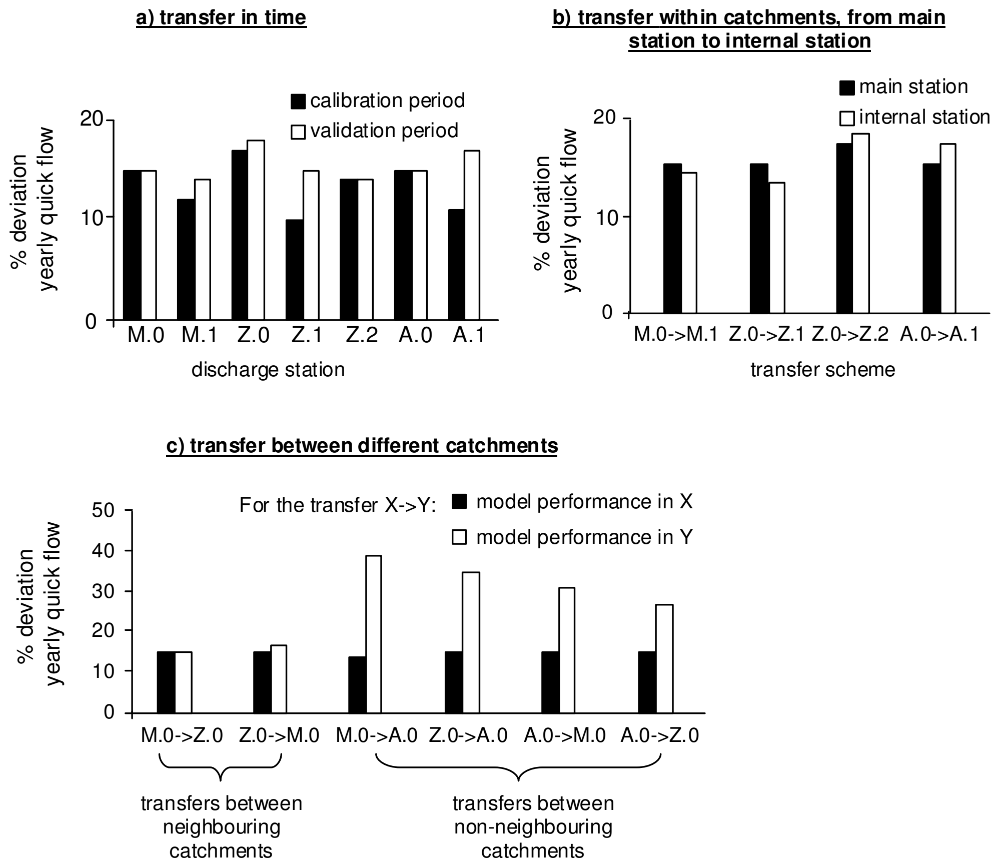


*Fig. 20: Impact of parameter transfers in time and space on the deviation of simulated yearly quick flow from the quick flow volume obtained by filtering observed stream flow time series. Black bars indicate the deviation in the catchment and in the time span wherefore parameters are optimised. White bars indicate the deviation in the catchment and in the time span whereto parameters are transferred. Codes of discharge stations are explained in **Table 8**.*

Implications for the simulation of land use impact

Fig. 21 illustrates the effect of a change in land use on the total stream flow, the slow flow and the quick flow component. A comparison is made between the actual land use of the Maarkebeek river basin and the hypothetical situation whereby the entire catchment is covered by pasture. The height of the vertical bars in **Fig. 21** depicts the variation in stream flow and flow components due to the use of different parameter sets (the optimal sets for the main stations of the Maarkebeek, the Zwalm and the Aa river basin) for a given land use scenario for the Maarkebeek catchment. The spread in quick flow for the actual and virtual land use scenario is remarkably small, most likely due to the fact that only relative parameter values are transferred. Slow flow varies strongly. Because of this, it is not clear whether the pasture scenario significantly affects slow flow. On the one hand, pasture is expected to consume more water compared to other agricultural land use (e.g. Brown et al., 2000) which occupies a large fraction of the catchment area in the actual land use scenario. On the other hand, pasture is known for its hydrological buffering capacity and is therefore expected to produce a relatively higher proportion of slow flow. Those two opposing mechanisms complicate the prediction of the overall impact of the land use change on slow flow. The conclusion that can be drawn from **Fig. 21** 'conversion to pasture does not significantly affect slow flow' is consistent with previous finding, though that conclusion is the result of a high level of noise caused by using different parameter sets, rather than from the resemblance of slow flow under the two land use schemes.

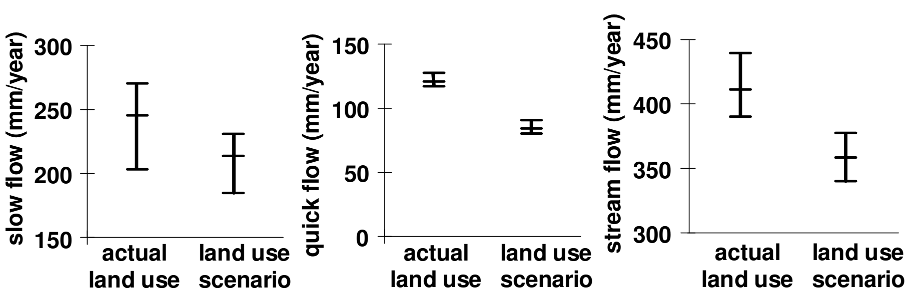


Fig. 21: Variation in model output due to the use of different parameter sets under the actual and a virtual land use scenario for the Maarkebeek catchment (1985-2000)

Table 9 presents the change in simulated stream flow and flow components for one particular parameter set – parameter set M, the optimal one for the Maarkebeek. The land use change results in a decrease in slow flow with 11 percent. Similar percentages are found using one of the other parameter sets. The variation in simulated slow flow caused by the use of different parameter sets is about 25%, larger than the difference between the land use scenarios. However, previous analyses revealed that parameter set A, the optimal one for the Aa catchment, does not result in a good fit for the Maarkebeek catchment. In case the model could be parameterised specifically for post-change conditions, a parameter set giving such low model efficiency would not be considered. Comparison of simulated slow flow between the parameter sets M and Z, both giving a good fit, shows a variation of 7%. In this case, the variation in model output between the pasture and the actual land use scenario is larger than the noise caused by the choice of parameterisation scheme. From previous it can be concluded that proper parameter estimation for post-change conditions could increase the model's capacity for simulating the effect of alternative land use scenarios on stream flow. There might however be other parameter sets leading to a reasonable model fit for the Maarkebeek. In other words comparing only parameter set M and Z might underestimate the noise caused by the transfer of parameters. The parameterisation noise is expected to be somewhat higher than 7%, yet most probably beneath 25%.

Table 9: Change in simulated stream flow and flow components if the entire Maarkebeek catchment is converted to pasture using the parameter set M, i.e. optimum for Maarkebeek (1985-2000)

	Land use scenario: actual	**virtual**	**absolute change**	**relative change**
stream flow (mm/year)	439	377	62	-14%
slow flow (mm/year)	230	205	25	-11%
quick flow (mm/year)	124	94	30	-24%

Conclusions

The analysis reveals that the transfer of parameter estimates between catchments with different environmental conditions, in this study from Zwalm or Maarkebeek to Aa, may be problematic especially for the simulation of slow flow. This has implications for the simulation of the hydrologic effect of land use change, whereby traditionally parameter estimates before the change are transferred to the hypothetical land use scenario. However, the hypothetical land use scenario might induce new environmental conditions affecting model parameters other than the strictly land use related ones. Soil hydraulic properties might change, and the problem remains how to translate a land use change to a change in these soil hydraulic properties. In case of the SWAT model, the groundwater parameters might get other optima. As demonstrated in this chapter, ignoring this shift in model parameters lowers the model efficiency and biases the interpretation of the simulated land use impacts. The transfer of relative values, taking into account the dependence of parameter optima on catchment attributes, explains the better fit for quick flow compared to slow flow. This opens a perspective for improving the simulation of the impact of land use on slow flow. Establishing a relationship between groundwater parameters and easily observable catchment attributes could render the parameterisation of virtual land use scenarios more realistic, leading to a more accurate impact prediction. In the SWAT model it can be expected that the coefficients that control the water movement between the root zone and the shallow aquifer, are related to land cover and the presence of confining soil layers. But without a formal relationship, this information cannot be incorporated into future model applications. Therefore, the following chapters attempt to construct such a quantitative regionalisation scheme for the most important parameters of the SWAT.

IV.4 Analysis of the spatial variation in the parameters of the SWAT as a basis for a location-based regionalisation

Introduction

Previous chapter has shown that for applications of the SWAT hydrological model in Flanders, both temporal and spatial transfers of parameter estimates lower the performance of the model, with the decrease being considerably larger for spatial than for temporal transfers. This chapter examines the spatial transferability of parameters in more detail.

The spatial variability of hydrological model parameters has for example been addressed by Andersen et al. (2001). The authors discussed the significance of the spatial variability in parameter optima for a large-scale application of the MIKE SHE model. In their study, the spatially distributed parameterisation obtained by a multi-site calibration led to a better model fit than the single-site calibration, treating model parameters as spatially invariant. Wooldridge and Kalma (2001) drew a similar conclusion for the comparison of a lumped and a semi-distributed parameterisation of the conceptual VIC model structure: the semi-distributed parameterisation results in a better model performance. In general, for large-scale applications of a hydrological model, insight in the spatial variation in parameter optima can improve the performance of a model. Besides, knowledge about the spatial variation in parameter optima might be of use for parameterising ungauged catchments. It can guide the selection of the gauged catchment(s) that is/are hydrologically similar enough to the ungauged site so that the loss of model performance after a transfer of parameters remains acceptable.

The spatial variability of model parameters can be looked at in two different ways: the parameters can be considered one-by-one (single parameter approach) or the entire parameter set can be examined as a whole (parameter set approach). Theoretically, the single parameter approach corresponds with analysing each hydrological process separately, whereas the parameter set approach considers the hydrological system as a whole. Beven (1993) has pointed out the importance of a parameter set based analysis. The effect of one parameter on the model output usually depends on the value of the other parameters. This implies that even if a hydrological process is similar for two catchment areas, two completely different parameter optima might be derived for these catchments. As a consequence, the link between a single model parameter and a particular hydrological process is not always clear. This can hamper the recognition of a spatial pattern in parameter optima.

The aim of this study is to examine the spatial variation in the parameters of the SWAT model within the Flemish part of the Scheldt river basin. Specific objectives are (I) to assess which catchments within the study region are hydrologically similar enough to allow transfers of parameter sets without a significant loss in model performance and (II) to assess which is the most appropriate approach for delineating zones: a single parameter or a parameter set approach. The results can be used for the parameterisation and the hydrological analysis of ungauged subcatchments in the Scheldt river basin.

Method

Following the VHA (Vlaamse Hydrologische Atlas), the Flemish part of the Scheldt river basin can be subdivided into nine subbasins. For one of these subbasins, Gentse Kanaalzone, no stream flow measurements were available; therefore this area was excluded from the analysis. The variation in parameter optima within each of the eight remaining subbasins of the Scheldt river basin is expected to be small compared to the overall variation in parameter optima. Huisman et al. (2003) and van der Linden and Woo (2003) concluded that the difference in parameter optima between nearby catchments is small, so that an exchange of parameter optima between such catchments does not significantly lower the performance of the SWAT-G and the SLURP model respectively. The assumption of uniform parameter optima within each of the eight Scheldt river subbasins is also supported by **Fig. 18**, **Fig. 19** and **Fig. 20** in the previous chapter: transfers within a catchment and to neighbouring catchments result in a smaller decrease in model performance than transfers to catchments at a greater distance. It can therefore be assumed that hydrological processes within one of the eight subbasins are similar for all catchments within that subbasin. The variation in parameter optima within one of the eight subbasins can be regarded as the uncertainty on the relationship between a particular hydrological process and a parameter value.

If model parameters do not vary much within each one of the eight subbasins of the Scheldt river basin, these subbasins can be used as a starting point for the delineation of zones with a uniform parameterisation. The eight subbasins are gradually merged into larger clusters in a hierarchical way. In each step, the two clusters that show the largest similarity are merged.

The used similarity measure is the inverse of the Euclidian distance between the two clusters, calculated with the average linkage method i.e. the average distance between all samples belonging to the two different clusters (Everitt et al., 1993).

The hierarchical merging of clusters is interrupted when the ratio of the within cluster variation in parameter optima to the between cluster variation gets too large. For the single parameter approach, the Kruskall-Wallis test, a non-parametric test for comparing two or more groups of observations on one variable, was used to evaluate whether the parameter optima of one particular cluster differ significantly from those of a second cluster. Because of the multidimensionality of the data, this simple statistical test could not be applied in the parameter set approach without modifications. In this approach, a principal components analysis (PCA) was executed to detect the main gradients in the dataset of the optimal parameter sets for the 25 catchments. The PCA-axes are linear combinations of model parameters with the first axis explaining most of the variation between the parameter sets, the second axis the second most, etc. with subsequent axes orthogonal to all preceding ones. Hence, the scores of the parameter sets on the first and the second axes summarise the parameter sets such that the most pronounced differences in parameterisation are still detectable. Therefore two clusters were considered significantly different in the parameter set approach if a Kruskall-Wallis test indicated a significant difference in the scores on the first or the second PCA-axis.

Spatial variability in parameter optima

As expected, the variation in parameter optima within each of the eight subbasins of the Scheldt river basin is small compared to the overall variation between the eight subbasins (**Table 10**). Consequently the eight subbasins make up suitable starting points for the delineation of zones with a uniform parameter set.

Table 10: Variation in parameter optima between (overall variation) and within the eight subbasins of the Scheldt river basin

Parameter	Overall variation	Variation within subbasins							
		Nete	Boven-schelde	Dijle	Demer	Dender	Brugse polders	Leie	Beneden-schelde*
GW_REVAP	0.1 - 0.18	0.16 - 0.18	0.1 - 0.13	0.13 - 0.16	0.13 - 0.16	0.10 - 0.12	0.15 - 0.17	0.1**	0.16
ALFA_BF	0.15 - 0.46	0.15 - 0.21	0.3 - 0.46	0.26 - 0.35	0.24 - 0.28	0.28 - 0.37	0.20 - 0.25	0.22 - 0.26	0.2
REVAPMN	0 - 45	0 - 6	18 - 45	10 - 25	3 - 18	9 - 33	0 - 6	6-8	0
GW_DELAY	10 - 31	10 - 14	16 - 23	12 - 18	14 - 20	15 - 17	17 - 26	31**	19
CN2	-16 - 24	-16 - -6	-10 - 5	10 - 24	-1 - 15	10 - 15	-2 - 2	7 - 11	-1
SOL_K	-5 - 25	8 - 23	-5 - 5	-2 - 15	5 - 22	4 - 10	18 - 25	1- 7	17
SOL_AWC	-2 - 21	9 - 21	-2 - 7	1 - 8	7 - 20	3 - 13	10 - 15	6 - 11	15

* Only one catchment is simulated in the Benedenschelde, so it is not possible to specify a range of parameter values.
** The two catchments simulated in the Leie have the same optimal value for GW_REVAP and GW_DELAY.

Single parameter approach

Fig. 22 depicts the zones delineated following the single parameter approach. For all parameters, two to four zones with significantly different parameter optima could be identified if the confidence level was set at 0.05.

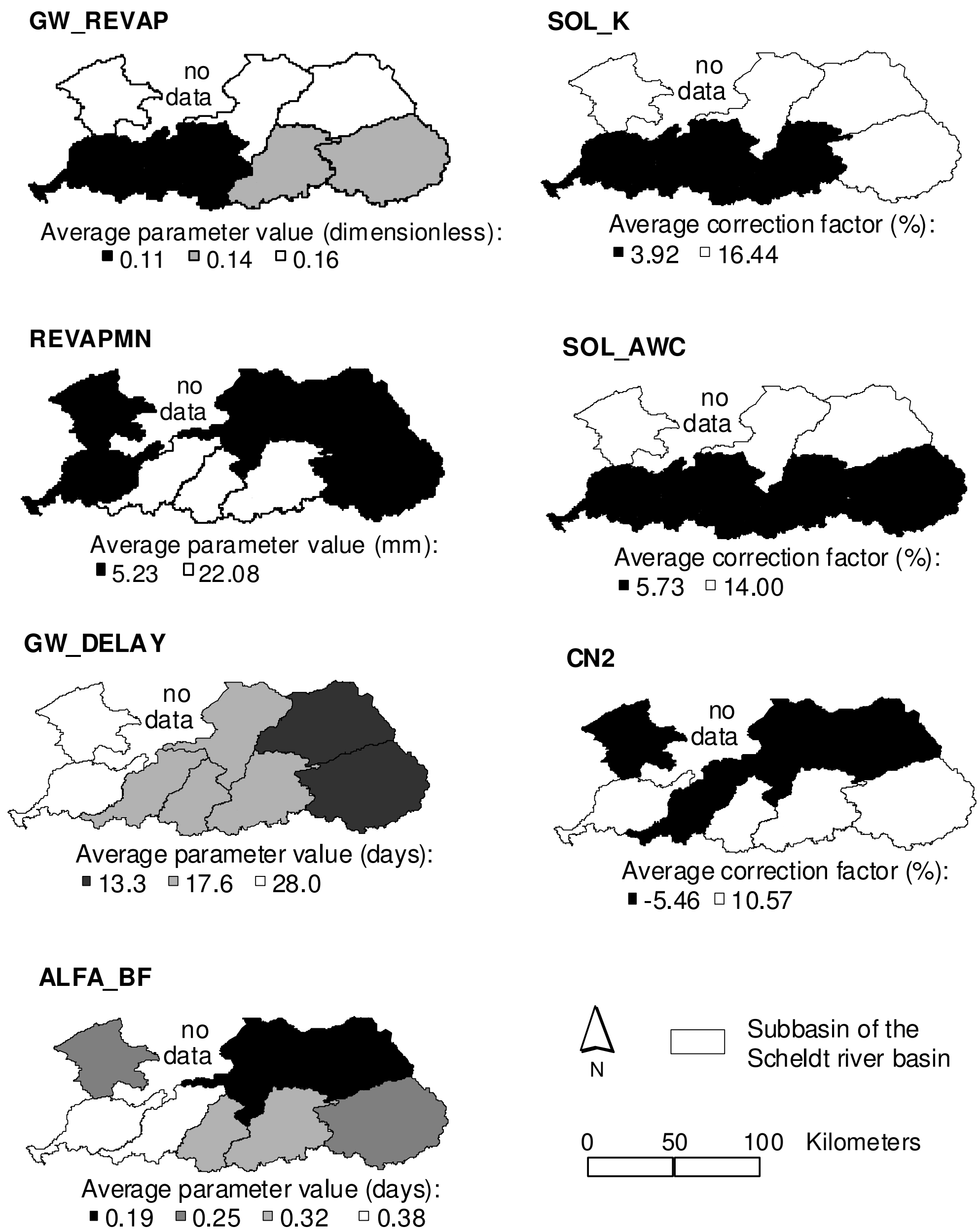


Fig. 22: Zones with a uniform parameter optimum delineated with the single parameter approach

The parameters GW_REVAP and REVAPMN, both controlling water movement between soil profile and shallow aquifer, show a north-south gradient. This means that water will more easily re-enter the soil profile through capillary forces in the north, probably because of the relatively shallow water table depth here. Besides, the larger GW_REVAP and smaller REVAPMN values in the north might be due to a difference in land use. More forested areas occur in the north, especially in the Nete and the Benedenschelde, having a greater rooting depth than other land use types and making it more likely that water from a shallow aquifer is lost by evapotranspiration. This last hypothesis is also supported by the fact that the catchments with a larger area under forest in the south (Demer and to a lesser extent Dijle), have relatively large GWREVAP and small REVAPMN values. Note that in contrast to climate or geology, land use does not always vary consistently between locations, consequently it is not unexpected that a regionalisation based on catchment attributes may outperform a location-based regionalisation as discussed in this paper.

The slow flow controlling parameters ALFA_BF and GW_DELAY both follow an east-west gradient. This pattern is hard to explain in physical terms. Because these parameters control water flow between the soil profile and the river system, they could be related to subsurface characteristics that are unknown to us at the moment. In this case, the location of a catchment can be considered as a proxy for these unknown features. One can therefore foresee that an attribute-based regionalisation would be less successful here than a location-based one.

In general, pedo-transferfunctions which are developed at the point scale have the tendency to underestimate soil hydraulic properties, probably because they do not consider the effect of heterogeneities like preferential flow paths affecting soil hydraulic behaviour at larger spatial scales. For the correction factors of the surface flow related parameters SOL_K, SOL_AWC and CN2 two different zones can be distinguished. The northern part of the study area is characterised by higher correction factors for the soil hydraulic features and a relatively small or even a negative correction factor for the Curve Number CN2. This spatial pattern can be understood as a difference in runoff generating mechanisms between the zones. In the northern part, soils have a high infiltration capacity so overland flow only occurs when soils are saturated whereas in the southern part, overland flow takes place more often.

Parameter set approach

The first and the second PCA axes explain respectively 58% and 31% of the variation in parameter optima, justifying the decision to interrupt the merging of parameter set clusters if the scores on the first or the second PCA-axis are not significantly different. **Fig. 23** depicts the three zones delineated following the parameter set approach. The average parameter optima for the three zones are given in **Table 11**.

Table 11: Average parameter optima for the zones delineated with the parameter set approach

Parameter	Zone I	Zone II	Zone III
GW_REVAP	0.15	0.1	0.12
REVAPMN	5	7	20
ALFA_BF	0.21	0.24	0.34
GW_DELAY	17	31	16
SOL_K	2.7	4.1	6.9
SOL_AWC	11	8	4
CN2	12	9	4

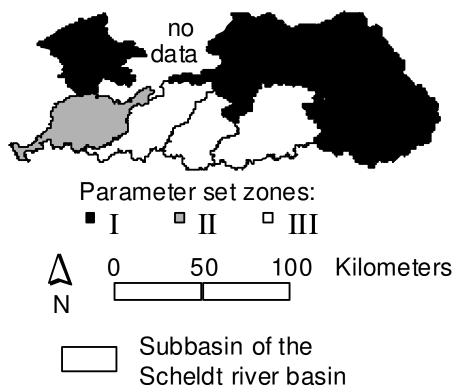


Fig. 23: Zones with a uniform parameterisation delineated with the parameter set approach

The results of the parameter set approach are more difficult to translate in physical terms than the single parameter analysis. The parameters set based zones roughly correspond with the north-south gradient that is observed for five out of seven model parameters in the single parameter approach, hence the parameter set based zones most probably have a physical basis comparable with the ones explained in the previous paragraph. This physical explanation refers to a catchment's abiotic properties, and does not directly relate to land use. According to the information in **Table 11**, zone I in the north and zone III in the South represent the extremes for most parameter values, whereas zone II that consists of only one Scheldt river subbasin i.e. the Leie subbasin, lies somewhere in between.

Comparing the performance of the single parameter and the parameter set approach

The performance of the two parameterisation strategies was evaluated by making four SWAT model runs for every study catchment: (1) with the local parameter optima (LOC); (2) with the region-wide average parameter optima (REG); and with the average parameter optima for the zones delineated with the (3) single parameter (SIN) and (4) parameter set (SET) approach. **Fig. 24** compares the model efficiencies for daily stream flow simulation.

Local parameter optima (LOC) outperform all other parameterisation strategies. Both zonation techniques (SIN and SET) deliver more effective parameter estimates than considering the entire study region as one single zone using the region-wide parameter optima (REG). This indicates that both zonation techniques deliver a useful scheme for the parameterisation of ungauged catchments within the Scheldt river basin. Considering the parameter set as a whole (SET) leads to more effective parameter estimates than a per parameter zonation (SIN), so the parameter set approach is the preferred technique in operational model applications. The better performance of the parameter set zonation can be explained by the fact that interactions between parameters are accounted for. On the contrary, the single parameter zonation did not take into account that the best performing value for one single parameter may depend on the value of the other parameters.

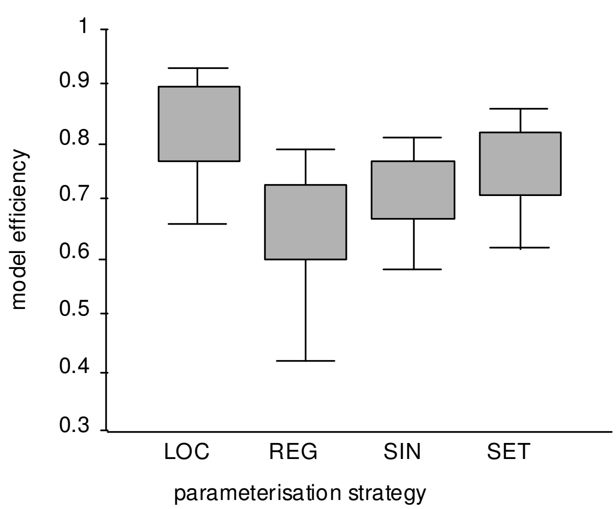


Fig. 24: Evaluation of the model efficiency for daily stream flow using four different parameterisation strategies: using local parameter optima for every catchment (LOC), using the region-wide average parameter optima (REG), and using the average parameter optima of the zones delineated with the single parameter (SIN) and the parameter set (SET) approach

Conclusion

For all calibrated model parameters, as well as for the parameter set as a whole, two to four zones with a uniform parameterisation were delineated. The observed spatial variation in parameter optima was sometimes hard to explain in physical terms, in particular for the parameter set approach. Nevertheless, the parameter set based approach delivered parameter estimates giving a higher model efficiency than the single parameter approach, which was easier to understand in physical terms. Therefore, if one wants to achieve a physically understandable and an effective parameter regionalisation, both zonation techniques should be applied independently and interpreted in combination. The results of the single parameter analysis can be helpful to understand and evaluate the outcome of the parameter set approach because these results might help to assess the physical soundness of the parameter set groups. The parameter set approach is preferred from an operational point of view: it results in a higher model efficiency.

The regionalisation schemes presented in this chapter can be used for two different purposes: (1) for large-scale simulations, they provide the means for a spatially distributed parameterisation and (2) to enable the estimation of parameters for large- or small-scale simulations of ungauged catchments. In both cases, the schemes can only be used for model applications within the Flemish part of the Scheldt river basin. In the next chapter, an attribute-based regionalisation will be proposed that can theoretically be applied outside the studied area. Moreover, the attribute-based regionalisation allows deriving parameter estimates for hypothetical scenarios, which is not possible with the location-based regionalisation.

IV.5 Attribute-based regionalisation of model parameters

Introduction

Previous chapter provided insight in the spatial variability of the parameters of the SWAT throughout Flanders. The delineated spatial zones corresponded to some extent with the spatial variation in catchment attributes. In an attribute-based regionalisation, parameters are directly linked to catchment attributes.

A careful selection of catchment attributes is a first condition for a successful parameter regionalisation. Most studies start from a preliminary list of attributes, based on expert knowledge, and conduct a correlation or a principal component analysis to select the most appropriate variables (e.g. Sefton and Howarth, 1998; Mwakalila, 2003). As mentioned by Seibert (1999), the type and number of the attributes that are used depend on the geographical scope of the study. In general, larger study areas show a greater variability in parameter optima, requiring a larger number of catchment attributes to explain that variability. Next to the geographical scope, the model structure, the time step and the objective of the simulation can also restrain the list of potentially useful catchment attributes. For example, stream flow characteristics may provide valuable information for parameter regionalisation if the main objective is to gain insight in the physical meaning of model parameters (Fernandez et al., 2000). For the prediction of flows under hypothetical or ungauged conditions, however, a regionalisation scheme that needs flow characteristics as inputs is useless.

When the most appropriate catchment attributes are identified, the regionalisation scheme can be formulated in either a discontinuous way, delineating zones within which parameters can be transferred without a significant loss in model performance, or in a continuous way, building a simple numeric model that calculates approximate parameter values given a set of catchment attributes. Kokkonen et al. (2003) mentioned that a simple transfer of parameters can outperform a continuous regionalisation, if catchments are hydrologically similar. Otherwise a continuous regionalisation can be useful. For constructing continuous regionalisation schemes, linear regression is by far the most utilised tool, despite its inability to cope with non-linearity and a high degree of interaction between model inputs and outputs. Artificial neural networks (ANNs) are more flexible model structures that can easily account for non-linearities and interaction effects (Lek and Guégan, 1999; Maier and Dandy, 2001). Because catchment attributes as well as model parameters are known to be interdependent, and because the relation between attributes and parameters is likely to be non-linear, an ANN is an interesting modelling structure for the regionalisation of model parameters.

This chapter discusses the regionalisation of the main controlling parameters of the SWAT model for the Flemish part of the Scheldt river basin (Belgium), based on a dataset of 25 catchments presented in chapter III. For the construction of the regionalisation scheme, linear regression is compared with feed-forward ANNs to evaluate whether the latter can improve the accuracy of parameter estimates. A bootstrap method is applied to assess the uncertainty on both regionalisation approaches. The results of these analyses can be useful for river flow simulations in ungauged basins, however, we will mainly interpret the results in function of the parameterisation of alternative land use scenarios as is often required in LCAs of agricultural or forestry systems. The aim of this study is to enhance the parameterisation of alternative land use scenarios in the SWAT model through a regionalisation procedure. Specific objectives are (1) to assess whether the non-physical parameters of the SWAT model are land use dependent, (2) to find the optimal way for deriving these parameters: regression or ANN, and (3) to estimate the uncertainty on the derived parameters and its effect on stream flow predictions.

Methodology

Model inputs and parameterisation

Data sources and calibration procedures were described in chapter III. The SWAT model was calibrated manually for the 25 catchments and afterwards the regionalisation scheme was derived. The manual calibration inevitably introduces subjectivity in the analysis. The parameter sets identified as optimal depend on the modeller's perception of the processes occurring in the catchment. Because many different parameter sets might result in an equally good model performance, one can expect that modellers having a different view on the model structure and on the prevailing hydrological processes can identify different 'optimal' parameter values. These different parameter values could lead to different though equally valid regionalisation schemes. In a regional calibration, the modeller's viewpoint is explicitly introduced in the regionalisation procedure. Fernandez et al. (2000) and Hundecha and Bárdossy (2004) for example, preferred to formulate the link between parameters and catchment attributes before model parameters are optimised, using this relation as an extra constraint during the calibration. This technique is supposed to facilitate the identification of parameter optima. Other authors took the opposite approach and tried to exclude subjectivity from the regionalisation by calibrating the model automatically (e.g. Parajka et al., 2005; Merz and Blöschl, 2004; Seibert, 1999). The approach in this study can be considered as a middle course between previous two viewpoints. The link between catchment attributes and model parameters was not formulated explicitly, but taken into account as 'soft' information in the manual calibration. Alternatively, soft information can be incorporated in a more explicit way, e.g. by using fuzzy measures for evaluating the agreement between parameter sets and qualitative expert knowledge (Seibert and McDonnell, 2002). In implicit as well as explicit considerations of soft information, the derived regionalisation scheme is one of the many possible schemes, namely the one lying the closest to the modeller's perception of the model structure and of the ongoing processes. So, validation of the regionalisation scheme on catchments that were not used for its construction also encompasses a test of the validity of the modeller's viewpoint.

Regionalisation of model parameters

As stated earlier, pedo-transferfunctions and the SCS Curve Number table can be considered as point or field scale regionalisation models for curve numbers and soil hydraulic parameters. These small scale regionalisation schemes were used to get a first approximation of parameter values. The deviation of the optimal parameter values from the ones predicted with pedo-transferfunctions or curve number tables was related to catchment attributes. Curve numbers and soil hydraulic parameters are typically defined at the field scale. This analysis should reveal the change in physical meaning of these parameters when they are applied at larger spatial scales i.e. at the catchment scale. Moreover, the analysis should improve the estimation of soil hydraulic parameters and curve numbers in the catchment scale model SWAT. For the four slow flow related parameters, no small scale relationship was available; therefore the absolute values of these parameters were regionalised.

The interdependence of model parameters implies that the regionalisation scheme for a certain parameter should depend on the scheme for the correlated parameter(s). In the construction of the regression equations, these interdependencies were taken into account by using the correlated parameters as input variables. In the ANNs, the correlation between model parameters was accounted for by using one network structure with multiple output nodes. A correlation analysis of model parameters was performed to identify the correlations that must be reflected by the regionalisation schemes. The non-parametric Spearman rank correlation coefficient was used because this coefficient can detect non-linear associations.

A preliminary list of catchment attributes that could be used as inputs for the regionalisation schemes was composed based on the available data and the physical meaning of the model parameters. The following factors were considered: catchment morphology and physiography, land use including the spatial distribution of land use within a subcatchment, texture of soil profile and substrate and the depth at which the shallow aquifer occurs (**Table 12**).

Table 12: Definitions and minimum and maximum values of catchment attributes for the 25 study catchments

Catchment attribute	Definition	Min	Max
Surface	Catchment area (km²)	2.24	209.93
Slope	Average slope of the catchment (%)	0.18	2.81
Drainage density	Length of rivers and drainage channels per unit area (km/km²)	0.57	1.75
Elongation	The ratio of the diameter of a circle having the same area as the catchment, to the catchment length	0.52	1.02
Forest	% of the area covered with forests, urban land use, pastures and arable land	0.36	43.05
Urban		7.21	24.66
Pasture		13.15	44.29
Arable land		22.93	61.31
Forest buffer	% of the area in a 100 m buffer surrounding the stream network, covered with forests, urban land use, pastures and arable land	0.6	53.17
Urban buffer		0	46.01
Pasture buffer		11.07	52.64
Arable buffer		0.6	65.93
Shallow aquifer	% of the area with a permanent aquifer at <2m depth	0	33.15
Clay subsoil	% of the area with a clay/sand substrate at <2m depth	0	29.9
Sand subsoil		0	16.68
Loam	% of the area with loam/clay/sandy loam/ sand as topsoil texture	0	92.17
Clay		0.01	14.32
Sandy loam		2.08	85.38
Sand		0	80.38

Before constructing the regionalisation schemes, data were rescaled to [-1; +1]. ANNs and regression equations were constructed stepwise to find the optimal amount and combination of input variables. For the ANN-based schemes, the popular feed-forward neural network was used, consisting of three layers: the input layer, one hidden layer and the output layer.

Assume m input nodes, l output nodes and n hidden neurons. The mathematical formulation of the feed-forward neural network is then as follows:

$$O = W_{H,O} * \tanh(W_{I,H} * I + \beta) \qquad \textit{Eq. 9}$$

With O : vector of output variables ($\in \Re^{l}$)

I : vector of input variables ($\in \Re^{m}$)

β : bias vector ($\in \Re^{n}$)

$W_{H,O}$: matrix of the weights between hidden and output layer ($\in \Re^{l \times n}$)

$W_{I,H}$: matrix of the weights between input and hidden layer ($\in \Re^{n \times m}$)

The amount of hidden nodes was assessed according to the guidelines of Rogers and Dowla (1994). Considering our relatively small dataset, three hidden nodes can be used if the number of input variables is equal to or less than four. Increasing the number of input variables and/or hidden nodes could lead to overtraining of the neural network.

Parallel to the ANN, a regression-based scheme can mathematically be represented as:

$$O = I * W_{I,O} + \beta \qquad \textit{Eq. 10}$$

With O : vector of output variables ($\in \Re^{l}$)

I : vector of input variables ($\in \Re^{m}$)

β : bias vector ($\in \Re^{l}$)

$W_{I,O}$: matrix of the weights between input and output layer ($\in \Re^{m \times l}$)

Uncertainty on the regionalisation schemes

The regression equations and the ANNs contain weights or parameters[†] ($W_{I,O}$, $W_{I,H}$ and $W_{H,O}$) that have to be optimised. These weights carry some degree of uncertainty, i.e. the relationship between catchment attributes and parameters is rather fuzzy. Our objective is to assess the uncertainty on these weights and propagate this uncertainty to the parameter estimates and finally to the simulated stream flow regime. So the uncertainty discussed in this paragraph, does not cover all potential sources of uncertainty in a hydrological model. Amongst others, it does not consider in a direct way the uncertain nature of the parameter

[†] From this point on, the term ‘parameter’ will be reserved for the parameters of the SWAT model, the term ‘weight’ will be used for the regionalisation models

optima. Parameter values deviating from the optimum can still give a good model performance. Thus if the evaluation of the regionalisation scheme is solely based on the comparison of predicted and optimal parameter values, one risks an unjust rejection of a regionalisation scheme. This problem can be avoided by explicitly considering the uncertainty on model parameters in the construction of the regionalisation scheme, as demonstrated by Merz and Blöschl (2004), or by focussing on the accuracy of the simulated stream flow instead of on the parameter estimates. This second approach is followed in this study. The uncertainty on the ANN-based and the regression-based regionalisation approach was quantified through a non-parametric bootstrap method. From the 25 catchment areas, five were completely excluded from the construction of the regionalisation schemes and were only used to evaluate the outcome. Two of these validation sites represent average conditions (in terms of parameter optima and catchment attributes) for the dataset, two others lie close to the extremes and one catchment possesses characteristics outside the range appearing in the dataset used for the construction of the regionalisation schemes. This choice of validation sites allows a thorough evaluation of the regionalisation schemes. Possible overtraining of the schemes, especially of the ANNs, should in this way be revealed.

From the 20 calibration sites, 100 bootstrapped samples are taken. One sample contains 18 catchments i.e., their catchment attributes and parameter optima. The sample size had to be large enough to allow the optimisation of the weights of the regression equations and ANNs. On the other hand, more than one catchment had to be excluded from each sample to enable the generation of a considerable amount of different samples. A sample size of 20 catchments only gives one possible combination (the entire data set). With a sample size of 19, 20 different combinations can be drawn. Finally, a sample size of 18 results in 20*19/2 = 190 possible combinations, from which 100 were at random selected. Weights were optimised for every sample i.e. for every combination of 18 catchments, resulting in 100 regionalisation schemes. As a consequence, for a given set of catchment attributes, 100 parameter estimates can be derived. This range gives an idea of the uncertainty inherent in the regionalisation scheme, and allows assessing which procedure, ANN or regression, has the largest degree of uncertainty.

Results and discussion

Construction of the parameter regionalisation schemes

To facilitate the comparison of ANNs and regression, the catchment attributes that serve as inputs were forced to be the same for the ANN as well as for the regression regionalisation procedure. The best performing schemes obtained with the stepwise procedure were as follows (see **Table 6** for parameter definitions):

- GWREVAP = f(REVAPMN, slope, shallow aquifer, %forest, %sand)
- REVAPMN = f(GW_REVAP, slope, shallow aquifer, %forest, %sand)
- GW_DELAY = f(slope, clay subsoil, shallow aquifer)
- ALFA_BF = f(elongation, shallow aquifer, slope)
- SOL_K = f(SOL_AWC , slope, %forest)
- SOL_AWC = f(SOL_K ,slope, %forest)
- CN2 = f(drainage density, %forest in buffer area)

Linear regression versus ANN: non-linearity in parameter regionalisation

Fig. 25 shows the linear and non-linear regionalisation schemes projected in two dimensions. For the soil hydraulic parameters, the outcome of the linear and non-linear approach is very similar. For the other parameters, the two schemes deviate for extreme values of the catchment attribute. Such a non-linearity can be understood as a threshold or a saturation effect: the attribute must exceed a certain threshold to affect the parameter optimum, or the effect of the attribute on the parameter slows down at extreme attribute values. Take for example the parameter controlling water transfer between shallow aquifer and soil profile (GW_REVAP). An increase in forest cover leads to a higher parameter value following the regression- and the ANN-based scheme, but the ANN-based scheme predicts that above a certain threshold, the rate of this increase will decline. Hence afforestation is expected to promote the water movement from the shallow aquifer to the soil profile. But in regions that already have a considerable area under forest the effect of further afforestation reduces. One possible explanation is that the water table declines after afforestation, so that the return of water to the root zone becomes less probable. The schemes for groundwater delay (GW_DLAY) predict larger parameter values the larger the area with a clayey subsoil, but this effect is only visible if the % of the area with a clay subsoil exceeds a certain threshold. A possible explanation is that water can easily circumvent small areas with a clay subsoil. Because the obstacle can be bypassed, it has little effect on the delay time.

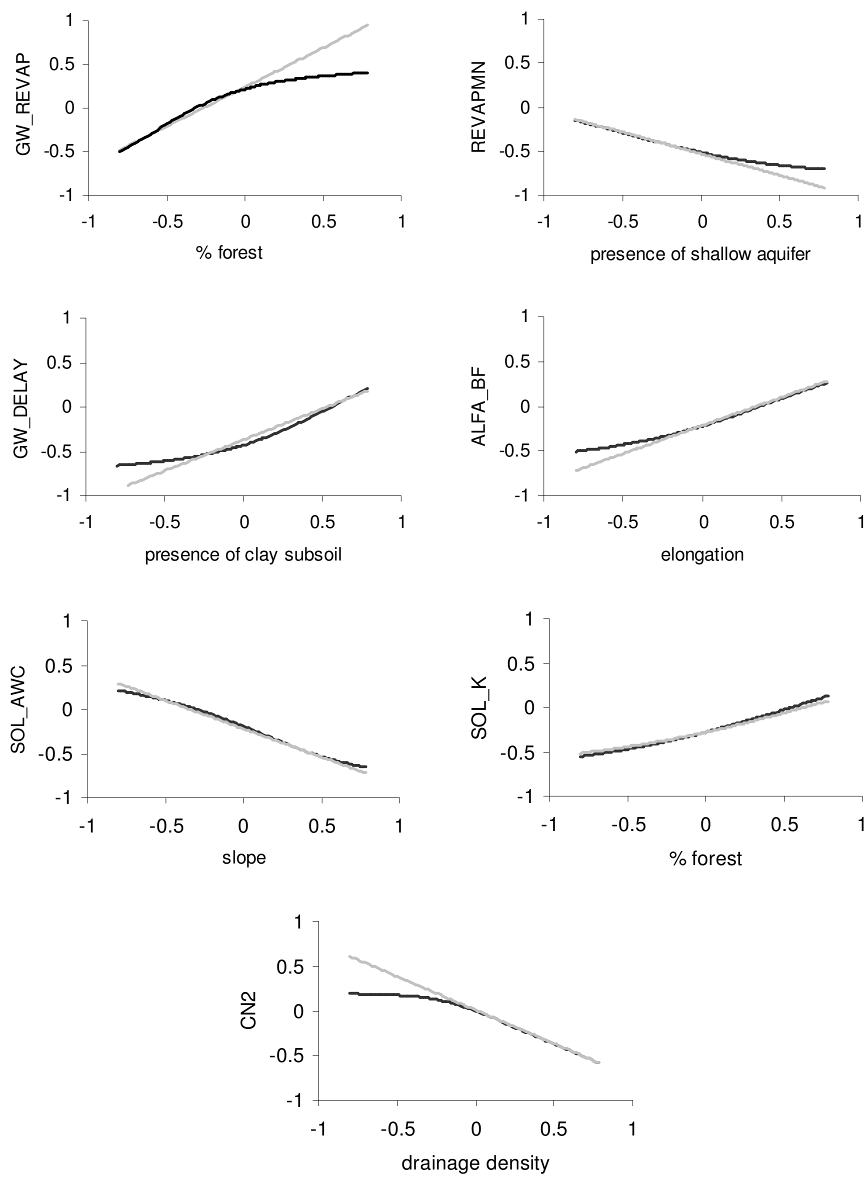


Fig. 25: Non-linear and linear regionalisation functions projected in two dimensions. All catchment attributes are set to their average value, apart from the one with the highest influence on the regionalised parameter. Parameters and attributes are rescaled to [-1;1]

Similar non-linear structures can be detected in the ANN-derived schemes for the threshold value REVAPMN, the recession constant ALFA_BF and the curve number CN2. The physical meaning of this non-linearity is unclear for the recession constant ALFA_BF. For the threshold value REVAPMN, the non-linearity can be interpreted as follows: the larger the area with a shallow water table, the smaller the volume of water that is needed before revap will occur i.e. before water can migrate from the shallow aquifer to the soil profile. But if the catchment area with a shallow water table is already large, the threshold value will approach the absolute minimum, zero, and because of that, the rate of decline will slow down. The non-linear behaviour of the curve number at low drainage densities can be due to the fact that the tabulated curve numbers are most appropriate for catchments with little or no artificial drainage. The tabulated curve numbers can be used without adjustment for drainage density in 'natural' catchments. In artificially drained catchments, correction factors are necessary.

Fig. 26 addresses the question whether the non-linear relationships lead to more accurate parameter estimates. This figure compares the parameter estimates obtained with linear regression and ANN with locally optimised parameter values. **Table 13** presents the R^2 of the regionalisation schemes for both the calibration and the validation sites.

Table 13: Accuracy of the parameter estimates for the linear regression-based and the ANN-based regionalisation scheme

Parameter:	**R^2 calibration (n=20)**		**R^2 validation (n=5)**	
	regression	**ANN**	**regression**	**ANN**
ALPHA_BF	0.58	0.55	0.55	0.53
GW_REVAP	0.63	0.72	0.49	0.61
REVAPMN	0.61	0.64	0.58	0.56
GW_DELAY	0.41	0.52	0.34	0.49
SOL_AWC	0.54	0.56	0.51	0.48
SOL_K	0.56	0.53	0.57	0.50
CN2	0.61	0.76	0.58	0.74

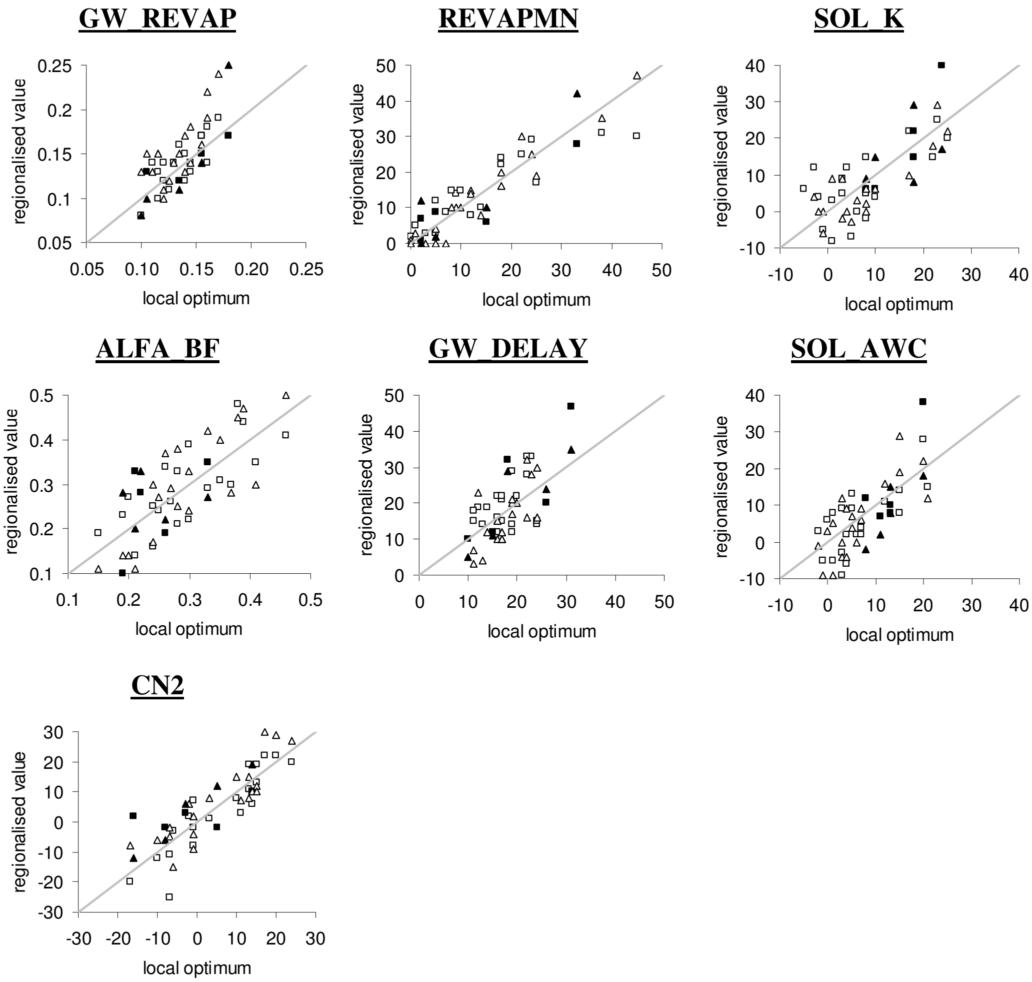


Fig. 26: Accuracy of parameter estimates obtained by regionalisation through ANNs (squares) and linear regression (triangles). White symbols indicate calibration sites, black symbols indicate validation sites

There is no technique that is preferred under all circumstances, for all catchments and for every parameter. Nonetheless three general trends can be detected in **Fig. 26**: (1) for some parameters, ANN outperforms regression analysis: the highest or lowest parameter values are over- or underestimated by regression and modelled adequately by an ANN, this is the case for parameters showing a physically understandable non-linearity e.g. groundwater delay (2) for other parameters, ANN and regression perform equally well and (3) in some cases, ANNs tend to do worse than regression analysis at sites with parameter optima and/or catchment attributes outside the range of optima and/or attribute values at the calibration sites.

The ANN- and regression-based regionalisations produce a similar result for REVAPMN and ALFA_BF. Based on the difference between ANN and regression depicted in **Fig. 25**, an underestimation of the lowest threshold values (REVAPMN) by the regression technique, and thus a relatively better performance of the ANN, could be expected. Though the threshold value for water transfer between soil profile and shallow aquifer (REVAPMN) parameter bears an extra constraint. It cannot drop beneath zero, therefore negative predictions are set to zero and no underestimation of this parameter can be detected. For the two soil hydraulic parameters, the linear and non-linear regionalisation schemes are very similar. As a consequence there is no notable difference in the predicted parameter values of the linear and non-linear scheme, apart from one outlier for the non-linear one. For groundwater delay (GW_DELAY), there also is one clear outlier for the non-linear scheme. All three outliers mark a catchment in the north of the study area, with parameter optima and catchment attributes that lie outside the range from the ones of the calibration sites. This suggests that ANNs have only a limited capability to extrapolate outside the range they are trained for. The validity of regression is also harmed under these conditions, but the resulting error remains smaller.

The comparison of the regionalised parameters with the optimal ones is a good starting point for the evaluation of the regionalisation schemes, but the accuracy of the flows simulated with these regionalised parameters is a more relevant indicator. This is presented in **Fig. 27** and **Fig. 28** respectively for yearly and daily stream flow. The regionalisation schemes lead to the most accurate flow simulations for the Molenbeek (ID = 18 in **Table 3**) and the Lombeekse beek (ID=14). These catchments are close to the average situation of the study region, in regard to their catchment attributes as well as their parameter optima. Moreover, these two catchments, located in the south of the study area, are characterised by a relatively small model error. The use of regionalised parameters results in a deviation of the simulated yearly quick flow of 12.7% and 7.51% in the Molenbeek catchment and 12.1% and 8.1% in the Lombeekse beek catchment for the regression and the ANN based scheme respectively. While ANNs produce a slightly better result for quick flows, the difference in performance between ANNs and regression for slow flows is small. This trend is also visible in the daily flows: peak flows deviate wider from the observed flows, in absolute and relative terms.

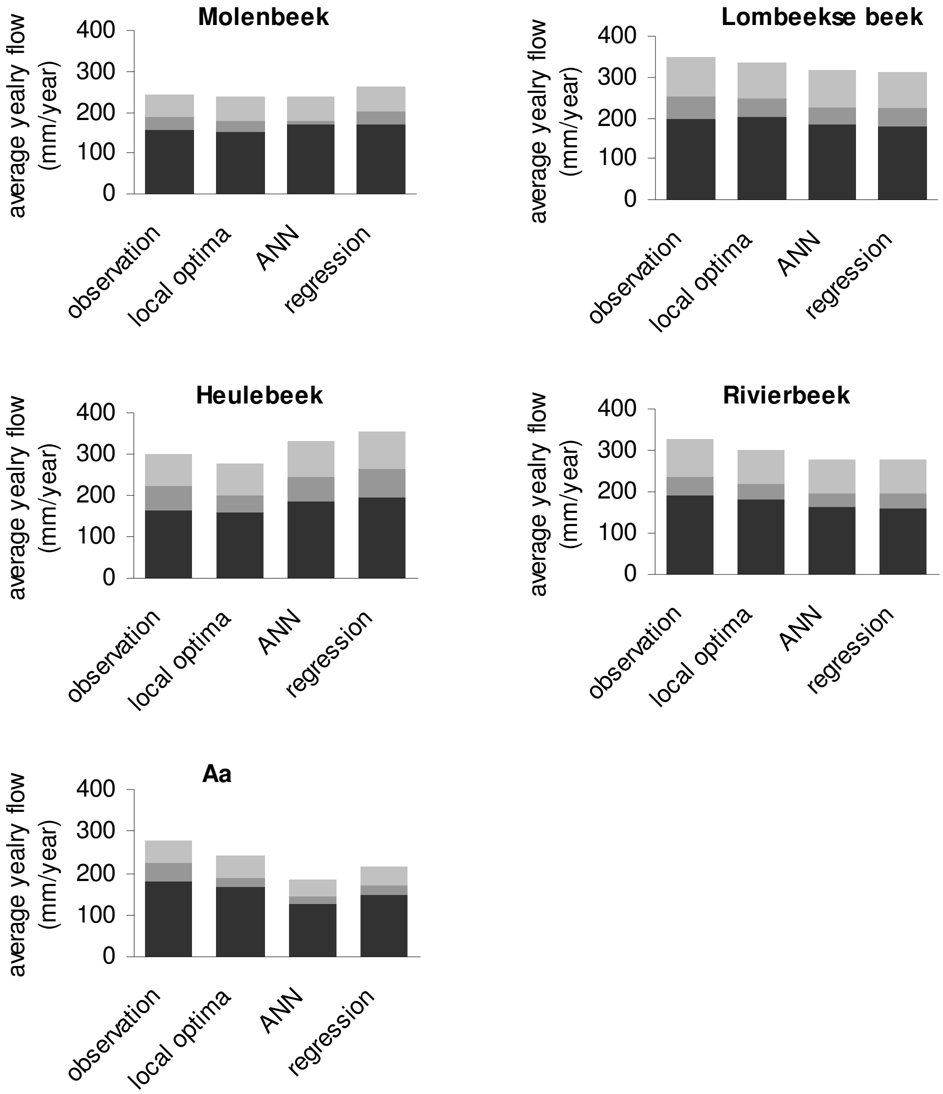
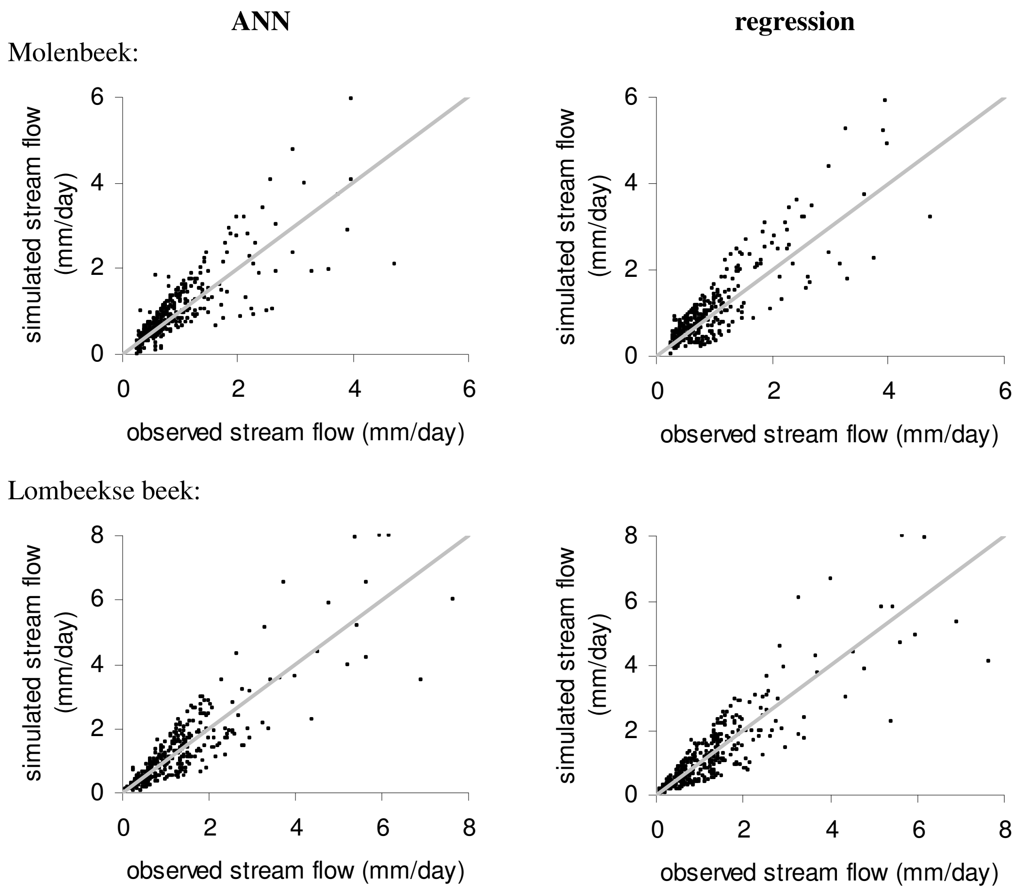


Fig. 27: Average yearly flow observations versus simulated average yearly flow components obtained with local parameter optima and parameters regionalised with linear regression and ANNs (■ slow flow ■ inter flow ■ quick flow). Results for the validation catchments.

In the Heulebeek (ID = 22) and the Rivierbeek (ID = 7) catchments, the difference in performance between ANN and regression is more pronounced, with ANN as the best option. The deviation of the simulated and observed average yearly slow flow becomes more important: 16.8% and 14.2% for the regression and ANN based schemes respectively in the Rivierbeek catchment, 12.4% and 17.4% for the Heulebeek. The deviation of the quick flow is comparable to the one for the Molenbeek and Lombeekse beek. The attributes and parameter optima for the Heulebeek and the Rivierbeek are still within the range of attributes and parameter optima of the calibration sites, but the model error is higher than in the Molenbeek/Lombeekse beek. The fifth validation site, the Aa catchment (ID = 25) lies outside the calibration range for attributes and parameters. The Aa is situated in the north of the study area and the model error for this catchment is relatively large. Slow flow simulation is more problematic than the simulation of quick flow, in accordance with this, the low flows are clearly underestimated using the regression based and especially when using the ANN-based regionalisation scheme.



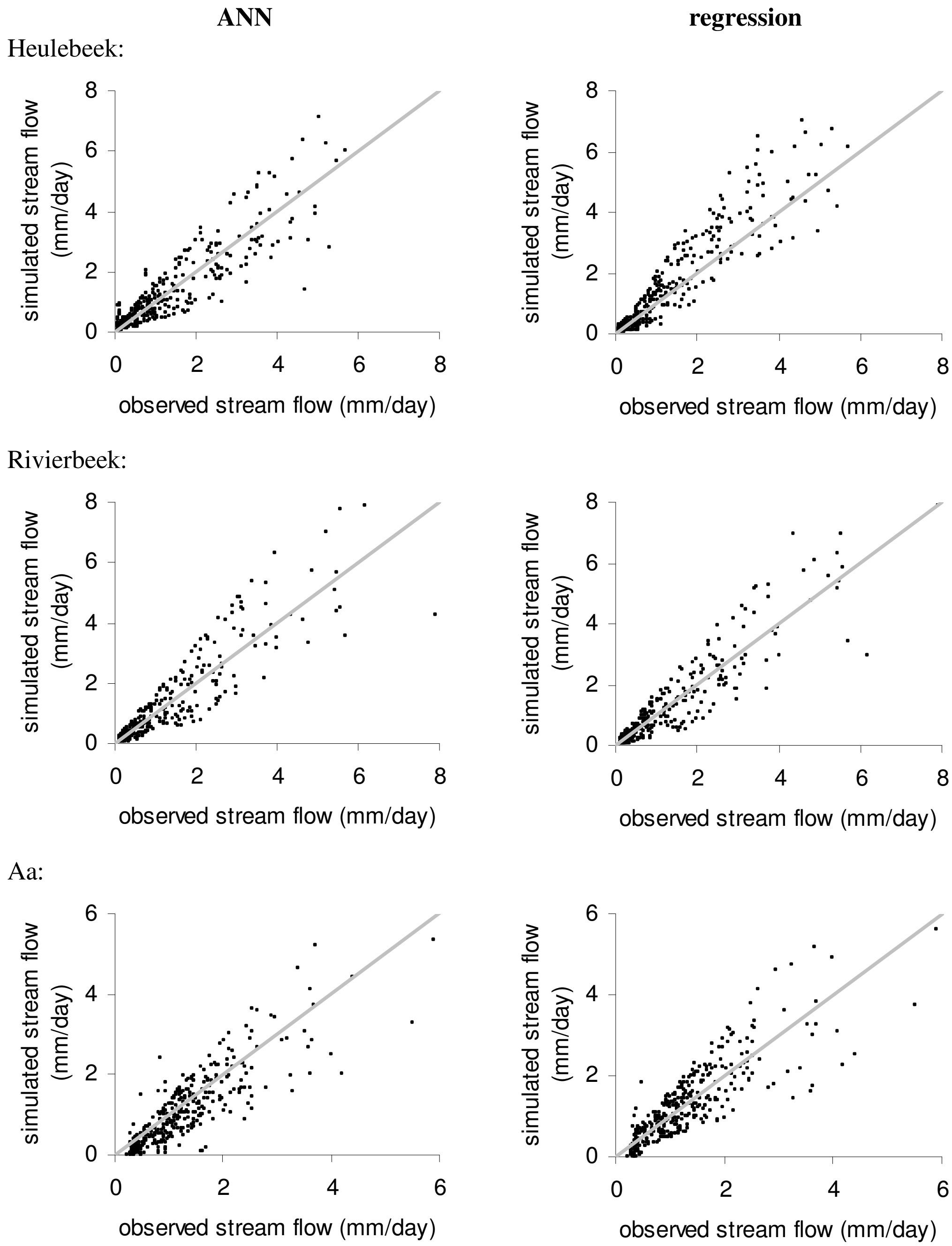


Fig. 28: Observed daily stream flow versus simulated daily stream flow using two different parameter regionalisation schemes. Results for the validation catchments for the year 2001

In general, the analysis suggests that the performance of a regionalisation scheme at a given site is proportional to the model error at that site (see also **Fig. 27**). If slow flow simulation is more problematic, the use of regionalised parameters yields an inaccurate low flow simulation; if quick flow simulation is problematic, the use of regionalised parameters leads to erroneous peak flow predictions. This implies that a high model performance for the catchments used for the construction of the regionalisation scheme is of vital importance for a successful regionalisation. Next to this, the range of situations wherefore the regionalisation scheme is valid should be determined. **Table 14** provides an approximate validity range based on the variation in parameter optima in the calibration data set and on the results of the validation tests. This range should be evaluated and refined by applications in other catchments. If the parameter values predicted with the regionalisation models lie within this range, these are likely to deliver reasonable simulations. Extrapolations outside this range should be avoided, but if absolutely necessary, simple linear regression seems to be the preferred technique here. A linear simplification is also preferred for non-linearities in the data set that have no physical meaning. Non-linearities that can be understood in physical terms can better be modelled with an ANN, as this can improve the accuracy of the parameter estimates.

Table 14: Approximate validity range for the regionalisation schemes

Parameter	Minimum	Maximum
ALPHA_BF	0.2	0.4
GW_REVAP	0.11	0.19
REVAPMN	0	40
GW_DELAY	12	30
SOL_AWC	-2	18
SOL_K	-5	23
CN2	-12	24

Uncertainty in parameter regionalisation

The uncertainty on the model parameters, expressed as the difference between minimum and maximum relative to the average of the 100 bootstrapped estimates, varies between 15% and 30% (**Table 15**). The uncertainties on the ANN-based schemes are in most cases larger than the uncertainties on the regression based schemes, a consequence of the larger number of weights for the ANNs. The larger uncertainties on slow flow related parameters compared to the quick flow related ones are due to the same reason: the schemes of the slow flow related parameters take more attributes into account. There is one notable exception: for the parameter controlling the rate of water transfer between soil profile and shallow aquifer

(GW_REVAP), the ANN results in a narrower uncertainty range than the regression equation. A possible explanation is the relatively large degree of non-linearity of the ANN-based scheme, as can be seen in **Fig. 25**. Because of this, the linear approximation is subject to a greater variability.

As with the evaluation of non-linearities, comparing the uncertainty on regionalised parameters is a good starting point for the evaluation of the two regionalisation schemes, but the uncertainty on the flows simulated with these parameters is of primary interest. The last record of **Table 15** presents the average interval width of the simulated daily flows. These values are relatively small compared to the uncertainty for the parameter estimates. The propagation of uncertainties on inputs through the SWAT model is not straightforward: the effect of the uncertainty on one parameter depends on the value of other parameters and model inputs. A detailed discussion of this uncertainty propagation process lies beyond the scope of this discussion. The most important outcome of this process is that, despite the large uncertainty on the model parameters, the uncertainty on the simulated flows remains limited.

Table 15 : Average width of the interval for the parameter estimates and the daily stream flow derived by applying a bootstrap method to the ANN-based and the linear regression-based regionalisation schemes

	Average width (%) of the interval for parameter estimates regionalised with:	
Parameter	**ANN**	**regression**
GW_REVAP	17	25
REVAPMN	22	19
GW_DELAY	24	23
ALFA_BF	30	27
CN2	21	18
SOL_K	21	19
SOL_AWC	19	15
Average width of the interval for the simulated daily stream flow (%)	**22**	**18**

Fig. 29 and **Fig. 30** compare the observed stream flow values with the range that is predicted with the bootstrap method respectively for a yearly and a daily time step.

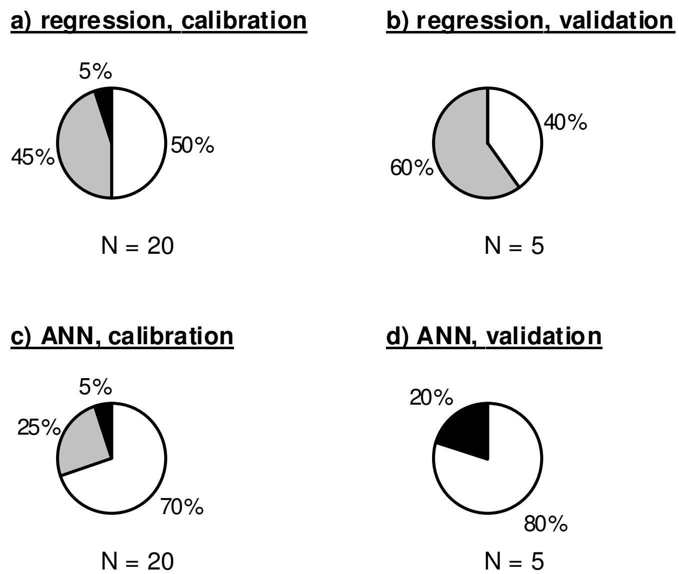
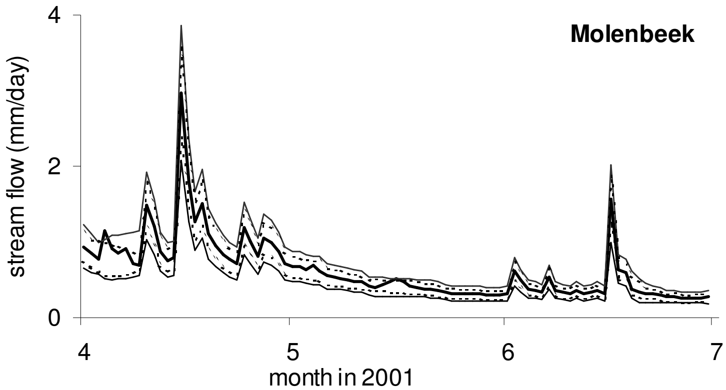
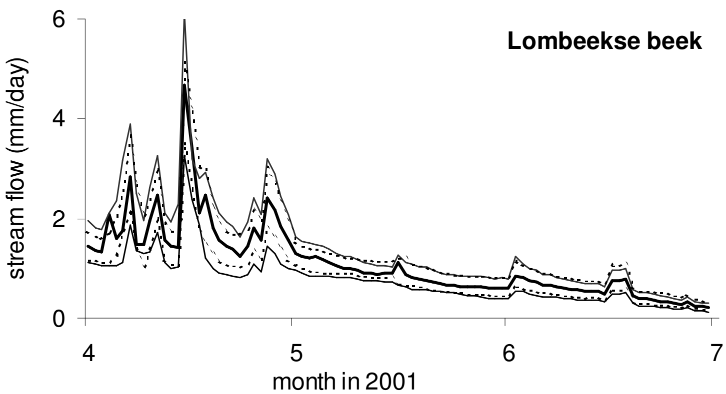


Fig. 29: Proportion of the validation and calibration catchments that have an observed average yearly stream flow in the interquartile range (□), in the predicted range but outside the interquartile range (■) and out of the predicted range (■) of the simulated average yearly stream flows obtained by applying a bootstrap method to the ANN- and regression derived regionalisation schemes

At the calibration sites, the predicted intervals with the ANN are more accurate than the ones predicted with linear regression. One catchment lies outside the range of the predicted model output for both schemes: the Schijn catchment in the north, a very densely artificially drained area. The model error is among the highest in our study region, what partially explains why the regionalised parameter values do not deliver an acceptable model fit. For the regression-based scheme, relatively more calibration sites lie outside the interquartile range (i.e. between the 25th and 75th percentile or not considering the 25% highest and 25% lowest predictions). Two possible reasons are that ANN-derived intervals are broader, and/or that the regression based intervals are less accurate. At the validation sites, one catchment lies outside the predicted range by the ANNs, this is the Aa catchment that also received inaccurate regional parameter estimates. For the regression, all validation catchments lie within the predicted range, but three out of five are outside the interquartile range. These correspond with the catchments that give the worst model fit for both regionalisation schemes: Heulebeek, Rivierbeek and Aa.


Molenbeek
stream flow (mm/day)
0
2
4
4
5
6
7
month in 2001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stream flow (mm/day)
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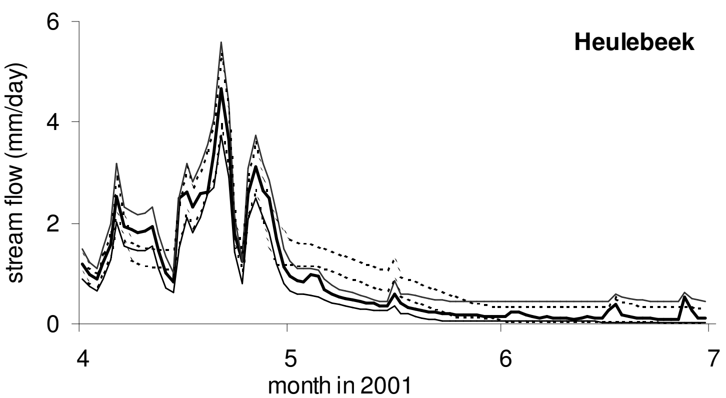
Heulebeek
stream flow (mm/day)
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month in 2001

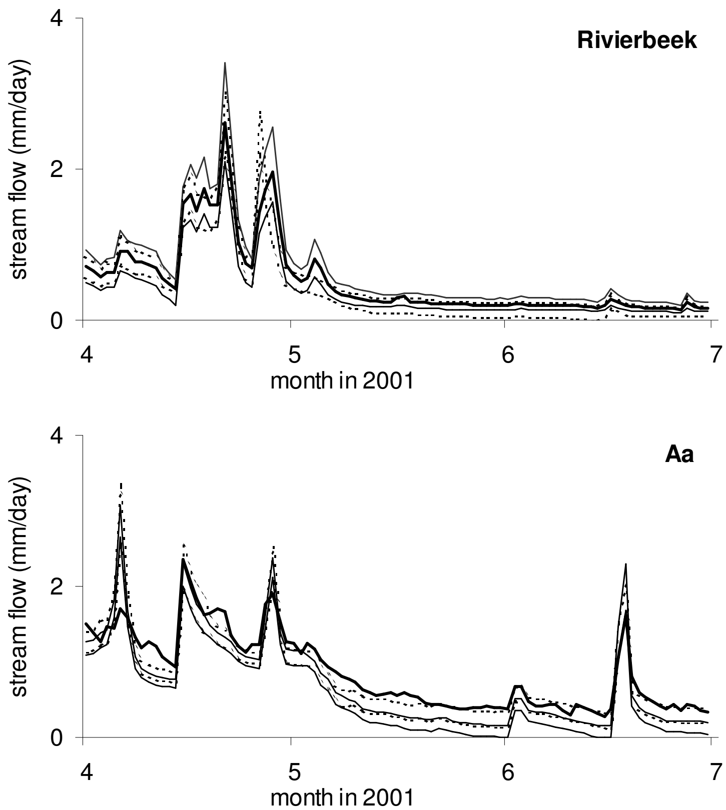

Fig. 30: Uncertainty bounds on the simulated daily stream flow derived by applying a non-parametric bootstrap method to the ANN-based (full line) and regression-based (broken line) based regionalisation scheme. Results for the validation catchments for a representative period of three months, april-june 2001. Observed stream flow is indicated in bold.

Comparable conclusions can be drawn for the uncertainty on the simulated daily flows, presented for a representative period of 3 months in **Fig. 30**. Regression-based bounds, that are generally smaller than the ANN-derived interval, capture the observed values most of the time, apart from some peaks and some low flow periods for the Aa, the Molenbeek and the Heulebeek. For the ANNs, longer periods do not fall within the predicted range for the Aa catchment, in particular during low flows.

Implications for the modelling of land use impact

In the past, regionalisation was typically applied in the context of stream flow predictions in ungauged basins, but it could also be used for the prediction of stream flow under hypothetical land use scenarios. Most land use impact modelling studies focus on crop related parameters like LAI (leaf area index), stomatal conductance, plant height etc. Crop related parameters mainly affect the simulated amount of evapotranspiration, and this effect propagates through the model structure to changes in all components of the hydrological cycle. Parameters that cannot directly be related to land use type are usually assumed unaffected by land use, despite that these may directly control the rate and the nature of hydrological processes that depend on land use. The slow flow related parameters of the SWAT model are an example of these.

The SCS curve number is an example of a process controlling, not strictly crop related, parameter that has been 'regionalised' for field scale applications. Land use is one of the factors that determine the tabulated curve number values. Our analysis indicates that the spatial organisation of land use plays an important role in the upscaling of curve numbers. If the SWAT model is applied in a semi-distributed mode, the spatial organisation of land use or soils within a subcatchment is not considered. This might be unimportant for model parameters other than CN2, therefore one might expect that neglecting the spatial arrangement of land use will not significantly affect the simulated slow flow volumes. If quick flow is an important flow component, accounting for the spatial organisation of land use, by adopting a fully distributed modelling approach or by adjusting curve number values, might enhance model parameterisation and the accuracy of the simulated flow components.

For the upscaling of soil hydraulic properties from point to catchment scale, the results of pedo-transferfunctions should be adjusted for the land use in the catchment. The presence of roots and zones with a higher degree of soil compaction is land use related, and can cause preferential flows and so affect water redistribution. From a theoretical point of view, soil hydraulic properties should therefore be adjusted when simulating the impact of land use. This chapter provides a way for the implementation of this theory in practical model applications, in the form of a parameter regionalisation scheme. These schemes are useful for modelling new equilibrium situations attained a considerable period after land use change. However, regionalisation schemes do not allow to simulate catchment hydrology during land use transition, i.e. before an equilibrium is reached.

Conclusion

It is demonstrated that land use plays an important role in the regionalisation of model parameters. Five out of seven model parameters could be related to land use, so that it can be concluded that regionalisation has the potential to improve the quality of studies simulating the impact of alternative land use scenarios on catchment hydrology. The most suitable technique depends on the goal of the study and the model under consideration. Linear regression is the most commonly used tool, but ANNs may provide a useful alternative in some cases, in particular if the non-linear relationship between parameters and catchment attributes can be physically understood. On the other hand, one should be careful with the use of non-linearities that have little physical meaning. Parameter optima are rather fuzzy and different parameter optima might exist, so that the detected non-linear trend might be due to the parameter optimisation process. In a linear as well as a non-linear approach, the parameter regionalisation scheme bears a considerable degree of uncertainty. This uncertainty, quantified with a non-parametric bootstrap method, lies between 15% and 30% for all parameters and regionalisation techniques. The uncertainty on the stream flow simulated with these regionalised parameters is about 20%.

IV.6 A comparison of parameter regionalisation strategies

By combining the results of previous chapters, the usefulness of the following six different parameter regionalisation strategies can be compared and discussed:

1. use of the default values provided by the SWAT i.e. the baseline scenario
2. use of average parameter optima for the entire study region
3. linking parameters to catchment attributes with multiple linear regression
4. linking parameters to catchment attributes following a non-linear scheme
5. delineating zones with a uniform parameterisation: parameter-per-parameter analysis
6. delineating zones based on the parameter set as a whole

Results

The linking of parameters to catchment attributes by non-linear models results in the highest average model efficiency for daily stream flow simulation. It is the best performing regionalisation strategy for 40% of the catchments, followed by the linear attribute-based regionalisation (24%). The delineation of zones based on the parameter set as a whole is the preferred regionalisation strategy for almost 25% of the catchments under study. Parameter set zones deliver the best result for 8% of the catchments. The use of default parameter values leads to inaccurate predictions, as demonstrated earlier. Region-wide average parameter values deliver a better result than defaults, but slow flow simulation remains problematic. Long-term average flows are generally better reproduced than daily flows, especially for the poorest performing regionalisation strategies. Hence at first sight the errors due to the simple parameter estimation strategies do not accumulate over time.

Discussion

Default settings versus more advanced parameter regionalisation strategies

At the beginning of this chapter (**Fig. 17**) the problems arising from the use of default parameter values for Flemish catchments were discussed. For the northern part of our study area, slow flow was overestimated with default settings. This was mainly due to an inadequate parameterisation of the revap process i.e. the transfer of water between shallow aquifer and root zone. The amount of revap was underestimated with default parameter values, hence evapotranspiration volumes were underestimated and too much water was diverted to the river network as slow flow. Because the attribute-based regionalisation schemes express the revap parameters as a function of the presence of a water table at shallow depth, slow flow simulation is considerably enhanced. The zones delineated in the single parameter and the parameter set approach more or less coincide with this catchment attribute, explaining why these strategies also lead to accurate slow flow predictions.

Default model settings delivered acceptable predictions of total flow volumes for catchments in central Belgium, but the timing and the steepness of slow flow recessions was incorrect. As a consequence, the efficiency for modelling stream flow prediction was acceptable but the efficiency for daily stream flow prediction was rather poor. The attribute-based regionalisation models take the shape of the catchment and subsoil properties into account for the estimation of GW_DELAY and ALFA_BF, two parameters that influence slow flow recession. This considerably improves the accuracy of daily stream flow simulation.

Attribute-based versus location-based regionalisation of model parameters

In our study, the attribute-based regionalisation performed slightly better than the location-based regionalisation. This conclusion is opposite to the findings of Merz and Blöschl (2004) and Parajka et al. (2005): in their case-study a location-based regionalisation delivered more accurate predictions than an attribute-based model. One possible explanation is that these authors used a conceptual hydrological model, which does not have a clear physical basis. So the relative performance of different parameter regionalisation methods seems to be application-specific. The model structure, the objective of the study and the characteristics of the study area can affect the outcome.

Model structure. The SWAT model has a clear physical basis; most model parameters relate to one distinguishable hydrological process. Parameters of conceptual models often are lumped representations of several real-world processes. One can imagine that such lumped parameters are more difficult to relate to catchment attributes because they may depend on many attributes. Moreover, the effect of one attribute may depend on the value of others. These problems also arise for the parameter of the SWAT, but to a lesser degree. In case of the SWAT, an attribute-based regionalisation can be pictured as a one-to-many projection, with one process that has to be linked to many attributes. Similarly, an attribute-based regionalisation of conceptual parameters can be presented as a many-to-many projection, with many processes (jointly represented by one parameter) that have to be linked to many attributes. The latter is far more complex than the one-to-many projection, and consequently less likely to yield an operational parameter regionalisation model.

Objectives of the model application. Attribute-based and location-based regionalisation models differ with respect to their potential fields of application. For estimating model parameters at ungauged sites within the study area, both techniques can be used. However, the location-based model is easier to use: it doesn't require any additional inputs whereas for the attribute-based scheme, the inputs need to be derived from (easily available) spatial data. Next to the parameterisation of ungauged basins within the study area, regionalisation schemes can be used to represent the spatial variability in parameter optima in a semi-distributed model application. When a model is applied in semi-distributed mode, non-measurable parameters are often assumed spatially invariant for the sake of simplicity and because data for a semi-distributed parameter specification are lacking. Regionalisation models can be used to derive parameter estimates for ungauged subbasins in this case, leading to a better implementation of the semi-distributed modelling concept. As in previous example, the location-based regionalisation is better suited for this field of application than the attribute-based approach; it does not only provide parameter estimates for a given catchment discretisation, but it also indicates which zones have significantly different parameter optima. In other words: it can serve as a guideline for determining an appropriate level of catchment discretisation.

The major advantage of the attribute-based regionalisation is that it can also be used outside the conditions wherefore it was constructed. For example, it can be used to estimate model parameters for alternative land use scenarios or for the modelling of ungauged basins outside the studied area. Of course, the reliability of the regionalisation schemes is questionable for conditions that lie outside the range of the conditions of the catchments used for the construction of the schemes. For example, for modelling the impact of climate change, attribute-based schemes must be derived for a larger area, covering the future climate that one would like to model. Parameter regionalisation schemes are known to perform rather poor if applied in catchments with climatic conditions that are under-represented in the dataset used for the construction of the regionalisation model (e.g., Abdulla and Lettenmaier, 1997).

Characteristics of the study area. The northern part of Belgium is a very heterogeneous region in many aspects. There is a wide variety of soil types, not only between the catchments but also within one catchment. Almost all land use types occur in every part of the studied region albeit in different proportions. Consequently, it is hard to divide the region in subregions with unique (hydrological) features. Parameter optima vary significantly over short distances and at the same time, one parameter set may suit several distinct locations within the region. This might explain why a location-based regionalistion model is less successful than an attribute-based model for our case-study.

Conclusion

Based on a data set of 25 small catchments within the Scheldt river basin, attribute-based and location-based regionalisation strategies were derived. Comparison of the model efficiencies for these different regionalisation strategies pointed out that attribute-based regionalisation is the preferred regionalisation strategy for most catchments. However, the difference in model performance between attribute-based and location-based schemes is small. Both strategies perform considerably better than the use of region-wide average values or the use of SWAT defaults. The latter technique still delivers an acceptable model behaviour in the central part of Belgium, but tends to overestimate slow flow volumes for catchments located in the north, east, and west of the study area. Therefore it can be concluded that default parameters do not fit Flemish conditions. The use of a more advanced parameter regionalisation strategy, either based on location or on catchment attributes, is recommended. The exact nature of the best performing parameter regionalisation strategy (linear attribute-based, non-linear attribute-based, single parameter zones and parameter set zones) depends on the objective of the study, the characteristics of the study area and the model structure. In the context of LCAs of land-intensive systems, the non-linear attribute-based regionalisation is preferred because this method delivers effective parameter estimates and it can be used to estimate parameters for hypothetical land use scenarios.

Chapter V: Impact evaluation*

In previous chapters, indicators reflecting the hydrological impact of agricultural and forestry production systems were proposed and a method was outlined to calculate these indicators with the SWAT model. Predictions made with a hydrological model such as SWAT are known to bear a considerable degree of uncertainty. It is thus necessary to perform a thorough evaluation of the predicted hydrological impact of land use systems. Therefore, this chapter discusses predictive uncertainty, with a focus on how it can be controlled by model users. The main objective is to assess the significance of the simulated stream flow response to land use change, which is elaborated for a case-study involving an afforestation in the Zwalm river basin.

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*Chapter V is adapted from:
Heuvelmans, G., Muys, B., Feyen, J. Reducing the predictive uncertainty of a hydrological model by constraining model inputs via landscape attributes. Submitted.
Heuvelmans, G., Muys, B., Feyen, J. Simulating the stream flow response to afforestation: relative importance of scenario uncertainty. Submitted.

V.1 Perspectives for minimising the predictive uncertainty of a hydrological model

Introduction

Predictions of hydrological models are known to bear a high level of uncertainty limiting the potential advantages of these models for LCA practitioners and policy makers. Reducing the uncertainty level could greatly improve the usefulness of hydrological models for real-life applications (e.g., Ewen and Parkin, 1996; Bathurst et al., 2004). To this end, we should gain insight in the different factors that contribute to this uncertainty, including the relative importance of these factors.

In general, two different sources of uncertainty are distinguished: (1) uncertainties or errors in the model structure and (2) uncertainty in the estimation of input variables and parameters (Uhlenbrook et al., 1999). Uncertainties in the model code can be due to a lack of knowledge about the hydrological processes occurring in the catchment, or to computational limitations encountered when turning process knowledge into computer code. In operational applications, one often utilizes one of the many available hydrological models. In this case, selecting a model structure that optimally matches the studied catchment can reduce model uncertainty (Wagener et al., 2001). Next to model uncertainty, input variables and parameters produce a second source of uncertainty. This is caused by errors and uncertainties of model input and output measurements and problems with identifying appropriate parameter values for a given set of input-output pairs. Input and parameter uncertainty can more easily be assessed and (to some extent) controlled by the user than model uncertainty in practical model applications.

The analysis presented in this chapter focuses on parameter and input uncertainty. In the following, the term 'parameter uncertainty' will be used to indicate the uncertainty due to model parameters as well as input variables. In case of a physically based hydrological model, parameter uncertainty refers to uncertainty due to weather data, land use parameters, soil parameters and non-measurable parameters like curve numbers. This study considers the latter three: soil, land use and non-measurable parameters in an application of the SWAT model.

In the past, discussions related to parameter uncertainty mainly focused on non-measurable parameters, because model users believed that measurable parameters (soil, land use or others) were not or only to a lesser extent uncertain. Nevertheless, because of measurement errors, spatial and temporal variability of parameters and scale effects – parameters that are measured at another scale than the one at which they operate in the model – these 'measurable' parameters might even become more uncertain than non-measurable ones. Hence an uncertainty assessment that only considers non-measurable parameters might underestimate the uncertainty on the model outcome.

More recently, the contribution of measurable parameters to predictive uncertainty is gaining attention. For example, Eckhardt et al. (2003) investigated the contribution of land use parameters to the uncertainty on stream flow predictions for the semi-distributed model SWAT-G. The authors concluded that the error on the average stream flow volume caused by the parameterization of land use can amount up to 10%. Christiaens and Feyen (2002a) and Anderton et al. (2002) calculated the uncertainty due to soil parameters respectively for the MIKE SHE and for the SHETRAN model. Soil hydraulic parameters caused a considerable uncertainty on the model output in both studies.

One compelling question is how uncertainty can be reduced without harming the reliability of the uncertainty assessment. Additional experimental data could help to put extra constraints on parameter estimates and so decrease the uncertainty on the model outcome (Uhlenbrook and Sieber, 2005). This can be implemented in various ways. One possibility of particular interest in land use impact studies is to further constrain soil and non-measurable inputs based on land use or other landscape properties. Wahl et al. (2003) suggested that a change in land use might alter soil hydraulic properties such that a considerable change in the stream flow volume can occur, especially during high flow periods. This suggestion is somewhat in contradiction with the findings of Huisman et al. (2004), who did not detect a significant influence of the changes in soil properties due to a land use transition on the predicted water balance terms. The relationship between non-measurable model parameters and land use and other catchment properties is, for example, illustrated by Hundecha and Bardossy (2004). Non-measurable parameters of the SWAT model have also been linked to catchment attributes, with land use as an important explanatory variable for some parameters (see chapter IV.5).

The objectives of this study were (1) to assess whether extra constraints like a land use specific quantification of soil parameters and uncertainty bounds for non-measurable parameters that are based on catchment attributes affect predictive uncertainty, (2) to compare the reduction of predictive uncertainty by the use of extra parameter constraints with the uncertainty reduction after including stream flow observations, and (3) to quantify the contributions of land use, soil and non-measurable inputs to the uncertainty on low, average and peak flows at a daily and a monthly time scale. The model under consideration is the semi-distributed hydrological model SWAT. The model was applied to the Zwalm catchment (Table 3, ID = 4), a tributary of the Scheldt draining an area of 114 km². The results should give insight in the way model users can control the uncertainty on the predictions by the way input data are gathered and assimilated.

Materials and Method

Study area and model inputs

The Zwalm catchment was selected as a study site for the assessment of predictive uncertainty. Daily stream flow was registered at the outlet and at two internal stations by the Flemish Environmental Administration (AMINAL). The available stream flow time series cover the period 1985-2001 for the catchment outlet, 1991-1996 for the internal station on the main reach draining an area of 31 km² and 1995-1996 for a second internal station on a tributary channel with a drainage area of 2 km². General information about input data can be found in chapter III. This paragraph explains how uncertainty ranges for parameter values were established.

To assess the impact of additional data on the magnitude of the uncertainty and on the relative importance of different soil, land use and non-measurable inputs, two different input ranges were defined: the *initial range* representing the overall variation in input values throughout Flanders, and *extra constraints* accounting for the impact of land use and other landscape properties.

For calculating the initial range for soil inputs, a soil classification based on soil texture was used. Five soil types were considered: sand, loam, sandy loam, loamy sand and clay. Using the Aardewerk database, the pedo-transferfunctions and regionalised correction factors (chapter IV.5), initial ranges were calculated for all parameters and soil types. A reclassification of soil types based on texture and land use was conducted to put extra constraints on the parameter values. The considered land use classes were forest, pasture and arable land. Theoretically this leads to 15 soil types, however, the number of soil types was limited to 10 because not all land use/soil texture combinations were present. New parameter ranges were then calculated for the reclassified soil types.

Initial ranges for non-measurable parameters were derived from the manual of the SWAT model and/or from the overall variation in parameter values from earlier SWAT applications in Northern Belgium (**Table 10**). Extra constraints were introduced based on parameter regionalisation models (see chapter IV). These regionalisation models include a bootstrap procedure, so that the parameter is not presented as a point estimate but as an interval. Moreover, the regionalisation models allowed considering the spatial variability of the non-measurable parameters: parameter ranges were calculated per subbasin.

Intervals for plant attributes were obtained from PlaPaDa (Plant Parameter Database, Breuer et al., 2003). The database queries were limited to literature sources from north-western Europe. Parameter values for forests relate to mixed, deciduous and pine forests. For arable land, parameter values represent crops occupying at least 5% of the area of arable land in the catchment. In theory, crop parameters are constrained by soil type; for example, the maximal height and LAI for a given crop are expected to be soil-dependent. In practice however, hard data about this relationship between crop and site characteristics are missing, so that it is at this moment not feasible to translate this qualitative understanding into reliable quantitative constraints on crop attributes. Consequently, for plant parameter values, no extra constraints were considered in this study.

Assessing predictive uncertainty with GLUE

The uncertainty on stream flow predictions was investigated with the General Likelihood Uncertainty Estimation (GLUE) procedure developed by Beven and Binley (1992). GLUE starts from the idea that many different parameter sets may deliver acceptable model behaviours, a phenomenon known as the equifinality of parameter sets. The parameter space is sampled and a likelihood measure is calculated for each parameter set. The likelihood measure reflects the correspondence between the model output obtained with that parameter set and observations. A threshold value for the likelihood measure is applied to come to a subset of parameter sets that are behavioural i.e. that result in an acceptable match between observed hydrological variables and model output. The probability distribution of the model outputs generated by the behavioural parameter sets is calculated, with the probability level of each sample proportional to its likelihood. The resulting uncertainty range is thus based on the agreement between simulation and observation. This level of agreement not only depends on the sampled parameter sets but also on errors and simplifications in the model structure. Consequently, the uncertainty calculated with GLUE reflects the total uncertainty inherent in using a hydrological model instead of directly measuring stream flow.

Applications of GLUE entail a number of subjective choices that might influence the outcome of the analysis. The sampling strategy has to be specified, including the number of samples and the assumed distribution of model inputs. A likelihood measure must be selected as well as cut-off criteria for identifying behavioural parameter sets. To keep the analysis manageable for complex hydrological models, it is often limited to the most sensitive model parameters. The choice of inputs to be included in the analysis may also bring subjectivity into GLUE.

It was decided to limit the GLUE analysis to 15 model inputs: five plant attributes, five soil attributes and five non-measurable parameters. These inputs were selected after a one-way sensitivity analysis of all relevant model parameter values (chapter III). The number of simulations was set to 10000. To ensure that this number did not significantly underestimate uncertainty, the width of the uncertainty intervals after 10000 simulations was compared with the interval width after 7500 simulations. The difference in interval widths was lower than 2%, so it can reasonably be assumed that maximal uncertainty is approached after 10000 samples.

The parameter space was sampled with the Latin Hypercube technique (McKay et al., 1979), a stratified sampling method. Parameters were assumed to be uniformly distributed and for a given parameter, the values for different subbasins, soil types and soil horizons were assumed to be correlated. Therefore, one value between 0 and 100 was sampled for every parameter, representing the relative position of that parameter for all locations (subbasins, soil types and soil horizons) within the location specific range. The likelihood of each parameter set was evaluated as the weighted-average Nash and Sutcliffe (1970) model efficiency for daily stream flow for the three gauging stations with weights proportional to the length of the stream flow records. Likelihood values below 0.6 were considered non-behavioural.

If GLUE were applied to ungauged basins, likelihood values could not be calculated hence the uncertainty should then be estimated from all sampled parameter sets. This may cause considerably wider uncertainty bounds on the model output. To assess to what extent the absence of stream flow data influences the width of the uncertainty bounds, the uncertainty was calculated using only the behavioural parameter sets (as one would do in a gauged catchment) and using all parameter sets (as if the catchment were ungauged). For both cases predictive uncertainty was calculated with initial and with extra input constraints. By comparing the uncertainty for all simulations with the extra input constraints and the uncertainty for the behavioural simulations with initial input constraints, we were able to evaluate which kind of data – stream flow records or input data – had the largest potential to reduce predictive uncertainty.

Identifying sources of parameter uncertainty

Empirical modelling techniques such as regression analysis are often used to mimic or complement complex environmental models for analyzing sensitivity, uncertainty or goodness-of-fit (e.g., Christians and Feyen, 2002b; Abebe and Price, 2003; Knightes and Cyterski, 2005). In this study, linear regression as described in Neter et al. (1996) was applied to evaluate the relative contribution of soil, land use and non-physical inputs to the uncertainty on the 5th, 50th and 95th percentile of daily and of monthly stream flow records.

First, a full model was built for every of the six studied percentiles:

$$Y_i = \beta_0 + \beta_1 * X_{i1} + \beta_2 * X_{i2} + ... + \beta_{15} * X_{i15} + \varepsilon_i \qquad \text{Eq. 11}$$

with i the simulation number (between 1 and 10000), Y_i the % deviation of the simulated percentile with parameter set i from the percentile with the highest likelihood value, X_{i1} to X_{i15} the deviation of the 15 input values for set i from the values of the parameter set with the highest likelihood value, β_0 to β_{15} regression coefficients and ε_i the error term. Then three reduced regression models were built for every studied percentile (1) with the regression coefficients of the five soil inputs X_{soil} equal to zero; (2) with the regression coefficients of the five land use attributes X_{luse} equal to zero; and (3) with the regression coefficients of the five non-measurable inputs $X_{nonphys}$ equal to zero. Coefficients of partial determination were calculated measuring the marginal contribution of one group of inputs to predictive uncertainty.

As an example, the coefficient of partial determination for land use was calculated as:

$$R^2_{luse} = \frac{SSR(X_{luse} \mid X_{soil}, X_{nonphys})}{SSE(X_{soil}, X_{nonphys})} \qquad \textit{Eq. 12}$$

$$SSR(X_{luse} \mid X_{soil}, X_{nonphys}) = SSE(X_{soil}, X_{nonphys}) - SSE(X_{soil}, X_{nonphys}, X_{luse}) \qquad \textit{Eq. 13}$$

with SSE the error sums of squares and SSR the regression sums of squares. The coefficient of partial determination for an input group is a measure for the explanative value of that group for the stream flow percentile under consideration.

The complete analysis was conducted four times for daily and monthly aggregated values respectively using all samples or only the behavioural samples and for the initial and the extra input ranges.

Results

Initial and constrained input parameter ranges

Table 16 lists the names of the 15 inputs included in the GLUE analysis and the definitions of the parameters that were not discussed in previous chapters.

Table 16: Name and definition of the 15 model parameters considered in the uncertainty assessment

	Parameter	Definition
Non-measurable parameters	GW_REVAP (dimensionless)	See **Table 6**
	REVAPMN (mm)	See **Table 6**
	ALPHA_BF (days)	See **Table 6**
	GW_DELAY (days)	See **Table 6**
	CN2 (dimensionless)	See **Table 6**
Soil parameters	SOL_AWC (mm water/mm soil)	See **Table 6**
	SOL_K (mm/hour)	See **Table 6**
	SOL_CBN (% soil weight)	Organic carbon content
	SOL_BD (g/cm³)	Bulk density
	SOL_Z (mm)	Depth of soil layer
Land use parameters	BLAI (dimensionless)	Maximum leaf area index
	CHTMX (m)	Maximum canopy height
	RDMX (m)	Maximum root depth
	GSI (m/s)	Maximal stomatal conductance
	T_BASE (°C)	Minimum temperature for plant growth

Table 17 gives a general overview of the reduction in the considered input parameter ranges with the introduction of extra constraints in the form of a land use specific soil classification and a regionalisation model linking non-measurable inputs to catchment attributes.

Table 17: Average, minimal and maximal reduction of the width of the parameter intervals after the inclusion of extra parameter constraints

Parameter	**% reduction in parameter interval width**		
	Average	**Minimal**	**Maximal**
GW_REVAP	39	37	41
REVAPMN	34	30	39
ALFA_BF	23	20	27
GW_DELAY	21	18	25
CN2	29	25	33
SOL_AWC:			
Upper soil horizon	48	45	53
Entire profile	27	10	53
SOL_K:			
Upper soil horizon	45	39	50
Entire profile	25	12	50
SOL_CBN:			
Upper soil horizon	53	51	58
Entire profile	28	14	58
SOL_BD:			
Upper soil horizon	41	36	48
Entire profile	24	11	48
SOL_Z:			
Upper soil horizon	42	40	46
Entire profile	32	19	46

The largest reduction in parameter interval width appears for the properties of the upper soil layers. Simulations with the extra constraints take into account that the upper horizons of soils under forest or pasture have higher carbon contents, lower bulk densities, higher saturated hydraulic conductivities and larger available water capacities than agricultural soils. These assumptions are in line with the available literature on the impact of land use on soil properties (e.g. Sonneveld et al., 2003). Moreover, agricultural soils are assumed to have a thinner uppermost soil horizon. This led to a reduction of the interval width for these properties of about 50%. The average effect of extra parameter constraints is less pronounced because this effect is much smaller for deeper soil horizons (**Table 17**: ‘upper horizon’ versus ‘entire profile’).

The major changes caused by the extra parameter constraints for the non-measurable parameters arise for the parameters controlling 'revap' i.e. water movement between the shallow groundwater table and the root zone. The extra parameter constraints take into account that the water table in the Zwalm catchment is out of reach of roots in large parts of the area, leading to lower GW_REVAP values and higher REVAPMN values. Minimal and maximal reductions do not differ much because the variables used by the regionalisation models are more or less uniform throughout the study area.

Selecting behavioural parameter sets

Each of the 15 graphs in **Fig. 31** shows the likelihood values for all simulations in function of one input parameter. In total, about 40% of the parameter sets are behavioural i.e. have a weighted average model efficiency for the three stream flow gauging stations larger than 0.6. For some parameters, the samples seem almost randomly distributed over the plot. For others, an optimal parameter range can be distinguished. The term 'optimal' is used here to indicate that simulations with superior likelihood values (>0.8) all occur within that range, however, not all simulations belonging to the 'optimal' range lead to superior likelihood values; many of them may even be non-behavioural. Moreover, behavioural albeit not superior likelihood values can occur outside the optimal range. Following this terminology, optimal parameter ranges can be delineated for two crop attributes (maximal LAI and rooting depth), all five soil attributes and all five non-measurable parameters. From these input parameters, GW_REVAP catches the eye: this is the only parameter having a clear range with a very limited amount of non-behavioural simulations. Consequently, in our model set-up this parameter can be considered as the overall most sensitive model parameter.

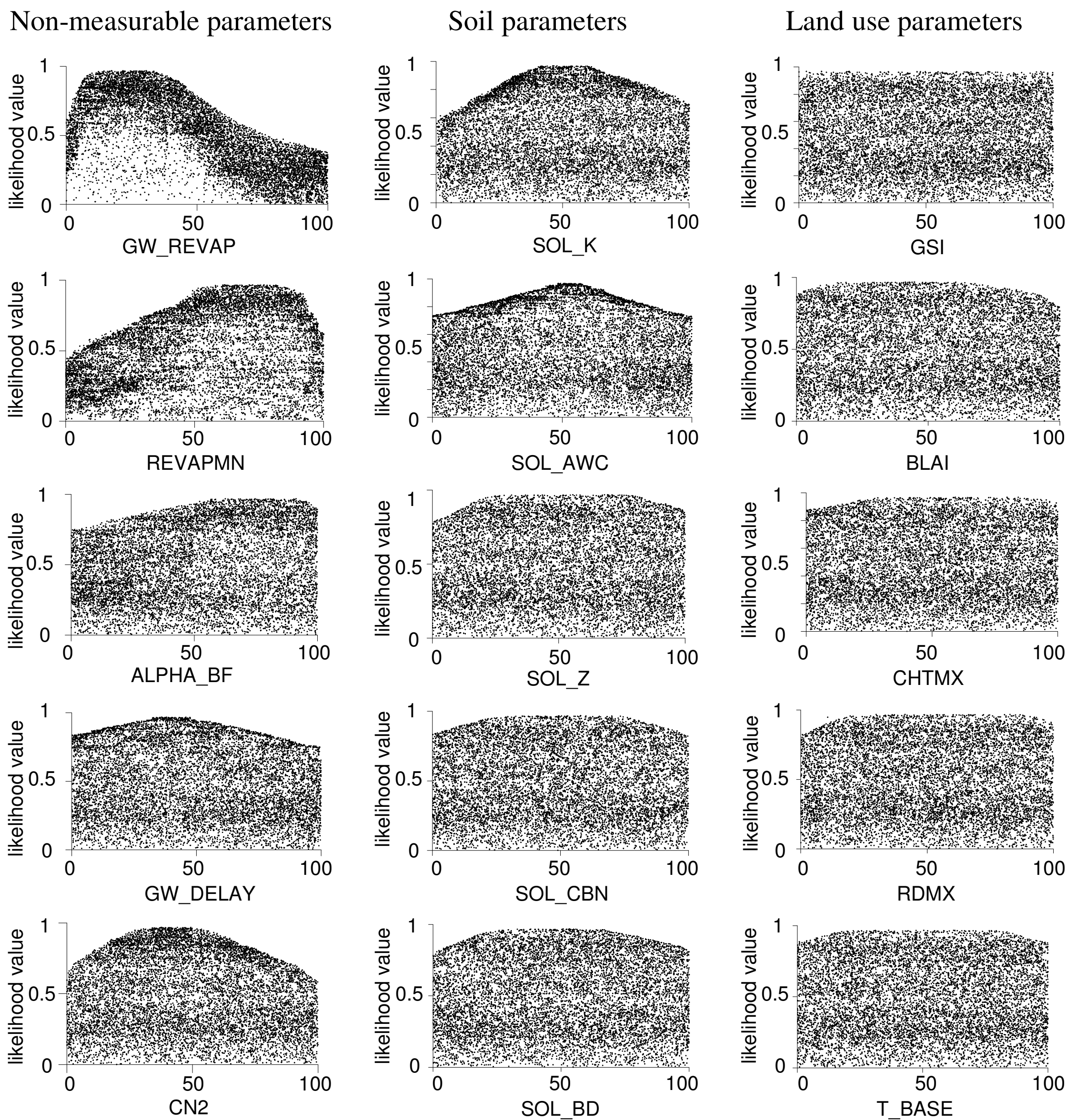


Fig. 31: Likelihood values of the 10 000 SWAT simulations in function of each of the 15 considered input variables. Values of input variables are rescaled to 0 – 100

Apart from the maximal LAI and rooting depth, the model seems relatively insensitive to crop attributes. Almost all considered values for crop attributes are equally likely to result in a behavioural model simulation. This implies that the introduction of extra crop input constraints is not really meaningful. Besides that it is practically not feasible, as explained earlier, it will most probably not increase the average likelihood value of the sampled parameter sets. For most soil and non-measurable inputs, an optimal parameter range can be identified. As a consequence, the initial ranges for non-measurable and soil inputs leave room for improvement.

Fig. 32 shows that the introduction of the extra constraints for soil and non-measurable inputs increases the share of behavioural simulations from 39% to 53%. This indicates that the newly introduced parameter ranges are not only physically sound, but also effective from an operational point of view. After all, the non-behavioural parameter sets can cause an additional but unnecessary widening of the uncertainty bounds in GLUE applications in ungauged catchments (when cut-off criteria cannot be applied). In this case, it is assumed that a larger uncertainty on the model inputs widens the uncertainty bounds on the model output. Moreover, it is assumed that the eventual reduction of the uncertainty bounds on the model output still captures the observed stream flow regime. To check these two assumptions, we should take a closer look at the predictive uncertainty.

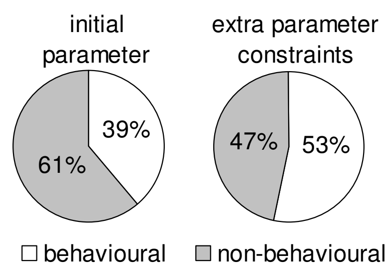


Fig. 32: Proportion of behavioural and non-behavioural parameter sets for the initial samples and for the samples including the extra parameter constraints

Predictive uncertainty assessment

Fig. 33 demonstrates the 95% uncertainty bounds for the stream flow simulations with and without the extra constraints for a daily and a monthly aggregation level. For each case, uncertainty bounds based on all simulations are indicated; as if the catchment were ungauged, as well as bounds that solely include behavioural model runs. A vertical line indicates the observed quantile.

As explained in chapter II, the 95th percentile of daily flows can be used as a flood risk indicator (**Fig. 33**, first row, third figure). The 5th and 50th percentile of the monthly flows (**Fig. 33**, second row, first and second figure) can be used as indicators for drought risk and average downstream water availability respectively. The figures on the first and second row present uncertainty bounds for indicator scores for a combination of land use types, as is the actual situation in the Zwalm river basin (summarized in **Table 7**). In practice, LCAs can require the calculation of indicator scores for one specific land use type e.g. for forests or for one particular agricultural crop. As an example, the third row shows the regional water balance indicators for forested HRUs on loamy soils in the Zwalm basin. This could be used in a LCA of forest products.

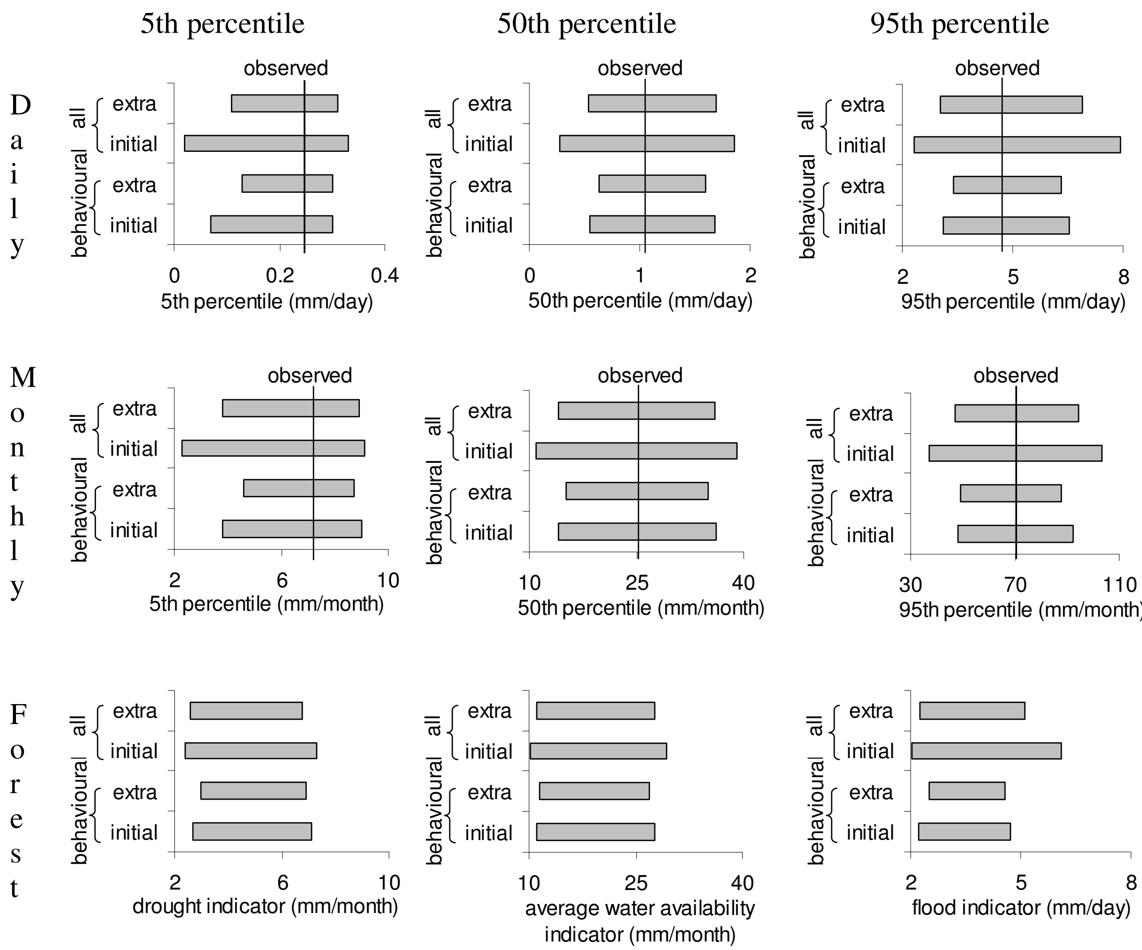


Fig. 33: 95% uncertainty bands for the 5th, 50th and 95th percentile of daily and monthly aggregated stream flow simulated with and without the extra parameter constraints. The third row presents indicator scores for drought risk, average water availability and flood risk for forests on loamy soils in the Zwalm river basin

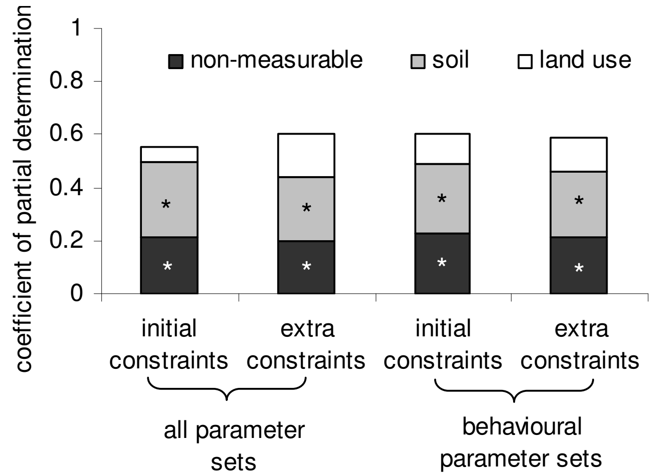
In general, the uncertainty bounds are wider for a daily than a monthly aggregation level. The uncertainty on low flows is larger than on peak flows in relative terms, but in absolute terms, the opposite is true. All calculated intervals capture the observed stream flow quantile. Apart from the initial constraints for the 5th percentile, the observed quantile even lies more or less in the centre of the predicted interval. The more eccentric location of the observed quantile can be explained by the eccentric location of the GW_REVAP and REVAPMN interval with the extra constraints compared to the initial range. As explained earlier, the initial parameter ranges tend to overestimate GW_REVAP and underestimate REVAPMN; in other words: they tend to overestimate the volume of water movement from the shallow aquifer back to the soil profile. As a consequence, slow flow volumes tend to be underestimated.

The introduction of new parameter constraints results in a considerably larger reduction of predictive uncertainty for the case that all simulations are used than for the case that only the behavioural samples are considered. Moreover, the predictive uncertainty for the all simulations/extra constraints case and the only behavioural simulations/initial constraints case is very similar. In other words, if the GLUE is applied in gauged catchments, with cut-off criteria based on model efficiency for stream flow simulation, then the use of extra parameter constraints has little effect on predictive uncertainty. On the other hand, when modelling ungauged catchments, the newly introduced parameter constraints can reduce predictive uncertainty to an order of magnitude as if stream flow measurements would have been available. This information is of particular interest in countries like Belgium with a countrywide database of soil properties but with a rather limited network of stream flow gauging stations.

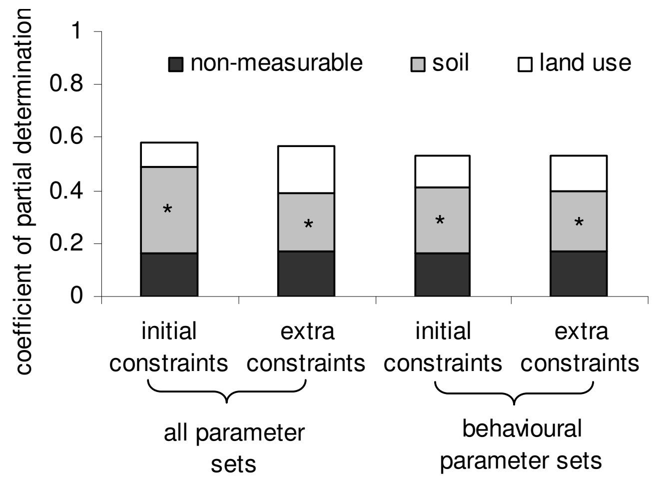
Sources of uncertainty

Previous paragraph concluded that a more careful gathering of input data can to some extent replace missing stream flow measurements. The question now arises which inputs contribute most to predictive uncertainty. **Fig. 34** depicts the relative contribution of soil, land use and non-measurable inputs to the uncertainty on the 5^{th}, 50^{th} and 95^{th} percentile of daily stream flow predictions. The four bars in each graph represent the results including all samples or only the behavioural parameters using the initial parameter ranges or the extra constraints. **Fig. 34** is based on daily aggregated values, monthly aggregated results are very similar.

5th percentile:



50th percentile:



95th percentile:

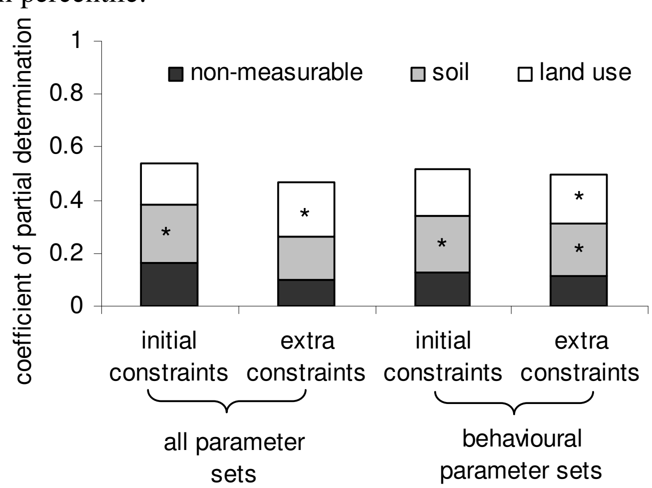


*Fig. 34: Relative contribution of non-measurable, soil and land use parameters to the uncertainty on the 5th, 50th and 95th percentile of simulated daily stream flow with and without the extra parameter constraints. Significant contributions are indicated with * (confidence level 0.95)*

If all samples derived from the initial input ranges are considered, soil inputs make by far the largest contribution to the uncertainty on all stream flow percentiles. Non-measurable parameters overall are the second most important explanatory variables for predictive uncertainty. Crop attributes make only a marginal contribution to the 5th and 50th percentile. The impact of crop attributes on the 95th percentile is somewhat higher; the effect is significant for daily aggregated values. This trend is in agreement with the expected impact of land use on the stream flow regime: land cover mainly affects processes occurring at the land surface, its impact on subsurface processes or groundwater dynamics is less pronounced (Bronstert et al., 2002).

If extra constraints are introduced, the contribution of the crop attributes to predictive uncertainty increases mainly at the expense of the contribution of soil inputs. For peak flows, crop attributes even have the largest effect of all parameter groups. Limiting the analysis for the initial input ranges to the behavioural samples produces a similar result, however, the increase in the contribution of crop and the decrease for soil inputs is less pronounced in this case. The introduction of extra constraints causes only very small changes in the coefficients of partial determination if only the behavioural samples are considered.

Discussion

The analysis presented in this manuscript indicates two different and more or less equally powerful perspectives for minimizing predictive uncertainty of SWAT simulations in Flanders: (1) constraining input parameters with stream flow observations, and (2) constraining input parameters via catchment attributes. The first option is straightforward, and is often considered as an absolute prerequisite for a reliable simulation. Theoretically, physically based spatially distributed hydrological models simulate all relevant processes in an explicit manner using measurable inputs, so strictly spoken, these models do not require stream flow data for constraining parameters. Many practical aspects however hamper a fully correct implementation of this modelling paradigm (Grayson et al., 1992; Beven, 2001): physical equations for large scale hydrological processes are lacking, spatially distributed data about model inputs are not always available etc. Consequently, constraining model parameters with stream flow data can increase goodness-of-fit (Andersen et al., 2001) and reduce uncertainty (Freer et al., 1996). The second option for reducing predictive uncertainty elaborated in this manuscript lies closer to the philosophy behind physically based spatially distributed modelling. The physical meaning of the model set-up was enlarged by constraining model inputs via catchment attributes. Because every catchment is unique (Beven, 2000), our approach for increasing the physical basis of simulations will not necessarily be successful for catchments with distinct hydrological characteristics. For example, Huisman et al. (2004) did not find a significant effect of the changes in soil inputs after land use change on the predictions of SWAT-G, a derivative of SWAT, for a German catchment. On the other hand, many studies seem to agree with the finding that the meaning of soil (hydraulic) inputs in catchment scale models does not correspond with the meaning of these variables at the point scale i.e. the scale at which they are measured. This scale discrepancy between observation and application causes a bias on the model predictions (Schaake, 2004). Adjusting point estimates of soil hydraulic properties is therefore necessary to obtain behavioural simulations (Niedda, 2004). In a first instance, correction factors for upscaling point estimates of soil inputs can be derived using observed stream flow time series. Nevertheless, to enable the simulation of ungauged catchments, one needs to gain insight in the physical factors affecting these correction factors for a given region and model structure.

Conclusions

The GLUE method was used to assess predictive uncertainty for an application of the SWAT model to the 114 km² Zwalm river basin. Extra input constraints, based on catchment attributes, were introduced and the reduction in predictive uncertainty assessed. The extra input constraints increased the number of behavioural parameter sets. If solely the behavioural parameter sets were considered, there was no remarkable difference in the width of the uncertainty bounds with and without the extra constraints. If we pretended that the catchment was ungauged and included all samples to calculate uncertainty bounds, a noticeable reduction in predictive uncertainty was observed. Predictive uncertainty then had the order of magnitude of the uncertainty calculated with the behavioural parameter sets and the initial constraints (i.e. a typical application of GLUE to a gauged catchment). The relative importance of soil, crop and non-measurable parameters was assessed with a regression analysis linking parameter values to predictive uncertainty. Coefficients of partial determination were calculated as a measure of the relative importance of a group of inputs for all samples and for the behavioural samples, and for the initial and the extra constrained input parameter ranges. In the case all samples were considered for the initial input parameter ranges, the effect of soil inputs overshadowed the effect of the non-measurable and the crop inputs. With the introduction of extra input constraints or when only the behavioural samples were included, the three groups were more or less equally important.

V.2 Simulating the stream flow response to afforestation: relative importance of scenario uncertainty

Introduction

With only 10% of its territory under forest, Flanders ranks among the regions with the lowest forest index (= % of the area occupied by forests) in Europe (Muys, 2002a). Moreover, the forested area is unevenly distributed over the region, with relatively more forests occurring in the sandy region in the north-east and a low forest index in the loambelt in the South. Recent policy initiatives aim at increasing the area under forest. By promoting the afforestation of agricultural land, environmental benefits such as reduced peak flows and reduced sediment and nutrient loads of rivers can be achieved. It has been suggested that a well-chosen spatial planning of afforested land can enlarge the beneficial environmental impact of afforestation (Lavabre et al., 2002; Muys, 2003). For example, afforestation of steep terrain or near-stream areas is usually assumed to have a relatively larger effect on the stream flow regime.

Although most studies seem to agree about the general trends concerning the impact of land use patterns on stream flow production, its expression in numerical terms is still uncertain. Experimental and observational catchment studies are usually performed at very small scales (a few km²) and so provide insufficient information to support land use planning in meso- or large-scale catchments (Wilk and Hughes, 2002). Moreover, these studies often have difficulties with separating land use change effects from the effect of other environmental variables, in particular the precipitation regime (Sullivan et al., 2004). Hydrological models are useful tools for simulating the effect of changing land use while keeping other environmental settings constant and for extrapolating results from paired watershed research to larger spatial scales (DeFries and Eshleman, 2004; Andréassian, 2004). However, the predictions of a hydrological model bear a considerable degree of uncertainty due to the uncertainty on the input data, problems with the identification of model parameters and errors or simplifications in the process description and model code (Uhlenbrook et al., 1999). In most land use impact assessments, the future land use itself is uncertain, causing an extra source of uncertainty, which in this study is referred to with the term ‘scenario uncertainty’.

This study makes use of the semi-distributed model SWAT to quantify the sensitivity of the quick and slow flow response to afforestation due to imprecise information of the extent and the location of newly planted forests. To this end, the SWAT model is applied to the Zwalm catchment, a region relatively poor in forests, at three different spatial scales having an order of magnitude of 1 km², 10 km² and 100 km². Afforestation scenarios differ with respect to the proportion of the area that is converted to forest (10, 20, 30, 40 or 50 %) and the spatial arrangement of the forested area over the catchment (randomly distributed, spatially clustered or mainly occurring on steep or flat terrain). In addition, scenario uncertainty is compared to the uncertainty inherent in hydrological modelling, that was assessed for the actual land use with the GLUE method in chapter V.1 The simulation results allow to assess: (1) the difference in quick flow and slow flow response between the considered afforestation scenarios and (2) the relative importance of scenario uncertainty compared to other uncertainty sources.

Method

Study area and model set-up were described in chapter V.1. The parameter regionalisation schemes presented in chapter IV.5 were used to calculate parameter values for the afforestation scenarios. Uncertainty inherent in using a hydrological model was assessed for the actual land use scenario with the GLUE procedure, as described in previous chapter V.1.

Generation of afforestation alternatives

The simulated afforestation scenarios vary with respect to three properties: the forest index (10, 20, 30, 40 or 50% of the catchment area), the scale of the analysis (~1 km², ~10 km², ~100 km²) and the spatial arrangement of the afforested pixels. The considered spatial scales form three nested catchments, as shown in **Fig. 35**. At each spatial scale, afforestation scenarios with four different spatial arrangements were generated: afforested patches are randomly distributed, spatially clustered, or associated with certain terrain feature (steep or flat terrain). In total, this gives 5 (forest indices) x3 (spatial scale) x4 (spatial arrangements: random, spatially clustered, preferentially on steep or on flat terrain) different afforestation scenarios. One single afforestation scenario can be realised in different spatial designs i.e. as different land use patterns. This means that within a given afforestation scenario (forest index, spatial scale and spatial arrangement), there exists uncertainty on the future land use. To calculate the effect of this within-scenario uncertainty on the stream flow response, five alternative implementations were generated for every scenario and the stream flow response to each of these scenarios was simulated with SWAT. In the following, the term 'afforestation alternative' will be used to address one specific design i.e. one specific land use pattern, the term 'afforestation scenario' refers to a set of five designs with the same forest index, spatial scale and spatial arrangement of afforested pixels. Because in reality it is unlikely that urban areas are afforested, only pixels that are currently under arable land or pasture were afforested. Moreover, the proportion of arable land to pasture was kept more or less constant so that simulated changes in stream flow can solely be attributed to changing forest indices and not to a changing ratio area pasture/area arable land. A maximum deviation of 10% was allowed from the present ratio.

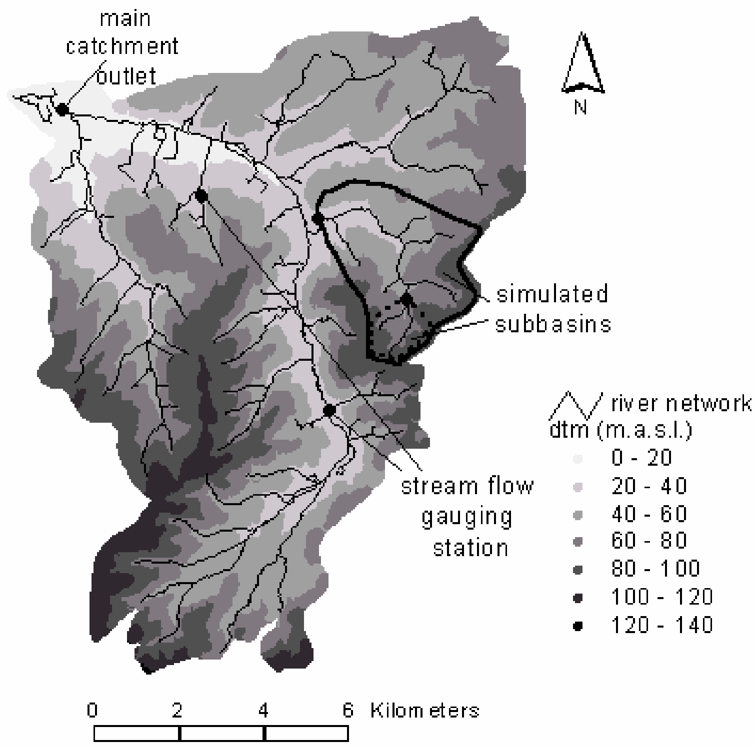


Fig. 35: Digital terrain model of the Zwalm river basin with indication of river network, stream flow gauging stations and simulated subbasins

To generate the afforestation alternatives, a map was constructed for every afforestation alternative representing the probability that a pixel (with an area of 1ha) is afforested. Such a map can be represented as a matrix M[i,j] with i x j the dimension (number of pixels) of the study area. Areas outside the catchment boundaries and urban areas were excluded by setting M[i,j] to zero for these pixels. For random afforestation alternatives, all non-zero pixels received an equal probability being one divided by the number of non-zero pixels. The generation of the spatially clustered afforestation alternatives started with the random selection of one non-zero pixel. Neighbouring non-zero pixels were added concentrically until the desired forest index was reached. For the generation of the afforestation alternatives with forests preferably occurring on steep or on flat terrain, the value of M[i,j] was made functional to the slope of the considered pixel. The range of slope percentages occurring in the catchment was subdivided into five intervals. Depending on the slope class of a non-zero pixel, the relative value of M[i,j] was set to 1, 2, 4, 8 or 16.

As mentioned before, no large variation of the ratio of the pasture area to the area arable land was allowed for any of the afforestation alternatives. Therefore the deviation of this ratio from the initial value was calculated each time a new pixel was afforested. The probability of all pasture (if relatively more pasture pixels have been afforested) or arable land pixels (if more arable land is afforested) was temporarily set to zero if the deviation exceeded 10%. This restriction was removed as soon as the deviation fell again below 10%.

Analysis of scenario uncertainty

The scenario analysis reveals which afforestation scenarios deliver a significantly different quick and slow flow response, in the hypothetical case of an error-free data set and a perfect model structure. As explained earlier, the scenario uncertainty considered in this manuscript covers three aspects: the uncertainty of the future forest index (10, 20, 30, 40 or 50% of the considered catchment), the scale of the afforestation scenario (~1km², ~10km² or ~100km²), and the spatial arrangement of the afforested patches (distributed randomly, appearing as one spatial cluster, or mainly occurring on steep slopes or flat terrain). Five different afforestation alternatives were generated for every afforestation scenario. The variation in predicted quick and slow flow response between the afforestation scenarios was analysed with three-way ANOVAs (one analysis for quick flow, a second one for slow flow). ANOVA requires that all treatments, in our case: all afforestation scenarios, have equal variances. This was evaluated with the Levene test. Neter et al. (1999) state that the Levene test may for this purpose be evaluated at low α levels because the F test for equality of factor level means is robust against nonconstancy of the error variance when the factor level sample sizes are approximately equal. In our case, the sample sizes for all afforestation scenarios are equal to five i.e. five afforestation alternatives for each scenario, therefore we can assume that ANOVA can be applied if no significant difference in error variance can be detected at an α level of 0.001 i.e. if no extremely large variations are present. If the prerequisite of 'equal' error variance is fulfilled, the ANOVA model can be built and the presence of interactions can be evaluated. The Tukey procedure can then be used to assess which spatial scales, forest indices and spatial arrangements result in a significantly different quick or slow flow response.

Results and discussion

Scenario uncertainty due to different implementations of an afforestation scenario

As discussed in the methodology section, ANOVA requires homoscedasticity i.e. variances in quick and slow flow for the different afforestation scenarios should approximately be equal. **Fig. 36** reveals some noticeable differences in standard deviation between the scenarios (p-value of 0.021 for quick flow, 0.049 for slow flow) but extremely large variations can not be detected, so that a three-way ANOVA may be applied. Nevertheless, it might be interesting to take a closer look at these results as high variances point out that scenario uncertainty for a given afforestation scenario is large. This implies that further specification of the afforestation scenario can cause a relatively large decrease in predictive uncertainty. Thus, in case of high variances, the usefulness of the modelling effort might benefit from a more detailed input from land planners and/or policy makers about the expected land use change.

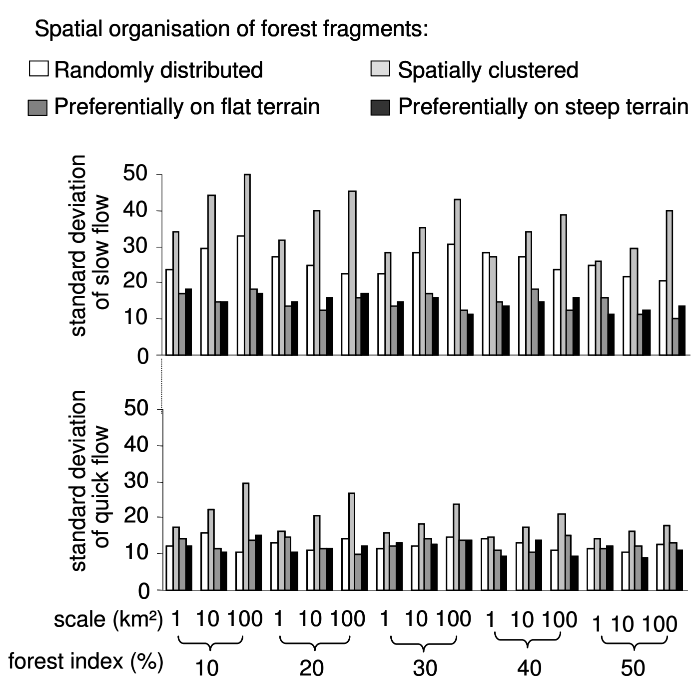


Fig. 36: Standard deviation of the simulated quick and slow flow response due to alternative implementations of afforestation scenarios

In general, the variance in quick and slow flow response can be expected to decrease when more constraints are put on the pixels that can be afforested. For example, larger forest indices limit the number of possible alternatives, leading to lower standard deviations. The preferential afforestation of steep or flat terrain affects the standard deviations in a similar way whereas the deviation is the highest for the spatially clustered scenario, followed by the randomly distributed scenario. The latter does not put any additional restriction on the pixels that can be afforested. A spatially clustered afforestation can also be present at every (non-urban) spot of the catchment, however, because the pixels must occur next to each other, and because neighbouring pixels are very likely to have a similar slope, extreme alternatives of all types can occur in this case (forests concentrated on steep slopes or on flat terrain etc.). The difference in standard deviation between the forest indices or spatial arrangements is more pronounced at larger spatial scales which can also be explained by an increase in the number of possible alternatives.

In practice, afforestation of arable land will most probably be effected as spatial clusters because this is the most practical and the most interesting for, amongst others, biodiversity. The scenario analysis indicates that the predicted quick and slow flow can vary widely, depending on the exact location of the forests. This scenario uncertainty can be reduced if more precise information about the location of the newly planted forest is available. In this study for instance, specifying whether the upstream (with steep slopes) or the downstream part (less sloping, soils with coarser texture) is afforested increased the reliability.

Effect of scale, spatial arrangement and forest index

The results of the three-way ANOVA are presented as profile plots in **Fig. 37** (quick flow) and **Fig. 38** (slow flow). **Table 18** lists the significance of the factor level effects. Second order interactions are insignificant for both quick and slow flow. However, **Table 18** points out a significant first order interaction between forest index and spatial arrangement for both response variables. The impact of spatial arrangement decreased with increasing forest index, therefore the curves of the profile plots are not parallel but converge at larger forest indices.

Table 18: P-values indicating the significance of the impact of forest index, spatial arrangement of forest fragments and spatial scale on quick and slow flow as derived with the three-way ANOVA

	Quick flow	**Slow flow**
Forest index (F)	**0.001**	**0.001**
Spatial arrangement of forest fragments (SF)	**0.020**	**0.036**
Spatial scale (SS)	0.112	0.102
F * SF	**0.040**	**0.041**
F * SS	0.091	0.143
SS * SF	0.499	0.736
F * SF * SS	0.839	0.844

Because important interactions exist, the effect of forest index cannot be considered independently of the effect of spatial arrangement and vice versa. However, because scale does not interact with the other factors and because it does not significantly affect the impact of afforestation scenarios on quick or slow flow, all further analyses could be performed independently of spatial scale.

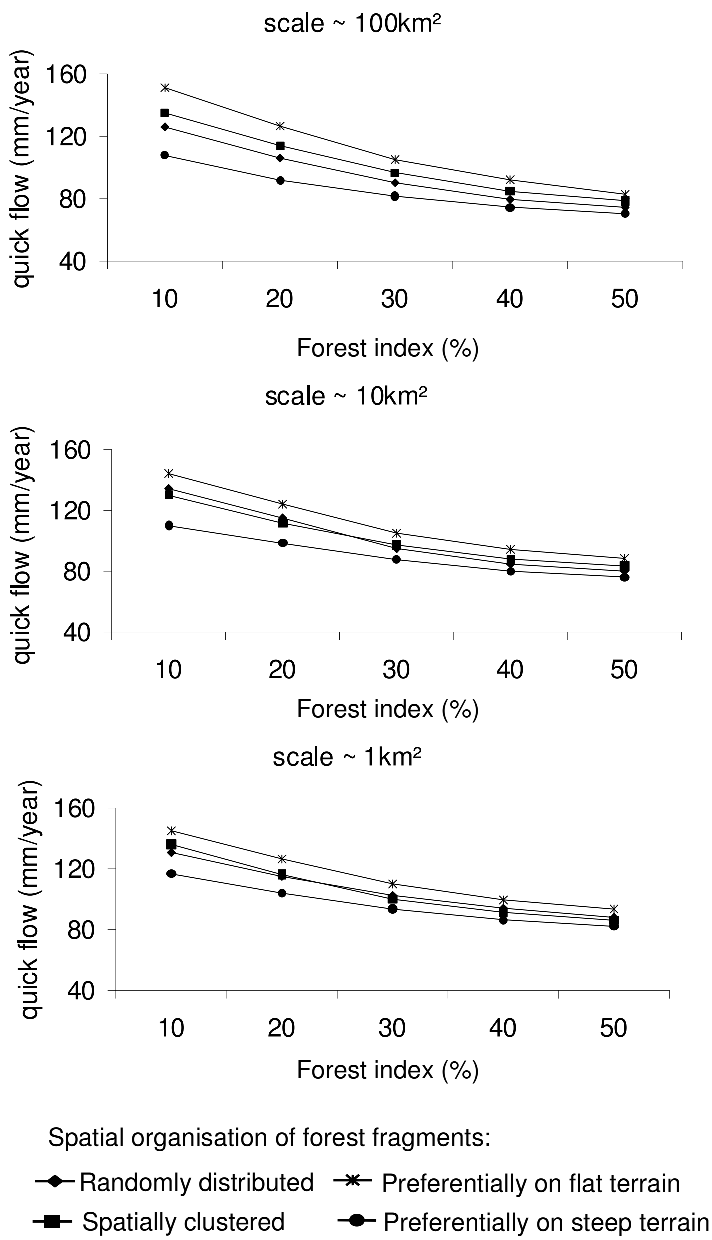


Fig. 37: Impact of spatial scale, forest index and spatial arrangement of forest fragments on simulated yearly quick flow

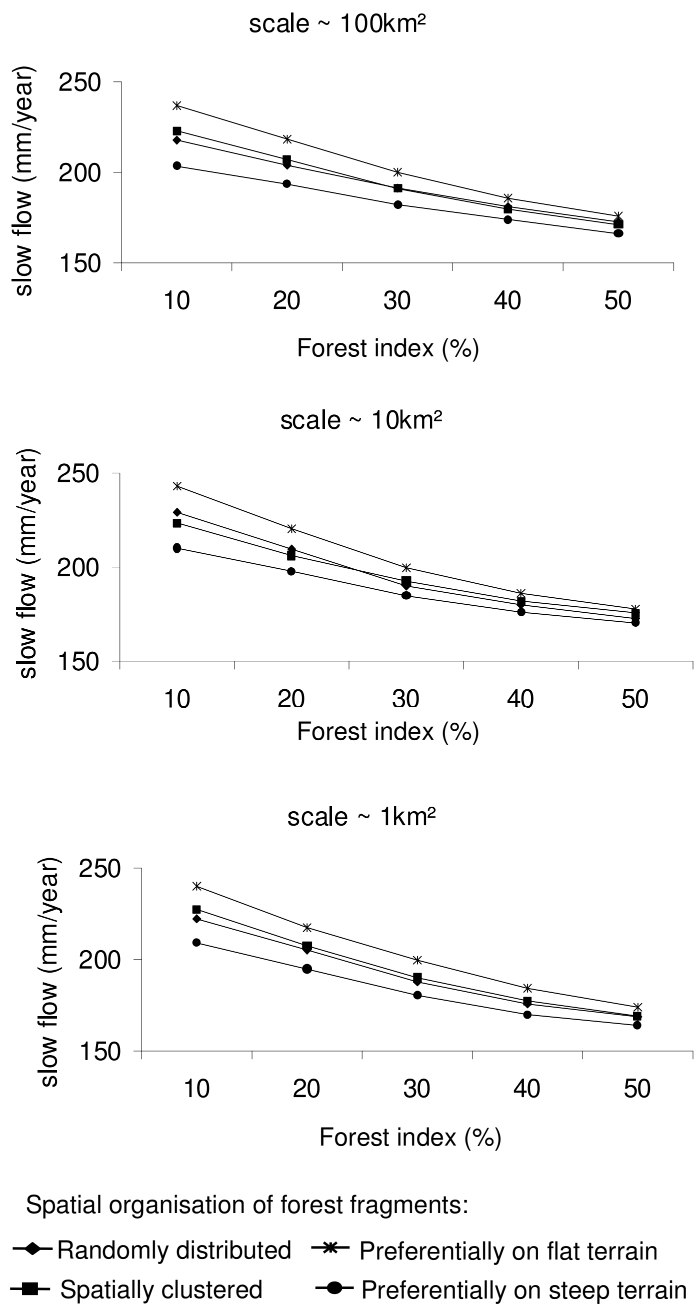


Fig. 38: Impact of spatial scale, forest index and spatial arrangement of forest fragments on simulated yearly slow flow

The outcome of the Tukey tests for detecting significant differences in quick and slow flow response between forest indices is depicted in **Fig. 39**. It should be emphasised that this analysis does not take model structural and input uncertainties into account. This topic will be discussed in the subsequent paragraphs.

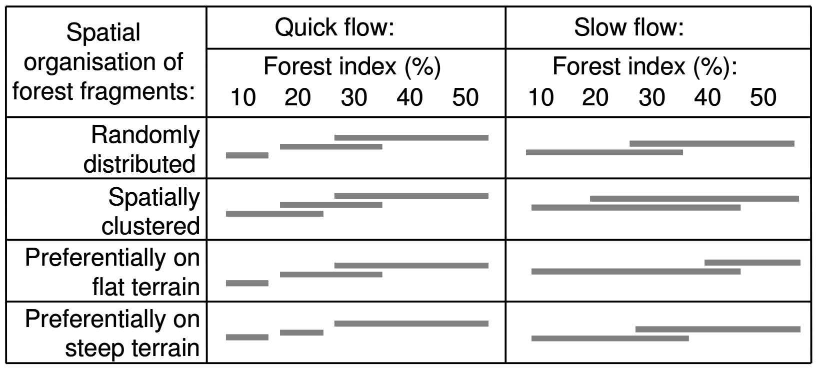


Fig. 39: Results of the Tukey tests for detecting significant differences in quick and slow flow response between afforestation scenarios. Bars connect forest indices that do not give a significantly different quick or slow flow response

An increase in forest index from 10 to 20% gives a significant reduction in quick flow for all spatial arrangements, except for the spatially clustered afforestation. In the latter case, an increase from 10 to 30% is required. If the region already has a high forest index, a relatively larger area has to be afforested before a significant change in quick flow appears. In other words, afforestation of regions poor in forests is more likely to cause a significant reduction in flood risk than an increase of the forest index in regions that already have a large area under forest. The impact on slow flows is generally smaller and less significant than the impact on quick flows, which is in agreement with literature (e.g. Bronstert et al., 2002; Fohrer et al., 2001). Forests can influence groundwater and thus slow flow volumes in two ways: by affecting the transport of rainfall to the aquifer and by extracting water from the aquifer system through deep roots (Le Maitre et al., 1999). The latter causes an increase in evapotranspiration compared to other land use types favouring a decrease of low flows. Next to this higher evapotranspiration, forests can facilitate infiltration (Bonell, 1993) so that more water is available for evapotranspiration or stream flow generation. These two opposing effects explain why the impact of forests on slow flows is site-specific (Robinson et al., 2003). Moreover, the impact of afforestation on low flows often varies in time: pre-planting drainage can cause a lowering of the water table, which is accompanied by a temporally increase low flows, however, this is most of time followed by a decrease in low flow due to forest growth (Johnson, 1998; Robinson, 1998). Given that the SWAT is used here to predict average long-term effects, the simulated small decrease in slow flow is in line with previous findings.

With respect to total stream flow, a meta-analysis of experimental catchment studies in temperate climates conducted by Sahin and Hall (1996) predicts a decrease of yearly stream flow between 20 and 40 mm per 10 percent change in forest index. The predictions for the Zwalm catchment indicate a slightly smaller change of the stream flow regime: between 9 and 31 mm yearly flow reduction per 10% change of forest index. Model simulations by Eckhardt et al. (2003) also revealed a decrease in average flow that is somewhat smaller than the figures given by Sahin and Hall (1996), namely 13 mm per 10% change in forest index.

Scenario uncertainty versus uncertainty inherent in hydrological modelling

Model structural and input uncertainty forms a well-known limitation for the applicability of hydrological models in land use impact assessments (e.g. Lukey et al., 2000). Therefore, the uncertainty inherent in the use of SWAT as assessed with GLUE for the actual land use is compared with scenario uncertainty to assess the relative importance of these uncertainty sources (**Fig. 40**). Because scale does not have a significant impact on the model output, **Fig. 40** lumps the results of the analyses at the three spatial scales per combination of spatial arrangement and forest index.

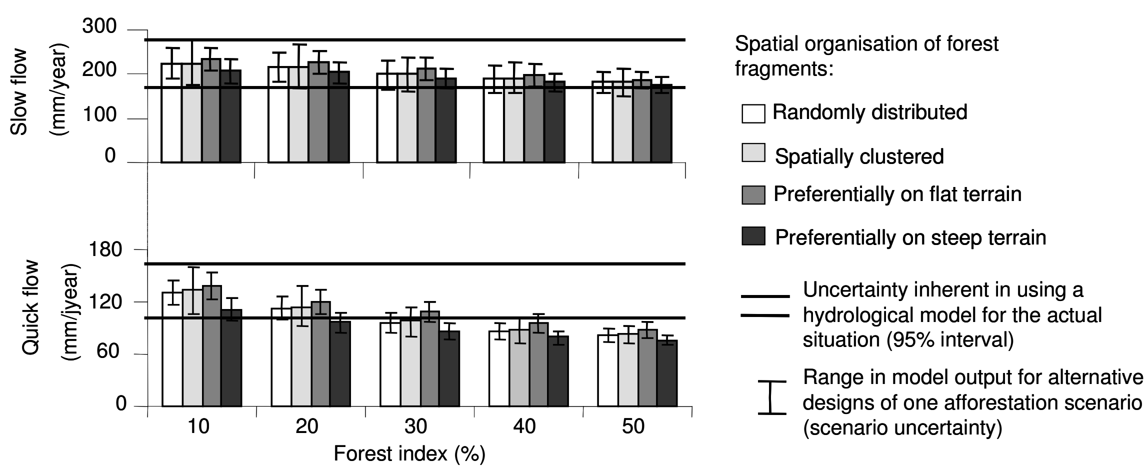


Fig. 40: Magnitude of scenario uncertainty and uncertainty inherent in using SWAT when simulating the impact of afforestation on average yearly quick and slow flow for the Zwalm catchment

Scenario uncertainty is in all cases much smaller than the uncertainty inherent in using the SWAT. Hence, a more detailed description of afforestation alternatives is not very meaningful: the uncertainty caused by the use of a hydrological model is much larger than the variation due to alternative versions of a certain afforestation scenario. Further decreasing the level of detail of the afforestation alternatives e.g. by ignoring the spatial arrangement of future forests is, however, undesired. For example, if 30% of the catchment area is afforested, with forests occurring preferably on steep slopes, the subsequent reduction of quick flow is larger than the uncertainty on quick flow predictions for the actual land use scenario. A random localisation of forest fragments requires a 40% increase in forest index to obtain a change in quick flow larger than the uncertainty on the predictions for the actual scenario. So despite that scenario uncertainty is relatively small, the characteristics of the future afforestation scenario having the largest impact on the model output need to be specified to strengthen the predictive capacity of the model. These characteristics can be identified by scenario modelling, as was demonstrated in this paper. In our case-study, scale seemed to be relatively unimportant whereas the spatial arrangement of the forest fragments is a substantial aspect especially at low forest indices. The relative importance of scale, spatial arrangement and forest index as well as the extent of the area that needs to be afforested before the predicted hydrological response becomes larger than the uncertainty on the simulations is most probably site-specific. Nandakumar and Mein (1997) report that the proportion of the catchment that needs to be afforested to obtain a significant hydrological response varies between 6% and 65%, depending on abiotic conditions. For example, afforestation of deep soils can cause a larger – and thus more easily detectable – change in runoff than afforestation of shallow soils, because soil depth can be a limiting factor for root development and hence for evapotranspiration of trees (Verbunt et al., 2005). Eckhardt et al. (2003) found that 25% of the area must be afforested to obtain a significant decrease in simulated average daily stream flow for simulations with SWAT-G for a catchment in central Germany. This is slightly higher than the threshold set by Bosch and Hewlett (1982) based on a review of experimental catchment studies, who concluded that a change in stream flow smaller than 20% is not detectable. In our case-study, at least a 20% (from 10% to 30%) increase in forest index is needed for a significantly different quick flow simulation. For forest indices up to 50%, no significant change in slow flow response could be observed. These results are comparable to earlier studies, though the separate analysis of quick and slow flow allows detecting a change in the predicted hydrological regime at relatively low forest indices.

Conclusion

The significance of the impact of different afforestation scenarios on the average yearly quick and slow flow predicted by the SWAT model was analysed for the Zwalm catchment at three spatial scales. Scenario analyses were performed to assess the impact of forest index, spatial arrangement and spatial scale on the predicted hydrological response, in the ideal case of an error-free dataset and a perfect model structure. These predictions were contrasted with the results of the GLUE-based assessment of uncertainty due to the use of a hydrological model for the actual land use scenario that was presented in previous chapter V.1. Scenario uncertainty, i.e. the variation in quick and slow flow response for different implementations of a given afforestation scenario, proved to be relatively small compared to input and model uncertainty. Nevertheless, it is desirable to specify the characteristics of the future afforestation scenario with the highest impact on the model predictions; otherwise the predictive capacity of the hydrological model might decrease, i.e., a more drastic land use change is required to obtain a change in stream flow regime exceeding predictive uncertainty. In our case-study, the spatial scale of the afforestation was relatively unimportant, but the spatial arrangement considerably affected the results at low forest indices. Changes in forest index of up to 40% (from 10% to 50%) did not induce a change in slow flow larger than predictive uncertainty. Quick flow changes surpassed predictive uncertainty after a 20% change in forest index (from 10% to 30%). The latter figure was obtained if forest fragments preferentially occur on steep terrain. If the newly planted forests are randomly distributed over the area, then 30% of the area needs to be converted to forests to get a significant quick flow change.

Chapter VI: Discussion and conclusion

As stated in chapter I, this thesis aimed at (1) completing the presently available impact assessment methods for land use in LCA with catchment scale water quantity impacts and (2) outlining a method to calculate these impacts. Chapter II addressed the first topic. The regional water balance impact category was introduced to account for the impact of land use systems on floods, droughts and downstream water availability. Chapters III, IV and V considered the problem of impact calculation and evaluation in the wider context of the hydrological modelling of ungauged areas or hypothetical scenarios. The used methods and concepts were mainly derived from hydrological sciences and had no direct connection with LCA. In this final chapter, the findings of previous three chapters are confronted with the available LCA literature about uncertainty assessment. It starts with a brief review of uncertainty assessment in LCA. Particular attention is devoted to the application of the concepts and methods to LCAs of agricultural and forestry production systems. Finally, the potential of the presented methodology for increasing the reliability of LCAs of agricultural and forestry systems is discussed.

Uncertainty in LCA

In the beginning of the 90's, the first studies about uncertainty in life cycle assessment were published. These first uncertainty assessments were rather qualitative. Data quality indicators were proposed reflecting the consistency of the collected inventory data in relation to the objectives of the study. These indicators referred to the reliability of data sources, the completeness of the data set, the temporal, geographical and technological similarity between the system under study and the system wherefore data were available in literature (Weidema and Wesnaes, 1996). Besides data quality indicators, rules of thumb were formulated to evaluate whether the environmental impacts of two systems differ significantly. Lindfors et al. (1995) proposed that emissions less than one order of magnitude and resource use less than 50 percent of difference should not be regarded as significantly different. A further refinement of these rules of thumb can be found in Finnveden and Lindfors (1998). The data quality indicators as well as the rules of thumb mainly refer to uncertainties in the inventory data. More recently, Björklund (2002) and Huijbregts (1998) presented comprehensive overviews of all uncertainty types. In general, uncertainty can result from data, models and choices that are missing, inappropriate or unreliable (Heijungs and Huijbregts, 2004). The term 'data uncertainty' or 'parameter uncertainty' is used to indicate the uncertainty due to missing, inappropriate and unreliable data. It also contains the uncertainty caused by handling spatial and temporal variability of data in a lumped way, as spatially and temporally averaged inventory data (Karjalainen et al., 2001). The term 'model uncertainty' groups all kinds of uncertainty generated in the impact assessment, due to simplified process representations or to a lack of or inaccurate knowledge about the processes at hand. Well-known sources of model uncertainty are amongst others the absence of spatio-temporal explicit models, and linear simplifications of non-linear processes (Huijbregts, 1998). Model and data uncertainties have been discussed extensively outside the field of life cycle assessments. For these two types, uncertainty assessment techniques used in environmental modelling have been applied in the context of LCA. Frequently used methods are amongst others Latin Hypercube or Monte Carlo sampling (e.g. Maurice et al., 2000) and fuzzy set methods (e.g. Ardente et al., 2004). Uncertainty due to missing, inappropriate or unreliable choices, however, is less widely discussed. This includes amongst others the choice of the functional unit, system boundaries and the valuation and weighting of impacts; issues that can be addressed through scenario analysis (Personen et al., 2000).

This chapter describes the possible sources of uncertainty and their relative importance in LCAs of land-intensive systems. With respect to the impact assessment methodology, it has often been stated that methods designed for industrial production processes need to be adjusted to become applicable to land-intensive production processes (e.g. Audsley et al., 1997). Some impact categories may become less important, the importance of others may increase, and new impact categories have been introduced e.g. soil salinisation (Feitz and Lundie, 2002). In line with this, it can be expected that some sources of uncertainty will become less important, others will become increasingly important and new uncertainty sources might appear. The following paragraph discusses how data, models and choices introduce uncertainties in LCAs of land intensive systems and summarises how these uncertainties were addressed for the calculation and evaluation of regional water balance impacts as presented in chapters III to V.

Sources of uncertainty in LCAs of land intensive systems

Data uncertainty

Case-studies on agri- and silvicultural products are a relatively recent topic in LCA: while LCA originated in the 60's, the earliest case-studies of land intensive systems were reported in the 90's. Standard databases do not yet include all necessary inventory data of agri- and silvicultural products, on the one hand because the method for assessing land use impact is still under development, new impact categories are being added requiring new sorts of data; on the other hand because data from existing agricultural and forestry research networks are not yet fully explored by LCA practitioners. The reliability of LCAs of agricultural and forestry products is therefore limited by data availability. Existing LCA databases are gradually being extended to include agricultural and forestry production chains. For example, Nemecek and Erzinger (2005) included data for arable crop production in Switzerland in the widely used ecoinvent database. Because databases are still under development, LCAs of agri- and silvicultural systems often use approximate data, derived for similar systems or places. An alternative method for overcoming data gaps is the use of environmental models for calculating the impact of land use on nutrient, water, energy, biodiversity etc. from more easily available data about the system to be modelled (crop characteristics, planting dates, management) and of site characteristics. Model inputs can be derived from readily available data sources i.e. general soil survey data, climatic data and plant parameter databases. Brentrup et al. (2000), for example, estimated NH_3, N_2O and NO_3 emissions with simple equations requiring easily accessible input data and used these estimates in an LCA of winter wheat production systems (Brentrup et al., 2004). In this thesis, the problem of missing stream flow data was addressed by using a modelling approach. As mentioned in the introduction, LCA practitioners usually assume that there is no universally valid hydrological model available that can be used for inventorying water flows. This idea contrasts with the claim of universal applicability sometimes made by hydrological model developers. The objective of this thesis was therefore to assess to what extent existing hydrological models can be useful in LCAs of land intensive systems.

Reconsider the overall structure of a model: O = M(I). If the model M() is applied to a given set of observed model inputs I e.g. precipitation, soil characteristics, crop characteristics etc., it can predict the desired model output O e.g. runoff. Taking this view on modelling, LCA practitioners are probably right: there is no single hydrological model that can deliver accurate predictions all over the world if only observed inputs can be used. This statement was affirmed in chapter IV.2 'Are SWAT defaults applicable in Flemish conditions?': running the uncalibrated SWAT did not yield reliable water balance simulations for all Flemish catchments. So one can conclude that the (uncalibrated) SWAT model – and most probably any other model – is not universally applicable. However, hydrological models that claim to be universally applicable rather look like: O = M(P,I). These models ask the user to specify not only the observed inputs I, but also the model parameters P. These parameters cannot be observed and should ideally be optimised with respect to locally observed input-output pairs. In the first equation, O = M(I), parameters were internal to the model code. They reflected the conditions under which the model code was constructed and their applicability - and thus the applicability of the model - outside this range is questionable. This means that the usefulness of the SWAT for inventorying water flows entering and leaving the system still depends on the availability of rainfall-runoff data. Such data are not available for all possible land use systems under all possible site conditions. This problem can be addressed by, amongst others, regionalising model parameters as elaborated in this thesis. Regionalisation models based on spatial proximity and on catchment attributes were built and their ability to estimate hydrological fluxes at ungauged sites and/or for alternative land uses was evaluated. The SWAT together with the regionalised parameters proved be a useful technique for inventorying water flows in LCAs of agricultural and forestry systems in Flanders. To maximise the usefulness of this approach, a cost-effective strategy for data gathering and assimilation was sought by calculating the relative contribution of different SWAT inputs to predictive uncertainty for gauged and ungauged catchments. It was concluded that the increased predictive uncertainty due to missing stream flow data can be compensated by a more detailed data assimilation strategy (regionalised parameters and a land use dependent soil classification). On the other hand, a more detailed data assimilation strategy did not cause a significant reduction of predictive uncertainty for gauged catchments.

The proposed method for overcoming data uncertainty by using SWAT assumes a site-specific life cycle assessment. However, LCA traditionally is a site-generic method i.e. the location of the extractions and emissions is generally not considered. This is mainly due to practical limitations. Gathering site-specific data is time-consuming. Moreover, for many products, the location of the production processes is not known either because the information is not available (e.g. it is hard to track the origin of the wood used for furniture), because the location is variable (factories using wood from different countries) or because one wants to assess a hypothetical production process (location not determined yet). In spite of these practical difficulties, the usefulness and feasibility of site-dependent LCAs has been shown in recent case-studies, see Bellekom et al. (2005) for an example on acidification, Basset-Mens et al. (2005b) for eutrophication. Although the method proposed in this thesis is in line with the general trend towards site-dependent assessments, the question arises whether regional water balance impacts can be calculated when a site-specific assessment is not possible.

If the location of the production process is not known at all, calculating regional water balance impacts is not very meaningful. In chapter V, it was demonstrated that there exists a considerable degree of uncertainty on the water indicators calculated with SWAT, so that even with a site-specific assessment, one can only detect a significant impact for relatively large changes in land use. Site-generic assessments increase the uncertainty on the model inputs which decreases the predictive capacity of a hydrological model so that the impact of realistic changes in land use most probably becomes smaller than the uncertainty inherent in using a model. In this case, a reliable estimation of changes in stream flow volume after land use change is not possible. A second problem is that a production system can affect the hydrology of a specific region, but not of the entire globe. Because of this, it is not very meaningful to make a completely site-independent assessment of water quantity related impact.

If the location is approximately known, water quantity impacts can be calculated as the average of a number of model simulations in the region where the production is assumed to take place. Alternatively, one can make a hypothetical model simulation, using the average characteristics of the region of interest as inputs. The regionalization schemes presented in chapter IV may be used for estimating model parameters. In this case, the analysis can be labeled as 'site-dependent' rather than 'site-specific'.

Model uncertainty

Models used for life cycle impact assessment consist of two parts: (1) (quantitative) modelling of impact pathways from the inventory data up to the environmental indicator and (2) (qualitative) modelling of the link between indicators and the main environmental themes (so-called areas of protection, endpoints or safeguard subjects). Indicators can be placed at any point of the impact chain between human interventions, listed in the inventory, and areas of protection. Two main approaches can be distinguished: (1) midpoint indicators referring to an intermediate point of the impact chain and (2) damage indicators directly referring to an area of protection or endpoint (Jolliet et al., 2003; Jolliet et al., 2004).

Consider the impact pathway of the regional water balance. Agricultural and forestry activities change the volume of water that is lost by evapotranspiration and the 'hydrological quality' (infiltration capacity, water holding capacity) of the land use system. This in turn alters both the absolute and relative magnitude of the water flows leaving the system i.e. surface, lateral and groundwater flow. Altered flow components cause a shift in low, average and high stream flows. For the method proposed in this thesis, the quantitative modelling of the impact chain is interrupted at this point. As pictured in **Fig. 41** midpoint indicators were used that were calculated from water balance variables. The connection between intervention (land use change) and indicators was established through quantitative modelling with the SWAT. The indicators were connected with the area of protection 'ecosystem health' through qualitative modelling i.e. the principle that the health of an ecosystem is related to its exergy buffering capacity was used to understand apparent conflicts between indicators for terrestrial and aquatic ecosystem health and to identify threshold values above/below which the health of an ecosystem becomes questionable.

Uncertainty might result from quantitative as well as qualitative modelling. The following paragraphs discuss how these issues were addressed in this study.

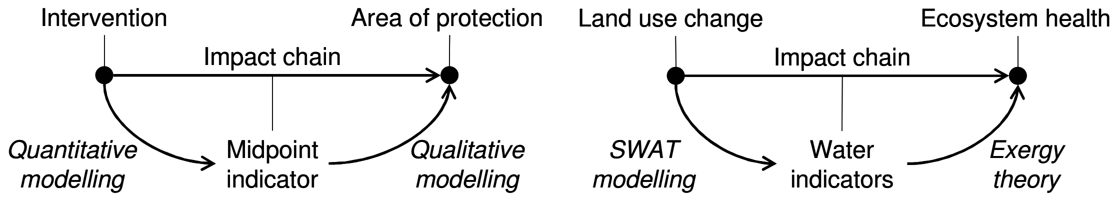


Fig. 41: Quantitative and qualitative modelling when using midpoint indicators in LCA: general concept (left) and the case of water balance indicators (right)

From inventory to environmental indicator

The impact of human interventions (i.e. of land use change) on environmental indicators (e.g. the stream flow regime) is usually calculated with a numerical model. In this thesis, this involved the use of the SWAT model to calculate the water balance of agricultural and forestry production. The same model structure and indicators can be used to assess water quantity impacts of other land use types e.g. of roads or mining sites, though in this case the model parameters should be calibrated using rainfall-runoff data from catchments where the considered land use (roads, mining sites etc) occupies a relatively large area.

The uncertainty on the numerical modelling was quantified for a case-study in the Zwalm river basin in chapter V.1. It was shown that the (one-sided) uncertainty on the regional water balance indicators was approximately 30-40% if the confidence level was set to 95%. This uncertainty range represents the total uncertainty caused by missing, unreliable or inappropriate model inputs (cfr. paragraph about data uncertainty) and errors or simplifications in the model structure. In other words, it reflects the uncertainty caused by using a hydrological model to generate stream flow instead of stream flow measurements. The specific contribution of model structural uncertainty can be assessed by an ensemble modelling approach i.e. simulating stream flow with multiple models using the same input data set (Breuer et al., 2005). A rough assessment of model structural uncertainty can also be obtained through a sensitivity analysis. For SWAT applications in Flanders, such a sensitivity analysis indicated that stream flow predictions generally are less sensitive to model structural aspects (**Table 4**) compared to model inputs (**Table 5**).

Hydrological modellers tend to regard uncertainties having an order of magnitude of 30-40% as (too) large, because these limit the usefulness of models for predicting the impact of environmental change. The rules of thumb adopted in LCAs, however, indicate wider uncertainty bounds: 50% for resources and 100% for emissions. The use of the SWAT for inventorying water flows in LCAs of land intensive systems thus scores relatively well with respect to reliability.

From indicator to area of protection

The connection between water balance indicators and the area of protection 'ecosystem health' was established through qualitative modelling based on the maximisation of exergy buffering capacity. Connections to other areas of protection that were not considered in this thesis can be found in literature e.g. using the principle that lower internal exergy levels (caused by increased exergy consumption) point out higher resource depletion rates to connect indicators with the area of protection 'resource availability'. Zaleta-Aguilar et al. (1998) followed this approach for river water depletion. Finnveden and Östlund (1997) calculated exergy levels of ores and so were able to aggregate depletion rates of different ores in one single resource availability indicator. Hence, the exergy concept can facilitate the joint interpretation of different environmental sub-problems for resource depletion assessment as well as for the assessment of ecosystem health. In the first case, the emphasis lies on minimisation of exergy consumption (which decreases internal exergy content), in the second case on maximisation of exergy buffering capacity.

The use of maximisation of exergy buffering as a measure of ecosystem health - or more general: the use of goal functions for ecosystem development - has often been criticised. Some authors proposed other goal functions that might be related to exergy buffering e.g. maximisation of resilience (Kirstensen et al., 2003). Others argued that the development and evolution of natural systems follows a random pattern, and therefore deny the existence of any goal function (e.g. Wilhelm and Brüggemann, 2000). This ongoing discussion highlights that the qualitative modelling of the link between indicators and areas of protection is uncertain. Standard methods to assess this uncertainty do not yet exist. Bockstaller and Girardin (2003) proposed two ways for improving the reliability of indicators that could be used in future work to assess the reliability of the qualitative modelling performed in this thesis: (1) a validation based on expert consensus and (2) comparison with other existing indicator(s) constructed for the same purpose but from a different background. The second alternative could be implemented by using different goal functions to interpret water balance indicators.

Uncertainty due to choices

At many points in a LCA, one needs to make choices that might affect the environmental profiles of products or systems. Three choices that are characteristic for the LCA methodology are the choice of functional unit, reference system and system boundaries.

In LCAs of agriculture and forestry, the *functional unit* is most of time defined as 1 kg of food product, 1 m³ of wood, 1 kg CO_2 sequestered etc. However, it might sometimes be appropriate to use one unit area as functional unit to reflect the delivery of non-market goods by agri- and silvicultural systems (Basset-Mens and van der Werf, 2005). Basset-Mens (2005) mentioned that the most appropriate functional unit depends on the considered impact category: for categories with a global impact, 1 kg or a similar unit can be used, whereas for regional impacts 1 hectare is preferred. Moreover, Haas et al. (2001) stated that impacts on biodiversity, landscape aesthetics and animal welfare are preferably expressed per farm. These approaches are quite different from the traditional ways of dealing with multifunctional production systems in LCA. Allocation, system expansion and - to a lesser extent - subdivision or splitting up multifunctional process in subprocesses delivering one single end-product, have proved to be useful for dealing with multifunctional industrial production (Ekvall and Finnveden, 2001). However, these techniques cannot easily be applied to land intensive systems for a variety of reasons. For example, exact identification and quantification of the number of produced functional units - which is a prerequisite for allocation - is not straightforward for non-market goods and services such as recreational value. Besides, it is often difficult to subdivide an agricultural production process with multiple end-products e.g. wheat and straw from a wheat crop (Mattsson, 1999). It may be helpful to subdivide the life cycle in an agricultural/forestry and an industrial part, so that the impacts caused by industrial subprocesses can entirely be attributed to the food or forest product(s) (and expressed per kg, m³, etc). For the agricultural part one could then use one unit area as functional unit to avoid the problem of allocation. The choice of the functional unit can have a large impact on the result (Marshall, 2001). For example, in a case-study comparing the environmental impact of forestry scenarios for CO_2 emission reduction (Heuvelmans et al., 2005), evergreen forests had the largest evapotranspiration per unit area, but expressed per kg CO_2 sequestered, the evapotranspiration was rather low for this land use type. Another example is the case of organic versus conventional agriculture. Conventional agriculture tends to cause a larger impact per unit area, but because productivity is higher, the impact per unit of end product can become lower than for organic systems (e.g. Nicoletti et al., 2001). To minimise the uncertainty due to the choice of the functional unit, it is thus essential that the selected functional unit fits the decision-making context.

The PNV (potential natural vegetation) was chosen as the *reference system* because this normalises the differences in inventoried water flows caused by varying abiotic conditions. In other words, regions with low natural stream flow levels should not a priori receive smaller water indicator values. However, the exact nature of the PNV and its environmental profile are not always well defined. Moreover, the choice of alternative reference systems e.g. the state before the intervention, can cause large changes in the impact assessment result.

As mentioned in chapter II, the uncertainty due to *system boundaries* in LCAs of land intensive systems mainly relates to the spatial and temporal variability of these systems. In chapter III, a sensitivity analysis of the SWAT model revealed that the water balance terms are relatively insensitive to the length of the simulation period. This indicates that the temporal extent of the system does not have a noticeable effect on the impact assessment results, if the considered time span is a multiple of one crop rotation. The impact of the uncertainty on spatial system boundaries was assessed for a case-study involving afforestation in the Zwalm region, as discussed in chapter V.2. The spatial system boundaries, or in other words: the spatial scale of the analysis (~1 – ~10 – ~100 km²), did not cause large uncertainties on the stream flow predictions. The relative proportion of the area that is converted to forest was a more important factor, and for a low forest index, also the spatial arrangement of the newly planted forests. However, overall, the uncertainty caused by imperfect knowledge of the land use was clearly smaller than the uncertainty inherent in using a hydrological model.

Trade-offs between uncertainty sources

The uncertainty on qualitative and quantitative modelling interacts with data uncertainty. Regarding quantitative modelling, simpler models usually are less data demanding and therefore lead to lower data uncertainties. On the other hand, simpler models are known to have a higher model structural uncertainty. There is thus a trade-off between data and model uncertainty, and one can expect that there exists an optimal model complexity, having the lowest possible total uncertainty, for every situation. LCA methods should ideally be flexible with respect to data demands to enable reliable simulations in varying situations of data availability. In this thesis, the SWAT was used for calculating water balance indicators because it provides the modeller many different modelling procedures with different data requirements. Building a regionalisation model for estimating model parameters when stream flow data are missing extended this flexibility. The regionalisation model decreases data uncertainty but at the same time, model uncertainty increases. In chapter IV.5, the model uncertainty caused by the parameter regionalisation was calculated. It amounts about 20%.

Next to its effect on quantitative model uncertainty, data uncertainty also affects the selection of indicators, in particular their location along the impact chain, and thus the qualitative model uncertainty due to the connection of indicators to areas of protection. Take for example the assessment of flood risk. The method proposed in this thesis opted to select indicators at the midpoint, i.e. the flood flow. Could the quantitative modelling of the impact pathway be prolonged to obtain a damage indicator? This would increase the complexity of the modelling: the reaction of species to water level changes must be known to assess the impact on biodiversity and ecosystem health, the extent of floods must be assessed including the damage that this causes to buildings etc. to estimate the impact on the man-made environment. Hence, as shown in **Fig. 42**, the use of damage indicators to reduce qualitative model uncertainty is only possible at the expense of the reliability of the quantitative modelling.

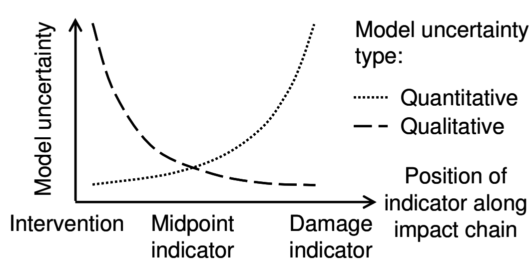


Fig. 42: Trade-offs between quantitative and qualitative model uncertainty in relation to the position of water indicators along the impact pathway

Fig. 42 also shows that a drastic reduction of quantitative model uncertainty can only be achieved at the expense of qualitative model reliability. Quantitative model uncertainty can be reduced by defining indicators close after intervention. Giegrich and Sturm (1998), for example, used the percentage of the area that is artificially drained as a water balance indicator. Calculating this indicator for a given production system is straightforward;

quantitative model uncertainty is small. The main uncertainty in this method however lies in connecting the indicator with the area of protection: does an increase in drained/irrigated areas always lead to a lower ecosystem health? Does ecosystem health decrease linearly with an increase in drained areas? Because of these large qualitative model uncertainties, one might conclude that indicators based on the environmental effects are preferable to indicators based on interventions. Van der Werf and Petit (2002) gave an additional argumentation for using effect-based indicators instead of intervention-based ones: the choice of means to reach environmental sustainability is left to the land manager. Together with the high quantitative model uncertainty when using damage indicators, this viewpoint supports our approach of using stream flow percentiles as indicators.

Conclusion

Based on earlier research, some shortcomings of existing methods for water quantity impact assessment in LCA were identified. First of all, the presently used indicators do not adequately describe the hydrological problems perceived by the society. Secondly, the reliability of methods for inventorying water fluxes passing land use systems was questionable. The 'regional water balance' impact category was introduced to cover impacts of land use systems on downstream water availability, flood and drought risk. The 5^{th}, 50^{th} and 95^{th} percentile of stream flow time series were proposed as indicators for these environmental problems. The SWAT model was used to calculate these indicators for a case-study in the Scheldt river basin. SWAT inputs were derived from existing databases and stream flow records were used to optimise model parameters. In practice, stream flow records are often missing in LCAs because the studied region is ungauged and/or because a hypothetical land use scenario is considered. To enable a reliable simulation under these circumstances, regionalisation models were built that estimate model parameters based on the location of the catchment or generally available catchment attributes. The uncertainty on the inventoried water balance terms caused by using a hydrological model instead of direct stream flow measurements was quantified with the General Likelihood Uncertainty Estimation procedure. The uncertainty caused by imprecise knowledge of future land use was assessed for an afforestation case-study. Uncertainty inherent in using a hydrological model was more problematic than the uncertainty on the future land use in our case-study. Compared to the rules of thumb adopted in LCA, uncertainty is reasonable, but in hydrological modelling, uncertainties of this order of magnitude are considered as limiting factors for simulating land use impact. Reducing quantitative model uncertainty could therefore increase the usefulness of SWAT for LCAs of land intensive systems. Besides, future work should try to more carefully assess the qualitative model uncertainties caused by linking indicators to the area of protection 'ecosystem health'. Finally, the transferability to other land use related environmental problems of the proposed methods and concepts for addressing data gaps and spatio-temporal variability should be evaluated.

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