TU Graz

Graz University of Technology

High resolution online data in sewer water quality modelling

Dissertation zum Erwerb des
akademischen Titels Doktor der technischen Wissenschaften
(Dr. techn.) der Studienrichtung Bauingenieurswissenschaften

Valentin GAMERITH

Verfasst am Institut für Siedlungswasserwirtschaft und
Landschaftswasserbau der Technischen Universität Graz

Betreuer:
Univ.-Prof. DDipl.-Ing. Dr. techn. Dr.h.c. Harald Kainz
Dr.-Ing. Dirk Muschalla

Begutachter:
Univ.-Prof. DDipl.-Ing. Dr. techn. Dr.h.c. Harald Kainz
Univ.-Prof. Dipl.-Ing. Dr. techn. Wolfgang Rauch

Graz, März 2011

Contact:
Valentin GAMERITH
valentin.gamerith@yahoo.com

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Acknowledgements

This doctoral thesis was realised over the last four years at the Institute of Urban Water Management and Landscape Water Engineering at Graz University of Technology. During this time I spent some weeks at TU Darmstadt, Germany and at INSA de Lyon, France and five months at Université Laval, Canada in the model*EAU* team.

Above all I want to thank Professor Harald Kainz who welcomed me at his Institute. He supervised and assessed this work, supported me in project work and always gave me the opportunities to travel and network what I highly appreciate.

My most profound thanks go to Günter Gruber, with whom I shared the office and worked constantly on numerous projects. Not only did he lay the basis for my work by his research, he also always supported me whenever need arose.

A big thank you to Dirk Muschalla who supervised my work and with whom I had the pleasure to work intensively on my research and publish several papers together. And who provided me with a great stay in Québec.

I would equally like thank my second assessor, Professor Wolfgang Rauch, who took his time to read through this work and give important advice.

Likewise I would like to express my gratitude to Jean-Luc Bertrand-Krajewski with whom I had the pleasure to discuss some of my work intensively during my stays in Lyon. Equally to Peter Vanrolleghem for welcoming me in the model*EAU* team in Québec and for his valuable inputs.

Thanks to the staff of the Holding Graz Kommunale Dienstleistungen GmbH Services – Abwasser (former Kanalbauamt Graz) for their great support with the measurement station and for providing the data for the case study catchment.

In addition I would like to thank all my working colleagues who became friends here at the Institute. Also Steffen, Frank and Jörg from Darmstadt (remembering our great shared rooms in Edinburgh and Tokyo), Marc and Xavi from Canada and many others I met over the last years.

My work would not have advanced in the same way without the help from my bachelor, diploma, and master candidates who all worked intensively on their topics: Hannes, Mario, Maxl, Berni, thanks!

Special thanks go to all my friends who accompanied me throughout my life here in Graz. A lot of fun, music, sports, games, evenings, discussions and other things I would not want to have missed. You know who you are.

Sincere thanks to my family who always supported me in my decisions.

Last but not least to the one friend who always supported and pushed me to continue my work (scarifying some shared evenings or week-ends to that purpose) and who gave me a lot of strength, motivation and joy since I know her.

Abstract

Over the last decades the modelling of sewer systems has been advocated by the scientific community and has become increasingly common also in practice. More recently, emerging measurement technologies allow measuring both hydraulics and pollutant concentrations in-situ with high temporal resolution directly in sewer systems.

This thesis treats the applicability of long-term high-resolution online data in state-of-the-art modelling procedures in sewer water quality modelling. A methodology is proposed to facilitate the necessary steps to get *from data to validated model results*. This includes the development and implementation of methods for data analysis, automated data validation and sensor calibration as well as a toolkit with state-of-the-art methods for global sensitivity analysis and the application of an available multi-objective optimisation algorithm based on evolution strategies for model optimisation and calibration. These methods are then applied to the *Graz West R05* case study, an urban catchment where high-resolution data on flow and pollutant concentrations has been measured continuously for several years now.

The developed set of data analysis and validation tools proved a good assist in assessing and assuring data quality for further processing in modelling. Discussion on the calibration of a UV/VIS spectrometer probe in wet weather conditions highlights the importance of local probe calibration and shows possible pitfalls. Two models are set up for the case study catchment. Two methods for global sensitivity analysis are applied and their performance is compared. In general, both methods identify the same model parameters as influential. A first methodology is proposed to evaluate the impact of using different events and/or objective functions on the model parameter sensitivities. A comparison of single- and two multi-event optimisation schemes for model calibration is carried out. It is shown that validation events are better reproduced by using multi-event calibration and that the two multi-event approaches performed equally well. Three approaches for sewer water quality modelling are compared and their performance for the case study catchment is discussed.

Overall the methodology provided sound results for the case study catchment and should be easily transferable to other networks. Also the application of the methods in practice can only be highly recommended. Nonetheless, it is advised to apply the presented methods with care and critical review of the boundary conditions and results as the application of mathematical sound procedures can lead to undue over-confidence in the results where engineering knowledge would contradict.

Kurzfassung

Die Modellierung von Kanalsystemen ist seit mehreren Jahrzehnten Gegenstand der Forschung und wird seit längerem auch in der Praxis angewendet. Neuentwicklungen in der Messtechnologie erlauben nun die zeitlich hoch aufgelöste Erfassung von Abfluss und Schmutzstoffkonzentrationen direkt im Kanalsystem. Die großen Datenmengen stellen dabei eine Herausforderung an das Datenmanagement und an die sinnvolle Anwendung der Daten in der Modellierung dar.

Diese Dissertation behandelt die Anwendbarkeit hoch aufgelöster Langzeitmessreihen in der Schmutzfrachtmodellierung von Kanalnetzen. Dabei wird eine Vorgehensweise entwickelt, die den Weg *von Daten zu Modellergebnissen* erleichtern soll. Dazu werden Methoden zur Datenanalyse, Datenvalidierung und Sensorkalibrierung entwickelt. Methoden zur globalen Sensitivitätsanalysis werden in ein bestehendes Optimierungsframework integriert, welches auch einen Optimierungsalgorithmus basierend auf evolutionären Strategien zur Modelloptimierung beinhaltet. Diese Methoden werden in Folge in der Fallstudie *Graz West R05* angewendet, wo seit mehreren Jahren kontinuierlich hoch aufgelöste Messreihen zu Abfluss und Schmutzstoffkonzentrationen aufgezeichnet werden.

Durch die entwickelten Methoden für die Datenanalyse und Datenvalidierung konnten die vorhandenen Messdaten sinnvoll geprüft und deren Qualität für die weitere Verwendung in der Modellierung gesichert werden. Eine Auswertung der Messergebnisse der installierten UV/VIS Spektrometersonde zeigte die Notwendigkeit einer lokalen Sondenkalibrierung und diskutiert deren Grenzen. Zwei Modelle wurden für das Einzugsgebiet der Fallstudie erstellt. Zwei Methoden zur globalen Sensitivitätsanalyse wurden implementiert, verglichen und ihre Anwendbarkeit diskutiert. Im Allgemeinen wurden dabei dieselben Modellparameter als einflussreich identifiziert. Ein erster Ansatz zur Bewertung der Sensitivität von Modellparametern bei Berücksichtigung von Kombinationen von Regenereignissen und/oder Zielfunktionen wurde entwickelt. Ein Vergleich der automatisierten Modellkalibrierung bei Optimierung auf eine Zielfunktion und zweier Ansätze der multikriteriellen Optimierung zeigt, dass mit multikriterieller Optimierung eine höhere Qualität der Ergebnisse in der Modellvalidierung erreicht wird. Dabei führen beide Ansätze der multikriteriellen Optimierung zu gleich guten Ergebnissen. Drei Schmutzfrachtmodelle wurden verglichen und deren Anwendbarkeit für die Fallstudie diskutiert.

Zusammenfassend liefert die vorgeschlagene Methodik wertvolle Einsichten und zufriedenstellende Ergebnisse für die Fallstudie und kann auch einfach auf andere Fallbeispiele übertragen und angewendet werden. Auch die praxisbezogene Anwendung der vorgestellten Methoden kann nur empfohlen werden. Nichtsdestotrotz wird angeraten, die Methoden mit Bedacht anzuwenden und die Ergebnisse kritisch zu hinterfragen. Gerade die Anwendung von komplexen Methoden verleitet zu übermäßigem Vertrauen in die Ergebnisse, auch wenn die sie dem Ingenieursverständnis widersprechen.

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List of acronyms

$\ldots_{eq}$	Equivalent concentration
ASCII	American Standard Code for Information Interchange
AWO	Accumulation and wash-off
BOD	Biological oxygen demand
CN	Curve number
COD	Chemical oxygen demand
CSO	Combined sewer overflow
CSV	Comma separated values (file format)
DISP	Removal coefficient (accumulation-wash off model)
DL	Depression losses
DWF	Dry weather flow
EE	Elementary effect
EF	Evaporation facto
ES	Evolutionary strategies
EU-WFD	EU water framework directive
GIS	Geographical Information System
GSA	Global sensitivity analysis
GUI	Graphical user interface
IF	Imperviousness factor
IL	Initial losses
iLim	Limit rainfall intensity (accumulation-wash off model)
IMP	Percentage of imperviousness
Institute	Institute of Urban Water Management and Landscape Water Engineering, Graz University of Technology
K	Pipe roughness
Ke	Wash-off coefficient (accumulation-wash off model)
M(V) diagram	Mass - volume diagram
MAn	Manning's n (pipe roughness)
MC	Monte Carlo
ME	Multi-event
MO	Multi-objective
NaN	Not a number
netCDF	network Common Data Form
Pinit	Initial accumulated mass (accumulation-wash off model)
Pmax	Maximum accumulated mass (accumulation-wash off model)
SA	Sensitivity analysis
SAC	Spectral absorption coefficient
SCS	Soil conservation service
SE	Single-event
SLP	slope
SWMM	Storm water management model
TF	Concentration time factor
TOC	Total organic carbon

TSS	Total suspended solids
UK	United Kingdom
US	United States of America
US-EPA	United Stated Environmental Protection Agency
UV/VIS	Ultraviolet-visible
W	Shape exponent (accumulation-wash off model)
WWTP	Waste water treatment plant
ZAMG	Central Institute for Meteorology and Geodynamics

1 Introduction[1]

In combined sewer systems only a certain amount of the total runoff during storm events can be hydraulically routed through the system and be treated by waste water treatment plants (WWTPs). Therefore, the exceeding combined sewage is generally either stored temporarily or spilled out of the system into receiving water bodies by means of combined sewer overflow structures (CSOs). The overflow from a combined system is composed of a mixture of sanitary sewage, storm water and – possibly – industrial waste water. Depending on the overflow structure the spilled water can be partially treated or be spilled untreated.

The spilled pollutants are known to have a major impact on the quality of the receiving water, notably the ecosystem and the aquatic milieu as well as leading to possible endangerment of public health. Especially in developed countries rules have been put in place trying to delimit theses discharges and to survey their effects. The costs for the demanded measures are important, the interest in a detailed understanding of the processes therefore evident. To evaluate the impacts, knowledge of the quantity and the quality of the spilled discharge is necessary.

Stormwater quality models have been widely used over the last three decades to describe the general system behaviour and assess pollution loads both transferred in and spilled out of combined sewer systems. These models are an appropriate instrument for evaluating the function and performance of the systems, facilitating the conception and planning of new systems, optimising existing systems, setting up rehabilitation strategies, etc.

However, sewer flow modelling involves different sources of uncertainties and focusing on sewer water quality modelling incorporates additional uncertainties in pollution load input and sewer quality processes (Willems, 2008). This is mainly caused by the complexity of the sewer processes and the dependency on numerous circumstances resulting in a lack of knowledge (Ashley et al., 1999). The model results are site-specific and their generality and transferability is still limited.

In addition the availability of measurement data is often limited (Mannina et al., 2006). While high-resolution data on precipitation and runoff have become more and more obtainable, exhaustive information on pollution concentrations is seldom available. Actually, the lack of field data is a critical aspect in modelling with serious consequences for model calibration (Bertrand-Krajewski, 2007).

The estimation of pollution concentrations is traditionally based on sample analysis. Samples are retrieved from the sewer system by automatic samplers and are then evaluated in standardised lab analyses. This method has several shortcomings: short duration campaigns, limited information obtained at insufficient time intervals, neglecting full dynamics

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[1] This introduction is partly composed of paragraphs from Gamerith et al. (submitted-a) and Gamerith et al. (accepted)

of runoff and pollutant concentrations, etc. Errors can result from the sampling process itself as well as sample conservation, transport and preparation (Bertrand-Krajewski et al., 2003).

Recently, in-situ spectrometer probes have been used more frequently to quantify pollutants transferred in sewer systems. They allow continuous high-resolution measurement and were shown to be comparable robust tools for measurement of a number of target parameters such as chemical oxygen demand (COD), total organic carbon (TOC), nitrate (NO_3-N) or total suspended solids (TSS) (Winkler et al., 2008a). The probes have to be calibrated to site-specific conditions based on laboratory analyses of water samples. Once installed, the probes allow assessing the full dynamics of pollution concentration encountered in sewer systems.

In Graz, Austria, an online monitoring station is installed at a CSO in the *Graz West R05* catchment. Equivalent pollution concentrations for COD, TOC and TSS are continuously monitored in-situ by an ultraviolet-visible (UV/VIS) spectrometer probe. It has now been in more or less continuous operation for over eight years (Gruber et al. 2005).

Based on the data collected over the last years, this thesis presents a consequent step further from the works carried out at the Institute of Urban Water Management and Landscape Water Engineering (*Institute* in the following) within the research topic *Management of Sewage Water Systems*, namely within the research project *Innovative Technology for Integrated Water Quality Measurement IMW* (BMLUW, 2005) and the associated works of Gruber (Gruber et al., 2006, Gruber et al., 2004, 2005) and Hochedlinger (Hochedlinger, 2005, Hochedlinger et al., 2006).

Starting from the available data the following **challenges** were identified in a preliminary screening process:

- How can the important amount of data be managed?
- How can the quality of the data be assessed and assured?
- How do sewer water quality models perform when using high-resolution, long-term data?
- Can the dynamics in the observed system be reproduced with current water quality model approaches?
- Can a benefit be drawn from the data in modelling, if yes at what costs?
- Can a framework be established that allows a step-by-step procedure to get from data to validated model results, independent from a specific case study?

An overview of the aims and hypothesis derived from these identified challenges as well as the applied methodology to address these challenges is given in the following paragraphs.

1.1 Hypothesis

Based on the experience in previous research linked to the measurement data and modelling, the following hypotheses were established in this work:

- The available high-resolution water quality data gives us a better understanding of the behaviour and dynamics of pollution transport encountered in the sewer system.

- Not all phenomena in the pollution transport processes can be assessed with traditional sampling methods.
- The high number of observations allows better model calibration.
- The performance of existing water quality models can be evaluated with the data.

1.2 Aims

The aims defined for this thesis can be divided in several objectives:

First to develop methods and tools that allow the management and quality assessment of the measured data and link the data to the sewer water quality models. This should provide a basis for a semi-automated data validation within the *OpenSDM*-framework currently being developed at the Institute (Camhy et al., submitted) as well as an estimation of the uncertainties to be expected in the measured data.

Secondly to set up and test state-of-the-art tools for sensitivity analysis, model calibration and assessment of model performance and link them to the sewer water quality models. This is realised within the *BlueM.OPT* framework (Bach et al., 2009).

The developed tools should then be applied to the data and models set up for the *Graz West R05* case study in order to:

- Estimate the uncertainties in the water quality measurements and analyse and validate the data with the developed semi-automated data validation tools.
- Perform a global sensitivity analysis to identify the most sensitive model parameters and estimate their influence on model output uncertainties and to identify storm events and/or objective functions that yield most information on the model parameters.
- Evaluate the performance of single- and multi-objective optimisation for model calibration.

Finally the applicability of the developed methods should be discussed and a framework proposed that allows following a step-by-step procedure *from data to validated model output* that is transferable to other case studies.

1.3 Methodology

In coherence with the aims defined in the last section, a methodology to reach these aims was developed as follows:

The first part of this work is dedicated to an overview and literature review of the state of the art in the management of combined sewer systems, measurement and data as well as modelling, sensitivity and uncertainty analysis and (automated) model calibration.

Based on this review, uncertainty estimation for the measurement data is carried out. Several works carried out at the Institute are connected to this topic: Derler (2009), Zillig (2010), Steger (in preparation) and Gamerith et al. (submitted-b). Therefore this work focuses on the estimation of uncertainties in the water quality measurements. For the semi-automated data validation, scripts are developed in [R]. These scripts will be implemented in the *OpenSDM*-framework in near future. The available data is then evaluated with the developed scripts.

Two models are set up for the *Graz West R05* catchment: a hydrological model in the software SMUSI by Schneider (2007) and Fuchsberger (2009) and a hydrodynamic model in SWMM by Veit (2009). The available models are thoroughly evaluated on the model structure (geometry, special structures, parameters, input data etc.).

In parallel, the *BlueM.OPT*-Framework is extended by the methods required to reach the defined aims: additional objective functions are coded, state-of-the-art global sensitivity analysis methods are implemented via a direct link to [R] and a tool to analyse and compare time series is further developed.

Next, both models are linked to the *BlueM.OPT*-framework and the developed methods are applied in order to:

- Determine and rank important model parameters in a global sensitivity analysis.
- Examine the impact of different objective functions on the results.
- Evaluate the performance of an evolutionary-strategies optimiser in model calibration.
- Evaluate the performance of different sewer water quality model approaches implemented in SMUSI.

Due to the significantly lower computational costs these steps are carried out only for the SMUSI model.

1.4 Structure

The structure of this thesis follows the methodology described above:

The first chapters (2 to 4) shortly describe the management of combined sewer systems, include a literature review on data and measurements and give a general overview of the modelling of sewer systems.

Chapter 5 details on the methods and software tools used and developed in scope of this thesis.

Chapter 6 describes the urban catchment *Graz West R05* and shows the implementation of the developed tools and methods following the structure of chapters 2 – 4.

Eventually, chapter 7 gives a summary of the work and an brief outlook for further research.

1.5 A short note on nomenclature

Concerning the wording and expressions used in this thesis, the author tried to be – whenever possible – in coherence with the recommendations given in Carstensen at al. (1997). Some of the used terms might be understood differently in different fields or applications: e.g. in this thesis the word “model” refers to both the underlying model mechanics (equations) as well as the physical catchment model (describing the structures, geometry etc.).

All abbreviations used in text are given in the *list of acronyms* in the first section. Most of them are widely used in the urban drainage field.

2 Management of combined sewer systems

This chapter first gives a short description of the definition of a combined sewer system. Next, pollutants and substances encountered in combined systems, their origins and their possible impacts on the aquatic environment are discussed. Finally an overview of legal requirements based on a short literature review is given.

2.1 General Information

Figure 2-1 shows the functioning of a combined (left side) and a separate (right side) sewer system. In *separate sewer systems*, sanitary sewage and stormwater are transported in separate pipes. In a *combined sewer system* both sanitary (and possibly industrial) sewage and stormwater is transported together in one pipe. This means that during storm events, stormwater enters the sewer system and is mixed with the sanitary sewage. As the capacity of the waste water treatment plants is limited in order to assure their proper functioning, the exceeding combined sewage has to be handled in some other way.

Over the last decades many *best practice* techniques were developed aiming to reduce the stormwater entering the system. However, especially in highly urbanised areas where no or only limited space for e.g. infiltration or detention is available, the water can only be either stored within or spilled out of the system by CSO structures. Depending on the overflow structure the spilled water can be partially treated or be spilled untreated. The spilled pollutants are known to have a major impact on the quality of the receiving water, notably the ecosystem and the aquatic milieu.

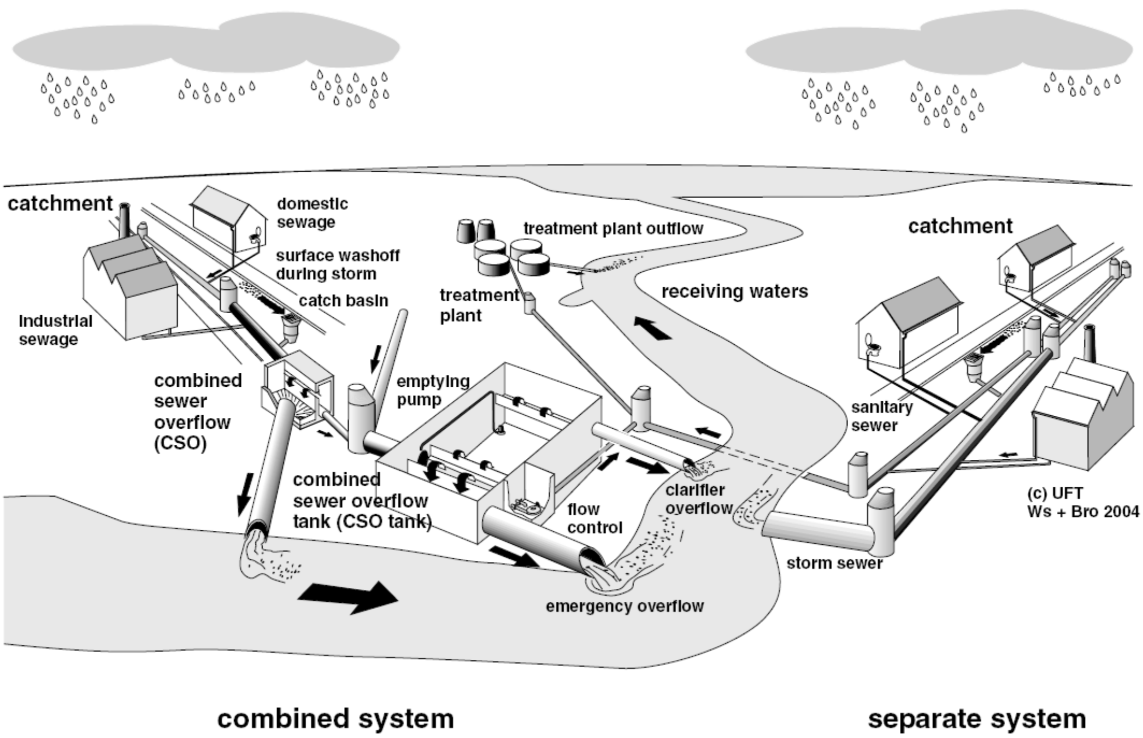

Figure 2-1: Comparison of combined and separate sewer system (Brombach et al., 2005, with permission from IWA Publishing)

CSO structures have two functions: first to hydraulically divide the inflow to reduce the hydraulic pressure on the downstream sewer system. And secondly – if a storage tank is in place – to pre-settle suspended solids that can eventually be carried on to the WWTP.

Exhaustive information on the design, functioning and management of such systems, overflow and storage structures can be found in basic urban drainage literature, as e.g. Butler and Davis (2000), Kainz et al. (2005) or Gujer (2007).

2.2 Pollutants in combined systems

During storm events, pollutants in combined systems originate from i) the pollutants in the sanitary sewage and ii) the pollutants in the stormwater.

In stormwater, pollutants are accumulated over the whole process duration of rainfall, runoff on the surface and runoff in the sewer system. In the atmosphere the water drops wash out suspended pollutants (aerosols). On the surface, deposed pollutants are mobilised by i) the impact of the water drop and ii) the runoff on the surface. In addition, possible deposits in the sewer system accumulated in dry periods due to small discharges can be re-mobilized if the total discharge in the sewer is high enough.

Several exhaustive studies have been carried out to characterize the pollutants encountered in sewer systems and to identify their sources. Intensive work was done in the 1970s and 1980s in the United Stated of America (US), e.g. by Pitt and Amy (1973), Sartor et al. (1974) and US-EPA (1983). The major findings were recently compiled into one database (Maestre and Pitt, 2005). Other studies were carried out for example in France (Deutsch and Hémain, 1984) and Switzerland (Rossi, 1998). A comprehensive overview of pollutants and concentrations based on data from Germany can be found in Brombach et al. (2005).

The main components that are generally analysed include:

- Sum parameters for organic matter as
    - biological oxygen demand (BOD_n),
    - chemical oxygen demand (COD)
    - total organic carbon (TOC)
- Total suspended solids (TSS), sum parameter
- Nitrogen (NH_4-N, NO_3-N, N_{tot})
- Phosphorous
- Heavy metals as Cd, Cr, Ni, Pb, Cu, Zn etc.

Exhaustive descriptions of these parameters and pollutants can be found in basic urban drainage literature as e.g. Butler and Davis (2000), Kainz et al. (2005) and Gujer (2007). In this work the focus lies on the sum parameters COD and TSS.

Recently more attention is being paid to priority substances defined by the European Union (European-Community, 2008) and micro pollutants like hormones, pharmaceutical and personal care products etc. This is still a field of current research and is not treated in this work. Further reading can be found e.g. in Engelhard (2006) or Hollender et al. (2007).

2.2.1 Impact on receiving waters

Due to the continuous loads discharged from WWTPs and the event-dependent loads spilled from the CSOs, potential danger can result for the receiving water ecosystem. According to Borchardt (1992) and Fischer (1998) spills from CSOs can lead to acute danger (over a time span up to some hours) for the receiving water due to hydraulic stress or chemical contamination. Delayed effects (some hours to some days) can result from chemical contamination, especially from oxygen consuming components (organic matter, ammonium). Bacteria and viruses can lead to a hygienic contamination, resulting in both acute and delayed effects. As long-term effects (weeks, month or even years) eutrophication, accumulation of pollutants as heavy metals in organisms and sediments and possible impacts of micro pollutants can be named (HSGSim, 2008, translated and modified). This leads to the main identified impacts on the receiving water:

- Hydraulic stress
- Ammonium / Ammonia toxicity
- Oxygen demand
- Solids
- Hygienic aspects
- Eutrophication
- Accumulation of heavy metals
- Aesthetics

Comprehensive descriptions of the different impacts can be found e.g. in HSGSim (2008) as well as in current guideline documents as the Austrian *ÖWAV Regelblatt 19* (OEWAV, 2007), the Swiss *Storm* guideline (VSA, 2007), or the German *BWK – Merkblatt M7* (BWK, 2008).

In order to assess these aspects, integrated models taking into account the sewer system, waste water treatment plants and the receiving water have been in discussion for a long time (see e.g. Beck (1976) and Lijklema (1993)). Eventually they were put in (scientific) practice in the last decade by Rauch et al. (1998a), Schuetze (1998), Rauch et al. (2002), Harremoes (2002) and Solvi (2006) among others. Recently the HSGSim working group on integrated modelling published a guideline document on integrated modelling (HSGSim, 2008, Muschalla et al., 2009). Only some citations are stated here, as the impact on the receiving water is not the focus of this work.

2.3 Legal basis

Several guidelines concerning the design and management of combined sewer systems exist in Europe. One of the driving forces to implement or revise guidelines in the last years was the EU-water framework directive (European-Community, 2000), where a *good status* or *potential* is required for all European surface water bodies. An overview of the legal situations in several European countries is given in Zabel et al. (2001). Concerning the availability of guidelines and regulations in Europe, Gamerith (2006) gives a short summary. A detailed overview of the regulations and guidelines in German speaking countries is given in HSGSim (2008).

Many of the current guidelines for CSO design and sewer management developed at national level recommend or require approaches using long term modelling, e.g. the German *Arbeitsblatt ATV A-128* (ATV, 1992), the UK *Urban Pollution Management Manual* (FWR, 1998), the French guideline *La ville et son assanissement* (CERTU, 2004) or the Austrian *ÖWAV Regelblatt 19* (OEWAV, 2007). While some guidelines focus on hydraulic modelling only, stormwater quality modelling became increasingly common over the last decades (mainly for researchers, less frequently for practitioners) to assess the pollutant loads transferred in and spilled out of combined sewer systems. Especially in order to assess possible negative effects on the receiving waters, several guidelines recommend water quality modelling in different levels of detail depending on the boundary conditions of the investigated catchment (e.g. FWR (1998), ÖWAV (2007), VSA (2007) and BWK (2008)). (Gamerith et al., submitted-a, modified).

3 Measurement and data

This chapter first addresses the challenges in measurements in urban drainage including a short description and overview of possible sources of uncertainties and errors. Next an overview of measurement principles for rainfall, hydraulics and water quality is given, with special focus on the devices and probes that are in place in the case study catchment *Graz West R05*.

The second part details on the challenges in data management and presents some methods for automated data validation and fault detection.

3.1 Measurements in urban drainage

"*Measurements together with observation are the basis for documenting, quantifying, describing, and understanding experiments, systems, and their variables. However, the measuring process is subject to uncertainties and errors that influence the results and must be considered in the interpretation of measured values*." (Gujer, 2008)

In urban drainage, measurements are crucial to assess the functioning and the performance of the system as well as predicting future system states e.g. by modelling. Different aims can be defined for a measuring task as protection against flooding, reduction or assessment of environmental impacts, design of WWTPs, real time control etc.

The main measured variables in urban drainage systems today – with focus on the sewer system – can be defined as follows:

- Rainfall as major input to the system.
- Hydraulics (water level / discharge) in the system to assess dry weather flow, parasite water, dynamics in wet weather flow, flood risk, functioning of CSO structures, real time control etc.
- Pollution concentrations to evaluate and reduce the impacts on the environment, to assess the functioning of CSO structures, design and operate WWTPs etc.
- Others as temperature, pH, conductivity etc.

As Bertrand-Krajewski et al. (2003) state it is absolutely necessary to use appropriate methods and techniques in order to i) calibrate sensors and analytical methods, ii) validate raw data and iii) evaluate measurement uncertainties in order to draw pertinent scientific and operational conclusions from the measurement results.

Compared to other measurement tasks, several additional challenges result from measuring in sewer systems (Bertrand-Krajewski et al., 2000):

- Especially in combined systems high dynamics in runoff and pollution concentrations are encountered. This means that i) a high measurement range has to be covered and ii) the measurement device must be robust to withstand the physical stress.
- The environment is very humid and aggressive. This can lead to corrosion problems for both mechanical and electronic components.
- As the environment is explosive, devices installed directly in the sewer have to be explosion proofed.

- The measured medium is inhomogeneous; solids are transported with the water. This means that measurement devices installed in the medium i) risk being damaged and ii) can pose a serious problem due to clogging.
- Accessibility is often limited.
- Trained personal for installation and maintenance is indispensible.

These boundary conditions add to the uncertainties and often pose serious problems in the realisation of a measurement campaign in sewer systems.

3.1.1 Uncertainties in measurements

"Results of measurements are random variables that are subject to probability density distributions. A single realization of a measurement can have any value in the range of this probability distribution. From repeated measurements we derive empirical density distributions, which we then characterize statistically. The true value of a variable to be measured is not known; we can approximate it, but we never know it for sure. " (Gujer, 2008)

It is assumed that input data uncertainty is connected to the problem that data collection is never accurate and is composed of random and systematic uncertainties. According to Uhl (1993) the distribution of the random uncertainties – derived from replicated measurements – around their mean can be described by several distribution functions. The assumption of a distribution function can be validated e.g. by a χ^2 test (Sachs, 1993). Frequently, especially with high number of replicate measurements, random uncertainties are Gaussian distributed (central limit theorem). In the following description, the random uncertainties are therefore assumed to be Gaussian distributed, an assumption that is generally adopted in urban drainage literature (e.g. Uhl (1993), Bertrand-Krajewski et al. (2000) or Gujer (Gujer, 2008)). This means that individual values x_i of the random variable X are subject to a certain probability density function f(x) with a mean value of value μ_x (the "true" measurement value, Equation 3-1) and the variance σ_x^2 (Equation 3-2). Density functions for normal and lognormal distributions (meaning that the natural logarithm of the measured variable is normally distributed, for measured variables where negative values are not permissible) are given in equations Equation 3-3 and Equation 3-4 respectively.

$$\mu_x = \int_{-\infty}^{\infty} x \cdot f(x) \cdot dx$$ **Equation 3-1**

$$\sigma_x{}^2 = \int_{-\infty}^{\infty} (x-\mu_x)^2 \cdot f(x) \cdot dx$$ **Equation 3-2**

$$f_N(x) = \frac{1}{\sqrt{2\,\pi\,\sigma_x^2}} \cdot exp\left(-\frac{(x-\mu_x)^2}{2\,\cdot \sigma_x{}^2}\right)$$ **Equation 3-3**

$$f_N(x) = \frac{1}{x \cdot \sigma_{lnx}\sqrt{2\,\pi}} \cdot exp\left(-\frac{(\ln x-\mu_{lnx})^2}{2\,\cdot \sigma_{lnx}{}^2}\right)$$ **Equation 3-4**

The empirical distribution of a random variable can be approximately determined by *n* multiple measurements of exactly the same object (replicates). In that case, the arithmetic mean m_x (Equation 3-5) is used as an approximation of μ_x and the empirical variance s^2 (Equation 3-6) replaces σ_x^2.

$$m_x = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i$$ **Equation 3-5**

$$s_x^2 = \frac{1}{n-1} \cdot \sum_{i=1}^{n} (x_i - m_x)^2$$ **Equation 3-6**

The expected value μ_x and average value m_x are yardsticks for the position of a distribution. The standard deviation σ_x, s_x, and variance s_x^2 are indicators of dispersion, i. e. yardsticks for the dispersion of variables around the expected or average value. The term dispersion is mathematically not accurately defined, but signifies the deviation of a realization of a random variable from its expected value (Gujer, 2008). Further detailed information on measurement uncertainty is given e.g. in the *ISO/IEC guide 98-3:2008* (ISO, 2008).

3.1.1.1 Classification of errors

The following descriptions are mainly based on Gujer (2008) and Uhl (1993). The measurement error can be classified according to Figure 3-1 in random, systematic and gross errors.

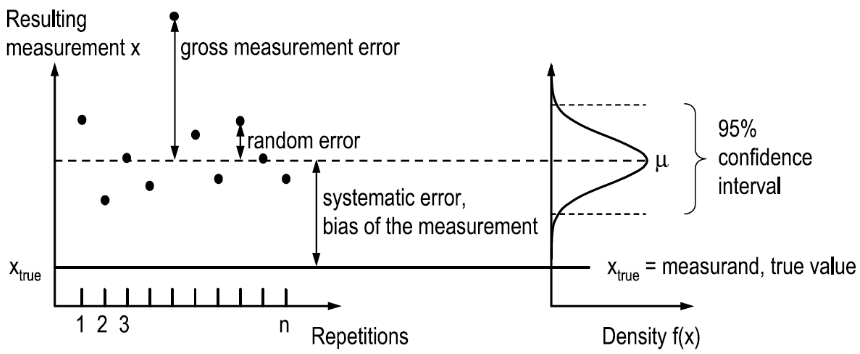

Figure 3-1: Gross, random and systematic errors (Gujer, 2008), after (Thomann, 2002)

Gross errors result from mistakes, operation and calculation errors. If possible they should be identified and removed from the data.

The **random error** would result from an infinite number of measurements under repeatability of conditions. As stated above, random errors are frequently normally distributed. In this case the arithmetic mean (see above) corresponds to the best estimated values of the measurand. The estimates of expected value and variance are again normally distributed. The variance of the arithmetic mean $s_{m_x}^2$ (Equation 3-7) characterizes the statistical properties of the remaining random measurement error, if several measured values are available. It decreases as the number of available results *n* increases.

$$s_{m_x}^2 = \frac{1}{n \cdot (n-1)} \cdot \sum_{i=1}^{n} (x_i - m_x)^2 = \frac{s_x^2}{n}$$ **Equation 3-7**

Random errors cannot be avoided but they can be reduced e.g. by choosing a more precise probe or a different measurement procedure.

A **systematic error** means that measured value always deviates in one direction from the true value. It can't be determined by increasing the number of measurements but requires additional experiments to be identified. It can have several sources (measurement device, 0-point error, etc.) and can be temporally constant or vary with time (drift). If the error can be identified it can also be corrected. If the systematic error is unknown, its value and sign are not quantifiable. One possibility to detect systematic errors is to install redundant measurements.

3.1.1.2 Sources and estimation of uncertainties in measured data

According to Bertrand-Krajewski et al. (2000) uncertainties in the eventually recorded measurement data – with focus on measurements in urban drainage – can result from several sources:

- Uncertainties due to the measurement device (intrinsic uncertainties, failures, measurement site conditions, etc.)
- Uncertainties due to site/location (effect of velocity and concentration profiles and heterogeneity, representativity of samples, etc.)
- Uncertainties due to sampling device (presence of a strainer, pumping velocity, cross-contamination, settling, etc.)
- Uncertainties linked to sampling time and space scales (number of samples / sampling at early beginning of an event etc.)

In actual measurement setups in urban drainage, generally time series of the variable of interest are recorded. This means that only one value *x(t)* from the measurand is obtained at any time step *t*. In this case no statistical statement is possible to describe the random measurement error. The measured value *x(t)* would correspond to any value from the probability distribution. For pragmatic reasons the value *x(t)* is assumed to be the expected value from the distribution (Uhl, 1993).

In addition, as stated before, several sources of uncertainties add to the total measurement uncertainty compared to only taking into account random errors. In order to quantify the actual uncertainty of measured data the

- measurement error of the measurement device (e.g. specified by the manufacturer or evaluated from replicate measurements) and an
- estimated error (based on knowledge, linked to the error source described in above)

have to be taken into account. Methods to evaluate the magnitude of these uncertainties are described e.g. in Bertrand-Krajewski et al. (2000) and Bertrand-Krajeswki et al. (2003).

3.1.2 Rainfall measurement

Rainfall measurements play a central role in the modelling of sewer systems as rainfall is by far the most important input variable that drives runoff and flow propagation. According to Schilling (1991) ideally a long data series (20 years or more) with one minute time resolution, 1 km² spatial resolution, and time synchronization errors below one minute should be available. In the context of integrated modelling, Rauch et al. (1998b) speak of long term series where temporal resolution of the data should be in the order of minutes.

An evaluation of a questionnaire from the World Meteorological Organization with 118 countries participating by Sevruk (Sevruk, 2002) showed that worldwide the following systems to measure rainfall are in use (in order of repartition): Float systems, tipping-bucket system, drop counter systems, weighing systems and optical systems. A detailed description of these systems can be found e.g. in Maniak (2005) or Thaler (2004). For high resolution measurements, tipping-bucket gauges are currently dominating but the number of weighing gauges and radar measurement is growing rapidly (Einfalt et al., 2002).

Continuous efforts have been done in the scientific community to assess the errors related to rainfall measurements. An exhaustive overview of systematic errors and their sources determined for rainfall gauges in different studies is given in Hoppe (2006). According to the cited sources, errors up to 25% are to be expected on the yearly average.

In order to reduce the measurement error, several studies highlight the importance of calibrating tipping-bucket rain gauges as tipping-bucket gauges generally underestimate strong intensities.(see e.g. Marsalek (1981) or Sevruk (1982))

In modelling also the spatial resolution in order to capture spatially distributed rainfall is topic of discussions and might lead to intensified research on radar measurements. Effectively the spatial distribution can have a major influence on the uncertainties especially for large rainfall events.

The question of whether to use one single or more rain gauges in sewer modelling depends on the task to be fulfilled. When using several rain gauges to account for spatial distribution, problems may arise from i) the time shift between the rain gauges recordings and ii) if one or more gauges record errors. This is for example addressed in Schilling (1991).

3.1.3 Hydraulics

Measurement devices for assessing the hydraulics in sewer systems are used in general practice since the 1980s (Bertrand-Krajewski et al., 2000). These measurements are installed for several purposes as assessing dry weather flow, parasite water, flood risk, functioning of CSO structures, real time control etc. Hydraulics can be measured either as water level or as flow. In combined sewer systems, generally open channel flow is measured. Combined sewer pipes can, however, become pressurized, posing an additional challenge for the measurement devices.

According to Bertrand-Krajewski et al. (2000), **water level measurement devices** can be classified in:

- Floating devices, water gauges
- Radar or ultrasonic devices (wave transit time shift)
- Indirect or direct pressure measurement devices

In general practice, ultrasonic devices and piezometric pressure cells are most commonly used. Ultrasonic devices are less prone to drift errors but are sensitive to temperature. This has to be compensated. Additional errors can be induced by foam, spider webs, roots, etc. (everything that obstructs the measurement path). The measurement principle of radar measurements is similar to ultrasonic devices but they tend to be more precise as they cover a wider range of the water level surface (Kainz et al., 2010).

For **flow measurement** a wide range of methods and devices exist: (Bertrand-Krajewski et al., 2000), (Kainz et al., 2010):

- Tracer measurements
- Q(h) - rating curves
- Hydraulic methods (Venturi channel and measurement weirs)
- v_m x A methods (as combined or separated sensors)
- Magnetic–inductive devices

Tracer measurements can be used for calibrating or validating flow data from other measurement devices or to derive rating curves but can evidently not be used for recording long-term time series data. Rating curves suffer from the effect of hysteresis (due to local acceleration) and cannot take into account effects as backwater. Therefore they are only of limited use in sewer systems. Hydraulic methods require a reduction of the effective cross section flow area and subcritical flow conditions. Effectively this can lead to problems with sedimentation and deposition (Hassinger, 2000).

The v_m x A methods calculate the flow by the continuity equation (Equation 3-8).

$$Q = v \cdot A$$ **Equation 3-8**

with Q … discharge ($L^3 T^{-1}$); v… velocity ($L T^{-1}$) and A … cross section (L^2)

This implies, that two variables – namely the water level (to calculate A) and the mean flow velocity (v_m) – have to be measured. Especially the assessment of the mean flow velocity is challenging as the velocity distribution is not uniform over the cross section. In practice different methods are used to determine the mean velocity: ultrasonic systems based on i) ultrasonic pulse-Doppler effect ii) ultrasonic correlation and iii) ultrasonic transit-time and radar devices (Kainz et al., 2010).

Magnetic-inductive devices derive the mean velocity and water level height by calibration curves from the resulting induced voltage. Due to practical reasons they are mainly installed in smaller pipes with circular cross sections (Hassinger, 2000). They are prone to long-term drift effects due to the build-up of biofilm leading to high maintenance requirements (Lucas, 2001).

An exhaustive overview of the advantages and drawbacks of the different methods is given in Bertrand-Krajewski et al. (2000). In the following the basic principles of the devices installed and used in the case study presented in chapter 6 are described. Detailed information on the installed devices is given in Hochedlinger (2005).

3.1.3.1 Ultrasonic pulse-Doppler flow measurement

The measurement principle of these sensors is based upon the determination of the flow velocity by means of the frequency shift in an ultrasonic signal due to the Doppler-effect (described by Christian Doppler in 1842). Ultrasonic waves are reflected by suspended particles and air bubbles in the sewer flow. It is based upon the hypothesis that the suspended material moves with the velocity of the water. The sensor itself – working both as sender and receiver – is fixed to the sewer bottom.

Based on two scans of the measurement window(s) (see Figure 3-2), the two reflected signals are correlated allowing to calculate the particle – and derived mean flow – velocity.

Using several measurement windows allows measuring the mean velocity in partly filled cross sections.

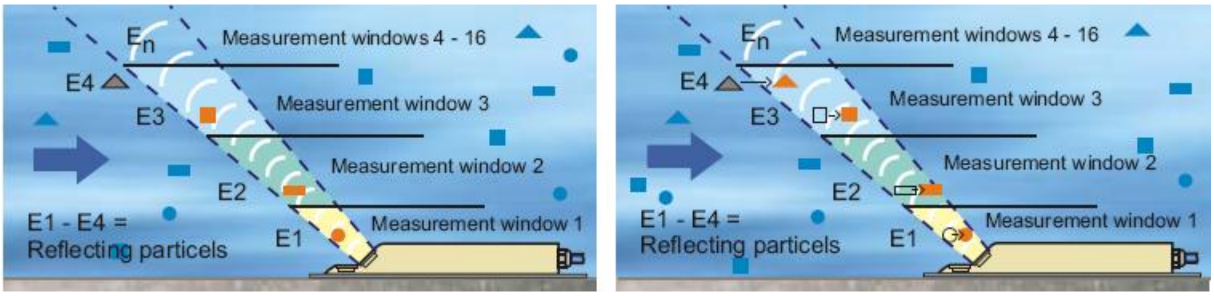

Figure 3-2: Measurement principle of ultrasonic cross-correlation (www.nivus.com)

The water level measurement can be either integrated in the bottom-bound sensor as pressure measurement or can be measure separately from the sewer ceiling.

Advantages of such probes are the easy installation and handling as well as the relative low impact on the flow characteristics (except when working in low flow conditions e.g. for assessing parasite water). As drawbacks can be named that: i) the water level has to be higher than 10 cm for proper functioning, ii) as the devices are installed directly in the media they risk being damaged and augment the risk of clogging and deposits in the sewer.

Uncertainties stated by the manufacturers range from 1% to 3.5% (Bertrand-Krajewski et al., 2000). Effective uncertainties have been reported to be in an order of about 20% (Hughes et al., 1995) up to 30% for sensors with integrated water level measurement (Hassinger, 2000).

3.1.3.2 Radar flow measurements

Contrary to the ultrasonic measurements, radar devices are contactless and measure only the surface water velocity. A radar beam is reflected by the sewer flow surface, the reflected signal is analysed on Doppler-offset to determine the surface velocity (see Figure 3-3).

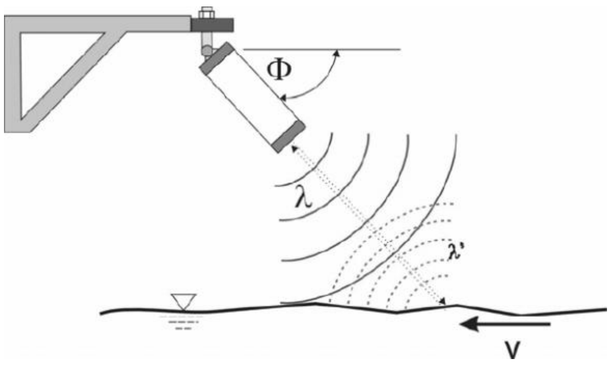

Figure 3-3: Measurement principle of a radar flow meter (Felder and Siedschlag, 2004)

As only the surface velocity can be measured, the mean velocity in the cross section has to be calculated. In general this is solved by multiplying the surface velocity with a cross – section specific scaling factor *k* that is dependent on i) water level, ii) position of local velocity measurement, iii) shape of the measurement cross section iv) roughness of the channel and v) the Reynolds' number (Hochedlinger, 2005).

An important advantage of this system is that there is no contact with the medium and that variables are measured with high accuracy. However, the k-factor used for determining the mean velocity has a major impact on the measured values. Also the measurement range is limited by the block distance (minimum required distance of device from water level).

3.1.4 Sewer water quality measurements

As described in chapter 2.2 the assessment of pollution concentrations and loads transported on the urban surfaces, in the sewer systems and eventually treated in the WWTP or spilled to the receiving waters has been a topic of intensive research over the last four decades.

This chapter focuses on the parameters that are analysed and investigated in the case study presented in chapter 6. Due to the high number of different pollutants encountered in sewer systems, sum parameters for particulate pollution as TSS and organic pollution as BOD_n and COD are often used to describe and assess pollution transport. This seems to be a reasonable approach as a detailed analysis of the combined sewage would be costly and simply not feasible due to the high number of required analyses.

In sewer water quality measurement it is generally agreed upon that the choice of the sampling location is crucial in order to obtain reliable results. The choice of the location depends on several boundary conditions as i) representativity of the measurements at this point (assuring full mixture, avoiding dead zones etc.), ii) the accessibility for installation and maintenance, iii) work security and iv) cost for installation and maintenance (Bertrand-Krajewski et al., 2000).

Compared to hydraulic measurement devices that have to be installed directly in the sewer system, measurement devices for water quality can be either installed directly in-situ or by bypass installations. A comparison of the advantages and drawbacks of the two methods is given in Gruber et al. (2006).

Concerning measurement continuity one can discriminate between grab samples (manually or by automatic samplers) with subsequent laboratory (lab) analysis and continuous measurement effected with suitable probes.

3.1.4.1 Manual or automated sampling and lab analysis

Representative sampling and sampling strategies are a topic not only of interest for urban drainage: see e.g. Gy (1998) as primer, Petersen and Esbensen (2005) discussing representative process sampling and Paakkunainen et al. (2007) discussing the applicability of sampling strategies in environmental emission measurements.

In sewer water quality sampling different sampling strategies are applied depending on the aim of the analysis:

- Constant sample volume with constant time steps.
- Variable sample volume, proportional to cumulated runoff volume at constant time steps.
- Variable sample volume, proportional to discharge at constant time steps.
- Constant sample volume with variable time step proportional to runoff volume.

A detailed description of the advantages and drawbacks of these different sampling strategies is given in Bertrand-Krajewski et al. (2000). The samples are then analysed by standard laboratory procedures on the pollutants or parameters of interest.

While this "traditional" sampling is often relatively easy to implement, this method suffers from many limitations and drawbacks: the short duration of campaigns and limited information obtained at insufficient time intervals do not allow an evaluation of the full dynamics and variability of flow rates and pollution concentrations. Other well-known limitations to this approach are sampling errors and errors due to sample conservation, transport and preparation (see e.g. Bertrand-Krajewski et al. (2003))

3.1.4.2 Continuous water quality measurement

Assessing pollutant concentrations in combined sewers by continuous devices shows a number of advantages compared to traditional sampling methods. Continuous high resolution data can be derived at relatively low cost. However, a correlation between the measured and the target parameter has to be defined. Especially the site specific wastewater composition (wastewater matrix) impacts on the derived parameters.

Several strategies and methods have been proposed over the last decades to assess pollutant concentrations by continuous measurements. As mainly used methods the following can be named (the cited literature focuses on measurements in the sewer system):

- **Turbidity** for TSS and COD; see e.g.: Ruban et al. (1993), Bertrand-Krajewski et al. (2000), Bertrand-Krajewski (2004) or Aumond and Joannis (2006) .
- **SAC 254** (spectral absorption coefficient at 254 nm) for COD; see e.g. Matsché and Stumwöhrer (1996), Häck (2000), Stumwöhrer et al. (2003).
- **UV/VIS spectrometry** for TSS, COD, Nitrogen; see e.g. Bertrand-Krajewski et al. (2000), Rieger et al. (2004), Gruber et al. (2005), Hochedlinger et al. (2006) or Rieger et al. (2008).
- **Ion – sensitive sensors for** Ammonium, Nitrate, Chloride and others; see e.g. Winkler and Fleischmann (2004) or Hochedlinger (2005).

Often also additional physical-chemical parameters **as conductivity, temperature and pH** are measured to obtain additional information.

3.1.4.3 UV/VIS spectrometry

The basic principle of UV/VIS spectrometry is to measure light absorption in different wavelengths in the visible and ultra-violet range and to derive target parameters based on the measured absorptions. An exhaustive description of the background on the measurement principles of these probes is given in Hochedlinger (2005). Compared to the other methods stated above, one major advantage of UV/VIS spectrometry is that a spectrum with a wide range of wavelengths is recorded allowing to deduce concentrations of several waste water compounds (see also Figure 3-5) with one probe at the same time. In addition, compared to e.g. the SAC 254 or turbidity, absorption at several wavelengths can be used to deduce the concentration for one target parameter.

The following description is based on the probe used in the case study (see also chapter 6) a *spectro::lyser* from the company *s::can.* A schematic design of the probe is shown in Figure

3-4. It measures the light attenuation (absorption and scattering) in the ultra-violet and visible range between 200 nm and 750 nm. A reference beam compensates effects from aging of the lamp and the detector. The width of the measurement window is 5 mm.

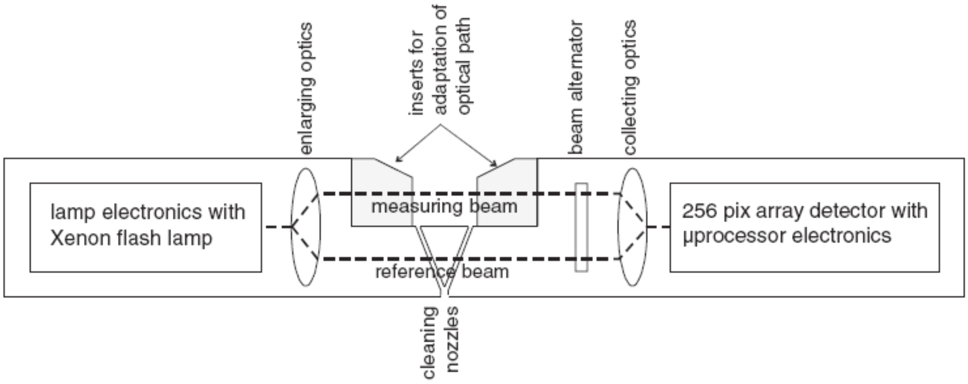

Figure 3-4: UV-VIS probe, (Langergraber et al., 2003, with permission from IWA Publishing)

A typical absorption spectrum is shown in Figure 3-5. Based on the measured attenuation in different wavelength ranges, so-called equivalent concentrations can be calculated for: i) organic matter, as chemical oxygen demand (COD_{eq}) and total organic carbon (TOC_{eq}), ii) total suspended solids (TSS_{eq}) and iii) nitrate ($NO_{3,eq}$). The target parameter concentration is calculated by Equation 3-9.

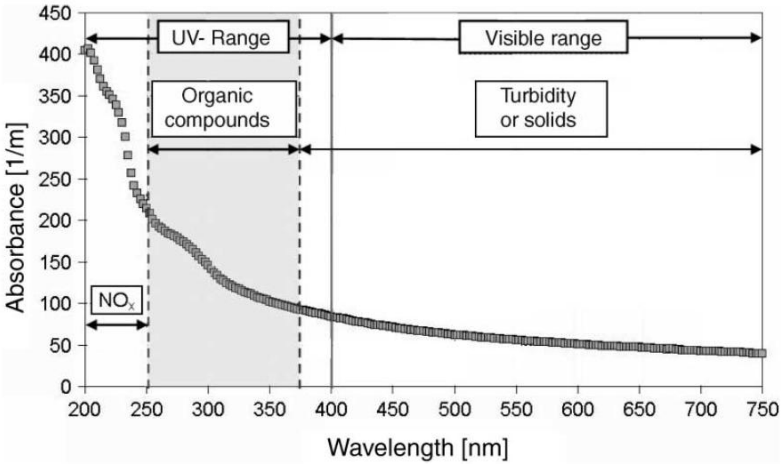

Figure 3-5: Absorption spectrum and ranges for parameters (Hochedlinger et al., 2006, with permission from IWA Publishing)

$$C_{eq} = \sum_{i=1}^{n} w_i \cdot A_i + K \qquad \textbf{Equation 3-9}$$

with C_{eq} … equivalent concentration (mg/L), w_i… factor for wavelength *i*,
A_i … measured absorption for wavelength *i* (1/m) and *K* … offset (-)

Several studies discussed the issue of probe calibration and highlighted the importance of adaption to the local wastewater matrix, e.g. Gruber et al. (2004), Gruber et al. (2005), Rieger et al. (2006), Torres and Bertrand-Krajewski (2008). Hochedlinger et al. (2006) focused on the comparison of different regression models for probe calibration. Winkler et al. (2008a) discussed the uncertainties in UV/VIS measurements based on lab measurements for raw wastewater samples and concluded that the device is comparable robust if the matrixspecific relationship between measured absorption and target parameter concentration is determined by a suitable correlation model. Torres and Bertrand-Krajewski (2008) showed that UV/VIS probes can reach equivalent or better results for TSS concentrations than turbidity meters when using an appropriate correlation model. Chapter 5.2.2.3 of this thesis is committed to calibration of a UV/VIS probe in wet weather conditions.

A comprehensive overview of measurement programs in Europe using UV/VIS spectrometry including a synopsis of the results and experiences is given in Hochedlinger (2005), and Rouault (2009).

3.2 Challenges in data handling

With the availability of online high resolution measurements for a multitude of variables more and more data becomes available. Evidently this data has to be stored in a proper way: possibly with small data volume, easy and ready data access, maintaining the original recording time step etc. In addition the raw data has to be analysed and checked on its validity – regardless of any preceding quality assurance processes.

As EPA (1999) state, although one may collect accurate and representative data, these data are of limited usefulness if they are not stored in an organized manner and analysed properly. When using a model, the model requires appropriate data for input parameters, as a basis for assumptions made in the modelling process and for model calibration and validation. Thus, one needs to properly manage monitoring data and perform some review and analysis of the data regardless of the analytical tools selected.

The following paragraphs give a short overview of the requirements in data management, analysis and validation. It is assumed that the measurement device is properly installed, calibrated and maintained. Topics as data transmission, errors due to analogue-digital conversion, choice of the time step etc. are not discussed. A detailed discussion on these points is given e.g. in Bertrand-Krajewski et al. (2000).

3.2.1 Data management

"All monitoring data should be organized and stored in a form that allows for ready access. Effective data management is necessary because the voluminous and diverse nature of the data, and the variety of individuals who can be involved in collecting, recording and entering data, can easily lead to data loss or error and severely damage the quality of monitoring programs. […] Data management systems must address both managerial and technical issues. The managerial issues include data storage, data validation and verification, and data access." (EPA, 1999)

In most cases the data recorded in urban drainage is in matrix form, associating one or more measured variables to a time stamp. Therefore, systems apt to store and access matrices in an efficient way seem to be the appropriate choice. In addition to the actual measurement data, one crucial point is the possibility to store meta-data. In this context meta-data is defined as data that gives additional information on the measured data, the measurement system, the sensor etc. This could be e.g. the location of the sensor, the maintenance records or a quality flag associated with one specific data point.

Only little literature is available on data management in urban drainage. Several articles touch the topic, e.g. Vanrolleghem et al. (1999), Bertrand-Krajewski et al. (2005), Winkler et al. (2008b) or Branisavlijevic et al. (2010). However, in these studies either proprietary software or customised solutions adapted to measurement installations on-site are applied, without further discussion on their design and functioning. Bertrand-Krajewski et al. (2000) state ASCII-files, tables or data bases as possible storing methods. Apart from data bases, these methods do not seem appropriate when dealing with high data volume. Data bases, on the other hand, can suffer from slow access time, especially if not properly indexed. Pokorný (2006) discusses current trends in database architectures and highlights the change in requirements and the need of adapting to the rapidly evolving IT world and to new data sources.

In other fields of research where high data volume in matrix form has to be managed (e.g. oceanography, particle physics etc.) efficient solutions have been developed by researchers over the last decades and are readily available (Camhy et al., submitted).

Currently a system based on open file and server standards is under development at the Institute, adapted to the points stated above. This is discussed in more detail chapter 5.2.1.

3.2.2 Data analysis and validation

Analysis and validation of the measured raw data is a crucial step to exploit the results obtained from the measurements. A measurement result, even if furnished by sophisticated methods is not always a proper picture of reality for several reasons. Therefore it is absolutely necessary to analyse and validate the data – separating “good” from “bad” measurements based on all available knowledge (Bertrand-Krajewski et al., 2000). In reality measurements are subject to numerous errors as missing values, outliers, noise, drift, shift etc. for which the sources can be numerous and cannot always be identified.

The importance of analysing and validating data is widely acknowledged. Intensive research on this topic is carried out since the 1970s especially in fields where fault detection is vital for the functioning of systems as e.g. in chemical process engineering. An exhaustive literature overview of a multitude of developed methods is given by Venkatasubramanian et al. (Venkatasubramanian et al., 2003a, Venkatasubramanian et al., 2003b, Venkatasubramanian et al., 2003c). In the field of urban drainage most publications in the 1990s were dedicated to the analysis and validation of rainfall or flow data (see e.g. Bennis et al. (1997), Joergensen et al. (1998) or Maul-Kotter and Einfalt (1998)). More recent publications deal with the requirements linked to the emerging high resolution online measurement devices as e.g. Mourad and Bertrand-Krajewski (2002) or Winkler et al. (2008b). Branisavlijevic et al. (2010) state that un-validated data can reduce the reliability of the measuring system, provide misleading conclusions and lead to erroneous decisions. In view of modelling, Kleidorfer (2009) stresses that a strict definition of data-uncertainties assumes that data contains uncertainties but not errors. Hence data errors have to identified and removed prior to modelling.

Based on a literature review, Mourad and Bertrand-Krajewski (2002) state that classical methods in signal processing, especially statistical tests and application of decision theory are mostly only applicable for random data and/or steady state processes. Non-steady state and partially autocorrelated time series which are typical in urban hydrology cannot be analysed with such methods.

Even after proper data analysis and validation one should always keep in mind that data rarely is “wrong” in the sense that an error can be eliminated during data processing, but often data is not representative for a specific modelling task. For example recorded precipitation data for a specific rainfall event can be measured in an accurate way, but still may not be suitable as input-data for a model when the spatial distribution is neglected (Kleidorfer, 2009).

3.2.2.1 Visual data analysis

The visual analysis of measured data is – especially in engineering disciplines – still a common procedure to check data manually. While it is true that with high data density and a high number of measured variables it is not a proper method to actually analyse and validate the measured data in detail, it can still give a good overview of the general system behaviour. Phenomena that are special to the measurement site, the measurement station or to the investigated system can be assessed qualitatively. This is an important basis for automated data validation as the system behaviour impacts directly on the validation tests that can be formulated for automated validation. As visual analysis adds to the available knowledge it can help to improve or refine an automated validation.

3.2.2.2 Semi-automatic data validation

The basic notion of data validation is to define data to be either valid or not valid. However, as Mourad and Bertrand-Krajewski (2002) discuss, validity can often not be determined that easily as this information can be related to i) the data themselves, ii) the sensors used, iii) the environment and the context of the measurement process, or iv) a combination of these three elements.

Mourad and Bertrand-Krajewski (2002) propose that data should be classified as A for reliable values, B for doubtful values and C for faulty, outlying or aberrant values based on several automated tests. The B categorised values should then be analysed manually and decision made based on expert knowledge. The idea of adding the B category is that some data cannot easily be classified in valid or not valid as not all knowledge can be weaved into automatic processes. A completely automatic validation would risk identifying data as wrong when it is correct. Some examples will be shown in the case study chapter of this work. In addition, data might be valid for one purpose but not for another. The proposed test in Mourad and Bertrand-Krajewski (2002) are: i) status of sensor, ii) physical range, iii) locally realistic range, iv) duration after maintenance, v) signal’s gradient, vi) material redundancy and vii) analytical redundancy.

Branisavlijevic et al. (2010) followed the proposed procedure for a case study in Serbia but carried out different tests, namely: i) zero test, ii) flat line test, iii) min-max test, iv) Grubb’s statistical test, v) PCA (principal component analysis) test for days with no rain and vi) a PCA test for rainy days. The PCA did not perform satisfactorily in wet weather conditions.

Piatyszek at al. (2000) propose a fault detection using a Kalman filter (Kalman, 1960) combined with a probability ratio test based on measured and simulated data.

Regardless of the applied method, the raw data always has to be kept in order to be able to trace the modifications and to apply refined test in future. The most suitable approach is to add the validation result as meta-data to the measurement data, specifying i) what data was validated, ii) by which test iii) adding meta information as date of validation, versioning, person applying the test etc.

4 Modelling

This chapter gives basic notions on the modelling of urban drainage systems in respect to hydraulic and sewer water quality models. First the challenges in modelling are shortly described. In a second part, model sensitivity and uncertainty are briefly discussed. Lastly an overview of possibilities in model calibration and validation is given.

4.1 Modelling of urban drainage systems

"*A theoretical construct that builds an abstract representation of a system is called a model. […] Because of the complexity of environmental systems, such models can be strongly simplified representations of structure and function of the underlying systems. Which aspects of a system should be described in more detail and which in a more aggregated way depends on the purpose of model application, on the available data and on the effort that can be put in model development and application. For this reason, there is not a unique "true" model of an environmental system, but there are several descriptions of the system (=model) each of which may be adequate for addressing another set of scientific questions*." (Reichert, 2009)

First computer models for simulating urban drainage systems were introduced in the 1970s and 1980s, evolving steadily until today (Rauch et al., 2002). As Kleidorfer (2009) states, today urban drainage simulation models are state of the art instruments for planners, consultants and scientists working in the field of urban hydrology and numerous commercial, freeware and open-source software products are available.

The **aim and purpose of modelling** an urban drainage system can vary greatly depending on the investigated task. WapUG (2002) stress that it is essential that the objectives of the model are clearly defined. The objective(s) can vary greatly, ranging from the prediction of overflow behaviour in regards to receiving water quality, identification of areas or critical points prone to flooding, design and optimisation of systems and retention tanks, real time control, prediction of future states, integrated modelling, etc.

Depending on the defined objective appropriate model(s) should be chosen. An exhaustive overview of criteria for the model choice is given e.g. in EPA (1999). Harremoes and Madsen (1999) stress that the concept of parsimony should be followed: the model should be as complex as necessary and as simple as possible.

Once a model is set up, **simulations** are carried out: *"Simulation means to experiment with abstract models in order to answer questions like "what would be, if …?". With the aid of mathematical methods we analyse the possible behaviour of a system. We will then use what we learn from model predictions to design, optimize, and operate real-world systems*." (Gujer, 2008)

In a **deterministic model** every set of variable states is uniquely determined by parameters in the model and by sets of previous states of these variables. This means that using the same initial conditions and boundary conditions always leads to the same model outcome. In **stochastic models** random effects are taken into account and the same input can lead to different model outputs. In the following only deterministic models are discussed.

4.1.1 Hydraulic sewer modelling

In hydraulic modelling, the rainfall-runoff-transport processes of the water flow on the surface and in the sewer system are described. According to Rauch et al. (2002), this process is well established and extensively applied and described in the literature. Several publications on good modelling practices have been issued over the last decade, e.g. Verworn (1999) focusing on hydrological modelling, EPA (1999) focusing on CSO modelling, WapUG (2002) on hydraulic modelling of sewer systems and HSGSim (2008) on the modelling of integrated systems. Concepts for coupling of sewer flooding to surface flow models (known as the concept of dual drainage) date back to the 1970s. An exhaustive literature review on this topic can be found in Smith (2006a) and Smith (2006b).

A large number of model approaches and also software packages exist for hydraulic modelling. In the following the modelled processes are briefly described and an overview of different modelling approaches is given. Figure 4-1 shows the relevant processes for modelling the rainfall-runoff-transport process.

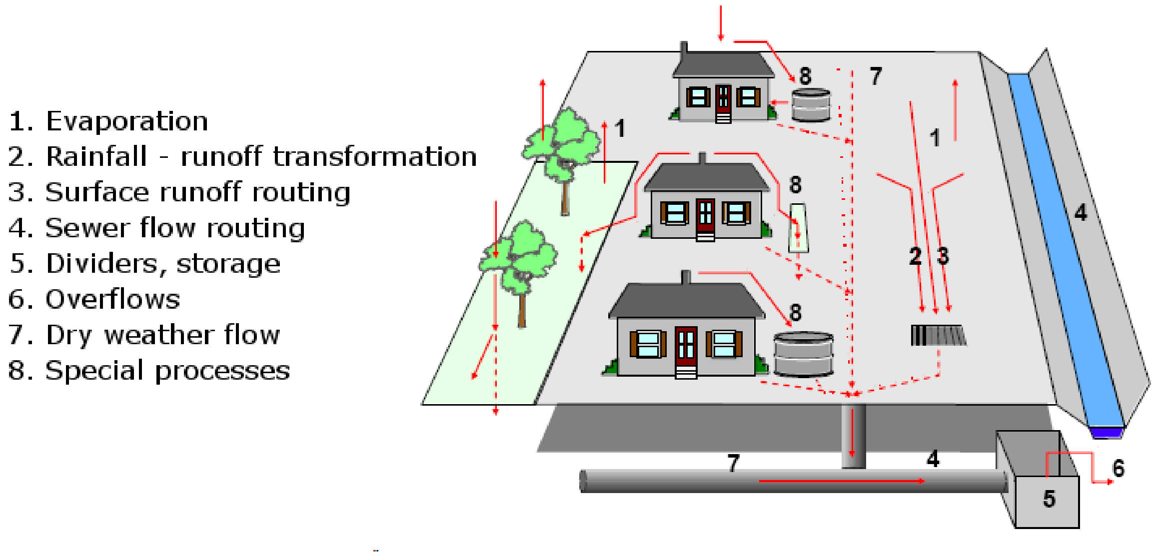

Figure 4-1: Relevant processes in the rainfall-runoff-transport process (Muschalla, 2008b)

4.1.1.1 Processes on the catchment surface

Processes on the catchment surface include the transformation of rainfall to runoff and the surface flow routing. In general an effective rainfall height is calculated from the observed rainfall by subtracting losses (as interception losses, depression losses, permanent losses or others), taking into account a runoff coefficient (possibly time-dependent) for impervious areas and infiltration for pervious areas. Special processes can be rain dependent infiltration or effects linked to snow cover and snow melt etc. A detailed description on the different processes can be found in basic literature as e.g. Butler and Davies (2000), CERTU (2004), Maniak (2005) and regulatory documents as ATV (1986) and ATV (1987). Different software packages use different approaches that are in general described in the user manuals. An overview of different approaches as given in HSGSim (2008, modified), is listed in Table 4-1.

Table 4-1: Model concepts for the processes on the catchment surface (HSGSim, 2008, modified)

Process	Model approaches/concepts
Rainfall – runoff transformation Impervious areas	• Different approaches taking into account initial and depression losses and runoff coefficient.
Rainfall – runoff transformation Pervious areas	• Neumann approach • Horton approach • US-SCS approach • Green-Ampt approach
Surface runoff routing	• Unit hydrograph • Time-area method • Kinematic wave approach • Linear reservoirs (possibly cascaded)
Special processes	• Rain dependent infiltration • Snow melt

4.1.1.2 Processes in the sewer system

Sewer flow in combined sewer systems is composed of both dry weather flow and stormwater flow during rainfall events. Dry weather flow is generally assumed to be either constant or following a pre-defined pattern. In sewer flow routing the basic processes of retention and translation of the runoff wave have to be calculated. In addition, the models have to be able to take into account storage, overflows, dividers, possibly pumping, orifices, control procedures etc.

Two major groups of sewer models can be named that are in use today:

- conceptual hydrological models and
- hydrodynamic models.

An overview of several model approaches for the two groups is given in Table 4-2 (HSGSim, 2008, modified).

Table 4-2: Model concepts for flow in the sewer (HSGSim, 2008, modified)

Process	Model approaches/concepts
Sewer flow – conceptual hydrological approaches	• Simple translation • Kalinin-Miljukov approach • Muskingum approach • Non-linear reservoirs • Additional static backwater
Sewer flow – hydrodynamic approaches	• Dynamic wave (full Barré de Saint Venant equations) • Diffusion wave • Kinematic wave

As the model concepts and underlying equations are exhaustively discussed in literature, and descriptions are given in basic urban drainage literature (e.g. Butler and Davies (2000), CERTU (2004) and Gujer (2007)) only a short overview is given here. Figure 4-2 shows typical models for design and analysis in urban drainage (based on VSA (1989)).

Comparisons of hydrological and hydrodynamic models have also been carried out at the Institute by Veit (2009) and Gamerith (submitted-a).

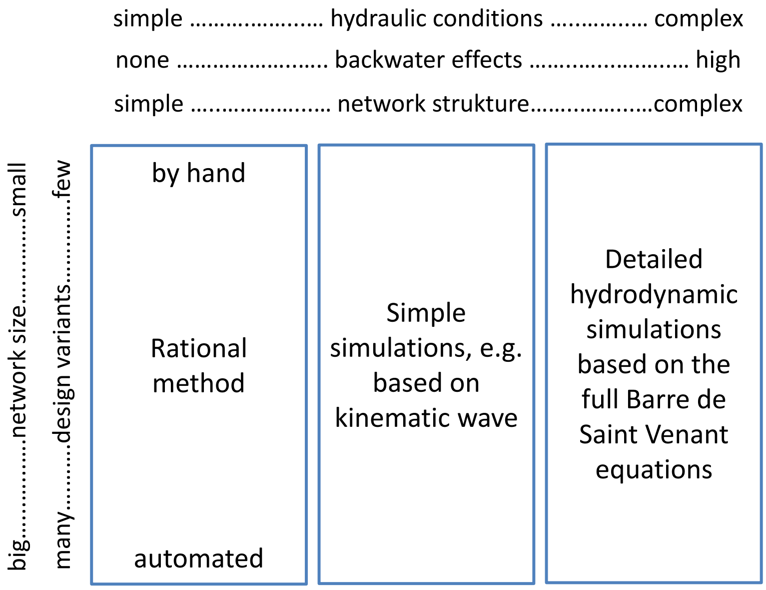

Figure 4-2: Typical models for design and analysis in urban drainage (based on VSA (1989), modified and translated))

Conceptual hydrological models most often use the concept of reservoirs for flow routing. They are based on volume balance calculation. Discharge is the only known value, water levels and velocities can only be deduced by the pipe geometry (linear, without hysteresis). The underlying equations can be solved analytically. The models have relatively low computational costs and are therefore especially suited for long-term simulations. Backwater and surface flooding can generally not be assessed (some model approaches, however, allow taking into account static backwater effects based on geometry). Evaluating downstream influence on upstream flow is not possible. In general the models are aggregated and have less data requirements than hydrodynamic models. The processes on the surface and in the sewer are often “blended”.

Hydrodynamic models are based on physical principles, generally solving the full Barré de Saint Venant equations. Therefore, discharge, water level and flow velocities are known values. They are computationally expensive as the underlying equations need to be solved by numeric solvers. As in general the models are more detailed than conceptual hydrological models, the data requirement is higher. In detailed models, a clear distinction between surface and sewer flow is possible and the model geometry is close to nature. They can take into account backwater effects, flooding etc. Pipes under pressure can be modelled. Concerning the implementation and solvers for the underlying equations, details are generally found in model manuals or descriptions as in e.g. Rossmann (2006) for SWMM.

4.1.2 Sewer water quality modelling

Sewer water quality modelling is still an issue of ongoing research and lively scientific discussion. Models have been developed since the 1970s and are widely used since the middle of the 1990s. It is generally agreed upon that a calibrated and validated hydraulic model is the basis for sewer water quality modelling (see e.g. WapUG (2002) or Verworn (1999)).

Simplified assumptions of storm water pollutant concentrations are often used in general practice, e.g. using a site mean concentration or event mean concentration approach. More complex models try to reproduce the processes on the surface and possibly in the sewer system. A comparison of these assumptions and approaches is discussed e.g. in Mourad (2005). Based on this work Gamerith et al. (submitted-a) conclude that using more complex models can lead to significant impact on design of overflow and storage structures. Evidently, simplified approaches as mean concentration approaches cannot account for the full dynamics of pollutant concentrations encountered in sewer systems as e.g. first or last flush effects.

Bertrand-Krajewski (2007) discusses the topic of sewer water quality modelling critically and highlights that most of the models were initially developed for research purposes and have been later on implemented in commercial software packages where limits and conditions of application have not been sufficiently emphasized, especially regarding the critical questions related to model calibration and validation based on observed or experimental data sets.

Concerning the level of detail, Bertrand-Krajewski et al. (1993) state that deterministic and detailed models are useful to understand the phenomena involved in sewers and are necessary for progress but remain too complicated for practical use in management or design offices. Ashley et al. (1999) details on different models and simulation software used in sewer water quality modelling and concludes that the boundaries between conceptual and detailed physically based models become more blurred with increasing computing power. It is, however, generally agreed upon that “complex” rather than “simple” is not automatically “better” (see e.g. Rauch et al. (1998a), Ashley et al. (1999) or Bertrand-Krajewski (2007)).

Different “philosophies” in sewer water quality modelling can also be noted in national guidelines for CSO design. The German guideline *A-128* (ATV, 1992) uses a site mean concentration approach and deems detailed sewer water quality modelling only applicable in accordance with the authorities. The UK *urban pollution management manual* (FWR, 1998) on the other hand requires water quality modelling and bases CSO design on values for ammonia and oxygen sag in the receiving water, allowing the use of detailed in-sewer-transport models.

It should also be noted that detailed modelling of in-sewer processes is only possible when using a hydrodynamic model in sewer flow modelling, as information on water levels and velocities is required, e.g. to assess shear stress in erosion of sediments.

4.1.2.1 Processes

According to Kanso (2004), four principal processes can be taken into account in sewer water quality modelling:

- Accumulation of pollutants on the surface in dry weather conditions.
- Wash-off and transport on the surface of the pollutants during wet weather conditions.
- Transport in the sewer system, including deposition (mainly in dry weather flow) and remobilisation (in stromwater conditions).
- Chemical and biological processes of the pollutants in the sewer network (oxygen sag, COD reduction, ammonification, H_2SO_4 etc.).

Concerning the pollutants on the surface, key studies were undertaken first in the US as already discussed in chapter 2.2. Sartor et al. (1974) proposed that the processes of pollutant accumulation and wash of follow an exponential behaviour. First model approaches were discussed by Metcalf and Eddy (1971), Alley and Smith (1981a) and Alley and Smith (1981b). According to Ashley et al. (1999), models have not advanced significantly since the 1970s when various empirical relationships were established. Leinweber (2002) concludes that most of the currently applied models use empirical exponential equations. Kleidorfer (2009) states that often a simple regression model is used. A detailed overview and discussion based on a literature review of different model approaches and software is given in Bertrand-Krajewski et al. (1993).

Concerning the processes of pollutant transport in the sewer pipes, first models were based on knowledge from fluvial sedimentation transport (as the model proposed by Ackers and White (1973)). Crabtree (1995) proposed a model approach based on investigation of sewer sediment characteristics. A thorough compilation of current knowledge and associated phenomena to sewer soilds as well as challenges in resarch is given by Ashley et al. (2005). Different model approaches and software are discussed in detail in Bertrand-Krajewski et al. (1993) and Ashley et al. (1999). An overview of recent studies on biological processe in the sewer system is given in HSGSim (2008).

4.1.3 Data requirements

Setting up a model requires data. Data used for model calibration and validation as rainfall, flow and pollutant concentration measurements has already been discussed in chapter 3.1. Here only a short overview is given, more information for practical use can be found e.g. in EPA (1999) and WapUG (2002). Depending on the used model the required level of detail can differ. First, sufficient data to set up the model structure is required: For modelling of the sewer network this comprises of data on network connectivity, geometry (pipe sizes, elevations, ground levels etc.) and detailed data on all special structures as overflows, storage tanks, pumps, possible controls etc. For the surface model the delimited subcatchments, their connection to the sewer system and an evaluation of imperviousness has to be available or evaluated. When taking into account pervious areas the soil type could also be of interest. Additional information such as land use, cadastral maps and aerial view photos can simplify the modelling task. Once the model structure is set up, base flow discharge and concentrations are defined, if possible based on measurements.

4.2 Model uncertainty

As effectively a model is a mathematical description of physical processes and simplifications of known or unknown processes are necessary, the results can only be an estimation of real behaviour and model predictions are always uncertain.

Beck (1991) describes uncertainties in environmental models, Deletic et al. (2009) classify uncertainties related to urban drainage modelling as follows:

- *Model input uncertainties* related to i) measured input data, ii) estimated input data and iii) model parameters.

- *Calibration uncertainties* related to i) measured calibration data uncertainties, ii) measured calibration data availability and choices, iii) calibration algorithms and iv) criteria functions.
- *Model structure uncertainties* related to i) conceptualisation errors and ii) numerical methods and boundary conditions.

As Kleidorfer (2009) states, uncertainties in urban drainage modelling attracted increasing attention of scientist only in the last years and are usually still neglected in non-scientific practical projects. Willems (2008) gives a comprehensive overview of recent works on this topic in the urban drainage sector.

Many methods for uncertainty analysis are based on **Monte-Carlo (MC) simulations**. In this method, model inputs or parameters are sampled from defined probability distributions. Different methods for the sampling procedure have been proposed. Reichert (2009) describes regular grid sampling, random sampling, Latin hypercube sampling and Hammersley quasi-random sampling. By applying the sampled values in model simulation runs, the uncertainties defined by the probability distributions are propagated from model inputs to outputs.

Currently methods discussed and applied for uncertainty analysis in urban drainage are mainly GLUE and methods based on Bayesian inference. Intensive discussion on the two approaches and their comparison is given e.g. in Freni et al. (2009) or Kleidorfer (2009).

The **General likelihood uncertainty estimation (GLUE)** is a method to assess uncertainties proposed by Beven and Binely (1992). It is based on the notion that as measurements and also model parameters are to some extent uncertain, there is no reason to expect that any one set of parameters will represent the true parameter set, and different parameter sets might perform equally well in model prediction. It is only possible to make an assessment of the likelihood or possibility of a particular parameter set to be an acceptable simulator of the system. GLUE requires a definition of a likelihood function, in most cases a goodness-of-fit function for comparing observations and model predictions. A threshold is defined for this function for values to be accepted and others to be discarded as non-behavioural. Monte-Carlo simulations are carried out, and the value of the likelihood function is calculated for each sampled parameter set. Parameter sets leading to values lower than the defined threshold are discarded. From the remaining sampled parameter sets cumulative parameter distributions and posterior parameter distributions can be derived and the error bounds (e.g. 0.25 and 0.75 percentiles) in the model prediction estimated. However, as discussed in Freni et al. (2008b) estimation of error bounds effectively depends on the chosen prior parameter distributions, the likelihood function and the defined threshold.

This method has been implemented and discussed in an urban drainage context e.g. by Mannina et al. (2006), Freni et al. (2008b) and Freni et al. (2008a).

Bayesian inference methods are a popular approach in environmental modelling as by using this methodology a personal (subjective) “degree of belief” – described by a probability distribution – can be introduced in the modelling process. The fundamentals go back to Bayes’ theorem after Bayes and Price (1763) for calculation of conditional probabilities. The main difference to GLUE is that acceptance of parameter samples is less informal. A detailed description of the theoretical background an possible application is given in (Reichert, 2009).

Examples for application in urban drainage are e.g. Kuczera and Parent (1998), Kanso et al. (2005), Kleidorfer et al. (2009) or Reichert and Mieleitner (2009),

4.2.1 Sensitivity analysis

"The goal of sensitivity analysis is to explore the change in model output resulting from a change in model parameters" (Reichert, 2009)

Sensitivity analysis (SA) is closely linked to uncertainty analysis of models. As Gujer (2008) states:

- Consideration of sensitivity will tell us whether the parameters are identifiable and which experiments would yield most information.
- Error propagation provides us with estimates of model prediction uncertainties.

In general practice, sensitivity analysis is often understood as a method to evaluate the impact of changes in a system on defined aims (e.g. using different sizes for storage tanks, using different throttle runoffs to evaluate impact on overflow volumes, etc.) and is often conducted by changing the value in question manually (e.g. stepwise) in a supposedly realistic range.

According to Gujer (2008) and Reichert (2009) **local sensitivity analysis** indicates how the prediction of a model with fixed parameters reacts to small changes of the parameters. It is based on linearization of the model equations at a given set of parameter values and describes only local model behaviour at this parameter set.

On the other hand **global sensitivity anlysis (GSA)** methods (also called *regional sensitivity analysis* by some authors) allow to describe the model response to parameter variation within a given prior distribution. This allows to improve the understandig of the model behaviour and is very closely related to uncertiainty analysis (Reichert, 2009). Depending on the applied method it can be used to:

- Separate influential from non-influential parameters.
- Rank the parameters by their importance.
- Analyse non-linearity and parameter dependencies.
- Identify implementation errors of the model.
- Study how uncertainty in the model output can be apportioned to different sources of uncertainty in the model input.

Several approaches have been proposed in literature to assess model sensitivity (see e.g. Saltelli et al. (2004)). However, as Campolongo et al. (2007) state, global sensitivity anaylsis is still carried out rarley in environmental models.

In optimisation frameworks Saltelli et al. (2004) suggest using SA first to determine the subset of input parameters driving most of the variation in model output in order to reduce the problem dimensionality and then to carry out a search on those parameters to establish their optimal values.

In the following two methods for a global sensitivity analysis are described that have been applied to the case study in this work, namely the evaluation of the standardised regression coefficients (SRCs) and the Morris screening method. Only few application examples of these methods exist in urban drainage: Sin et al. (2010) applied the SRCs in waste water treatment plant modelling. Hoppe (2006) used the Morris screening method with the ATV A-128 (ATV, 1992) guideline example. A comparison between the performances of sensitivity measures from Morris screening and variance-based methods is presented in Campolongo and Saltelli (1997).

A comprehensible evaluation of the sensitivity measures for both methods based on a SWMM model of an example catchment presented in the ÖWAV guideline 11 (OEWAV, 2009) is given in appendix 1.

4.2.1.1 Standardised regression coefficients

The following description is mainly based on Saltelli et al. (2005) and Sin et al. (2010).

The method of *standardised regression coefficients* (SRCs) is based on multivariate linear regression of model outputs obtained from Monte-Carlo (MC) simulations. For each model output of interest, a linear model is fitted to the output of the MC simulations relating model output y to model parameters Θ_i varied in their defined range (Equation 3-1). The model output has to be a scalar, so when using time series they have to be aggregated to a single meaningful value.

$$y_{reg} = a + \sum_i b_i \cdot \theta_i \qquad \textbf{Equation 4-1}$$

with a, b … regression coefficients

The standardized regression coefficients β_i are obtained by scaling the regression coefficients b_i, using the standard deviation of model input and output of the MC simulations according to Equation 4-2.

$$\beta_i = \frac{\sigma_{\theta_i}}{\sigma_y} \cdot b_i \qquad \textbf{Equation 4-2}$$

with σ_{θ_i} … standard deviation of model input (parameter) and
σ_y… standard deviation of model outputs

The SRCs β can take values between -1 and 1 and can be interpreted as follows (Saltelli et al., 2004):

- They are multi dimensionally averaged over a set of possible values of the other parameters.
- A high absolute value indicates a large effect of the corresponding parameter Θ_i on the output.
- A negative sign indicates a negative effect on the output; a positive sign indicates a positive effect on the output.
- Coefficients close to zero mean that the output is not sensitive to that parameter.

The squared SRCs β_i^2 describe a measure of the variance in the model output due to each parameter Θ_i. A value β_i^2 of 0.6 would signify that 60% of the output variance results from parameter Θ_i, provided that the $\sum_i {\beta_i}^2 = 1$. In general $\sum_i {\beta_i}^2 \leq 1$, corresponds to the coefficient of determination R^2. If the sum is 1 the relationship between output and parameters is indeed linear.

Based on these properties, SRCs are a useful and powerful method to separate influential from non-influential parameters and rank the parameters by their importance. However, while they are a relatively simple method to evaluate parameter sensitivity, they are an inappropriate tool if non-linear effects occur. According to Saltelli et al. (2004) the regression can be deemed as successful if the coefficient of determination R^2 is high (0.7 or more). Low R^2 values (< 0.3) show that the regression analysis is inappropriate for the sensitivity analysis. This is also discussed in the case study example of this work in chapter 6.7.

An exemplary result from SRC evaluation with the ÖWAV guideline 11 example catchment (OEWAV, 2009) is shown in Figure 4-3. The sensitivities for the parameters percentage of imperviousness (IMP), pipe roughness (*MAn*) and the subcatchment slope (*SLP*) for the maximum flow at the catchment outlet are evaluated. Details on the evaluation for this example are given in appendix 1.1.

All three parameters are identified to have an effect on the model output (maximum flow), ranking *IMP* higher than *MAn and SLP*. Positive SRCs indicate that increasing these parameters also increases the evaluated objective value (i.e. higher *IMP* an *SLP* values increase the maximum flow). Negative SRCs signify the contrary (increasing pipe roughness leads to lower maximum flows). The high R^2 value of 0.91 indicates that approximate linearity holds for the multivariate linear regression and that the results can be assumed to be valid.

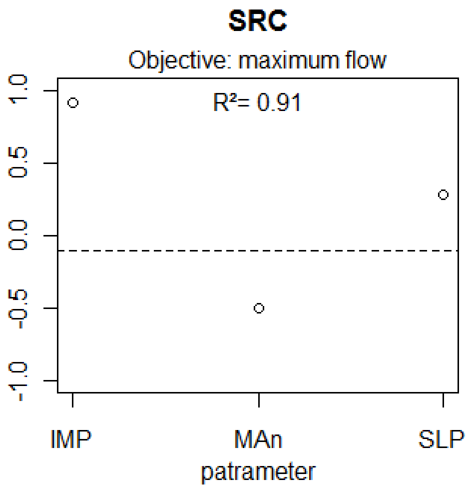

Figure 4-3: Exemplary results for SRC evaluation for a 3-parameter model

4.2.1.2 Morris screening

The Morris screening method was first proposed by Morris (1991), modifications to the original approach were proposed by Campolongo et al. (2007). The following description is mainly based on these two works and descriptions given in Saltelli et al. (2004).

The Morris screening is a one-at-a time method based on factor fixing, meaning that only one parameter is varied in each model run. It is designed to work at low computational costs and provides an average of local sensitivities across the parameter range and indicates which parameters may be considered to have effects which are i) negligible, ii) linear and additive, or iii) non-linear or involved in interactions with other factors.

A computational grid (screening gird) is composed from the k-dimensional parameter space (using k parameters θ). Parameters are scaled from their original limits and distributions to a uniform distribution between 0 and 1. For each parameter set defined in the grid, one model run is performed.

Each parameter $\theta_{i\ (i=1\ldots k)}$ is assumed to vary across p selected levels in the defined space of input parameters (becoming a unit hypercube by scaling the parameters from 0 to 1). For each parameter, two sensitivity measures are computed: μ, which assesses the overall influence of the factor on the output, and σ, which estimates the ensemble of the parameter's higher order effects, i.e. non-linear and/or due to interactions with other factors.

Therefore, so called elementary effects $d_i(\theta)$ (EE) are computed. The EE method is based on the construction of r trajectories in the input space, typically between 10 and 50. The design is based on generating a random starting point for each trajectory and then completing it by moving one parameter at a time in a random order (Campolongo et al., 2007). Variation of the parameter is defined by the *grid jump*, describing the number of levels that are increased or decreased for computing the elementary effects. For each parameter, r elementary effects are calculated. The cost of the experiment is therefore r*(k+1). Two trajectories are exemplarily shown in Table 4-3 for four parameters, four levels p = {0, 0.33, 0.67, 1} and a grid jump of 2.

Table 4-3: Exemplary trajectories for the Morris screening

Run	Θ_1	Θ_2	Θ_3	Θ_4	
1	0.33	0.00	0.33	0.67	Random starting point, 1st trajectory
2	**1.00**	0.00	0.33	0.67	First trajectory
3	1.00	**0.67**	0.33	0.67	
4	1.00	0.67	**1.00**	0.67	
5	1.00	0.67	1.00	**0.00**	
6	0.00	0.67	0.33	1.00	Random starting point, 2nd trajectory
7	**0.67**	0.67	0.33	1.00	Second trajectory
8	0.67	**0.00**	0.33	1.00	
9	0.67	0.00	**1.00**	1.00	
10	0.67	0.00	1.00	**0.33**	

For a given parameter set $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_k)$, the elementary effect of the i^{th} parameter is calculated based on the model outputs by Equation 4-3. The model output y has to be a scalar value.

$$d_i(\theta) = \frac{y(\theta_1, \ldots, \theta_{i-1}, \theta_i + \Delta, \theta_{i+1}, \ldots, \theta_k) - y(\boldsymbol{\theta})}{\Delta}$$ **Equation 4-3**

with i… index, Δ … a value in {1/(p-1),…,1-1/(p-1)}, p … number of levels, θ_i…model parameter i, $\boldsymbol{\theta} = (\theta_1, \theta_2, \ldots, \theta_k)$ model parameter vector, y … output

The finite distribution of the elementary effects associated with the i^{th} parameter is denoted F_i. The sensitivity measures μ and σ are respectively the mean and the standard deviation of the distribution F_i. Campolongo et al. (2007) proposed to use the distribution of absolute values, denoted G_i, with a mean denoted μ^*.

Interpretation of the values μ* and σ: A high value of μ* shows that changes in the parameter have – averaged over the other parameters – a high effect on the model output. The parameter is therefore sensitive.

A high value of σ for the parameter θ_i means that the elementary effects relative to this factor are significantly different from each other, i.e. the value of an elementary effect is strongly affected by the choice of the point in the input space at which it is computed, i.e. by the choice of the other parameter values. In contrast, a low σ indicates very similar values of the elementary effects, implying that the effect of θ_i is almost independent of the values taken by the other parameters (Saltelli et al., 2004).

Morris (1991) proposes a graphical analysis of the results to estimate the importance, ranking and interaction effects. An exemplary result from Morris screening with a 3-parameter model using the ÖWAV guideline 11 example catchment (OEWAV, 2009) is shown in Figure 4-4. As for the SRCs, the sensitivity measures for the parameters percentage of imperviousness (IMP), pipe roughness (*MAn*) and the subcatchment slope (*SLP*) for the maximum flow at the catchment outlet are evaluated. Details on the evaluation for this example are given in appendix 1.2.

As for the SRCs, all three parameters are identified to have an effect on the model output, ranking *IMP* higher than *SLP* and MAn. The relatively high σ-values indicate non-linearity or interaction effect for the parameters.

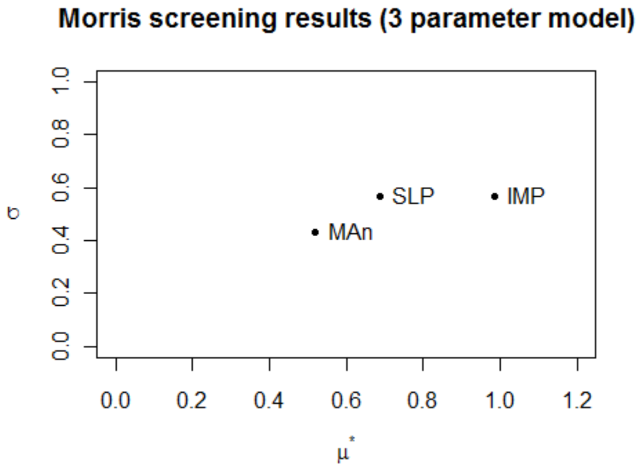

Figure 4-4: Exemplary results from a Morris Screening run for a 3-parameter model

4.3 Model calibration and validation

The term model calibration is generally used to describe the process of varying the model parameters in order to fit simulated to measured values:

EPA (1999) define calibration *as "the process of running a model using a set of input data and then comparing the results to actual measurements of the system. If the model results do not reasonably approximate actual measurements, the modeler reviews the components of the model to determine if adjustments should be made so that the model better reflects the system it represents."*

FWR (1998) state that *"the basis of the calibration procedure is a comparison of predicted performance with measured observations […]. The aim of the procedure is for both the* *shape and the dimensions of the hydrographs and pollutographs to be representative of the observed phenomenon."*

Model validation describes "*the process of testing the calibrated model using one or more independent data sets.*" (EPA, 1999) and is discussed in more detail at the end of this chapter.

Model calibration can either be done manually or automated. In **manual calibration** the model parameters are changed "by hand" in order to improve the fit of measured and simulated values. Manual calibration is time consuming, highly subjective and the calibration quality is mainly dependent on the experience of the modeller (Gamerith et al., 2008). Reichert (2009) state that in an early stage of analysis, manual calibration can be useful, as the process of changing parameter values and analysing their effect on the model results improve the understanding of model behaviour. With respect to the number of required numerical simulations, it may be a recommendable solution as it can provide a reasonably good fit with a relatively small number of simulations.

In **automated calibration** model parameters are determined from optimisation algorithms by minimising (or maximising) one or more objective function(s). As the resulting parameter values are optimised in view of the chosen objective function, the choice of the function is crucial. Many different algorithms as well as objective functions have been proposed in literature and will be discussed in more detail in the following.

Concerning the **model calibration in practice**, based on a survey in France, Gromaire et al. (2002) state that while calibration is highly recommended by researchers, application by practitioners remains difficult. The users often use trial and errors on roughly qualitative estimations based on limited data sets.

In order to calibration a model, **measurement data** is vital to enable the adaptation to site-specific conditions. As discussed in the previous chapters, measurements are always subject to errors. Especially rainfall as input variable is often highly uncertain and spatial distributions are neglected (Verworn and Kenter, 1993). In addition the distribution of the measurement values has to satisfy the calibration needs and impacts on the generality of the model: e.g. using only small storm events for calibration will most likely not allow prediction of large events. CERTU (2004) state that automated calibration only makes sense if measurement data in good quality can be provided for the whole region of interest. Otherwise, these methods might risk in giving a false feeling of calibration quality as they are based on mathematically sound assumptions. Harremoes and Madsen (1999) stress that "*the universality of the calibrated/validated model does not go beyond the universality of the data series used for the analysis in question"* and that "*many of the parameters of the model are not identifiably for the simple reason that the time series in question does not contain information required to determine the parameters."*

A lot of **critical discussion** on model calibration can be found in literature:

Rauch et al. (2002) state that "*detailed deterministic models include so many functions and parameters that a stringent calibration of the model is virtually impossible."* and that *"it is an inevitable fact that any deterministic model shows a certain deviation from reality."* and its results will be uncertain.

Butler and Davies *(2000)* advise modellers "*that it would be a reckless or naive modeler who stated, "the results of the model are correct". The modeler would be far wiser to recommend the results as being useful."*

Bertrand-Krajewski (2007) stresses that "*reproducing observations is not equivalent to explaining phenomena"* and advises strongly against over-confidence in the models even if "calibrated" and "validated".

Another major criticism is that depending on the complexity of the model, the identification of parameter values can be a difficult task. A high number of – oftentimes correlated – parameters can lead to various sets of parameter values that perform equally well (Beven and Binley 1992). This is linked to uncertainty estimation as discussed in chapter 4.2

4.3.1 Calibration procedures

According to Schmitt et al. (2008), only few methodical recommendations for model calibration exist regardless of the importance of that topic. A literature review showed that several procedures are proposed with different levels of details e.g. in FWR (1998), EPA (1999), Verworn (1999), WapUG (2002), CERTU (2004) or Schmitt et al. (2008). It is generally agreed upon that first dry weather flow and then wet weather flow is calibrated and that calibration of water quality models is to be done after proper calibration of the hydraulic model.

4.3.2 Quality criteria - objective functions

One crucial point in the model calibration-validation process is the question how to asses and evaluate the model performance.

Bennett et al. (2010) discuss several methods that exist to evaluate the performance of environmental models: data division methods, direct comparison methods, residual methods, transformation methods, spatial methods, multi-criteria methods and diagnostic based evaluation methods. Dawson et al. (2007) state that the direct comparison and residual methods based on graphical or mathematical comparisons of predicted and observed values are widely used in hydrology. For automated calibration procedures, the direct comparison and residuals methods seem particularly suited due to their simplicity of calculation and their objectivity.

Different criteria are proposed and discussed in literature since the 1970s, mainly in watershed modelling (see e.g. Diskin and Simon (1977), ASCE-Task-Committee (1993) or Gupta and Sorooshian (1998)). For urban runoff modelling an early discussion is given by Ramachandra and Han (1987). CERTU (2004) list some functions that are in wider use. A compilation of a multitude of criteria was done by Dawson et al. (2007) and Dawson et al. (2009) who list a number of quality criteria for hydrological watershed modelling and provide an on-line tool, *Hydrotest,* to calculate the evaluation metrics.

An exhaustive recent review and discussion of quality criteria used in environmental models is given in (Hauduc, 2010).The following paragraphs are mainly based on this work.

Concerning the **choice of objective function for model calibration** Hauduc (2010) states that depending on the modelling objectives, the goodness-of-fit of the model can be defined as the capability of the model to capture one or several characteristics of the observed data, namely i) mean, ii) peak's timing, iii) peak's magnitude or iv) mean variations. Thus, to characterise the goodness-of-fit of the model, different quality criteria can be used. These criteria vary in the way the observed and predicted data are computed:

- Normalized metrics (in general to the number *n* of observations) allow comparing different data sets.
- Using absolute criteria keeps the original units of the variables.
- Relative criteria are free of units and allow comparing different variables.
- Comparison of residuals obtained with simplistic models (e.g. mean observed values, seasonal values, averaged time series etc.) are used to define the improvement over this simplistic model.

In addition, the criteria can emphasise small or large errors or magnitudes:

- Logarithmic and power transformations with an exponent < 1 (e.g. square root) give more importance to small errors or low magnitudes.
- Exponential or power transformations with an exponent > 1 give more importance to higher errors or higher magnitudes.
- Absolute values and even power values avoid error compensation when summing them up.

Therefore the choice of the function is essentially dependent on the modelling objective. Chapter 6.8.2 of this work is dedicated to this question. In the following the expression *objective functions* will be used equally *quality criteria*.

4.3.3 Calibration algorithms

According to Rauch and Harremoes (1999), the task of calibrating deterministic urban drainage models is essentially an optimisation problem. For complex models an automatic calibration can lead to an optimisation problem with numerous local minima. However, many mathematical optimisation methods require an objective function with only one minimum to “directly” search the minimum by derivation. Therefore, the selection of an appropriate optimisation method is crucial. In general, purely numeric methods that do not impose a strict condition to the objective function are better preforming (CERTU, 2004).

Often Monte Carlo simulations are used to determine the best performing parameter set, especially if uncertainty evaluation is of interest. However, in general these methods require a high number of simulations as they do not converge to an optimum but chose parameter sets randomly. In view of rainfall-runoff modelling Sorooshian and Gupta (1985) indicate that calibration should be solved by global optimisation routines. A comparison of several techniques for rainfall-runoff modelling is given in Cooper et al. (1997).

One type of method that seems appropriate to deal with these requirements are **evolutionary algorithms (EA)**. Evolutionary algorithms mimic the process of evolution of living organisms for searching for the solution to problems. They belong to the global optimisation procedures, which do not make assumptions on the continuity of the objective function and which do not require information on its derivatives. In addition, EAs allow the consideration of linear and non-linear constraints and the handling of complex optimisation problems (Muschalla, 2008a). Babovic (1998) distinguishes the following four main streams: i) evolution strategies , ii) evolutionary programming, iii) genetic algorithms and iv) genetic programs. An exhaustive overview of applications of evolutionary algorithms in urban drainage is given in Muschalla (2006). An evolutionary algorithm for model calibration was used in this work and is further described in chapter 5.4.4.

4.3.4 Multi-objective optimisation

In multi-objective (MO) optimisation, more than one objective function is used to determine an optimised parameter set. As Yapo et al. (1997) state, while practical experience with model calibration shows that no single-objective function is adequate to match all the important characteristics, research in automated calibration methods focused mainly on the selection of single-objective measures. Multi-objective algorithms started to evolve in the middle of the 1990s (Muschalla, 2006), e.g. Gupta and Sorooshian (1998) strongly advocating MO calibration for hydrologic models or Rauch and Harremoes (1999) outlining the possible application of genetic algorithms in multi-criteria decision analysis in urban drainage.

In this work the terminology “single-objective – single-event optimisation” (SE), “single-objective – multi-event optimisation” (ME) and “multi-objective” (MO) optimisation is used. As described in Gamerith et al. (accepted), this terminology is based on the suggestions by di Pierro et al. (2006). In SE optimisation, one single objective function is minimised using one single rainfall event. SE optimisation might be applied in practice due to the lack of data as only a small number of samples available for water quality modelling, only few events measured that satisfy the addressed objective etc. In ME optimisation, an objective function is minimised for more than one independent rainfall event each. In “multi-objective” (MO) optimisation, more than one objective function is considered at the same time.

When using more than one objective in model calibration, several techniques have been applied in an urban drainage context:

- optimising for each objective separately and averaging the parameters or building a “synthetic” parameter set by using e.g. a weighted sum approach (Dayaratne and Perera, 2004), (di Pierro et al., 2006).
- reducing the multi-objective problem to a single-objective one by weighing and summing the objective function values (van Griensven and Bauwens, 2003).
- evaluation of Pareto-optimal solutions (di Pierro et al., 2006), described below.

Deb (2001) highlights the strength of evolutionary algorithms in a multi-objective context: If an optimisation problem has multiple optimal solutions, evolutionary algorithms can be used to capture multiple optimal solutions in the final population. This ability to find multiple optimal solutions in one single run makes evolutionary algorithms particularly suited to solving multi-objective optimisation problems

Mathematically, a vector of k objective functions $F(\vec{x}) = (f_1(\vec{x}), \dots, f_k(\vec{x}))$ is minimised (or maximised - the following notations, however, are based on the assumption that all functions are minimised), where $\vec{x} = x_1, \dots, x_n$ is an n-dimensional decision variable vector (e.g. a model parameter vector) from some Ω universe (Van Veldhuizen and Lamont, 2000).

4.3.4.1 The concept of Pareto-optimality

The concept of Pareto-optimality was first introduced by *Vilfredo Federico Pareto* in the late 1890s. Deb (2001) describes this concept in view of MO optimisation. Van Veldhuizen and Lamont (2000) give the following definitions of *Pareto-dominance*, *Pareto-optimality*, *Pareto optimal set* and *Pareto-front* (provided all objective functions *f(x)* are minimised):

Pareto-dominance: A vector $\vec{u} = (u_i, \dots, u_k)$ dominates a vector $\vec{v} = (v_i, \dots, v_k)$ if and only if *u* is partially less than *v* : $\forall i \in \{1, \dots . k\}: u_i \leq \ v_i \ \wedge \exists i \in \{1, \dots, k\}: \ u_i < \ v_i$. ,denoted as $\vec{u} \preceq \vec{v}$

Pareto-optimality: A solution $x \in \Omega$ is said to be Pareto optimal with respect to Ω if and only if there is no $x' \in \Omega$ for which $\vec{v} = F(x')$ dominates $\vec{u} = F(x)$

Pareto optimal set: $\mathcal{P}^* \coloneqq \{x \in \Omega | \neg \exists x' \in \Omega : F(x') \preceq F(x)\}$

Pareto front: $\mathcal{PF}^* \coloneqq \{\vec{u} = F(x) = \ f_1(x), \dots, f_k(x) | x \in \mathcal{P}^*\}$

When considering the objectives as independent, MO optimisation that uses the concept of Pareto-optimality for the selection of best performing individuals results in an approximated Pareto-front. Figure 4-5 exemplarily shows an approximated Pareto-front obtained by a MO-optimisation process for minimisation of two objectives. An objective function is minimised for each of the two independent objectives *A* and *B*. Several Pareto-optimal solutions are obtained (black dots). The optimal solution for each objective can be identified as the upper left and lower right solutions of the Pareto front, marked as *optimum solution – Objective A* and *optimum Solution – Objective B* (red dots).

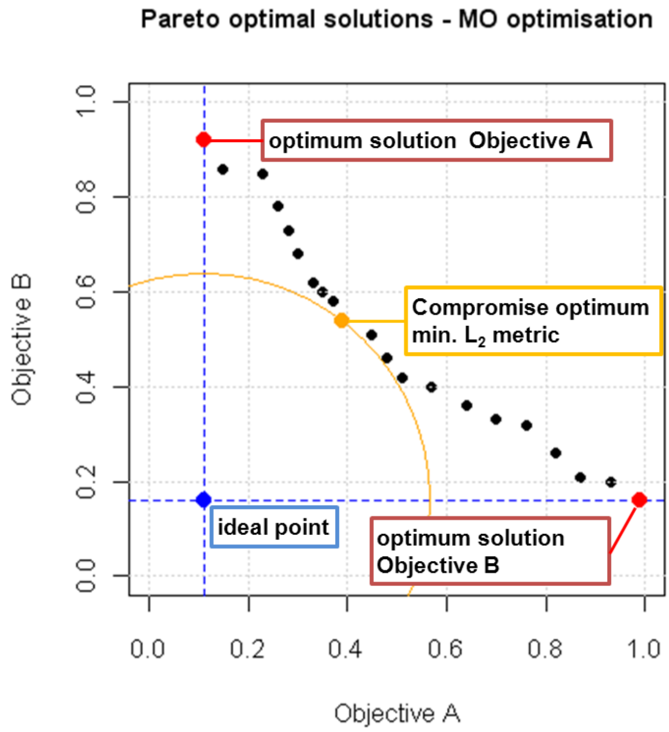

Figure 4-5: Pareto optimal solutions in multi-objective optimisation & compromise optimum solution by L_2 metric

A compromise optimum can be determined by the minimum L_2 metric (Equation 4-4) – also known as the minimum Euclidian distance – from the ideal point (Deb, 2001).The ideal point is defined by the optimal solutions for objectives A and B.

$$L_2(x) = \left(\sum_{i=1}^{N} (f_i(x) - z_i)^2 \right)^{\frac{1}{2}}$$ **Equation 4-4**

with i … index, N … number of objectives, $f_i(x)$ … value of objective i for solution x,
z_i … value of ideal point for objective i.

4.3.5 Validation

"Validation is the process of testing the calibrated model using one or more independent data sets." (EPA, 1999)

Once the model has been calibrated, it has to be validated by independent measurement data. A lot of discussion in literature was done whether to use the word **validation** or **verification** for this procedure. Especially in literature from the UK the term "verification" is commonly used, e.g. by Butler and Davies (2000) or WapUG (2002). Carstensen et al. (1997) state that the term "validation" is often used but that "*serious arguments are put forward against this term*". They state that *"the term verification is frequently interchanged with validation but the use of the term validation is advocated here".* Bertrand-Krajewski (2007) recommends to *"abandon the term validation, which, according to many authors, leads to an undue confidence in the model."* Gujer (2008), again strongly advocates the term validation as "e*nvironmental sciences cannot typically verify their models."*. In this work, the term **validation** is used.

Generally it is recommended that approximately half of the available data is used for calibration and the other half for validation. The model is run without any further adjustment using independent set(s) of rainfall data. Then the results are compared to the field measurements collected concurrently with these rainfall data. If the results are suitably close, the model is considered to be validated. Consequently at least the same quality criteria (objective functions) as used in calibration should be evaluated. As for calibration, validation data should be provided for the whole region of interest. As Butler and Davies (2000) state "*The verification is, strictly speaking, only valid for that particular location and only over the range of available data.".*

Some documents as WapUG (2002), give rough estimates for some target values as e.g. volume error or peak flow difference as minimum requirements to be reached in a calibration-validation process in order to deem a model "sufficiently" calibrated. CERTU (2004) advise that a good test consist of comparing the "errors" observed in validation data to those from the calibration data. If they are in the same order of magnitude one can consider that the model(s) have been well chosen to correctly represent the studied phenomena.

5 Materials and Methods

In this chapter the materials and methods developed and used in this work – especially for the application to the case study discussed in the next chapter – are presented.

After a short description of the development tools, first the methods used and developed for data management, analysis and validation are presented. The second part deals with the modelling software that was used for modelling the case study catchment. The third and last part discusses the BlueM.OPT framework and the extensions developed in scope of this work that were used for global sensitivity analysis, assessment of model calibration quality and automated model calibration.

5.1 Development tools

As main development tools Microsoft Visual Studio 2008 (supporting the Microsoft .NET framework) and the software [R] were used in this thesis. For minor data manipulations Microsoft Excel 2010 was used.

The Microsoft .NET Framework is a software framework for Microsoft Windows operating systems. It includes a large library, and it supports several programming languages which allows language interoperability (each language can utilize code written in other languages.) The .NET library is available to all the programming languages that .NET supports. (http://en.wikipedia.org/wiki/.NET_Framework, Nov. 24th 2010). In Visual Studio 2008, mainly Visual Basic .NET and Intel Fortran 10 – a Fortran compiler that can be integrated in Visual Studio – were used as programming languages in this work.

[R] is a language and environment for statistical computing and graphics. It provides a wide variety of statistical (linear and nonlinear modelling, classical statistical tests, time-series analysis, classification, clustering, ...) and graphical techniques, and is highly extensible via so called *packages.* [R] is available as Free Software under the terms of the Free Software Foundation's GNU General Public License in source code form (http://www.r-project.org/, Nov. 24th 2010).

5.2 Data management, analysis and validation

Concerning data management, one framework solution is currently being developed at the Institute. For data analysis and validation, several tools were developed in Visual Basic and [R] in scope of this thesis.

5.2.1 OpenSDM: an Open Scientific Data Management framework

The following description is taken from Camhy et al. (submitted) in slightly modified form.

Based on the long term experiences in online sewer monitoring at the Institute, currently an open source platform for data management (called OpenSDM) is under development. The underlying architecture is not focused solely on urban drainage but provides a powerful tool to work with scientific data in general. The underlying framework and a core system will be available as open source. The development is based on the following notions:

- Don't re-invent the wheel: available open source technologies and standards are used and further developed.

- Allow flexible data storage, depending on the needs or allowing to link solutions already in place. Currently implemented connectors include: text-based files, scientific data formats – e.g. netCDF (Rew and Davis, 1990) – and relational databases. All of them can be accessed and managed within the same platform.
- Provide the possibility to link any data. Data types can be defined freely, existing elements can be re-used.
- Server-based: Store the data on servers for easy accessibility and data sharing.
- User and access rights can be assigned on any level.
- Scripts can be implemented on server level or applied locally in many different programming languages, versioning support allows following changes.

The platform is still under development. Some parts, however, could already be used in this work.

5.2.1.1 netCDF data format

Measurement data from the case study catchment (see also chapter 6.2) was implemented in the OpenSDM framework using the *netCDF* (network Common Data Form) data format. netCDF describes not only a scientific data format but also several tools and libraries connected to that format. They are organised by the University Corporation for Atmospheric Research (UCAR), a non-profit consortium of North American member universities and international affiliates, in scope of an open source project.

The netCDF data contains a header with meta-information (e.g. data source, comments, units, quality information, geographical information) and the actual data in multidimensional arrays. A detailed introduction to the data format is given in Rew and Davis (1990). As Cohen et al. (2006) discuss, the high performance data access shows significant advances compared to relational data bases in terms of computational speed. As discussed in Reussner and Camhy (2010) netCDF is a promising candidate for a standardised format for scientific data management, data archiving and data transfer.

5.2.2 Data analysis

For analysing the available measurement data, several tools and scripts described in the following were developed in scope of this thesis.

5.2.2.1 Data pre-treatment

Concerning the pre-treatment of the measurement data, a toolkit named *ConvertSensorData* was developed in Visual Basic .NET that allows to**:**

- Convert rainfall time series data from and into different formats with different output time steps.
- Automatically identify rainfall events from a rainfall time series and evaluate the event's characteristics.
- Analyse measurement gaps in any measurement time series and interpolate missing values.
- Construct equidistant time series from time series with varying time steps.

- Convert measurement time series into formats used by different simulation models.

The rainfall time series conversion supports several input formats: i) all raw data formats from the rain gauges installed in the case study catchment (both tipping bucket and weighing gauges), ii) time series in the format provided by the Austrian Hydrographical Service and iii) a generalised CSV (time stamp – value in mm/min) format. As output formats, several formats required by different modelling software packages (SMUSI, BlueM, KOSIM, and SWMM 5) and a generalised CSV export are available.

Rainfall event separation is based on defining a dry period that separates two events (i.e. based on observations in the catchment) and a minimum event rainfall depth. As output a CSV file is generated, including an event numeration, the start and end time, event duration (min), precipitation sum (mm), maximum precipitation intensity (mm/min) and antecedent dry time (h) for each event.

A screenshot of the GUI of the *ConvertSensorData* tool is shown in appendix 2.1.

5.2.2.2 Data visualisation

For data visualisation the tool *WAVE*, developed in the *BlueM* framework (see Bach et al. (2009) and chapter 5.4) and several scripts developed in [R] were used.

WAVE is based on the .NET library TeeChart. It allows visualising time series with a high number of data points, offering the user a multitude of visualisation and design options. The main features include:

- Import of multiple data formats as e.g. result files from different modelling software packages (BlueM, SMUSI, SWMM 5, SIMBA, HYSTEM) and a generalised ASCII import bridge.
- User defined axes for visualising data with different units in the same plot, as e.g. rainfall, discharge and pollutant concentrations.
- Direct link to *BlueM* for visualisation of simulation results, optimisation steps, scatter plots etc.

Many of the time series graphs presented in this thesis were done in *WAVE*. In this work, the time series import function for ASCII and CSV files was expanded, allowing importing files with user defined date and time formats. An example of the GUI for data import is shown in appendix 2.2.

5.2.2.3 UV/VIS probe calibration analysis

A script for the analysis of the UV/VIS probe calibration results was developed in [R]. Input are n measured lab values for k reference samples and measured values derived from the spectra from the UV/VIS probe for the same k samples (possibly with j different probe calibrations).

The script allows to:

- Evaluate laboratory measurements: calculate the uncertainty distribution from n measured values of a measurand, with mean, median, standard deviation and 0.05 and 0.95 quantiles, calculated by the mean ± twice the standard deviation (see also chapter 3.1.1) for each of the k reference samples.

- compare lab and probe values for the *k* samples and *j* probe calibrations by calculating and plotting residual errors (absolute and relative) and a scatter-correlation plot for both pollution concentrations and fluxes.

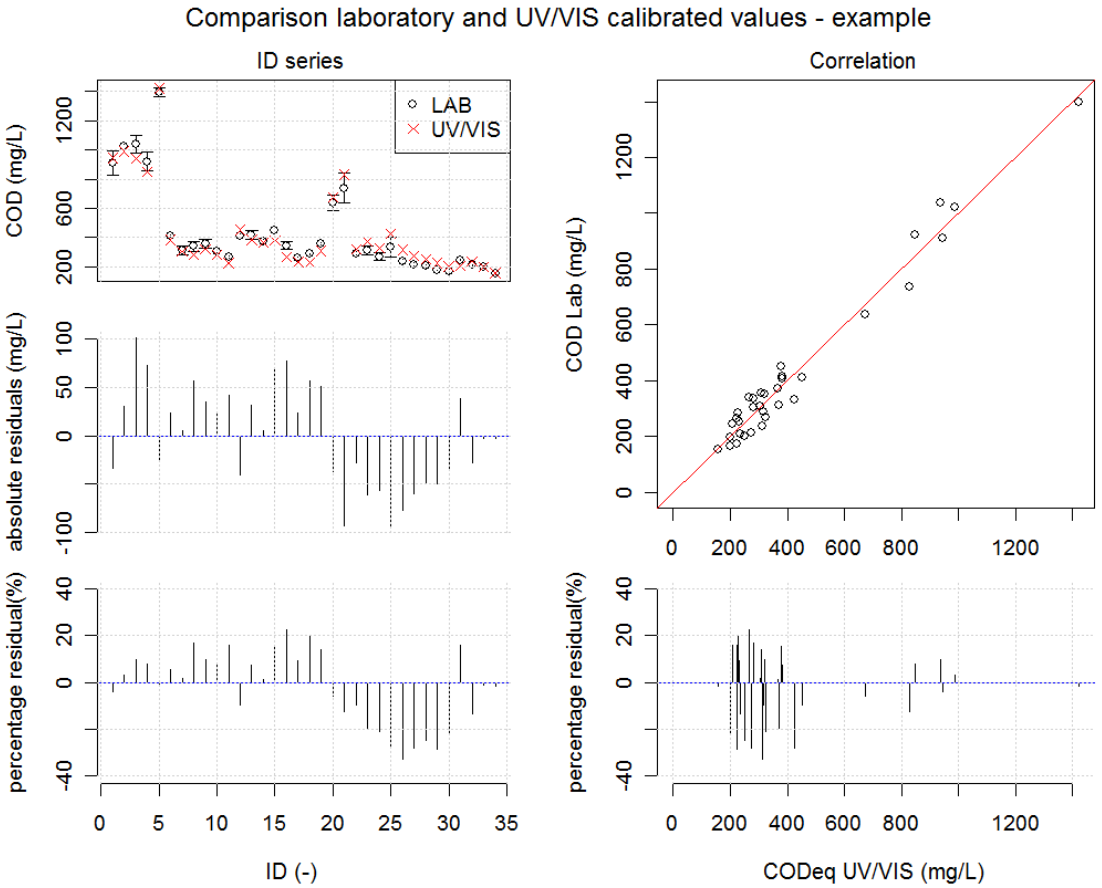

Figure 5-1: Exemplary results from UV/VIS probe calibration analysis

An exemplary output from the script is shown in Figure 5-1: The right hand side (from top to bottom) shows: i) a plot of the lab values (where the whiskers indicate twice the standard deviation) and measured UV/VIS probe values for the *k* samples, ii) absolute residuals and iii) relative residuals (percentage error calculated by Equation 5-1) for the *k* samples. The right hand side shows i) a scatter-correlation plot of lab and probe values and ii) the sorted relative residuals.

$$percenatge\ error = \frac{C_{lab} - C_{probe}}{C_{lab}} * 100 \qquad \textbf{Equation 5-1}$$

with C_{lab} … concentration from lab analysis (M L^{-3}), C_{probe} … concentration from UV/VIS probe (M L^{-3})

While the script was developed for treating the output of the UV/VIS probe calibration it can be easily adapted to any other measurement probe.

5.2.2.4 Rainfall time series analysis

A script was developed in [R] for rainfall time series analysis. Inputs are *n* rainfall time series with time stamp – value format using a specified unit for rainfall intensity (i.e. mm/min or mm/5 min). The script allows to:

- Calculate and plot cumulative rainfall over any defined period for the *n* time series.
- Compare the residuals of the cumulative values for two time series.
- Evaluate daily, monthly and annual statistical values (sum, mean, median, min, max).
- Automatically define dry weather days based on a user-defined maximum rainfall depth/day and maximum rainfall intensity.
- Calculate weighted rainfall over a defined period with user-defined weights.
- Replace missing values in one time series by substituting them with data from another time series, possibly multiplied with a user-defined factor.

5.2.2.5 Dry weather analysis

The [R] script developed for dry-weather analysis is a top-up for the rainfall analysis script described above. Based on the automated definition of dry weather days, any time series (e.g. flow or pollution concentrations) can be analysed.

The script allows to:

- Evaluate daily statistics as sum, mean, min-max, median, number of NaN values.
- Plot time series and box plots for the derived statistical values.
- Determine an average dry weather flow patter based on a user-defined choice of days and/or periods.
- Evaluate the effect of antecedent dry days.

5.2.2.6 Storm event analysis

The [R] script developed for individual storm event analysis is linked to a prior storm event separation. As input a table with event numeration, start- and end date for each event and a separate table with the corresponding measurement data (i.e. flow and pollutant concentrations) is required. As input e.g. the CSV output from the *ConvertSensorData* tool described above can be used.

The script then allows calculating and visualising the measured data, pollutant fluxes and a corresponding $M_{(V)}$ (mass/volume) diagram. An example for the script output is shown in Figure 5-2, showing inflow (L/s), TSS_{eq} concentrations (mg/L) and TSS_{eq} flux (kg/min) on the left hand side and the corresponding $M_{(V)}$ diagram on the right hand side.

The $M_{(V)}$ diagram plots normalized values of pollutant mass $\frac{cumulated\ mass\ (kg)}{total\ event\ mass\ (kg)}$ against runoff volume $\frac{cumulated\ runoff\ volume\ (m^3)}{total\ event\ runoff\ volume\ (m^3)}$. This allows an interpretation of the dynamics in the pollutant concentrations: e.g. in Figure 5-2, 40% of the event TSS load is associated with approximately the first 20% of runoff volume.

This information can be used e.g. to identify and asses first flush effects as discussed in Geiger (1984) and Bertrand-Krajewski et al. (1998). A comprehensive overview and discussion on the first flush is given in Bertrand-Krajewski et al. (1998), who points out that the observation of a peak concentration at the beginning of an event is not sufficient to define a first flush especially in view of storage tank design (e.g. for retaining a certain amount of pollutants with the first part of the runoff volume). Hence, often normalised values for mass and volume are compared by the means of $M_{(V)}$ plots and a certain pair of values is defined for identifying a first flush effect. Bertrand-Krajewski et al. (1998) proposes a 30/80 definition, meaning that 80% of the pollutant mass is transported in the first 30% of the volume. Other definitions range between more (20/80) and less restrictive (25/50).

An effect postulated in Brombach et al. (1995) is the occurrence of a last flush due to the remobilisation of settled pollutants during the emptying phase of storage facilities. This effect could be identified for the case study described in chapter 6.

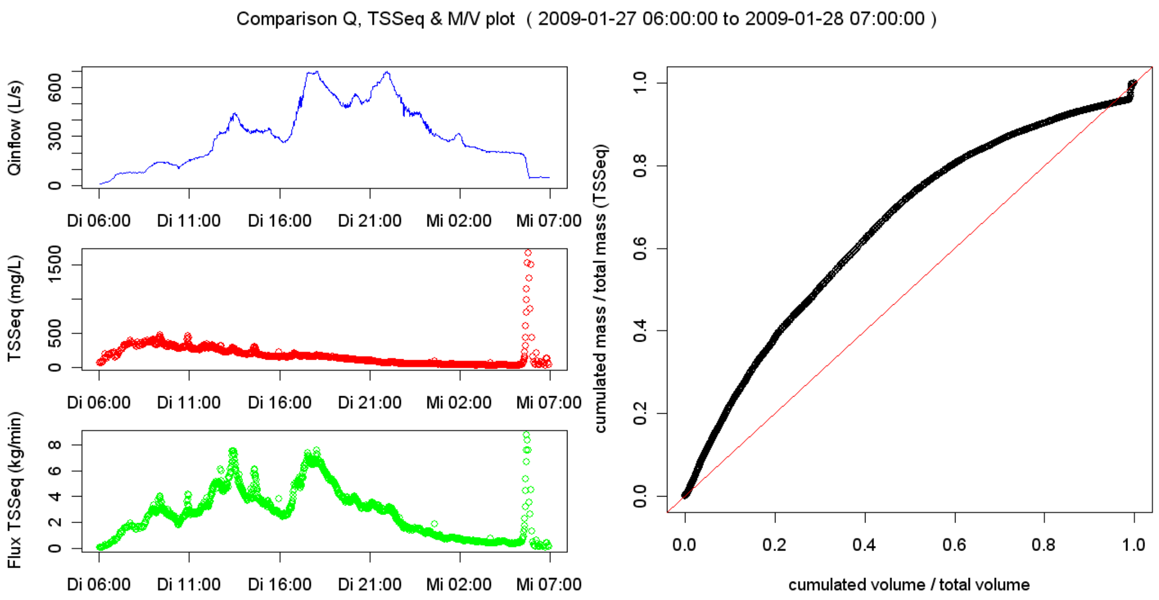

Figure 5-2: Exemplary results from automated storm event analysis

5.2.3 Semi-automated data validation

For semi-automated data validation, scripts were developed in [R] based on the notions described in chapter 3.2.2.2: Based on several tests, data is classified either in valid (A), not valid (C) or subject to additional, visual validation (B). Input for the script can be any time series matrix including one column for time stamp and *n* columns for *n* variables. For each test one additional column per variable with the classification results is added to the time series matrix, indicating the applied test and the evaluated variable.

An implemented export routine allows to export the data in text or CSV files, specifying how flagged values should be treated (i.e. replacing the values classified as (C) by NaN, zero or any other value).

In this thesis, several tests were implemented as described below. Additional tests are currently under development (principal component analysis for pattern recognition, flat line-test etc.) and can be implemented easily in the existing script structure. Eventually the routines should be linked to the *OpenSDM* framework described in chapter 5.2.1.

5.2.3.1 Physical measurement limit

This test is based on a comparison of the measured value and the physical measurement limits of the sensor. Each value is flagged either as valid (A) if it is within the defined range or not valid (C) if it is not.

For example water level measurements from contactless ultrasonic probes lower than 0 and higher than the installation height of the sensor are classified as (C).

5.2.3.2 Site specific measurement limit

This test is based on the comparison of the measured value to a user-defined site specific measurement limit of the sensor. The definition of the limits is “weaker” than for the physical measurement limits, allowing values to be classified as (B). Therefore four limits are defined: a lower and an upper limit for the (C) and (B) classification each, where: lower limit for (C) classification < lower limit for (B) classification and upper limit for (B) classification < upper limit for (C) classification. Values between the limits for (C) and (B) are classified as (B). Values between the lower and upper limit for (B) classification are classified as (A).

For example water level measurements in a sewer between 0 and some millimetres or centimetres (to be decided based on expert knowledge of the site) are classified as (B) as they might actually occur but are – most likely – not valid.

5.2.3.3 Analytical redundancies: cross check of variable values

This test allows validating values for one variable (called *evaluated* variable) based on a cross-check with another variable (called *conditional* variable). This allows e.g. to compare data from different sensors or different measurement locations. Therefore, a cross validation matrix as shown in Table 5-1 is defined, that allows comparing any two variables from the same or different time series matrices, provided the matrices have the same row dimension.

Table 5-1: Cross-validation matrix to check analytical redundancies: structure

Condition variable (i.e. column of time series matrix)	Logical comparison (greater than – lesser than)	Condition variable: value for comparison
Evaluated variable (i.e. column of time series matrix)	Logical comparison (greater than – lesser than)	Evaluated variable: value for comparison

Both the conditional and the evaluated variable are compared by a logical operator (either “greater than” or “lesser than”) to a user-defined value for comparison for each time stamp. If both logical comparisons are true, the evaluated variable is classified as (B) for the time stamp.

Table 5-2: Cross-validation matrix to check analytical redundancies: example

Variable	Logical comparison	Value for comparison
Water level at CSO	lesser than	weir height (scalar value)
Overflow discharge	greater than	zero

An example for a possible cross-validation matrix is given in Table 5-2: If the measured water level at a combined sewer overflow is lesser than the weir height, all overflow discharges greater than zero are classified as (B).

5.2.3.4 Residuals from moving average

This test allows calculating the residuals from any time series and its moving average over a user-defined period and a user-defined moving window for averaging (defined as number of time steps). Minimum and maximum allowed values of the residuals (either absolute or relative) are defined by the user. If the calculated residuals are higher or lower than the defined maximum or minimum values respectively the evaluated variable is classified as (B).

This test is can be used to identify noise in a time series but was shown to be highly sensitive to the defined min- and max values (Mourad and Bertrand-Krajewski, 2002).

5.3 Modelling software

As modelling software SMUSI (developed at TU Darmstadt) and SWMM 5 (developed by the US-EPA) were used in this work. A short description of the software and underlying model assumptions is given in the following paragraphs.

5.3.1 SMUSI 5.0[2]

SMUSI is a detailed hydrological deterministic rainfall-runoff and pollution load model that computes the dominant characteristics for the assessment of the effect of overflow structures on receiving water bodies. In this study a research version of SMUSI 5.0 (Muschalla et al., 2006) was used.

The simulated processes include runoff formation and concentration from pervious and impervious areas, and superposition of dry-weather flow and storm water runoff in collecting pipes and structures as well as translation and retention of hydrographs and pollutographs in sewer systems.

5.3.1.1 Hydraulic model

The hydraulic model of the SMUSI software covers all relevant phenomena presented in chapter 4.1.1. Rainfall-runoff transformation on subcatchments takes into account initial and depression losses, and the percentage of imperviousness. For pervious surfaces, the SCS method (US-SCS, 1972) is used. Runoff concentration on the surface is calculated by a parallel linear reservoir model. Secondary sewers are lumped into the surface model. Flow propagation in the main sewers is calculated by the Kalinin-Miljukov approach. This approach is based on the definition of *n* cascaded linear reservoirs with constant length and retention constants for a sewer section (see e.g. Maniak (2005) for a detailed description). Static backwater can be considered.

5.3.1.2 Implemented water quality models

Pollution concentrations in the runoff are calculated based on three components:

a) The imported water and surface runoff from pervious areas are considered as unloaded. This approach is reasonable as particles in stormwater essentially originate from the impervious surfaces of the catchment (Bertrand-Krajewski et al., 1993).

b) The concentration of the surface runoff from impervious areas is calculated based on either a constant storm water concentration or on accumulation and wash-off processes (AWO). Any accumulated pollutants in sewer pipes are considered in the surface processes. Sedimentation and erosion processes in the sewer systems are

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[2] The model description is in large parts taken from Gamerith et al. (2009, with permission from IWA Publishing) in a slightly modified version.

not considered separately. This assumption can be deemed valid for steep sewer systems where no important in-sewer deposits are to be expected. Its performance, however, is limited in flat sewer systems with significant deposits.

c) The dry weather flow is defined with its time-varying pollutant concentration and flow patterns.

In the following the equations used in the model for the three approaches for calculation of pollutant concentrations from impervious surfaces are described in detail as their performance was compared and assessed in this work for the case study presented in chapter 6.

Constant storm water concentration approach: In this approach, the pollutant concentration of storm water runoff from impervious areas is calculated as an annual average value, based on the effective precipitation and the yearly-accumulated load (see Equation 5-2). The annual accumulated mass can be defined separately for each subcatchment.

$$C_{prec} = \frac{Ma_{year}}{r_{eff}} \cdot 100$$ **Equation 5-2**

with C_{prec} … pollution concentration (M L^{-3}), Ma_{year} … accumulated mass per year on impervious areas (M L^{-2}) and r_{eff} … effective precipitation on impervious areas (L).

Accumulation and wash-off approaches: Storm water pollutant concentration can optionally be calculated by an accumulation and wash-off approach. In that case, pollutant concentrations in the storm weather runoff from impervious areas depend on antecedent dry weather periods and precipitation intensity.

For the accumulation process during dry weather periods, an exponential asymptotic build-up equation, which is also implemented in SWMM is used (Equation 5-3). This approach is based upon the suggestion of Sartor et al. (1974), which is further described by Alley and Smith (1981a). Here the nomenclature according to Bertrand-Krajewski et al. (1993) is used.

$$\frac{dMa}{dt} = ACCU - DISP \cdot Ma$$ **Equation 5-3**

with t… time (T), Ma … accumulated mass (M), $ACCU$ … accumulation rate (M T^{-1}) and $DISP$ … removal coefficient (T^{-1}).

For the wash off process from impervious surfaces, two different approaches are used and compared in this work. First, an approach according to Metcalf and Eddy (1971), which is used in numerous simulation models and further described by Alley and Smith (1981b).

$$\frac{dMa}{dt} = -Ke \cdot i(t) \cdot Ma$$ **Equation 5-4**

with t … time (T), Ma… accumulated mass on impervious surfaces at time t (M), $i(t)$ … rainfall intensity at time t (L T^{-1}) and Ke … wash off coefficient (L^{-1}).

To solve this relation within discrete time steps Equation 5-4 becomes Equation 5-5.

$$Me(t+\Delta t) = Ma(t) \cdot (1 - e^{-Ke \cdot i(t+\Delta t) \cdot \Delta t}) \qquad \textbf{Equation 5-5}$$

with: *Me* … the mass of particles entering the sewer during the time step t (M) and Δ*t* … time step (T).

Secondly, an expanded version of this approach is implemented. It introduces an exponent ω as rainfall intensity shape factor described in Bertrand-Krajeski et al. (1993) and a maximum rainfall intensity i_{lim} proposed in Deyda and Sieker (1996).

$$Me(t+\Delta t) = Ma(t) \cdot \left(1 - e^{-Ke \cdot i(t+\Delta t) \cdot \left(\frac{i(t+\Delta t)}{i_{lim}}\right)^{\omega} \cdot \Delta t}\right) \qquad \textbf{Equation 5-6}$$

with: ω … shape factor for rainfall intensity (-) and
i_{lim} … maximum rainfall intensity (L T^{-1}) (for i > i_{lim} ω is set to 0).

5.3.1.3 SMUSI model parameters – hydraulic model

In the following the parameters used in the SMUSI model are shortly described and parameter limits based on a literature review are discussed. This information was used as basis for the sensitivity analysis methods and in the automated model calibration in the case study application.

Evaporation factor (*EF*)

An annual and daily evaporation pattern is hard-coded in SMUSI. It is based on an annual potential evaporation of 642 mm, typical for the Hessen region in Germany. As the pattern itself cannot be changed, a factor was implemented that allows scaling the pattern, effectively increasing or reducing the potential annual evaporation. In SMUSI, evaporation reduces the effective rainfall depth and empties the depression storages during dry weather periods.

As the potential evaporation is highly dependent on the climate region, limits for the evaporation factor were based on the actual potential annual evaporation for the case study region Graz. Yehdegho et al. (1994) determined a potential evaporation for the Graz airport measurement station between 1971 and 1991 to 682 ± 16 mm. Fank (2009) states potential evaporation rates between 681 and 741 mm from 2005 to 2008 at the Wagna measurement station (45 km south of Graz). Inter-annual variations determined from a time series from Vienna are in an order of magnitude of ± 15%.

Based on this information, the limits for *EF* were set arbitrary to ± 20 % (0.8 to 1.2)

Initial losses (*IL*)

In SMUSI initial losses are subtracted directly from the rainfall depth at the beginning of an event.

Table 5-3 gives an overview of parameter limits as defined in literature and the limits chosen for modeling. For pervious surfaces no initial losses are defined as the SCS approach is used.

Table 5-3: Initial losses compiled from literature

Literature	Impervious area	Pervious areas
	mm	mm
ATV (1986)	0.2 to 0.5 only valid for separate events	
Verworn (1999)	0.15 to 0.8, in general 0.5	2.0 to 10.0
ATV-DVWK-165 (ATV, 2004)	0.3 to 0.7	neglectable
DWA A – 118 (DWA, 2006a)	0.3 to 0.7 only valid for separate events	-
Schmitt and Illgen (2001), values from literature	0.2 to 0.5	0.2 to 1.0
Desbordes (1974), cited in CERTU (2004)	0.2 to 1.5 defined as interception by vegetation	
Kaufmann (1988), cited in CERTU (2004)	0.5 defined as interception by vegetation	
Chosen parameter limits	0.15 to 0.8	-

Depression losses (*DL*)

In SMUSI, depressions are being filled at the beginning of a rainfall event after covering the initial losses. The depression storage is emptied based on the evaporation rate. In the SMUSI model, depression losses vary with the slope of the sub-catchment, classified in four categories (1 to 4 from flat to steep) according to the DWA A-118 guideline (2006a). The parameter value for *DL* is used for flat areas (category 1). For category 2 it is multiplied by 2/3, for categories 3 and 4 by 1/3, leading to an effective reduction of the depression losses for steeper subcatchments.

Table 5-4 gives an overview of parameter limits as stated in literature and the chosen limits. For pervious surfaces no depression losses are defined as the SCS approach is used.

Table 5-4: Depression losses compiled from literature

Literature	Impervious area	Pervious areas
	mm	mm
ATV (1986)	0.2 to 1.8; only valid for separate events; in practice often higher values reported	1.0 to 8.0 depending on surface type and slope, including depression losses
Verworn (1999)	0.4 to 2.5 in general 1.8	2.0 to 5.0 in general 3.0
ATV-DVWK-165 (ATV, 2004)	0.5 to 2.0	-
DWA A – 118 (DWA, 2006a)	0.5 to 2.0 only valid for separate events	-
Schmitt and Illgen (2001), values from literature	0.2 to 2.5	1.0 to 5.0
ASCE (1992), cited in Rossmann (2007)	1.25 to 2.5 (converted from inch to mm)	2.5 to 7.5 (converted from inch to mm)
CERTU (2004)	0.2 to 3 depending on slope	3 to 15 depending on slope
Chosen parameter limits	0.2 to 3.0	-

Imperviousness factor (*IF*)

In SMUSI the imperviousness describes the percentage of the total subcatchment area that is considered as impervious. Hence, changes in the percentage of the imperviousness affect the size of both the impervious and the pervious areas. For the GSA and automated model calibration procedure, the determined impervious percentage is multiplied by the imperviousness factor *IF*. The actual runoff coefficient for impervious surfaces is always 1.0, *IF* however has a close relationship to runoff coefficients defined in literature. A comprehensive overview given in (Illgen, 2009) based on German literature states runoff coefficients limits for partly to fully impermeable surfaces between 0.15 and 1.

Based on this information, the limits for *IF* were set as 0.15 to 1 (-)

Concentration time factor (*TF*)

Concentration time in the subcatchment was determined assuming a runoff velocity of 1 m/s for runoff in the secondary sewers and a surface concentration time of 3 minutes. Both values are estimates. As variations in maximum velocities and variations in the effective length are expected, the estimated concentration time is multiplied by a factor TF

The limits for *TF* were set arbitrary as 0.5 to 3 (-)

SCS curve number (*CN*)

Runoff from pervious surfaces in SMUSI is calculated with a method based on the US-SCS approach (US-SCS, 1964). It takes into account the rainfall history of the precedent 21 days and determination of actual runoff is based on a curve number (CN) value. The curve number is dependent from the hydrological soil group and the land use. Parameter limits for the curve number were derived from the USDA technical report TR20 (USDA, 1986), for the category "Open spaces, lawns, parks, golf courses, cemeteries, etc."

Chosen parameter limits: 40 to 85 (-)

Pipe roughness (*K*)

This parameter takes into account the pipe friction as well as possible local energy losses. In SMUSI it affects the retention constant for the Kalinin-Miljukov approach.

Table 5-5: Pipe roughness compiled from literature

Literature	Roughness
	mm
DWA A -110 (DWA, 2006b)	0.5 to 1.5 0.25 for throttle pipes
Dimensioning with the rational method cited e.g. in Gujer (2007) or OEWAV (2007)	1.0 to 1.5
John (2009)	up to 3.0 for corroded (concrete) pipes
WapUG (2002)	*The condition of the pipe can have a significant impact on the roughness of the sewer*
Chosen parameter limits	0.5 to 3

5.3.1.4 SMUSI model parameters – sewer water quality model

In the following the parameters for the surface accumulation and wash-off model approaches are discussed. It is important to note that the parameter names vary in different publications even though essentially the same processes and parameters are described. In order to clarify the use in this work, Table 5-6 gives an overview of the parameters as described in the SMUSI input files and the corresponding parameter names stated in publications describing this model approach: Alley and Smith (1981a), Paulsen (1987) and Bertrand-Krajewski et al. (1993). The last column gives the parameter name as used in the following in this work.

Table 5-6: Parameters for the water quality model in SMUSI and chosen parameter names

SMUSI parameter name		description	corresponds to	Chosen name
Pmax	kg/ha	Maximum accumulated mass on surface	$K_1 = K/K_2$ (Alley and Smith, 1981a) *ACCU/DISP* (Bertrand-Krajewski et al., 1993) P_0 (Paulsen, 1987)	***Pmax***
Panf	kg/ha	Initial accumulated mass on surface	-	***Pinit***
K1	1/d	Accumulation or removal coefficient	K_2 (Alley and Smith, 1981a) *DISP* (Bertrand-Krajewski et al., 1993) K_1 (Paulsen)	***DISP***
K2	1/mm	Wash off coefficient	*Ke* (Bertrand-Krajewski et al., 1993) K_2 (Paulsen, 1987)	***Ke***
K3	-	shape factor exponent	ω (Bertrand-Krajewski et al., 1993)	***W***
i_{grenz}	mm/min	Limit rainfall intensity	-	***iLim***

Maximum accumulated mass on surface (*Pmax*)

Pmax describes the maximum pollutant mass (limit of exponential function) accumulated on the surface in kg/ha. Verworn (1999) cites works where limits of respectively 4.4 to 12 kg/ha (Paulsen, 1987) and 8.0 to 12 kg/ha (de Vries, 1992) for COD were used. Mourad (2005) assumed values between 0 to 200 kg/ha for model calibration for TSS. Based on values for *DISP* and *ACCU* (see Equation 5-3) cited in Mourad (2005) limits for *Pmax* can be calculated to 4.25 to 45 kg/ha for TSS. Muschalla (2006) used a value of 6.0 kg/ha for BOD_5.

Chosen parameter limits: 4.0 to 50.0 (kg/ha)

Initial accumulated mass on surface (*Pinit*)

Pinit is used in SMUSI as the initial pollutant mass (kg/ha) at the start of a simulation. This value is essentially relevant if single events are simulated. The limits are consequently set to the same as for *Pmax*.

Chosen parameter limits: 4.0 to 50.0 (kg/ha)

Removal coefficient (*DISP*)

This coefficient represents the removal of accumulated particles due to wind, traffic, degradation etc. Table 5-7 shows limits used in literature for this parameter.

Table 5-7: DISP coefficient compiled from literature

Literature	DISP (d^{-1})
Novotny et al. (1985)	0.2 to 0.4
Bujons and Herremans (1990)	0.08
Muschalla (2006)	0.15

An evaluation of the underlying equation shows that for *DISP* <<, close to linear approximation of pollutant build-up is reached. For a *DISP* value of approximately 3, the impact of the dry weather period is negligible (pollution built up after *t*=1 day reaches 95 % of *Pmax*).

Chosen parameter limits: 0.01 to 3.0 (1/d)

Wash-off coefficient (Ke)

Ke is a model parameter used in the wash-off equation. Bertrand Krajewski et al. (1993) state that "*the standard value of Ke = 0.18 mm^{-1}. However it has been shown that Ke needs to be calibrates for each catchment"*. Muschalla (2006) chose 0.9 for BOD_5 and Mourad (2005) used limits of 0 to 1 for model calibration on TSS.

Chosen parameter limits: 0.01 to 1.0 (1/mm)

Shape factor – exponent (W)

In Bertrand-Krajewski et al. (1993), limits for *W* are stated with 0.8 < W < 2. These limits are also chosen here

Chosen parameter limits: 0.8 to 2.0 (-)

Limit rainfall intensity (iLim)

This parameter was introduced by Deyda and Sieker (1996). For intensities i > iLim the shape factor exponent *W* is set to 0. This means that the wash-off is reduced for intensities smaller than *iLim.* Muschalla (2006) chose values from 0.1 to 1.5 in a local sensitivity analysis. These limits are also chosen here

Chosen parameter limits: 0.1 to 1.5 (mm/min)

5.3.1.5 SMUSI model parameters – overview

Table 5-8 gives a comprehensive overview of the parameters used in the SMUSI model as described above, including the abbreviation, a short description and the minimum and maximum values used in sensitivity analysis and automated model calibration.

Table 5-8: overview of SMUSI model parameters and chosen limits based on a literature review

Parameter	unit	short description	Min	max
EF	-	Evaporation factor	0.8	1.2
IL	mm	Initial losses	0.15	0.8
DL	mm	Depression losses	0.2	3.0
IF	-	Imperviousness factor	0.15	1.0
TF	-	Concentration time factor	0.5	3.0
CN	-	SCS curve number	40	85
K	mm	Pipe roughness	0.5	3.0
Pmax	kg/ha	Maximum accumulated mass on surface	4	50
Pinit	kg/ha	Initial accumulated mass	4	50
DISP	1/d	Removal coefficient	0.01	3.0
Ke	1/mm	Wash off coefficient	0.01	1.0
W	-	Shape exponent	0.8	2
iLim	mm/min	Limit rainfall intensity	0.1	1.5

5.3.2 SWMM 5

SWMM (Storm Water Management Model) is a hydrodynamic rainfall-runoff simulation model that was first developed in 1971 in the US and has undergone several major upgrades since then. The latest re-write is version SWMM 5 (Rossmann, 2007) from the US-EPA (United States Environmental Protection Agency). It is available as free software and open source.

The hydraulic model of SWMM covers all relevant phenomena presented in chapter 4.1.1.

Rainfall-runoff transformation takes into account initial and depression losses, and a runoff coefficient for impervious areas. Snow cover can be taken into account. Subcatchments can be divided into pervious and impervious subareas. Surface runoff can infiltrate into the upper soil zone of the pervious subarea, but not through the impervious subarea. Impervious areas are themselves divided into two subareas - one that contains depression storage and another that does not. Runoff flow from one subarea in a subcatchment can be routed to the other subarea, or both subareas can drain to the subcatchment outlet. Infiltration of rainfall from the pervious area of a subcatchment into the unsaturated upper soil zone can be described using three different models: i) Horton infiltration, ii) Green-Ampt infiltration and iii) SCS Curve Number infiltration (Rossmann, 2007).

Runoff concentration on the surface is calculated by a kinematic wave approach (see e.g. Smith (2004) or Veit (2009))

Flow propagation in the sewers is calculated by solving the full Barré the Saint Venant equations (see e.g. Maniak (2005) or Butler and Davies (2000) for theoretical background and Rossmann (2006) for details on the computation in SWMM).

A sewer water quality model comparable to the model described for SMUSI is implemented in SWMM.

In scope of this work the presented methodology for sensitivity analysis and automated calibration were not applied and sewer water quality was not computed with SWMM. Therefore a detailed description of the model equations and model parameters is not given here but rather referred to Rossmann (2007).

5.4 *BlueM.OPT* framework

BlueM.OPT is an optimisation framework that was developed at TU Darmstadt over the last several years. The framework allows to link different simulation models to (optimisation) algorithms. While initially developed solely for optimisation purposes, the code was recently expanded (some parts in this work) to implement Monte Carlo and global sensitivity analysis methods. A screenshot of the general GUI is shown in appendix 2.3.

The models and algorithms can be freely combined. The object-oriented code, written in the .NET framework facilitates the implementation of additional simulation models or algorithm classes.

Communication between the algorithms and the simulation models takes place via text files. This makes BlueM.Opt extremely flexible as to the type of simulation model that is used – additional simulation models can easily be incorporated, provided that they have text-based input and output files. Communication via application programming interfaces is also possible.

Interfaces to the following **simulation models** are currently implemented in BlueM.OPT:

- BlueM.Sim (Bach et al., 2009)
- SMUSI (see chapter 5.3.1)
- SWMM 5 (see chapter 5.3.2)
- Additionally a class for UV/VIS probe calibration using absorption spectra and laboratory reference measurements as input was implemented in scope of this thesis.

Concerning **optimisation**, any type of problem can be optimised, provided that there are i) input variables or parameters that can be varied and that ii) one or more objective functions can be formulated. Model parameters can be grouped for optimisation. This allows reducing the dimensionality of the optimisation problem and helps to avoid over-parameterisation. All solutions are stored in a database so that detailed analyses and comparisons between different solutions can be performed in post-treatment (Bach et al., 2009). As major available optimisation algorithms in BlueM.OPT the following can be stated:

- PES – Parametric Evolution Strategy (Muschalla, 2006)
- CES – Combinatorial Evolution Strategy (Hübner and Ostrowski, 2008)
- a HYBRID approach (i.e. PES + CES), (Hübner and Ostrowski, 2008)
- Hooke & Jeeves – a hill-climbing algorithm for single-objective problems (Hooke and Jeeves, 1961)

In this work, the PES algorithm was used (see also chapter 5.4.4).

A **plain Monte Carlo** method is implemented allowing to randomly sample parameters from user-definable parameter distribution functions and calculating any available objective function for each parameter set. The outputs are stored in an ACCESS data base and can be used in post-treatment. In this work, the evaluation of the standardised regression coefficients in global sensitivity analysis was based on this method.

For **sensitivity analysis** the tool *SensiPlot* allows visualising 3D-response surfaces for evaluation of any available objective function for two parameters using gridded parameter sampling. Figure 5-3 shows an example for the evaluation of volume error against two parameters for sewer translation time (*TF1* and *TF2*), computed in a 10*10 grid within the defined parameter limits.

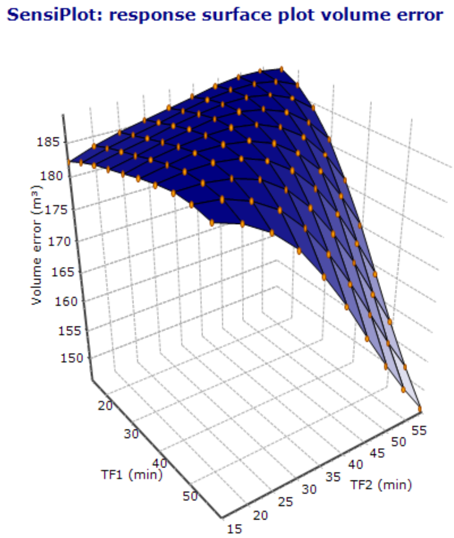

Figure 5-3: Exemplary result from the *SensiPlot* tool: response surface of volume error due to variation of sewer translation times

In scope of this thesis the screening method of Morris (see chapter 4.2.1.2) was implemented via a link to [R].

In the following the methods used, modified or developed in this thesis are described in more detail.

5.4.1 *SCAN* class for UV/VIS probe calibration

A class named *SCAN* was implemented in BlueM.OPT for UV/VIS probe calibration. This class can be used as simulation model and can be linked to all available optimisation algorithms for optimising any of the implemented objective functions. The model is described by Equation 3-9 in chapter 3.1.4.3.

Inputs are a reference time series (e.g. values from lab analysis of reference samples), the measured spectra, a text-file with the weighing factors for each wavelength and offset for each compound, and the required text files for the optimiser including information on the parameter to vary and the objective functions to be calculated. The weighing factors and offset can be then be optimised as model parameters within predefined parameter limits. Any combination of wavelengths and/or wavelength ranges can be used in optimisation.

As for all other applications, model parameters can be grouped. Hence, the weighing factors can be varied either independently for each defined wavelength or be grouped over subsets of wavelengths (assigning the same factor to each wavelength within this subset).

5.4.2 Implemented objective functions

One major input to the BlueM.OPT framework in scope of this thesis was additional coding for the objective function evaluation routine as well as the implementation of 32 additional objective functions. The implemented functions are based on a literature review by Hauduc (2010) and Hauduc et al. (submitted). A list of all implemented functions is given in appendix

3.1. All implemented functions were tested by comparing the results to a manual calculation in EXCEL for a test-dataset.

The following modifications were added to the code in scope of this work:

- For comparing time series (i.e. calculating objective function values from a reference and a simulated time series) a hash-table is generated that allows comparing time series with different time resolution, provided both series have at least one time stamp in common. Hence, time stamps in the two series also don't need to be equidistant except if the evaluated objective function requires them to be.
- Redundant file-reading of the reference time series was removed, leading to a significant performance improvement when evaluating a high number of objective functions.
- Not-a-Number (NaN) values in time series and as result from objective function evaluation are allowed and can be handled by the optimiser and the database connection.
- The code was slightly adapted to allow optimisation of daily patterns in SMUSI.

All modifications were implemented in a way that they can be generically used by all applications (models, optimisers, MC, GSA) within the BlueM.OPT framework.

5.4.2.1 TimeSeriesCompare tool

Based on the implemented objective functions, a generic tool (*TimeSeriesCompare*) for time series comparison was developed in scope of this work. It can be used as stand-alone-tool to evaluate all objective functions implemented in BlueM.OPT for pre-calculated time series. Input are a reference time series, *n* time series for comparison and a set of text files with information on the objective functions to be evaluated, the evaluation time span and the input file format. Supported formats include a generalised CSV format and outputs from BlueM and SMUSI. All calculated objective functions are stored in an ACCESS database for post-treatment.

This tool was applied for evaluation of quality criteria in waste water treatment plant modelling by Hauduc et al. (submitted).

5.4.3 Sensitivity analysis

For sensitivity analysis the following tools were applied:

In [R] the package *sensitivity* (Pujol, 2009) was used for evaluation of the SRCs and the Morris Screening runs. Several [R] scripts were developed in this work for evaluation and presentation of the results as shown in chapter 6.7 for the case study.

The implemented Monte Carlo method with post-treatment of the simulation results stored in the ACCESS database was used for the evaluation of the SRCs in [R]. In [R] the SRCs were calculated using the package *sensitivity*. In addition the coefficient of determination R^2 and the squared SRCs were calculated in post processing. R^2 was determined from a multivariate linear regression between the model outputs and the parameter vectors from Monte Carlo simulation.

For the screening method of Morris a new class was developed in BlueM.OPT in scope of this work. Therefore a [R] connector developed by statconn (www.statconn.com) was integrated in BlueM.OPT. It allows direct communication of .NET code with [R].

The BlueM.OPT framework is used to handle the initialisation, model application runs and evaluation of objective functions. The computational grid (trajectories) based on the definition of design repetitions, levels and grid jump (see chapter 4.2.1.2) is determined by calling the appropriate function from the [R] *sensitivity* package.

After each simulation run, results from BlueM.OPT are stored to the [R] workspace. As final evaluation step, the μ* and σ for the elementary effects are evaluated in [R] and the results saved in a [R] workspace file. Detailed evaluation can be done as post-treatment in [R].

An overview of the workflow for sensitivity analysis with BlueM.OPT is given Figure 5-4.

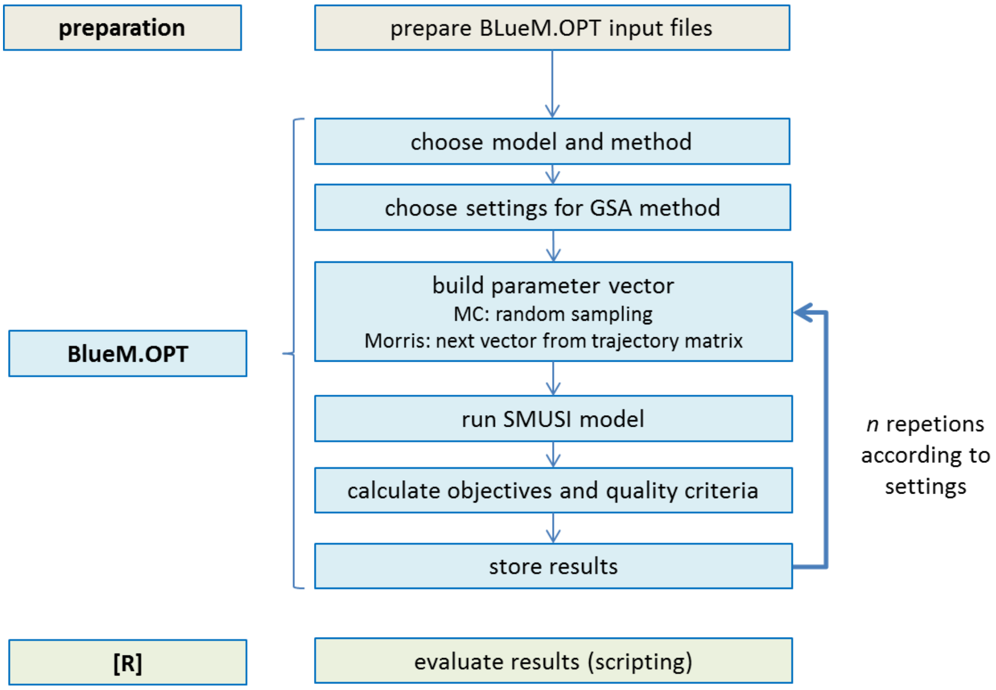

Figure 5-4: Workflow for GSA with BlueM.OPT and [R]

5.4.4 PES – EVO – evolutionary strategies optimisation algorithm

The algorithm was developed by Muschalla (2006) in scope of his PhD thesis and is further discussed in Muschalla (2008a).

The algorithm is a modified version of a classical self-adaptive Evolution Strategy (Schwefel, 1995). The selected algorithm has been extended with methods extracted from the non-dominated sorting genetic algorithm (Deb et al., 2000) and the strength Pareto evolutionary algorithm (Zitzler et al., 2001). In opposite to the classical Evolution Strategy it can be used as single and multi-objective algorithm and allows the evaluation of a multitude of objectives and constraints simultaneously based on a weighted sum approach or using the concept of domination and Pareto optimality (see chapter 4.3.4.1).

Figure 5-5 shows exemplary results from a multi-event optimisation with the PES algorithm for a SMUSI application example. On the left hand side, the settings for the algorithm are given. The chart shows two objectives plotted against each other, each of the dots represents the result from one model run with a specific parameter set. The green dots show the determined Pareto-optimal solutions.

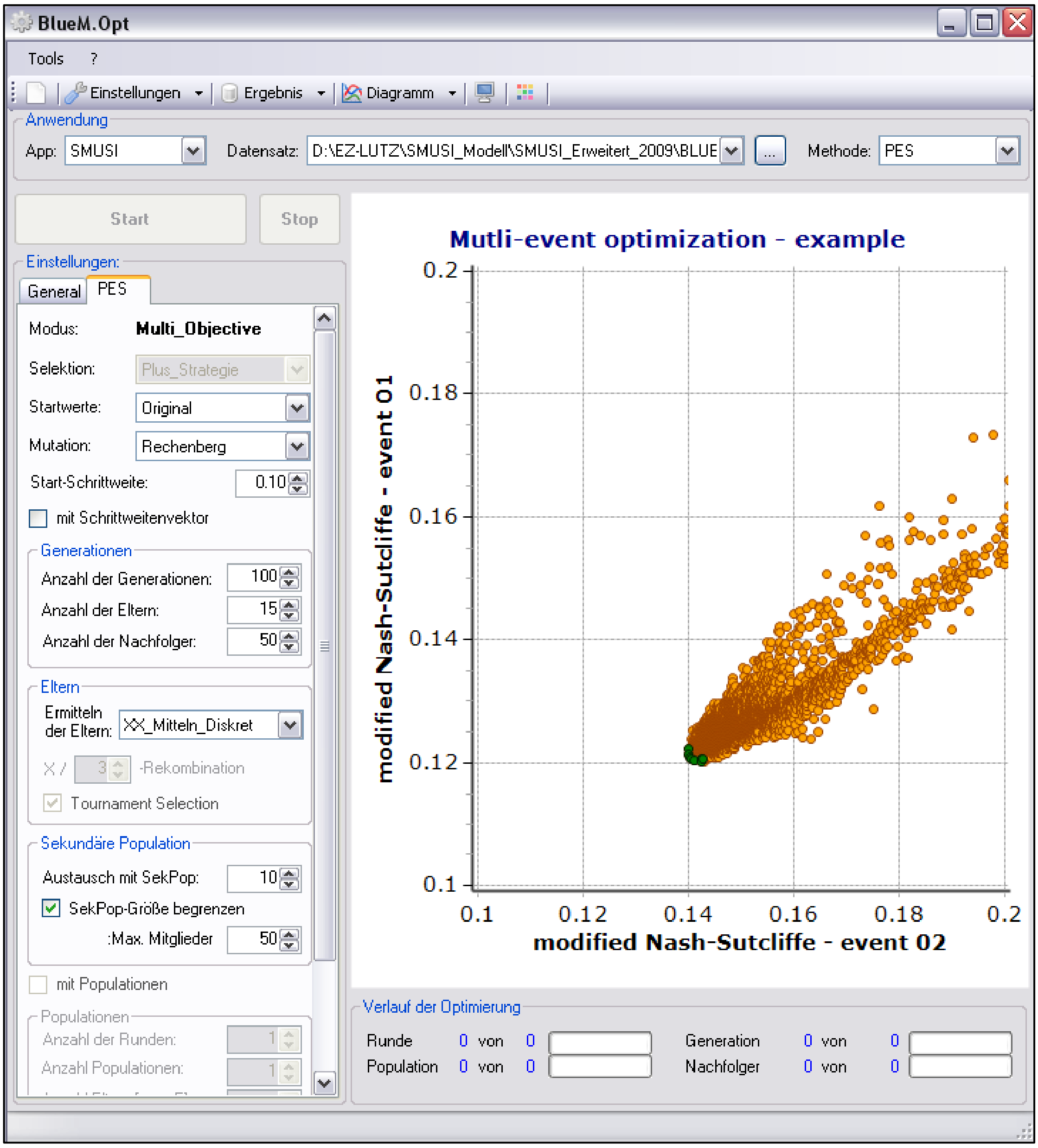

Figure 5-5: Exemplary results from BlueM.OPT PES in multi-event optimisation

6 Case study Graz West R05

This chapter details on the application of the developed methods presented above to the urban case study catchment *Graz West R05* that has been under intensive investigation over the last decade, namely within the research project *Innovative Technology for Integrated Water Quality Measurement IMW* (BMLUW, 2005). Several associated works have been published in the last years by Gruber (Gruber et al., 2006, Gruber et al., 2004, 2005) and Hochedlinger (Hochedlinger, 2005, Hochedlinger et al., 2006).

In this section, first the catchment and the installed measurement station and probes are shortly described. The calibration and uncertainty estimation for the UV/VIS measurements in wet weather conditions are is discussed.

Next, the methods presented in chapter 5 are applied to the case study. Analysis and validation of the available data is carried out. The modelling of the catchment with SMUSI and SWMM is discussed and the output of the two hydraulic models is compared. Results from sensitivity analysis with the screening method of Morris and the SRC evaluation are presented. The impact of the choice of different storm events the objective functions is discussed. Automated model calibration based on the available data for both hydraulics and sewer water quality is carried out. In sewer water quality modelling, three sewer water quality model approaches are compared and the performance of single- and multi-event optimisation is discussed.

Overall the performed steps show how to apply the developed methods on a real-world example in a stepwise procedure to get from data to validated model output.

6.1 Catchment description[3]

The *Graz West R05* catchment is located in the western part of the city of Graz, the second largest city of Austria. The city of Graz lies in the south-eastern foothills of the Alps at 353 m altitude and is divided by the Mur River. The average annual rainfall depth is 830 mm.

The catchment and sewer network was successively expanded between 2004 and 2006. No detailed information about the construction stages is available for this period. It currently covers approximately 4.6 km² of which about 1.3 km² are impervious. Surface slopes range from 0.5% to 4% in the main part of the catchment, becoming steeper with up to 10% in the most western part.

A few smaller and two larger indirect dischargers are situated in the catchment. The population density is approximately 43 inhabitants/ha (about 19500 inhabitants in total). The average dry weather flow, evaluated for 2009, is 40 L/s.

The sewer network is combined with some separate sewer connections. A variety of sewer profiles from circular pipes ranging from 150 mm diameter up to oval cross sections 1300/1950 and special cross sections, are in place. The total network length is currently 46.5 km. An in-sewer storage with a constant throttle runoff of about 150 L/s and a total

[3] This chapter is taken from Gamerith et al. (2011) in slightly modified form (with permission from CHI Press).

volume of approximately 2300 m³ was installed in 2005. A combined sewer overflow (CSO) is situated at the catchment outlet, denoted *R05* according to the numeration by the municipality of Graz. The overflow volume is spilled directly into the Mur River. Overflow starts at an inflow of about 500 L/s.

Detailed data on the catchment and the sewer system was obtained from cadastral maps, a digital sewer map, aerial view photos, and land use maps provided courtesy of the municipality of Graz. An overview of the catchment is given in Figure 6-1.

The catchment and sewer network were successively expanded between 2004 and 2006. No detailed information about the construction stages was available. In addition the measurement station was offline from 2007 to late 2008. Therefore the focus on the data and models used in this thesis lay on the years 2003 and 2009. Before the expansion, the catchment area was 3.35 km² (1.08 km² impervious surface) with about 11800 inhabitants.

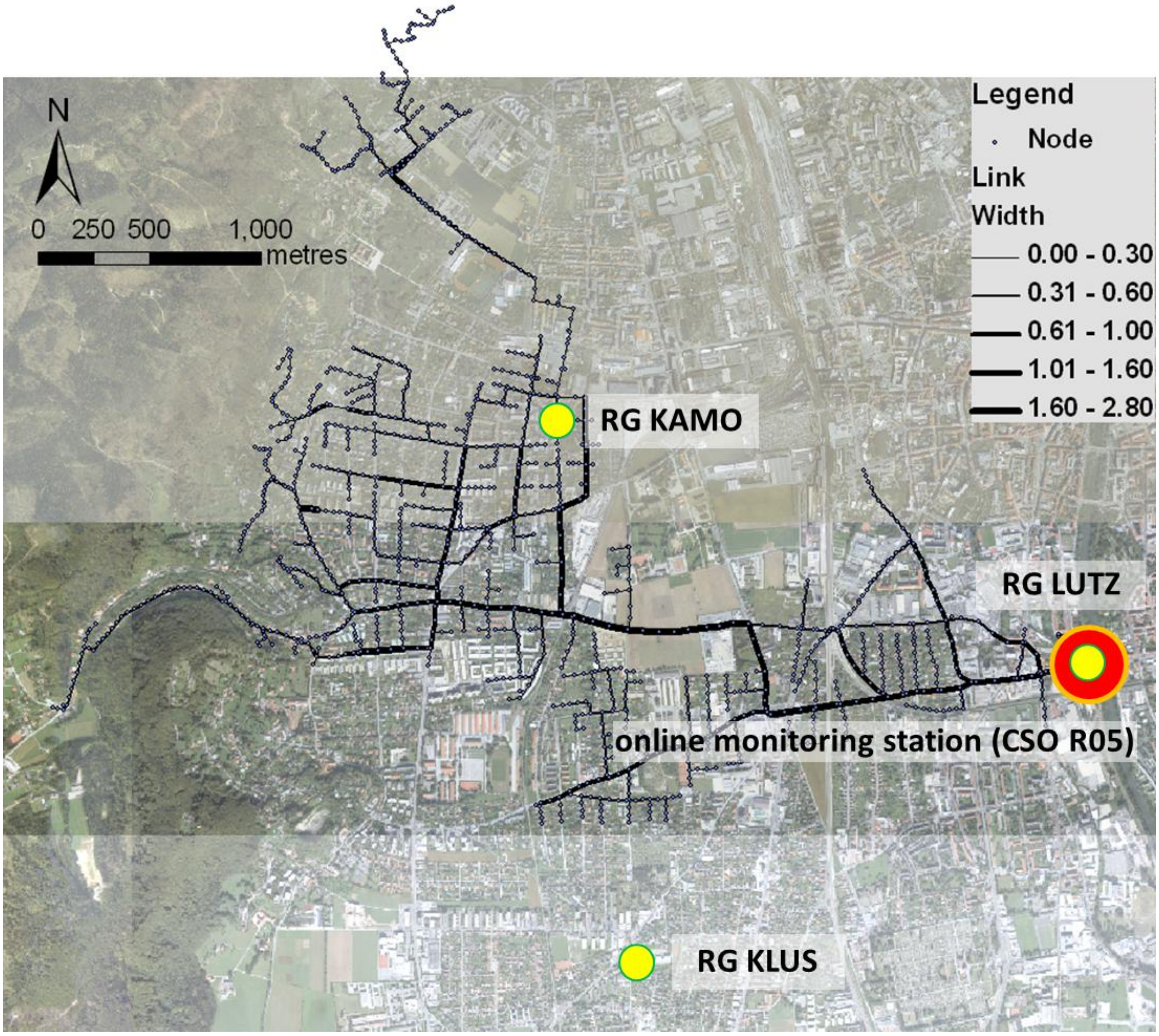

Figure 6-1: *Graz West R05* catchment – sewer map, aerial view photos, location of rain gauges, online monitoring station (Gamerith et al., 2011, modified - with permission from CHI Press)

6.2 Measurements in the Graz West R05 catchment

Currently three rain gauges and an online monitoring station at the catchment outlet are installed in the catchment Graz West R05 as shown in Figure 6-1. The installations and measured parameters are discussed in the following.

6.2.1 Rainfall measurements in the Graz West R05 catchment

Precipitation data is available since summer 2003, where two rain gauges – a tipping-bucket and a weighing gauge – were installed at the same location at the south boundary of the catchment. The weighing gauge was removed in late 2006. Since November 2008 three tipping-bucket rain gauges are installed in the catchment as shown in Figure 6-1. They are serviced on regular basis twice a month by the Institue. The rain gauges are calibrated (static and dynamic calibration) every two years based on the work of Thaler (2004). Details on the calibration are also given in Hochedlinger (2005). A screening and evaluation of all available rainfall time series was carried out by Derler (2009). An overview of the installed rain gauges, measurement period and identified measurement gaps or errors is given in appendix 5.1.

The tipping-bucket gauges register each 0.1 mm of precipitation at a discrete time stamp. For modelling purposes the rainfall data is aggregated to (mm/5 min) and (mm/min) values.

Denotation of the rain gauges used in the following is based on the location where they are installed:

- KAMO is the most northern rain gauge installed at the public school *Karl Morre*. The rain gauge is placed in the centre of the flat roof of the two storey building in a rather densely urbanised area with surrounding 4 storey buildings. Due to the installation on the roof, the rain gauge is not shadowed by buildings or trees etc. but the measurements might be influenced by the installation height.
- The rain gauge LUTZ is installed directly at the location of the online measurement station Graz sewer R05 close to the home-centre *Lutz*. The rain gauge is shadowed by the 5 storey home-centre building to the west and by a road bridge to the north. The measurements can be assumed to be influenced by the installation location.
- The most southern rain gauge KLUS is installed at the public school *Klusemanngasse*. The rain gauge is placed on a lawn and is not shadowed by buildings or trees.

6.2.2 Online monitoring station: probes and measured parameters[4]

In 2002 an online sewer monitoring station was installed directly at the CSO R05 at the catchment outlet. It was set up under the auspices of the Austrian interuniversity research project named *Innovative Technology for Integrated Water Quality Measurement IMW* (BMLUW, 2005). It continuously measures hydraulic and water quality parameters. An overview of the layout and instrumentation of the station is given in Figure 6-2.

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[4] This chapter is taken from Gamerith et al. (2011) in slightly modified form (with permission from CHI Press).

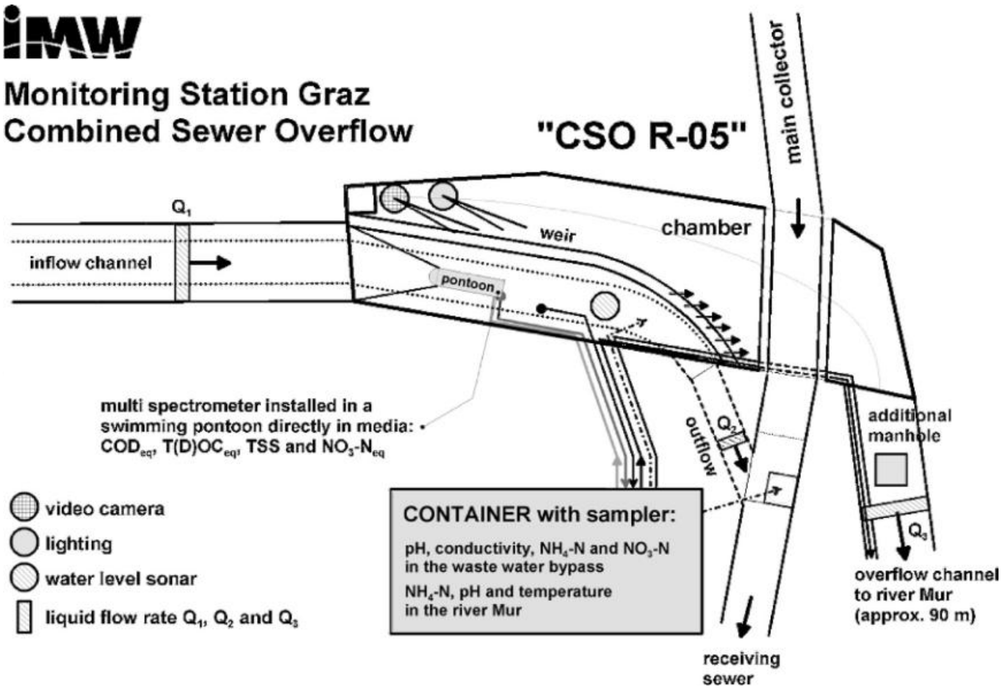

Figure 6-2: Layout and instrumentation of the sewer online monitoring station *Graz Sewer R05* (Gruber et al., 2004, modified, with permission from IWA Publishing)

An overview of the parameters measured, probes used and measurement periods is given in Table 6-1. Flow meters are installed in the inflow and in the overflow channel. An additional ultrasonic probe to measure the water level is installed directly in the overflow chamber. Water quality measurements are provided by a UV/VIS spectrometer probe installed directly in the overflow chamber in a floating pontoon. The installed probe is a *spectro::lyser* from the company *s::can* as described in chapter 3.1.4.3. A bypass was operated in irregular intervals for additional water quality measurements. The bypass is situated in the measurement container (see Figure 6-2); the sampling hose is attached directly to the pontoon. In addition an automated sampler is installed that allows the drawing of reference water quality samples for probe calibration.

Table 6-1: Measured parameters at Graz Sewer R05 monitoring station (Gamerith et al., 2011, with permission from CHI Press)

Parameter	Unit	Measurement method	Location	Period
HYDRAULICS				
Q inflow	L/s	radar	inflow channel	2002-ongoing
Q overflow	L/s	ultrasonic	overflow channel	2002-ongoing
Water level	m	ultrasonic	CSO chamber	2002-ongoing
WATER QUALITY				
COD_{eq}, TOC_{eq}, TSS_{eq}, $NO3_{eq}$	mg/L	UV/VIS spectrometer	floating pontoon	2002-ongoing
Conductivity	µS/cm	inductive	floating pontoon	2009-ongoing
NH_4-N, NO_3-N	mg/L	ISE probes	bypass	temporarily
Conductivity	µS/cm	conductive	bypass	temporarily
pH	pH	ISE probes	bypass	Temporarily

In dry weather conditions all data is logged with a standard interval of 3 minutes. In the case of storm conditions, flow data is logged more frequently with the smallest attainable interval of 1 minute. The change of the interval is triggered by the water level in the CSO chamber. The flow meters and water quality probes are connected to an industrial PC suitable for exterior installation. The PC controls the monitoring station and manages intermediate data storage. All sensors are directly linked to the station PC either via bus interfaces or via analogue inputs (4 mA to 20 mA).

A camera is installed inside the overflow chamber allowing a remote live view of the station. The camera is triggered by the CSO chamber water level to automatically record in case of storm events. Figure 6-3 shows a picture from the overflow chamber with the installed floating pontoon in dry weather conditions.

Further details on the measurement station are given in Gruber et al. (2004), Hochedlinger (2005) and Gruber et al. (2006).

Figure 6-3: View of the overflow chamber and floating pontoon (remote shot from the installed camera, 2010-02-02)

6.2.2.1 Probe location

In sewer water quality measurement it is generally agreed that the choice of the sampling location is crucial to obtain viable results (Bertrand-Krajewski et al., 2000). The decision to install the UV/VIS sensor in a floating pontoon allows continuous measuring in the uppermost layer of water. As this layer reaches the overflow first, this measurement location seems appropriate to assess overflow concentration. Deducing concentrations over the cross section might not be valid as complete mixing needs to be assumed in that case.

Installing the probe directly in the sewer demands a robust installation that can withstand both the strong dynamic stresses due to hydraulics (flows can reach more than 10 m³/s at the measurement site in storm weather conditions) and the aggressive environment (e.g. corrosion problems, grease, clogging). As it is installed directly in the sewer, all instrumentation has to be explosion proofed. A comparison of the pros and cons of direct in-sewer and bypass installation is given in Gruber et al. (2006).

6.3 UV/VIS spectrometer probe calibration and error estimation in wet weather conditions[5]

Concerning the UV/VIS spectrometer probe, several sets of reference measurements in both dry and wet weather conditions were obtained for local probe calibration over the last years. Details on the dry weather calibration and the use of different regression methods for local probe calibration are given in Hochedlinger (2005) and Hochedlinger et al. (2006).

The main goal in scope of this thesis was to estimate the reliability of in-situ UV/VIS measurements in highly dynamic wet-weather conditions, where important variations of measured pollutant concentrations as well as event-specific changes in the wastewater matrix are encountered. The evaluation is based on the work of Steger (in preparation) who carried out the measurement campaign and sample analysis as well as setting up the probe calibration runs described below.

To address this question water quality data was analysed by:

- The in-situ UV/VIS spectrometer at the Graz Sewer R05 online monitoring station.
- Manual sampling with a peristaltic-operated sampler at the same location and corresponding time stamps with subsequent standardised lab analysis.
- Analysis of the manually taken samples by an identical UV/VIS probe in the lab.

The reference samples were collected close to the UV/VIS probe by an automatic peristaltic-operated sampler. The sampling hose is fixed to the floating pontoon. One sample corresponds to a composite sample over the filling time period of one bottle which takes between of 3 and 5 minutes. Over the sampling duration, three absorption spectra were recorded by the in-situ UV/VIS spectrometer (triggered manually). These spectra are then averaged and used for calculating the derived water quality parameters. As already stated in Hochedlinger (2005), it is essential to check the absorption spectra from the UV/VIS probe before averaging them. Several spectra had to be removed due to erroneous measurements. The manually taken samples were analysed in the laboratory on COD and TSS. All samples were tripled to estimate the lab analysis uncertainty. In total 36 samples from 6 different storm events as shown in Table 6-2 were obtained.

Table 6-2: Events and number of samples for UV/VIS probe calibration

event ID	sampled IDs	ID range	date	first sample	last sample
-	#	-	yyyy-mm-dd	hh:mm	hh:mm
1	5	1 to 5	2008-09-25	14:33	15:00
2	8	6 to 13	2008-09-25	18:48	19:52
3	3	14 to 16	2008-11-13	15:54	16:50
4	8	17 to 24	2008-11-21	18:28	19:39
5	8	25 to 32	2008-12-01	11:39	12:30
6	4	33 to 36	2009-03-06	10:07	11:06

[5] This chapter is based on the works of Gamerith et al. (submitted-b) and Steger (in preparation)

Figure 6-4 shows the results from the lab sample analysis for TSS and COD mean values determined for the 36 tripled samples in form of a boxplot. In order to increase legibility, different scales were chosen for TSS and COD. TSS concentrations range from about 60 to 730 mg/L, with a median of 153 mg/L. COD concentrations are wider spread, ranging from about 150 to 1400 mg/L, with a median value of 310 mg/L.

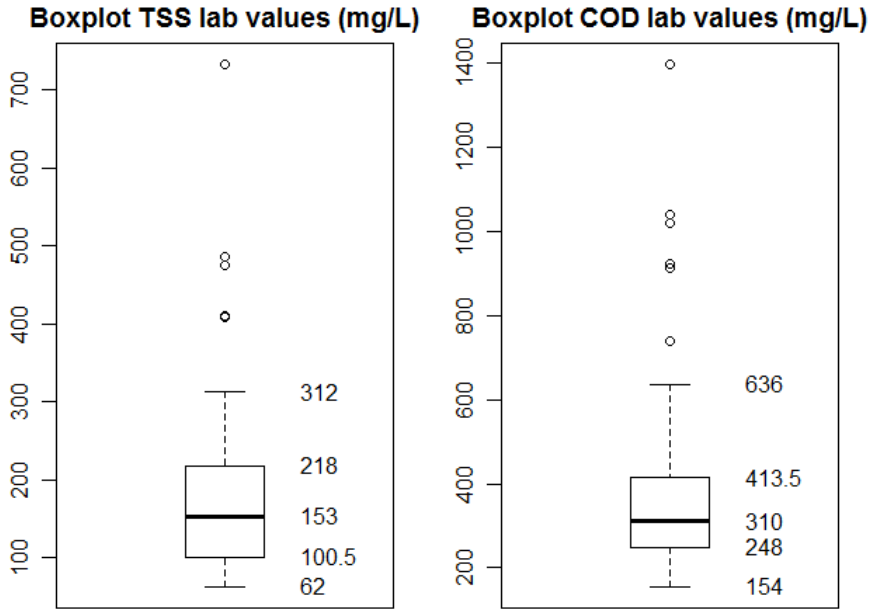

Figure 6-4: Boxplots for TSS and COD mean lab values for the 36 samples

The uncertainties from the lab analysis were estimated from a triple analysis of each sample. For each triple, mean and standard deviation were calculated.

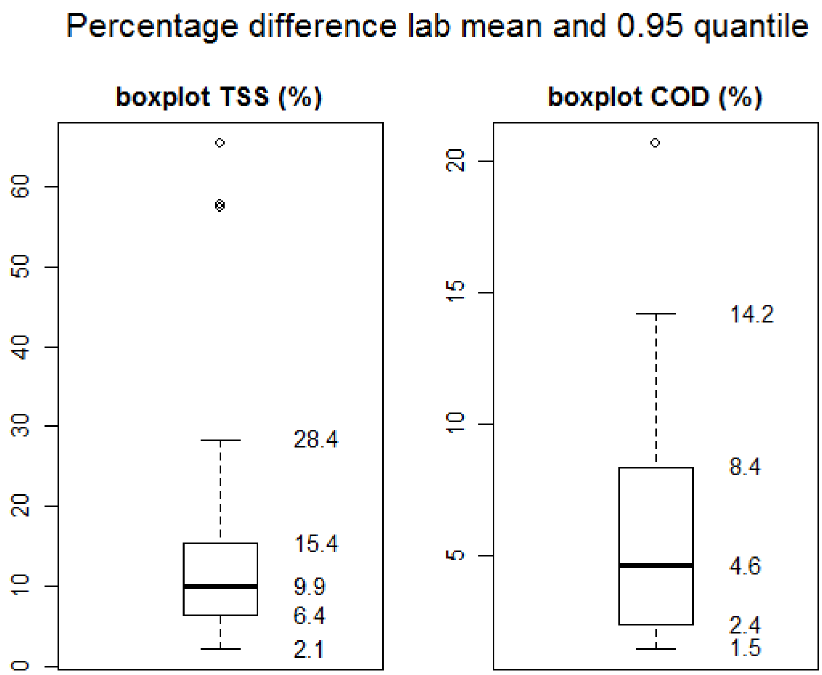

Figure 6-5: Boxplots of percentage difference between mean and 0.95 quantiles for the lab analysis of TSS and COD for the 36 samples

Figure 6-6 shows exemplarily the first two sampled events on September 25th 2008. It shows i) precipitation intensity (upper right axis), ii) flow in the inflow and overflow channel (left axis) and iii) COD and TSS concentrations on the lower right axis. For COD and TSS the solid lines correspond to the values from the UV/VIS probe using a *global calibration* provided by the manufacturer and the dots show the corresponding mean lab values. It is apparent that the lower concentrations between 18:45 and 20:00 are better fit than the higher concentrations obtained between 14:30 and 15:00. It is important to note that the manually triggered samples from the UV/VIS probe over the sample duration are not shown in the graph, as they are recorded separately.

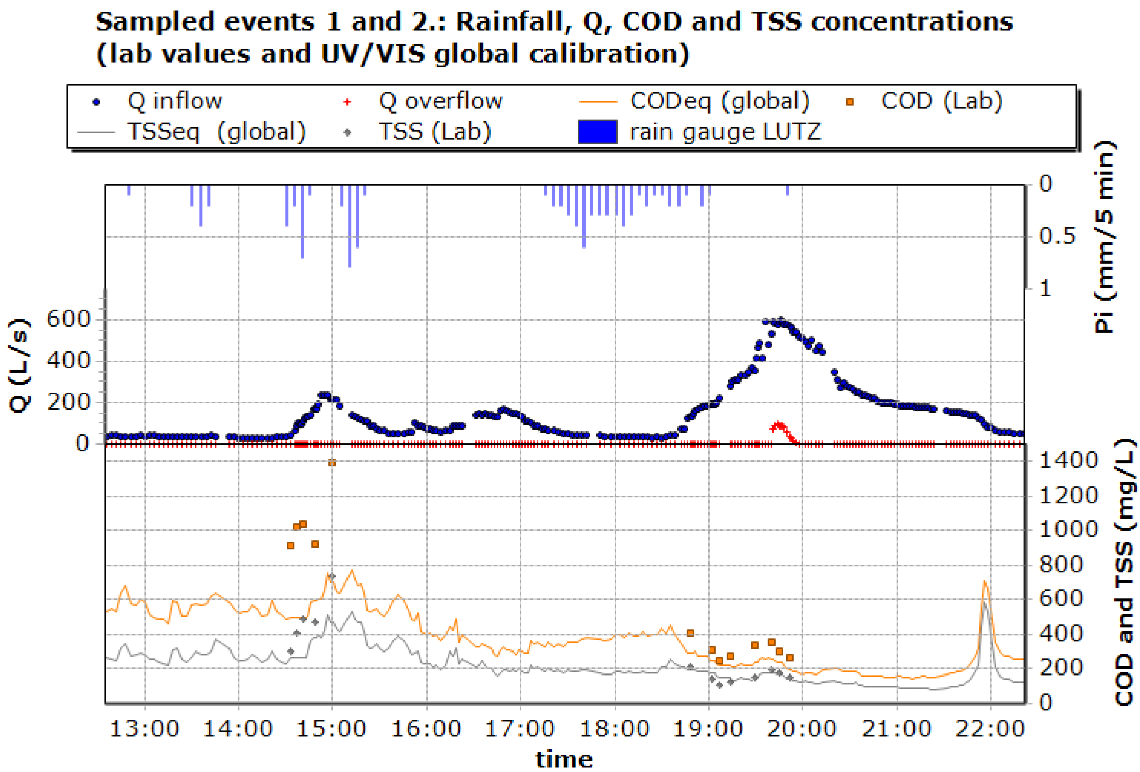

Figure 6-6: Sampled events 1 and 2 for UV/VIS probe calibration

Based on the obtained sample data set for COD and TSS:

- The results obtained from the two identical probes were compared. This is described in Steger (in preparation).
- Probe performance and uncertainties when using a predefined, global calibration were estimated (described in section 6.3.1.).
- The effect of local probe calibration by i) simple regression methods (section 6.3.1) and ii) coupling with the BlueM.OPT optimiser (section 6.3.3) when using samples from different events was compared. Local probe calibration was carried out after validation of the raw spectra.

6.3.1 Evaluation of global probe calibration

For evaluation of the global probe calibration, COD and TSS equivalent concentration were calculated from the recorded spectra by using a global calibration that is provided by the manufacturer. In this context, a defined range of wavelengths from the recorded spectrum as well as the weighing factors and offset as described in Equation 3-9 (chapter 3.1.4.3) is understood by *global calibration*. The equivalent concentrations are then calculated based on this probe calibration. For evaluation and visualisation the script developed in this work as described in chapter 5.2.2.3 was applied.

Figure 6-7 and Figure 6-8 show the results from a global probe calibration for COD and TSS respectively. The left hand side of the plots shows the measured concentrations from the UV/VIS probe and the lab values of 6 events (including the whiskers for the 0.05 and 0.95 quantiles), the absolute residuals and the percentage error (from top to bottom) for each of the 36 samples. The right hand side shows a correlation plot of the UV/VIS and mean lab concentration values and the percentage error sorted by UV/VIS concentration values.

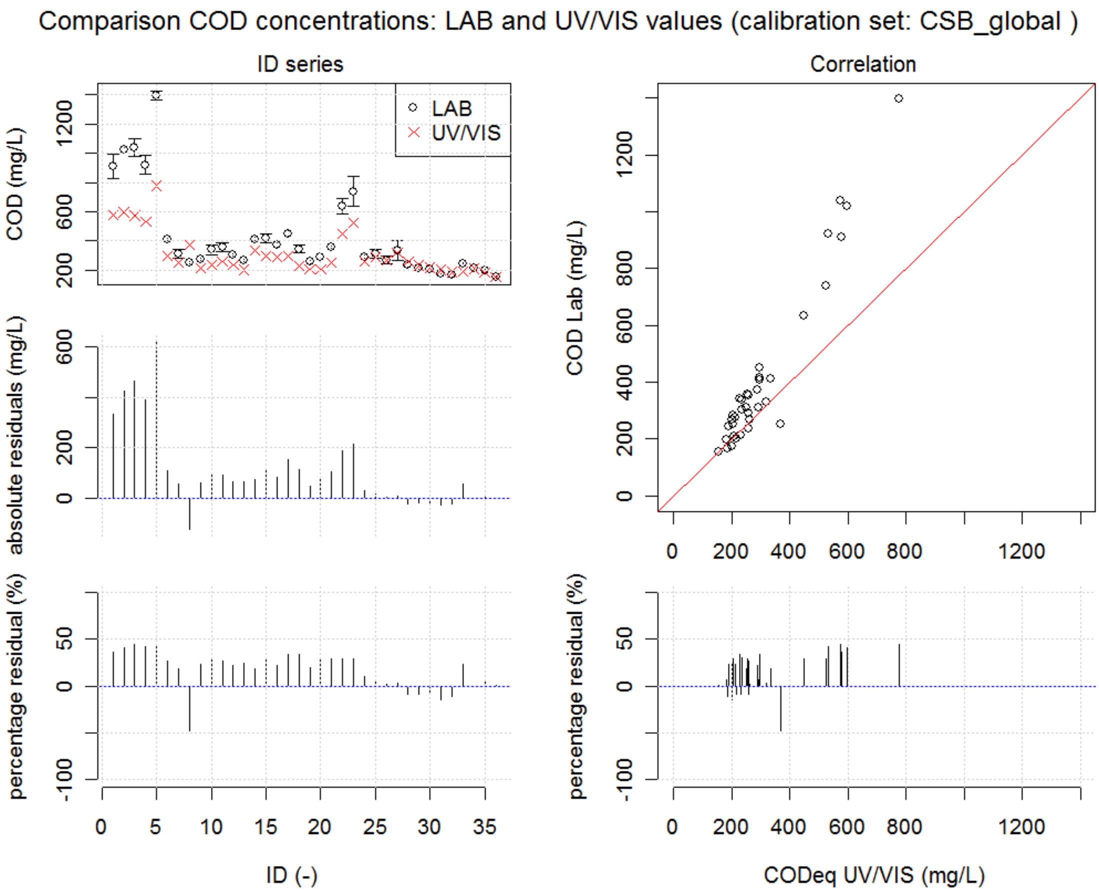

Figure 6-7: Evaluation of global UV/VIS probe calibration – COD concentrations

The evaluation for COD in Figure 6-7 shows that with the available data the global calibration led to a percentage error of up to 50% compared to the lab values. The error has systematic behaviour as is clearly visible from the correlation and residual plots. With this calibration, lower concentrations are significantly better fit (i.e. sample IDs 24 to 36), where the UV/VIS values lie – with one exception – within the 95% confidence interval of the lab analysis. Concentrations are generally under-estimated with this calibration; especially for higher concentration values (IDs 1 to 5) this becomes significant.

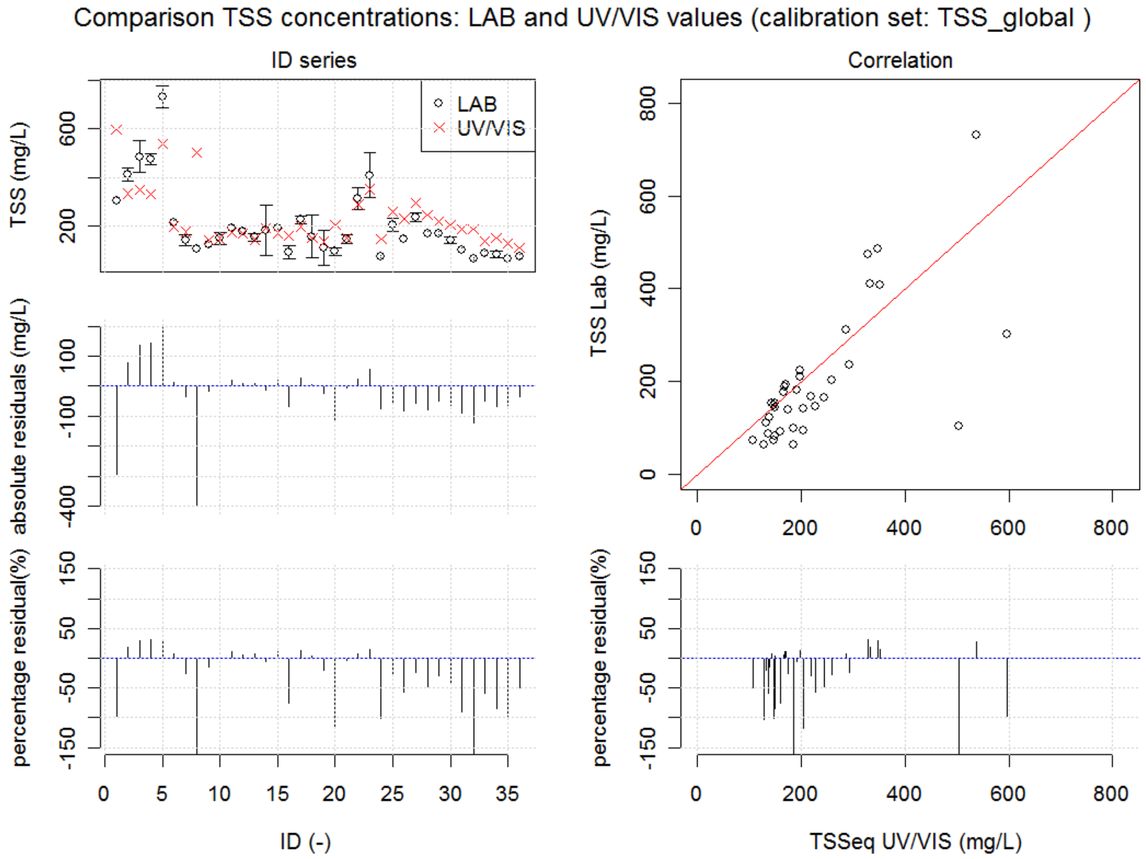

Figure 6-8: Evaluation of global UV/VIS probe calibration – TSS concentrations

As discussed above, the evaluation for TSS (Figure 6-8) shows that the errors from the lab analysis are significantly higher than for the COD analysis. Concerning global probe calibration, the errors have less systematic character than for COD. It can be identified that lower concentration values are generally over- and higher concentration values under-estimated. Percentage errors of more than 100% are obtained for low concentration values.

The impact of the wastewater matrix in different events can be seen in the upper left plot showing the direct comparison of lab and UV/VIS concentration: UV/VIS concentration values obtained for events 2 and 3 (IDs 6 to 16) are in the same order of magnitude as for events 5 and 6 (IDs 25 to 36), however, the lab values for events 5 and 6 are visibly lower.

Two outliers can be identified in the correlation plot (corresponding to sample IDs 1 and 8). The analysis of the raw spectra showed that in both cases one of the three recorded spectra was erroneous. This influenced the averaged spectrum used for calculating the concentration value. The erroneous spectra were removed manually and the remaining spectra for this ID were then averaged again for local probe calibration.

6.3.2 Local probe calibration: simple regression methods

A linear and a non-linear regression were performed (both in the software [R]) between lab mean concentrations and the concentrations obtained from global calibration. The application of regression methods is a practical approach that can also be applied by end-users who do not have access to the measured absorption spectra. For non-linear regression a power function was chosen based on a prior evaluation of the data.

Values from the global calibration were corrected by the obtained regression coefficients and the results for the two regression methods compared. Table 6-3 shows the obtained regression coefficients and the resulting relative residual errors (0.05 and 0.95 quantiles) with the corrected UV/VIS data.

Table 6-3: Regression for lab measurements and UV/VIS global calibration values

Regression	Formula	Obtained regression coefficients		relative residual errors (lab – corrected UV/VIS)	
		a	b	0.05 quantile	0.95 quantile
Linear	$y = a + b \cdot x$	-180.93	1.96	-29.7%	24.8%
Non-linear power function	$y = a \cdot x^b$	0.17	1.36	-27.9%	17.8%

While both regressions lead to a significant reduction of the errors in the investigated concentration range, linear regression is not suited for extrapolation as applying it to low concentration values would result in negative values due to the negative intercept (*a* – coefficient). Figure 6-9 shows a plot of the obtained corrected COD_{eq} UV/VIS values with non-linear regression from global calibration. Relative residual errors are reduced to an order of magnitude of 25-30% (when not taking into account the outlier at ID 8 resulting from an erroneous spectrum). Additional plots on the regression are given in appendix 4.

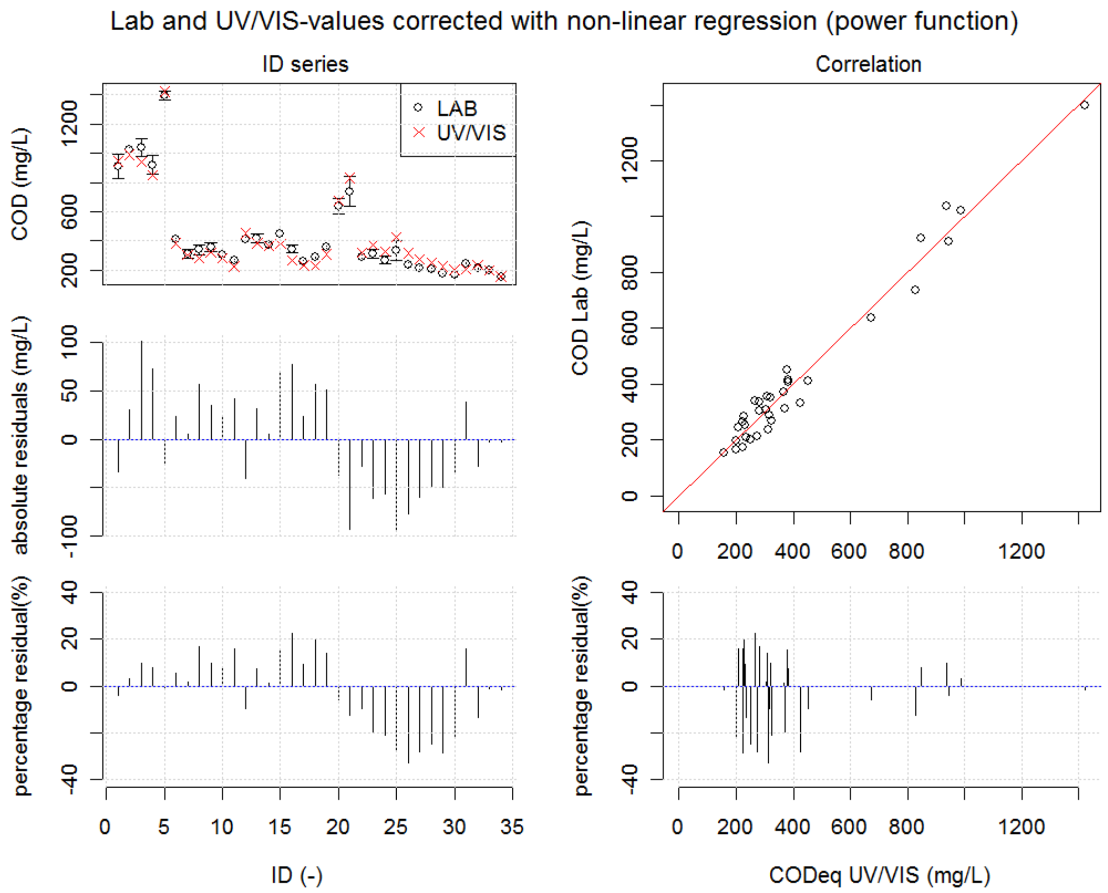

Figure 6-9: Results for UV/VIS probe calibration – UV/VIS COD_{eq} values corrected by non-linear regression with power function ($a*x^b$).

6.3.3 Local probe calibration: coupling with BlueM.OPT optimiser

The local probe calibration described in this section was carried out in BlueM.OPT using the *SCAN* model class developed in this thesis (see chapter 5.4.1). Calibration was done separately for each event and against all the available data to evaluate the impact of the calibration data set on the probe calibration uncertainties. Different sets of wavelengths and weighing factors were used for COD_{eq} and TSS_{eq} calibration. As reference values, the mean values from lab analysis were used. In total, 32 optimisation runs were performed where the following combinations were investigated:

- Wavelength ranges as proposed by the manufacturer for COD and TSS.
- The whole range of available wavelengths.
- One offset value.
- Grouped weighing factor, constant over all considered wavelengths.
- Variable weighing factors for each considered wavelength. In the following, only results for grouped factors are presented, as variable factors lead to over-parameterisation (i.e. 200 factors with only 36 reference points).

The used ranges for the wavelengths and the factor values are not stated here as they are classified information from the company. Details on the optimisation runs are given in Steger (in preparation).

In the following the results are presented for COD only, as the noisier lab values impacted on the TSS calibration quality and in the further work only COD was used as target variable (i.e. in sensitivity analysis and model calibration). The general behaviour discussed below, however, is valid for both COD and TSS.

Figure 6-10 and Figure 6-11 show the calibration results when using sample IDs from one single storm event. The orange vertical lines in the upper left plot delimit the IDs used for calibration. The corresponding values in the scatter correlation plot are also shown as solid orange dots.

Figure 6-10 shows the results for calibration on event 1 (IDs 1 to 5) using the wavelength range proposed by the manufacturer and a grouped weighing factor, constant for all considered wavelengths. With this calibration, the calibrated IDs can be fitted satisfactorily with percentage errors < 10%, within the error estimates from the lab analysis. However, validation on other events shows significantly higher errors than using the global calibration with up to 100% percentage error. In addition a systematic behaviour can be identified as all but the calibrated values are overestimated by this calibration, leading to throughout negative residuals.

Figure 6-11 shows the results for calibration on event 4 (IDs 17 to 24) using all available wavelengths and a grouped weighing factors, constant for all considered wavelengths. The same behaviour as for calibration on event 1 can be noted: the samples that were used in calibration are well fit. In addition events 2 and 3 where a similar concentration range was measured are also well fit. However, validation on events 1, 5 and 6 again yields worse results than using the global calibration. From the validation data, lower concentrations are generally overestimated, higher values underestimated by the calibration.

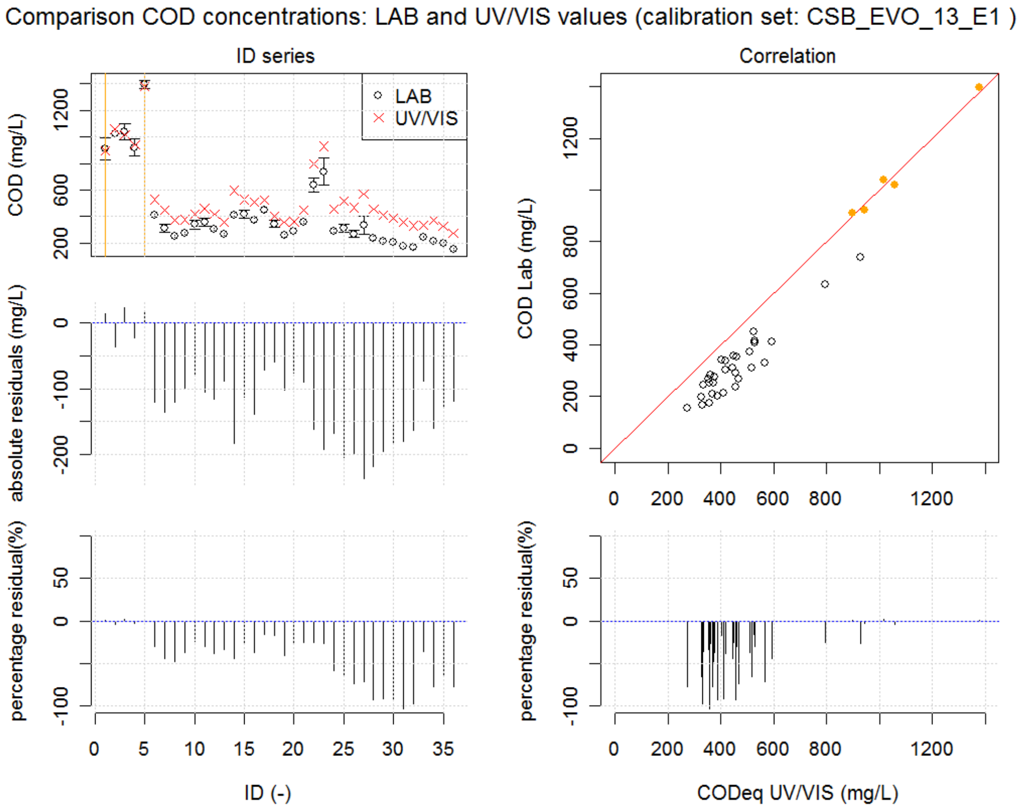

Figure 6-10: Results for UV/VIS probe calibration: event 1 (IDs 1 to 5) COD calibration using the wavelengths proposed by the company and a grouped weighing factor.

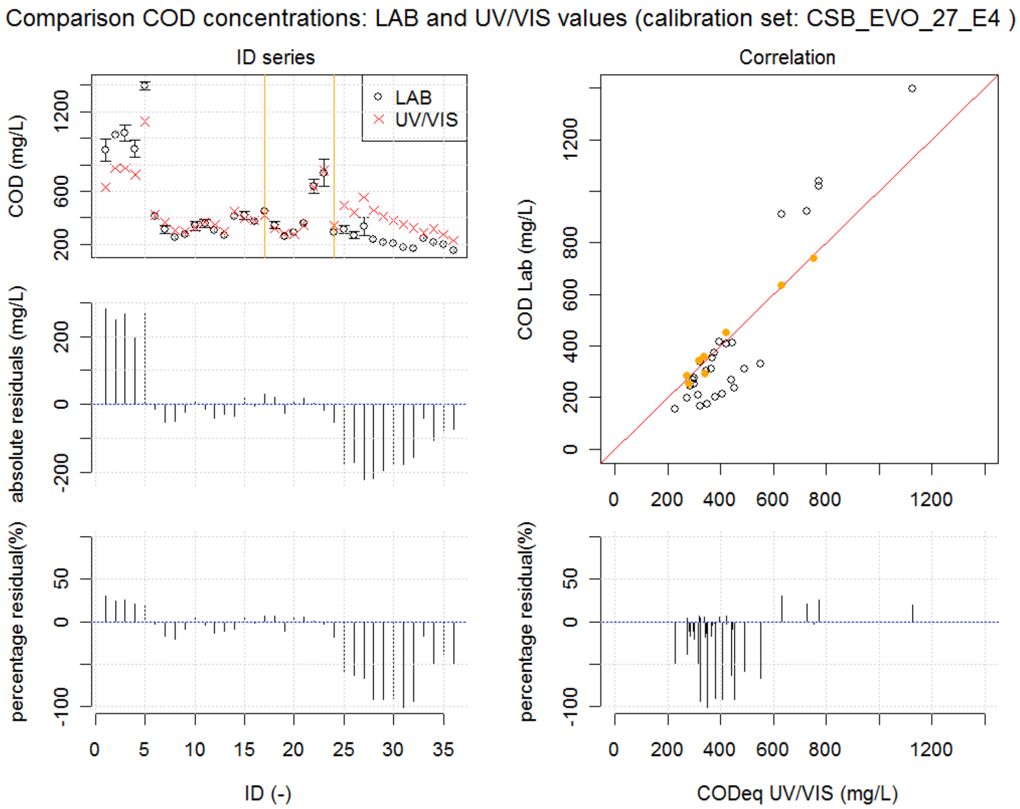

Figure 6-11: Results for UV/VIS probe calibration: event 4 (IDs 17 to 24) COD calibration using all available wavelengths and a grouped weighing factor.

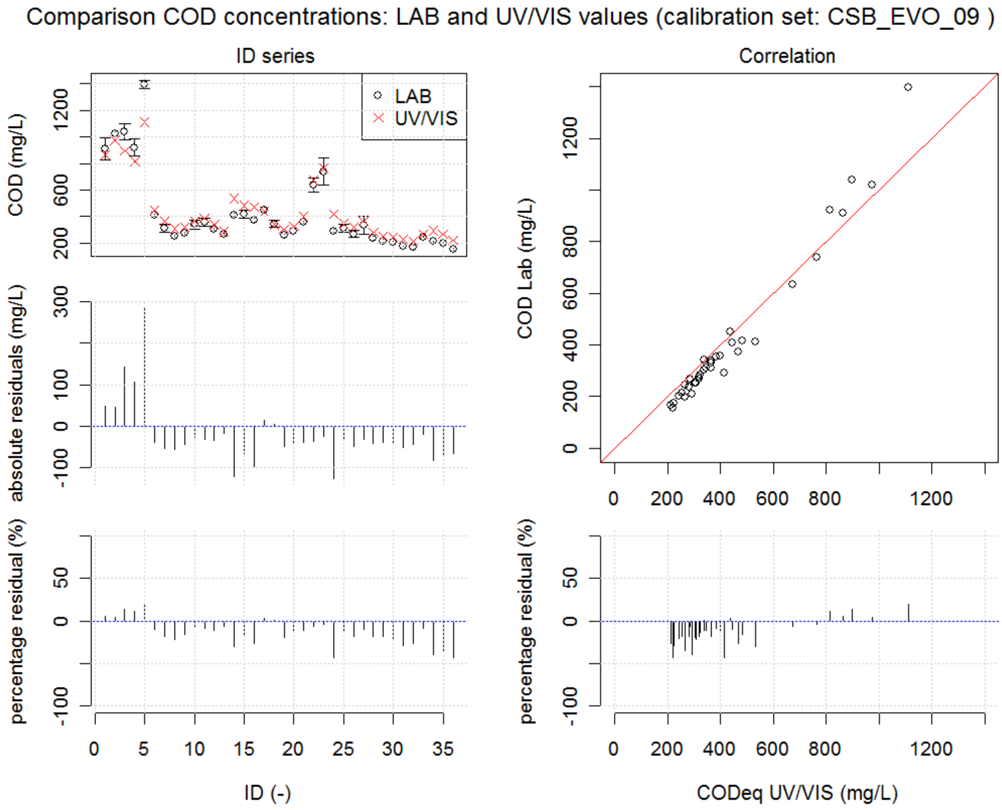

Figure 6-12: Results for UV/VIS probe calibration: COD calibration using all sampled IDs and all available wavelengths

Figure 6-12 shows the results obtained when using all sampled IDs in a calibration with all available wavelengths. Here, the overall fit is generally better than when using the global calibration. Errors are in the same range as for the values corrected by non-linear regression. A systematic error can be identified, where higher values are slightly underestimated and lower values overestimated by the UV/VIS probe calibration. While the calibration shows significant improvement compared to calibration on single events it has not yet been validated against additional sample data to prove its validity.

6.3.4 Summary – UV/VIS probe calibration

The evaluation of the global calibration highlights the importance of local probe calibration as significant errors of up to 50% for COD and up to 100% for TSS with systematic behaviour were identified when using the global probe calibration.

With simple regression (linear and non-linear regression) between lab concentration values and concentration values obtained by the global probe calibration, the errors could be reduced to an order of magnitude of 25 to 30%. However, special attention has to be paid when extrapolating concentration ranges from the regression results: i.e. in the presented example correction by linear regression would lead to negative values for low concentration values.

Several optimisation runs were performed with the BlueM.OPT PES optimiser for local probe calibration in order to evaluate the calibration on single events, using different wavelength ranges and weighing factors. The following major finding can be stated:

- Caution is advised when calibrating UV/VIS probes locally to samples from one single rainfall event or events with similar concentration ranges. In that case not all possible effects and variations in the wastewater matrix can be assessed. For the presented results the calibration events were well fitted (percentage errors < 10%). However, relative errors for the validation samples reached over 100% with systematic error behaviour. This means that actually higher total errors are obtained than when using the global calibration.
- As already highlighted in previous studies, the validation of the raw spectra is crucial to avoid errors in the averaged spectrum used for calculation of the derived concentration value.
- When using samples from one event, no difference in calibration quality was identified when using more wavelengths then the ones proposed by the company for calculation of the derived target variables.
- For the available data no significant amelioration of the results compared to a correction by simple regression could be identified.

Future work should focus on the collection of additional samples to validate the calibration with more data, especially for low concentration ranges that are not yet covered by the samples. In addition it is advised to implement automated validation of the raw spectra in the data validation process.

6.4 Data management *OpenSDM*

All data measured by the online measurement station has recently been implemented in the data management framework *OpenSDM*. As file format for the measurement data netCDF (Rew and Davis, 1990) was chosen.

Data recorded at the Graz sewer R05 measurement station in scope of the IMW2 project (2002 – 2007) was converted from an Oracle database to the netCDF format. Data recorded more recently is directly integrated in the netCDF file system. As the OpenSDM framework is server based, data can be provided by a server via internet (see also Camhy et al. (submitted)). The framework is currently under development.

In this work data of interest was acquired from the OpenSDM test-platform currently in use at the institute. [R] scripts for data analysis and validation were run off-line on a local PC. In near future, these scripts will be implemented on the platform, allowing server-based data validation and a direct link of validation results to the netCDF file system.

6.5 Analysis and validation of the available data

For data analysis and validation, first an overall screening of all available data from 2002 to 2010 was carried out. A table showing the results from this screening is included in appendix 6. In this thesis the period of 2009 was chosen for in-depth analysis and to test the developed tools described in chapter 3.2.

In this chapter, first the analysis of rainfall data is discussed. The second part describes the visual data analysis for rainfall, flow and water quality measurements and discusses the identified system behaviour. The last part describes the application of the semi-automated data validation tools developed in this work (see also chapter 3.2.2.2) to the available data.

6.5.1 Rainfall data – analysis and pre-treatment

A screening and prior evaluation of all rainfall time series was carried out by Derler (2009). For all three rain gauges installed in the catchment, first an overview of the available data since 2003 was compiled. In a second step a detailed analysis of the data from 2009 was carried out. The *ConvertSensorData* tool (see chapter 5.2.2.1) was used for automated storm event separation and evaluation of the event's characteristics as total rainfall depth, maximum intensity, dry time and event duration. According to the observed runoff conditions in the Graz West R05 catchment, events were treated as separate with a dry time of 4 hours between two consecutive rainfall recordings. Minimum total rainfall depth was set to 1 mm after a first screening of the catchment runoff behaviour. Based on this evaluation the rainfall data was visually analysed event by event to identify obvious measurement errors.

The *ConvertSensorData* tool was run for all 3 rainfall time series. 73, 88 and 98 events were identified in 2009 for the three rain gauges LUTZ, KLUS and KAMO respectively. A comprehensive table of the identified events is given in appendix 5.2. Based on this evaluation the results were manually compared in EXCEL and visualised in WAVE to check for matching and / or missing events for each of the rain gauges. Based on this analysis a final event numeration was defined.

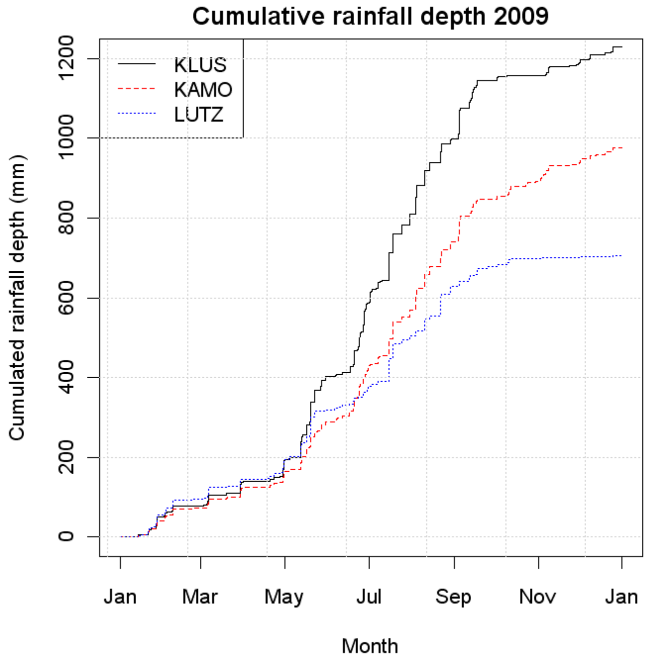

Figure 6-13: Cumulative rainfall depth for the three rain gauges in 2009.

The rain gauge KAMO proved to be the most stable for the measurement period 2009: no measurement gaps or obvious errors could be identified for this rain gauge. The rain gauge LUTZ showed many erroneous data points and measurement gaps. As stated in chapter 6.2.1. the rain gauge is shadowed by a 5 storey building and a road bridge what might explain the erroneous recordings. Therefore it was not further considered in the modelling of the catchment. However, the data was still useful, e.g. for identifying spatial distribution in the rainfall.

A comparison of the annual rainfall depth (Table 6-4) and the cumulative rainfall curves showed that the rain gauge KLUS measures systematically higher values than the rain gauge KAMO (see Figure 6-13). A more detailed analysis showed that for smaller intensities their difference is close to zero. For larger intensities, however, difference reaches over 30%. This might be linked to the

- rain gauge calibration as the KAMO gauge was calibrated in summer 2009, the KLUS rain gauge one year earlier.
- different installation height: the KAMO gauge is installed on the flat roof of a two storey building, the KLUS gauge on ground level (both +1.5 m gauge height).

A reference value for annual precipitation in 2009 from the Graz-Thalerhof gauge (Table 6-4) from Austria's national weather service agency *Central Institute for Meteorology and Geodynamics* (ZAMG) lies in between the two. With the available information, no clear statement can be derived on which values are more reliable.

Table 6-4: Annual rainfall depth 2009 for the three rain gauges and ZAMG reference value

Annual rainfall depth (mm)			
RG_KLUS	RG_KAMO	RG_LUTZ	Graz-Thalerhof*
1228.8	976.8	(706.5)	1141

*http://www.zamg.ac.at/fix/klima/werte09.pdf, March 8th 2011

For the KLUS rainfall time series, a gap in the measurements was identified between October 9th 2009 and November 6th 2009. This gap was filled by substituting the missing values with values from the KAMO time series, applying a factor of 1.2 to the values recorded by the KAMO rain gauge. This factor was determined from a comparison of the cumulative rainfall curves and the resulting residuals from cumulative rainfall. Plots for this visual comparison are given in appendix 5.3.

6.5.2 Visual data analysis

In scope of this work, the available data from 2003 and 2009 from the online measurement station was analysed in more detail as this data was used for modelling of the catchment. First the data was analysed for each month and then on an event-by-event basis. This analysis allowed identifying the general system behaviour and assessing several phenomena. This knowledge of the system was then used for the semi-automatic data validation. For the visual comparison the components i) rainfall data ii) flow data (inflow and overflow) iii) TSS_{eq} and COD_{eq} concentrations and iv) preliminary model results from a pre-calibrated SMUSI model were visualised in the same chart.

6.5.2.1 Monthly analysis

First, a visual analysis of the data for each month was carried out. From this analysis

- obvious measurement gaps and errors,
- periods with noisy data (especially for water quality measurements) and
- shift and drift effects

could be identified. Summarising tables for hydraulics and water quality parameters can be found in appendix 6. All identified errors were then cross-checked with the available logging manual where e.g. maintenance or measurement failures are recorded by hand in EXCEL. Periods identified as erroneous were not considered for modelling purposes.

An example for this overview analysis is given in Figure 6-14 for December 2009. There, a measurement gap can be identified between December 14th and December 17th 2009. In addition a shift in the concentration measurements can be identified on December 05th 2009. The reason for the shift could not be identified: no maintenance or failures were logged in the logging manual.

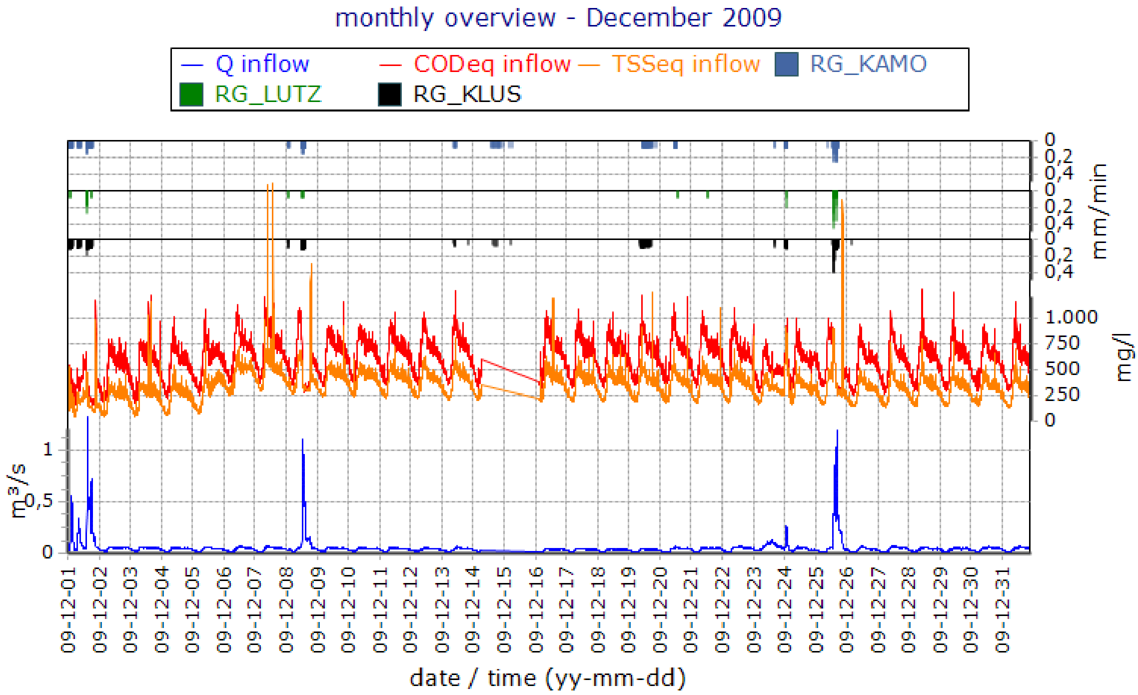

Figure 6-14: Visual analysis – example for December 2009

In addition, some catchment-specific points could be identified from this first analysis:

- Effectively, the measurement limit set for the flow meter in the inflow channel seemed too low. A maximum flow of approximately 2.5 m³/s was recorded. Results from a preliminary hydrodynamic SWMM simulation, however, showed maximum flow rates up to 15 m³/s. This is discussed below in more detail (see paragraph 6.5.2.2).
- The overall effect of the in-sewer storage on the runoff behaviour of the catchment could be assessed.
- A time shift between rainfall and runoff measurements for the measurement period up to November 2009 was identified. This could be allocated to different handling of summer- and wintertime on the rain gauge measurements and the online measurement station.

6.5.2.2 Measurement limit for inflow channel flow meter

Since most of the sensors at the measurement station are connected to the industrial PC by an analogue connection (currents of 4 mA to 20 mA), measurement limits are defined by two sources:

a) the physical measurement limit of the sensor itself; and

b) the limits defined for the analogue connection of the sensors to the PC (equivalent values for 4 mA and 20 mA).

Generally limits for the analogue connection are defined as *reasonable* limits for each sensor, knowing that the bigger the span the less precise the results will be.

For the radar flow meter in the inflow channel, measurement limits are determined by the minimum required distance from the water level (physical limit) and the definition for the analogue connection between 0 (4 mA) and 2500 L/s (20 mA). The maximum of 2500 L/s was chosen based on a dry weather calibration for the flow meter by Haas (2005).

Additionally the flow meter internally stores all measured data digitally for about 10 days. Figure 6-15 shows the effect of the two limits for an extreme rainfall event in June 2008, where the internal storage of the flow meter was read out manually after the event.

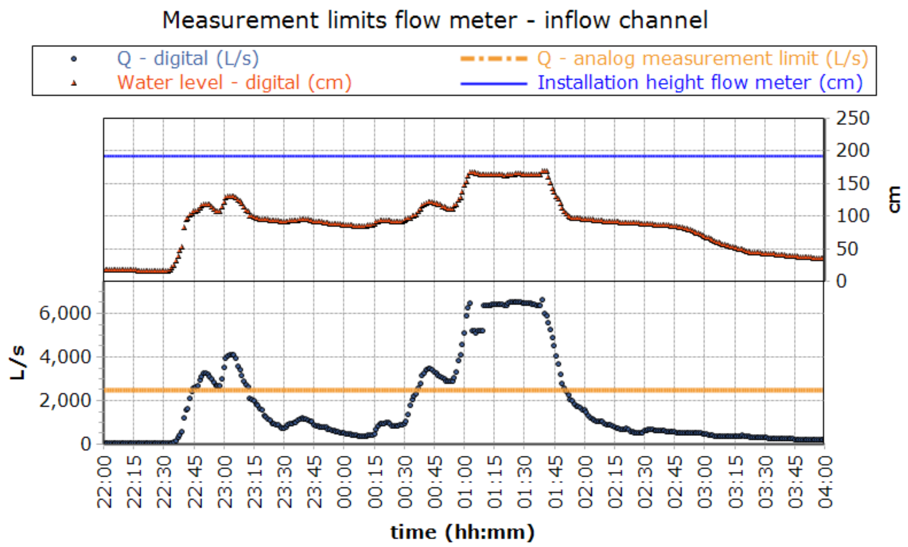

Figure 6-15: Analogue and digital measurement limits, flow meter inflow channel (Gamerith et al., 2011, modified, with permission from CHI Press)

The digital data from the internal storage of the flow meter (Q-digital) shows that the first peak of the event was recorded completely. The second peak surpassed the physical limit of the flow meter (minimum distance to water level). A maximum flow of about 6000 L/s was measured. Due to this physical limit, no higher values can be recorded by the flow meter.

In the data transmitted to the PC and eventually stored in the database, however, both peaks are cut off at the defined measurement limit of 2500 L/s (shown by the dash-dotted orange line).

This shows the importance of setting measurement limits with care, as important data loss may be the consequence. Currently an evaluation of the analogue limits is under way and they will be adapted in near future.

6.5.2.3 Event by event analysis

After the first analysis of the data by month, a detailed visual analysis for each event that had been identified from the rainfall time series analysis was carried out for 2009 in order to identify and assess:

- Errors in rainfall data or flow data by a rainfall-runoff comparison.
- Spatially distributed rainfall events.
- Snowfall and snowmelt (rainfall-runoff comparison).

- First flush effects.
- Effect of the in-sewer storage on both hydraulics and pollutant concentrations.

This information was then used to determine

- Settings for the tests applied in semi-automated data validation.
- Events suited for sensitivity analysis and model calibration.

In the following, some exemplary events will be presented and discussed, where system specific behaviour can be identified and the importance of this analysis can be shown.

Example 1 is shown in Figure 6-16. On the upper right axes, rainfall intensity for the KAMO and KLUS rain gauge are shown, measured flow (blue line) and simulated flow (orange line) in the inflow channel on the left axis. The simulated flow was calculated with a pre-calibrated SMUSI model for 2009, assigning both rain gauges KLUS and KAMO as described in chapter 6.6.1.

The figure shows the effects of erroneous rainfall measurements: the KLUS rain gauge was clogged between June 6th 2009 and June 17th 2009. Only some values were recorded in this period. A sudden release of the dropping funnel happened on 2009-06-17 at about 8:45. The difference in cumulative rainfall sum between the two rainfall time series over this period is within the range of variation determined in the rainfall analysis. As the gauge was not completely clogged, identification of erroneous measurements can be difficult with fully automated routines.

A comparison of the measured and simulated hydrographs shows the impact of this measurement error on the simulation results: The discharge on June 16th is significantly underestimated by the model. The sudden release on 17th of June leads to a high peak in the simulated runoff that is consequently not recorded by the flow meter.

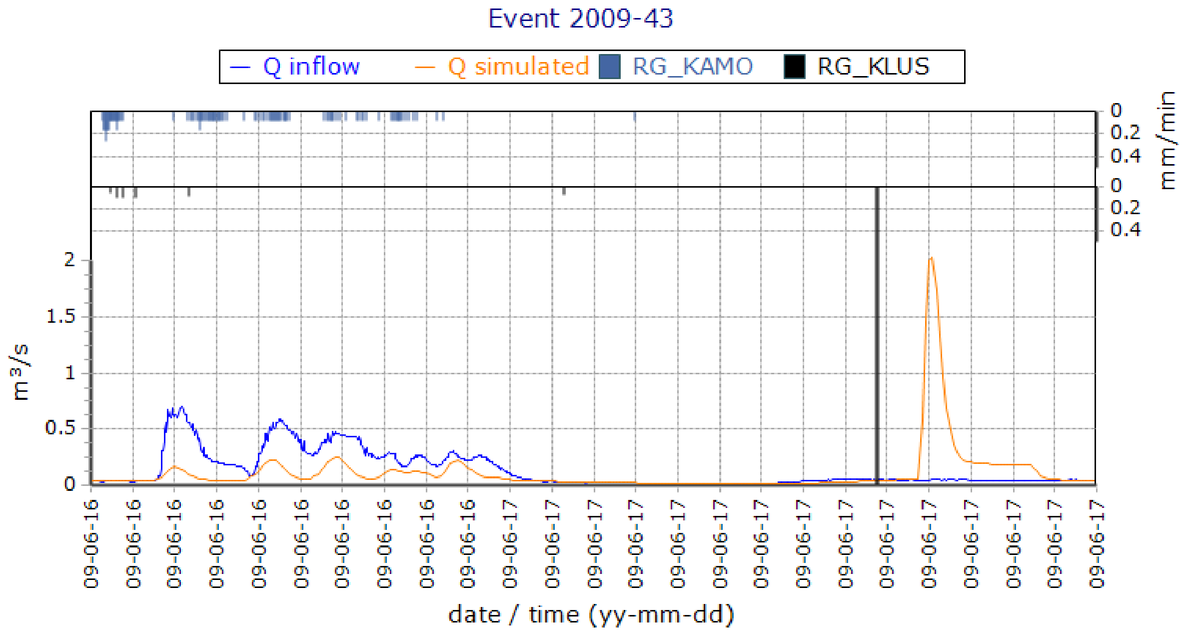

Figure 6-16: Clogging of a rain gauge and effect on model results – event 2009-043

Example 2 (Figure 6-17) gives a good overview of the system behaviour that can be identified by a visual analysis. In this figure rainfall data from the three rain gauges (3 upper right axes), the inflow discharge (left axis) and the inflow equivalent COD concentration (lower right axis) are shown for one event in Mai 2009.

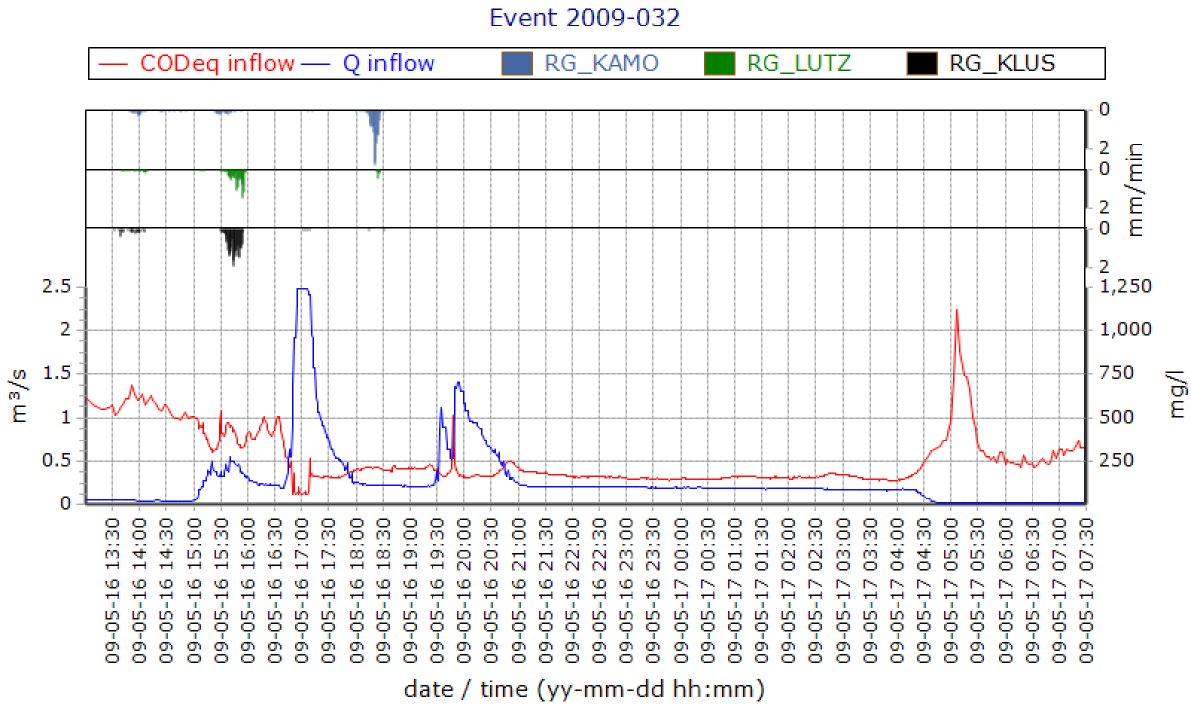

Figure 6-17: Example of identifying system behaviour – event 2009-032

A comparison of the rainfall recordings shows that large intensities were measured in the south of the catchment between 15:30 and 16:00 h at the rain gauge KLUS. For this rainfall event, the LUTZ rain gauge recorded lesser but still important intensities up to 1.5 mm/min. The most northern rain gauge KAMO recorded significantly lower intensities. About 3 hours later (18:30 – 19:00 h), an important rainfall event was recorded at the KAMO rain gauge, where nearly no rainfall was recorded at the other two rain gauges. This effect is also visible in the inflow discharge measurements. The first event, recorded in the southern part of the catchment led to a significantly higher peak than the second event recorded in the northern part.

This effect would not have been identified when using only one rain gauge. The comparison of rainfall and runoff allowed identifying the events as spatially distributed and not erroneously recorded.

In addition, the time shift between the rainfall and the discharge measurement discussed above can be seen in the chart. The response time of the catchment should be close to immediate for the rainfall recorded at the LUTZ gauge (that is installed directly at the online measurement station). The measurements, however, show a difference of about 1 hour. As stated above, this was allocated to the different summer- and wintertime settings for the rain gauges and at the online measurement station.

The measurement limit of the flow meter of approximately 2.5 m³/s as discussed in the previous chapter can be identified at the peak of the first event (around 17:00 h).

The effect of the in-sewer storage can be seen in the discharge measurements at the end of the events between 21:00 and 04:30 h. The storage is emptied at a constant rate of about 150 L/s. Emptying of the 2300 m³ storage would take about 4:15 to 5 hours (depending on the dry weather flow entering the storage) at this rate. Effective emptying times after large events vary between 6 to 8 hours. Possible sources for this could be i) activation of additional volume upstream the storage due to backwater in the system, ii) infiltration to the sewer system or iii) connected drainage mains. The real reason, however, cannot be identified without further investigations in the catchment.

For COD_{eq} concentration, the dilution effect is clearly visible at the beginning of the event: concentrations decrease with increasing flow. Over the empting period of the storage tank, pollutant concentrations are close to constant. In addition a concentration peak at the end of the emptying of the in-sewer storage identified. This behaviour is observed for the majority of rainfall events where the storage tank is activated. It can also be identified with the storm event analysis script described in chapter 5.2.2.6. This evaluation however is only feasible for events where Q is lower than the measurement limit of 2.5 m³/s and where concentration measurements are available for each time step. Otherwise biased results are obtained. The event shown in Figure 6-17 is therefore not suited for this evaluation.

Example 3 in Figure 6-18 shows the analysis results (TSS_{eq} concentration) for an event on March 29th 2009. On the left hand side, discharge in the inflow channel, TSS_{eq} concentrations and TSS_{eq} flux is shown (from top to bottom). The right hand side shows the $M_{(V)}$ diagram for this period. A peak in concentrations and flux can be identified at the beginning of the event and at the final emptying of the in-sewer storage tank.

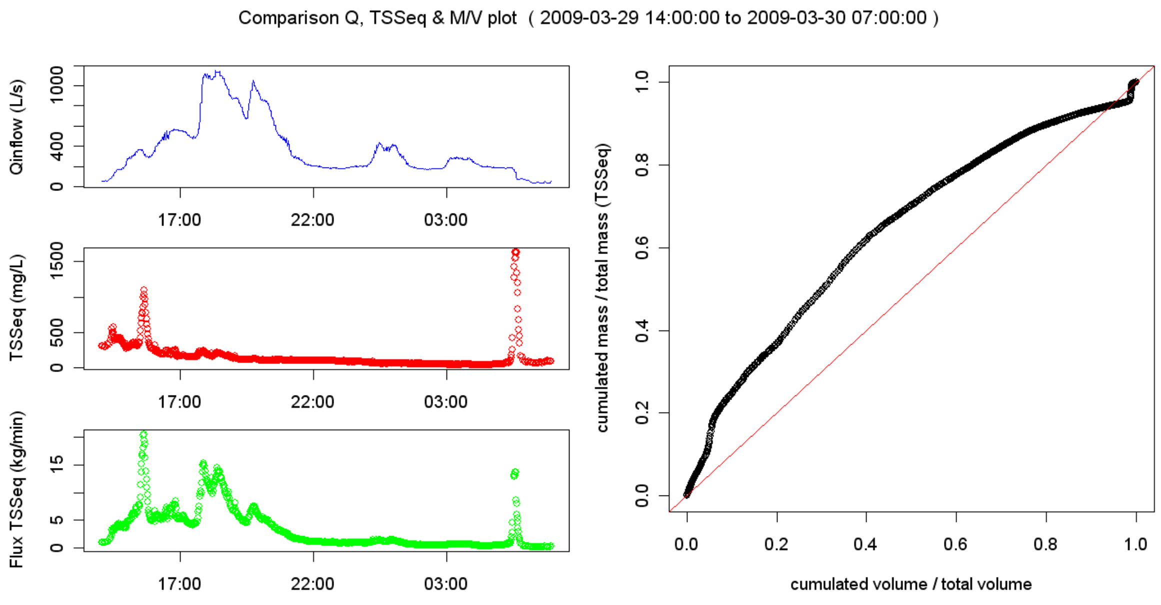

Figure 6-18: Storm event evaluation for TSS – event 2009-15 on March 29th 2009

The concentration peak at the beginning of the event could be interpreted as a first flush effect. However, as stated in chapter 5.2.2.6 a concentration peak does not necessarily signify a first flush effect and the $M_{(V)}$ diagram can be used for this identification. The least restrictive definition from literature is 25/50, meaning that 50% of the pollutant mass is transported in the first 25% of the volume. This threshold is not reached for the event shown in Figure 6-18.

A comparison of all events from 2009 that satisfied the data requirements showed a high variability in the $M_{(V)}$ diagrams for the Graz West R05 catchment. Peak concentrations and fluxes at the beginning of an event were observed for some events, however not systematically. In no case even the least restrictive definition for a first flush of 25/50 (50% of the pollutant mass in the first 25% of runoff) is reached. An analysis of 45 storm events from 2003 carried out by Dorfer (2005) also showed a high variability in the events. Again, no first flush could be identified from the $M_{(V)}$ diagrams based on the limits stated in literature.

However, the defined $M_{(V)}$ ratios were mostly chosen arbitrarily based on different case studies and were intended as limit design criteria for storage tanks, i.e. to decide if it is sufficient to capture a first proportion of the runoff volume and spill the rest. Effectively, even if these ratios are not met, a concentration peak at the beginning of an event can impact on the receiving water if an overflow occurs at the same time. One major advantage of the online measurements is that they allow picturing this effect in full detail.

Another interesting effect is the peak in concentration and fluxes at the end of the event: this happens exactly in the final phase of the emptying of the in-sewer storage. This effect postulated by Brombach et al. (1995) was systematically observed for most of the events where the in-sewer storage was activated. An important observation is that this peak is not only visibly in concentrations but also in the flux – indicating that it does not simply result from the lower dilutions due to the decreasing discharge. Possible sources could be the surge of pollutants by the final emptying of the tank or the backwater in the secondary sewers leading to an accumulation of raw sewage after a rainfall event.

6.5.3 Semi-automatic data validation

After the visual analysis of the data, the semi-automatic data validation routines were formulated based on the knowledge of the system behaviour. The visual analysis and also addition meta-knowledge about the system proved to be crucial to be able to formulate the tests and set the limits correctly. As discussed in chapter 3.2.2.2, several automatic tests are applied to the data based on the method proposed in Mourad and Bertrand-Krajewski (2002), flagging the data with (A), (B) or (C) for each test, where (A) declares the data as valid, (C) declares the data as erroneous and (B) demands for additional analysis as no clear statement is possible with the applied test.

The following tests were run on the data:

- Minimum-maximum (min-max) test for physical measurement limits and locally realistic range.
- Cross validation with other measurement data.
- Residual analysis from moving average.

For each test one column is added to the measurement data matrix, indicating the applied test and the validated variable. The raw data is not changed during validation. A combined flag from the tests is then created for each variable, where:

- All time stamps are first flagged with (C).
- If no test results in a (C) value and at least one test results in a (B) value, the combined flag is set to (B).

- If no test results in a (C) or (B) value, the combined flag is set to (A).

An overview of the variables and applied tests in this work is given in Table 6-5. Variable names are used as in the netCDF files. All relevant variables for modelling of the catchment were chosen for validation. A table with the settings used for all variables and tests is given in appendix 7.1.

A min-max test was carried out for all variables. Cross validation tests were only possible for the hydraulic measurements as no analytic redundancies were available for the water quality parameters. The residual test from the moving average was only done for water quality parameters, as the hydraulic measurements showed low noise. The time difference between two consecutive time stamps was also validated as it indicates previous periods of measurement gaps.

Table 6-5: Overview of tests in semi-automated data validation

Variable	**Unit**	**Description**	**Tests**		
			min max	cross validation	moving average residuals
		Hydraulics			
H_CSO	m	Water level at CSO	x	-	-
H_sewer_inflow	m	Water level in inflow channel	x	-	-
H_sewer_overflow	m	Water level in overflow channel	x	-	-
Q_sewer_inflow_mcb	m³/s	Discharge inflow channel	x	x	-
Q_sewer_overflow	m³/s	Discharge in overflow channel	x	x	-
		Water quality			
CODeq_inflow	mg/L	COD from global UV/VIS calibration at pontoon	x	-	x
TSSeq_inflow	mg/L	TSS from global UV/VIS calibration at pontoon	x	-	x
		Other			
Delta_t	min	Delta between time stamps	x	-	-

The evaluation period for the data was from 2008-11-03 to 2010-01-17. In total, 174989 data points were recorded in that period. Table 6-6 shows a summary of the time series for the investigated variables, giving an overview of minimum and maximum values recorded for each variable as well as the number of NaN values in the recordings. It can be seen that for COD_{eq} and TSS_{eq} about 3000 NaN values are recorded corresponding to approximately 1.7% of the total number of values.

Table 6-6: Time series summary 2008-11-03 to 2010-01-17 for the investigated variables

Variable	Unit	minimum measured value	maximum measured value	NaN values
				#
H_cso	m	-0.525	1.64	6
H_sewer_inflow_mcb	m	0	1.687	6
H_sewer_overflow	m	-0.001	1.88	6
Q_sewer_inflow_mcb	L/s	-4.375	2482.81	6
Q_sewer_overflow	L/s	-625	2481.56	6
CODeq_inflow	mg/L	0	1292	3196
TSSeq_inflow	mg/L	0	2300	2649
delta_t	min	1	1.67E+05	1

In the following the results for the different tests are briefly presented and discussed.

The **min-max** and the **cross validation** test proved to be robust tests to detect erroneous data, especially for the hydraulic variables. For the water quality variables, definition of min-max ranges proved difficult, as no obvious limits could be identified in the visual data analysis.

Table 6-7: Results from min-max and cross validation test

	Min-Max test results		Cross-validation test
	B flagged	C-flagged	B-flagged
	#	#	#
H_cso	-	96	-
H_sewer_inflow_mcb	51	6	-
H_sewer_overflow	169219	79	-
Q_sewer_inflow_mcb	316	851	940
Q_sewer_overflow	166294	449	167659
CODeq_inflow	18	3196	-
TSSeq_inflow	15	2650	-
delta_t	2323	22	-

An overview of the results from these two tests for all investigated variables is given in Table 6-7. Based on these two tests, only few erroneous data points are identified for the hydraulic variables in the inflow. This seems reasonable as the hydraulics also proved stable in the visual analysis. For the measurements in the overflow channel, a high number of (B) flagged values are identified by both the min-max and the cross validation test. This results mainly from the periods when the overflow channel is dry (i.e. when no overflow event occurs). In this case, the measurement system still provides values <> 0. Concerning the water quality parameters, the (C) flagged values correspond – with one exception – to the NaN values recorded in the raw data. Only few (B) flagged values were identified with the min-max test, so no significant additional information could be deduced on the validity of the water quality variables from these two tests.

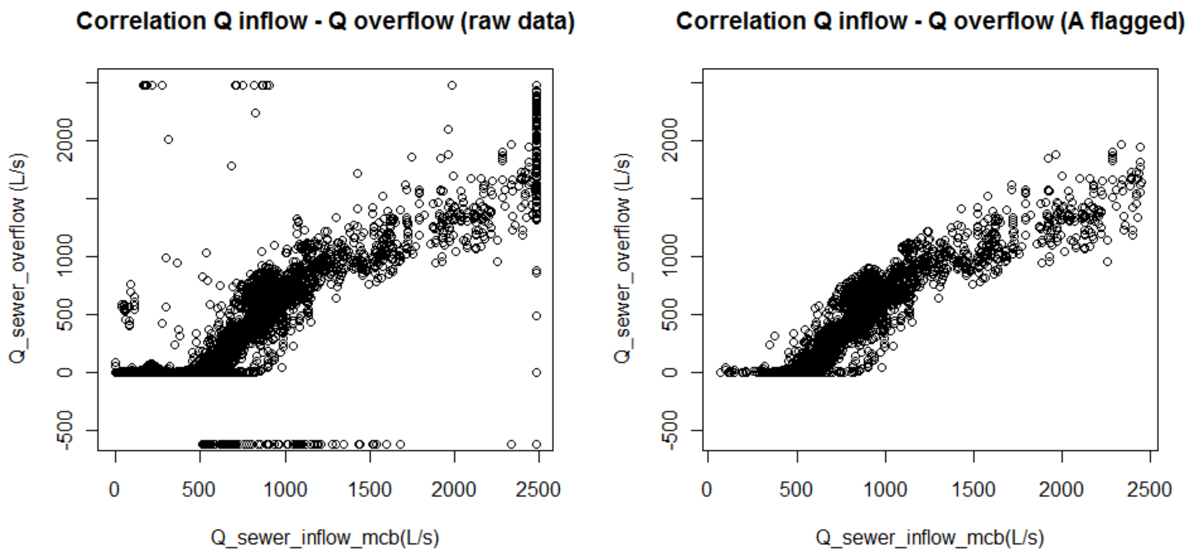

Figure 6-19: Comparison of raw and validated data (min-max and cross validation test) example of correlation Q-inflow Q-overflow.

Figure 6-19 shows a correlation plot of discharge in the inflow and the overflow flow channel. The left hand side shows a plot of the raw data, the right hand side a plot of the validated, (A) flagged data. It can be seen that

- all data points outside the measurement limits were elimiated by the min-max test.
- The cross validation check with the water level in the CSO chamber allowed to flag data in the overflow channel where a discharge higher than 0 is recorded, but no overflow occurs.
- Cross validation of the discharge values in inflow and overflow allowed to flag values where the overflow discharge is higer than the inflow discharge.

Data that was flagged as (B) by the cross validation test was analysed in a post-processing in more detail. It could be shown that for discharge values greater than 0 in the overflow channel where the water level in the CSO chamber is beneath the crest height either i) the measurement is indeed erronous or ii) the water level of the Mur river causes a backwater in the overflow channel.

For cross validation where overflow discharge is higher than inflow discharge also several reasons could be identified: i) the measurement is indeed erronous, ii) due to the spatial distance of the two sensors, on some occasions discharge in the overflow channel can be higher than in the inflow at the end of an event and iii) on rare occasions it could be interpreted as a backwater effect from the main collecting sewer that is induced in the throttle and leads to an overflow event.

In appendix 7.2 additional validation results for hydraulic variables are shown in several correlation plots of hydraulic data similar to Figure 6-19.

The **residual analysis from the moving average** was only carried out for the water quality variables. Tests with hydraulic variables did not yield satisfying results as only low noise could be identified and the test was highly sensitive to abrupt changes in flow conditions.

For this analysis, NaN values first have to be removed from the raw time series. For the test, the maximum allowed absolute residuals or residual percentage errors and the window of the moving average calculation (as the number of consecutive time steps) have to be defined. After several tests, the window for averaging was set to 5 time steps. This means that averaging in storm weather conditions is generally done over 5 minutes and over 15 minutes in dry weather conditions.

Figure 6-20 shows the results from this method for COD_{eq} concentrations for May 2009. The raw data series, the calculated moving average and the corresponding residuals are plotted from top to bottom (all in mg/L). The *x*-axis shows the count of time steps (one step corresponding to 3 minutes in dry weather and 1 minute in wet weather conditions). Noisy data can be identified e.g. in the first quarter of the plot (time step 2500 – 5000) by high and dense residuals. In addition some apparent outliers can be identified in all three plots. The periods with low noise and lower concentration values correspond to wet weather runoff.

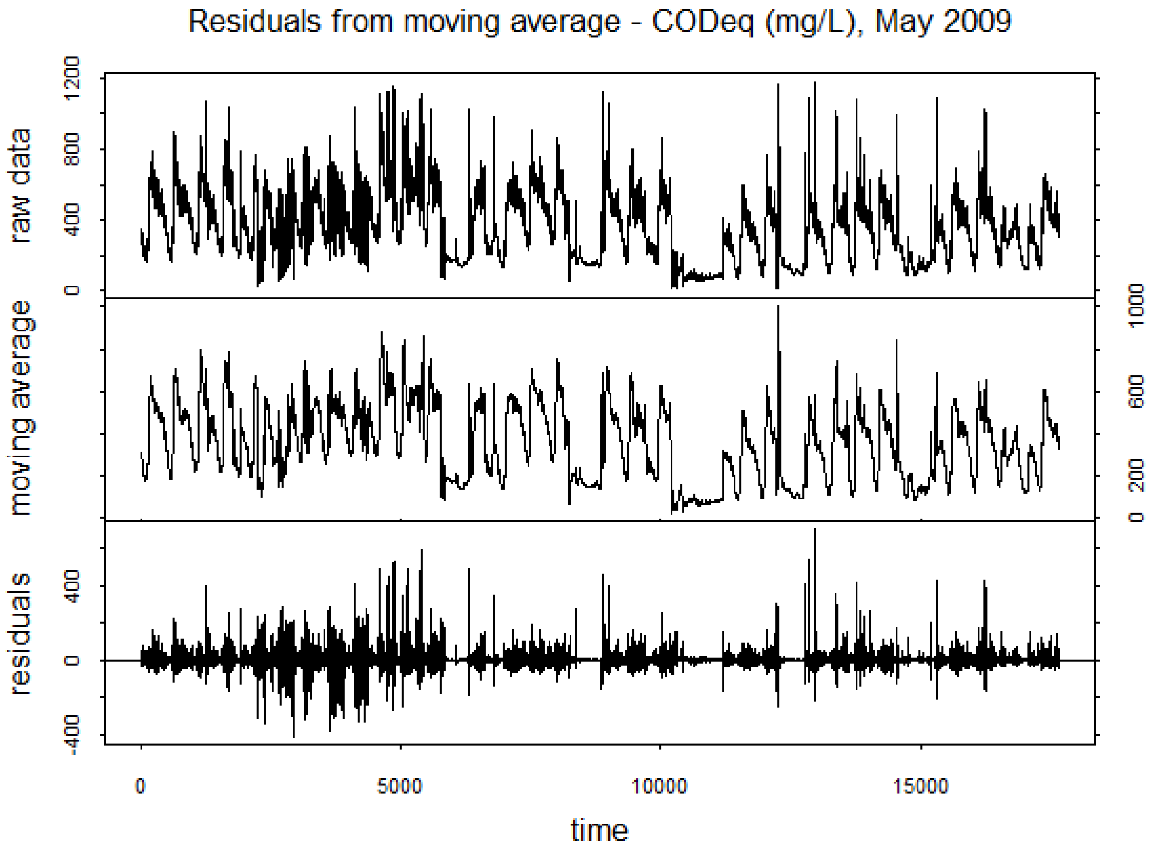

Figure 6-20: Results for moving average filtering (COD_{eq} in May 2009)

For validation purposes, the relative residuals were calculated as they seem to be a more appropriate measure than the absolute values due to the high variation range of the measured values. For the validation test, limits for the relative value were set to ± 25%. This choice was based on the evaluation of the UV/VIS probe calibration discussed in chapter 6.3. For the complete data set, 4865 values were (B) flagged for COD_{eq} and 13596 values were (B) flagged for TSS_{eq}. This corresponds to 2.8% and 7.9% of the total data points respectively.

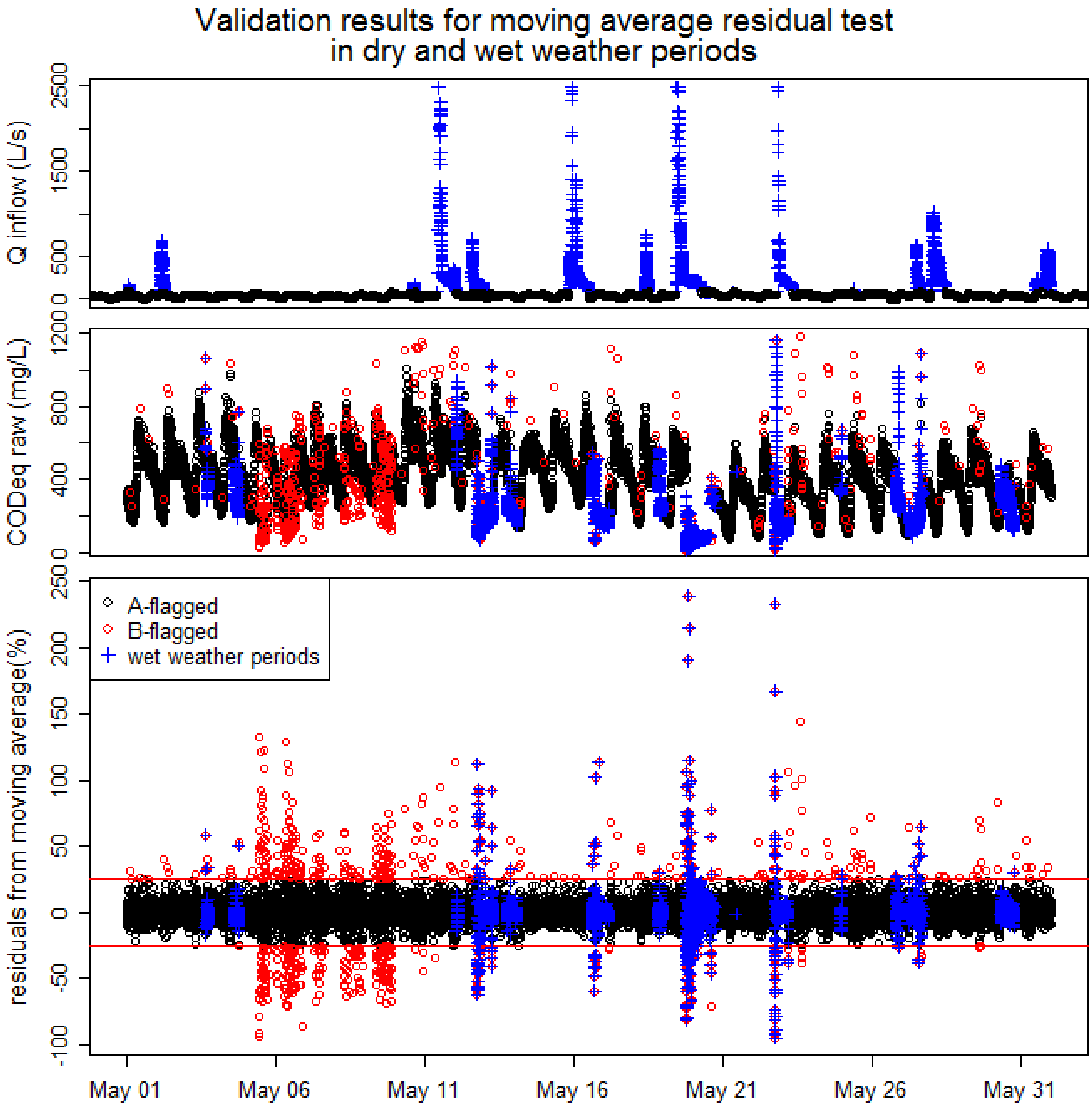

Figure 6-21: Validation results for moving average residual test – COD_{eq} in May 2009

This method, however, leads to problems in highly dynamic conditions as are encountered during wet-weather. Figure 6-21 shows a plot of validation results for May 2009: from top to bottom the inflow, the raw COD_{eq} concentrations and the relative residuals from the moving average are shown. The horizontal red lines in the residual plot delimit the 25% range defined as limit for the test. The red dots show all (B) flagged values. The blue crosses show wet weather periods.

It can be seen that abrupt changes in concentrations that are actually encountered in wet weather conditions (i.e. the last flush effect discussed in chapter 6.5.2.3) are flagged B by this test. Therefore this validation can only give an indication to the user who then has to decide which values (or periods) to use or discard. Based on the results it is proposed to first eliminate outliers with high residual errors (e.g. more than 50%) and then to substitute the dry weather concentration measurements with the moving average. Evaluation of the B-flagged values from wet weather periods should be done separately. Actually, for the data shown in Figure 6-21, none of the B-flagged values in wet weather conditions would be flagged C.

6.5.3.1 Post-processing

After running the automated scripts, generally all data flagged as (B) should be analysed in more detail and then be classified as either (A) or (C). Based on this classification:

- Generally all (C) flagged values should be substituted by NaN values.
- Some values that are (C) flagged can be substituted by a real value based on expert knowledge:
  E.g. in the presented case study, measurements indicating a flow in the overflow channel where no overflow occurs were substituted by zero rather than by NaN. For water quality measurement with high noise, values were substituted by the moving average rather than by NaN.
- Some values might not be wrong but still might not be useful for further processing or to answer the problem in question. In the presented case study, e.g. flooding of the overflow channel by the Mur river would have an impact on calculating a mass balance of inflow-overflow. It is proposed to introduce an additional flag (D) for these values, indicating that the value is not wrong but not useful in this special context. This allows deciding in the post-processing if the values should be substituted by NaN, any other value (e.g. zero in our case) or be kept as is in further processing. This might prove especially helpful for a third party screening or working with the validated data, possibly in another context.

The modified data should be stored in an additional file or matrix column. The raw data should always be kept as recorded as this makes the modifications traceable and allows e.g. to apply refined tests in future.

6.5.4 Dry weather flow evaluation

Based on the rainfall data analysis and using the data (A)-flagged by the data validation tests, a detailed analysis of the dry weather flow was carried out. Some results from this evaluation are presented in the following.

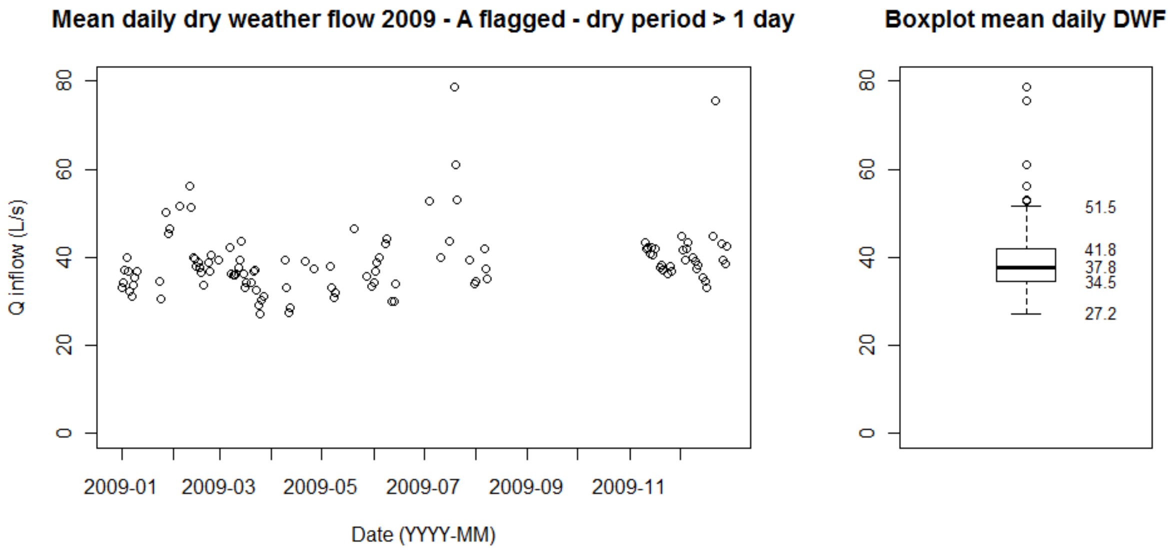

Figure 6-22: Mean daily dry weather flow evaluation for 2009

First all days where no rainfall event had been identified and where all values for the inflow were (A)-flagged were determined for 2009. Based on the rainfall event classification, antecedent dry days were determined. Figure 6-22 shows the time series- and boxplot of the mean daily dry weather flow for all days with antecedent dry periods longer than one day. The median of the mean DWF is at 37.8 L/s, half of the values lie within the quartiles of 34.5 and 41.8 L/s respectively. However, some significant outliers can be identified.

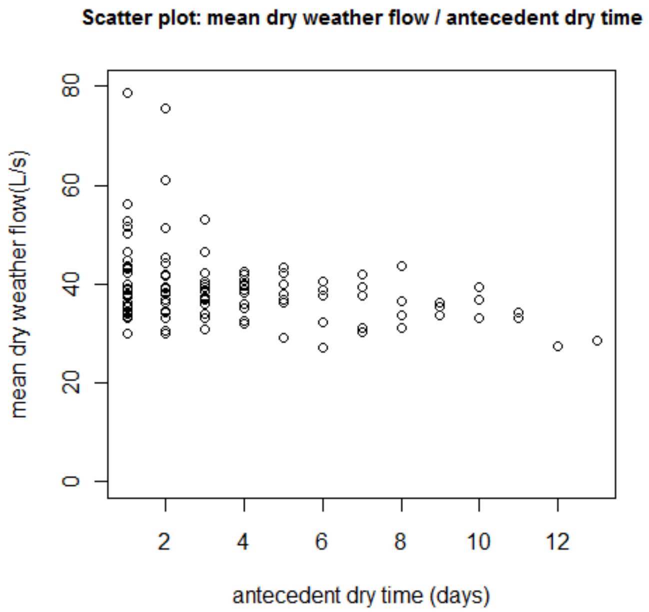

Figure 6-23: Scatter plot of mean dry weather flow against antecedent dry weather days

In Figure 6-23 the scatter plot of mean daily DWF and antecedent dry weather days is shown. It can be seen that high values (> the double interquartile indicated by the whisker in the boxplot) in the mean daily DWF occur only up to 3 days after a rainfall event. This is also valid for the minimum and maximum daily dry weather flow values (see appendix 7.3). This behaviour allows the interpretation that either infiltration occurs to the sewer system after larger rainfall events or that drainage mains are connected to the sewer system.

An average dry weather pattern was composed from the available dry weather data. This pattern was then used for the modelling of the catchment.

6.5.5 Summary – data analysis and validation

To summarise the data analysis and validation procedure of the *Graz Sewer R05* data the following major findings can be stated:

- A **visual data analysis** is strongly advocated. It allows identifying obvious measurement gaps and errors. In addition it helps to understand the behaviour and overall functioning of the system. Also a comparison with preliminary model results in the visual analysis proved useful as even an uncalibrated model can picture the overall effects of the rainfall data on the runoff behaviour. The analysis is, however, a laborious process and takes up a non-negligible amount of time.
- The **semi-automated data validation** provided satisfying results. The tests were parameterised according to observations from the visual analysis and knowledge

about the system. The currently implemented validation tests were sufficient for the purpose of this work. A refinement and implementation of additional tests is nonetheless strongly recommended.

- The **min-max** and **cross-validation tests** proved to be stable and especially suited for validation of the hydraulic variables. In-depth analysis of the (B) flagged values highlighted site-specific behaviour in the measurements, especially concerning the overflow discharge.
- The evaluation of the **residuals from the moving average** showed good performance for the water quality variables. It is recommended to use relative and not absolute residuals for the evaluation. However, while this method is appropriate for measurements in dry weather conditions it is not fully recommended for highly dynamic storm weather conditions where abrupt changes can occur. Based on the results it is proposed to substitute the dry weather concentration measurements with the moving average and to evaluate the B-flagged values from wet weather periods separately.
- It is proposed to add a (D) category to the validation routines, as some values might be correctly measured but might not be useful in this special context or to treat the problem in question.
- Overall the procedure provided a sound data base for the following modelling exercise.

6.6 Modelling of the Graz West R05 catchment

For modelling of the Graz West catchment, models were set up in both SMUSI (see chapter 5.3.1) and SWMM 5 (see chapter 5.3.2).

As stated above, the catchment and sewer network was successively expanded between 2004 and 2006 and the measurement station was offline from 2007 to late 2008. Therefore, two models with different network structures were set up in SMUSI, one representing the status before the expansion in 2004, the second representing the current network structure. In SWMM one model using the current structure was set up. In the following the models are briefly described. Detailed information on the model set up is given in the corresponding references.

6.6.1 SMUSI 5.0 – hydrological model

An aggregated model for the Graz West R05 catchment representing the network structure in 2003 was set up in SMUSI (Schneider, 2007). In this model, the catchment was aggregated to 44 subcatchments and 41 main collectors. In the following this model is referred to as the *SMUSI 2003* model. This model was adapted recently by Fuchsberger (2009) to represent the current network structure as of 2009. There the sewer system was aggregated to 57 subcatchments and 56 main sewer sections in total. In the following, this model is referred to as the *SMUSI 2009* model.

The representation of the catchment in SMUSI is shown in Figure 6-24. The solid subcatchments represent the subcatchments modelled in the SMUSI 2003 model. Two subcatchments were modified in the expansion (checked pattern). The striped subcatchments were added in the 2009 network expansion.

A detailed description of the model set up procedure as well as the model representation of the in-sewer storage is given in Fuchsberger (2009). The geometry input files for the SMUSI 2009 model are shown in appendix 8.

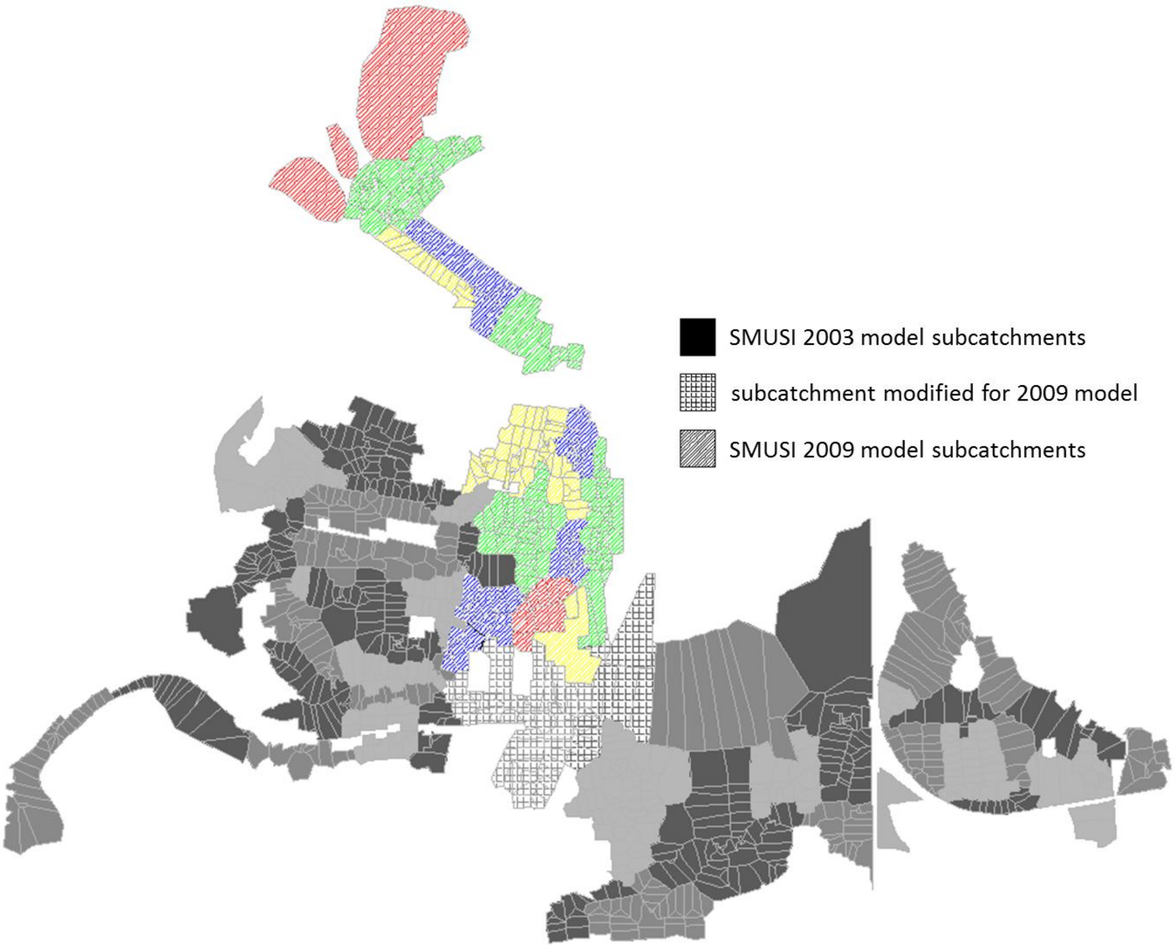

Figure 6-24: Overview of subcatchments in the SMUSI 2003 and SMUSI 2009 models.

6.6.1.1 Spatial rainfall distribution – assignment of rain gauges

As discussed in chapters 6.5.1 and 6.5.2 only two of the three rain gauges installed in the catchment – namely the KAMO and KLUS rain gauges – were used in modelling as the LUTZ rain gauge showed many erroneous recordings. As the KAMO rain gauge was installed in late 2008, only data from the KLUS rain gauge was used with the SMUSI 2003 model.

Assignment of the rain gauges to the subcatchments was done in a geographical information system (GIS) by splitting the catchment by an orthogonal line at the bisection between the KLUS and the KAMO rain gauge. Figure 6-25 shows the assignment of the rain gauges to the subcatchments. The KLUS rain gauge was assigned to the subcatchments south of the red line (checked pattern). The KAMO rain gauge was assigned to the northern part (subcatchments with sold pattern).

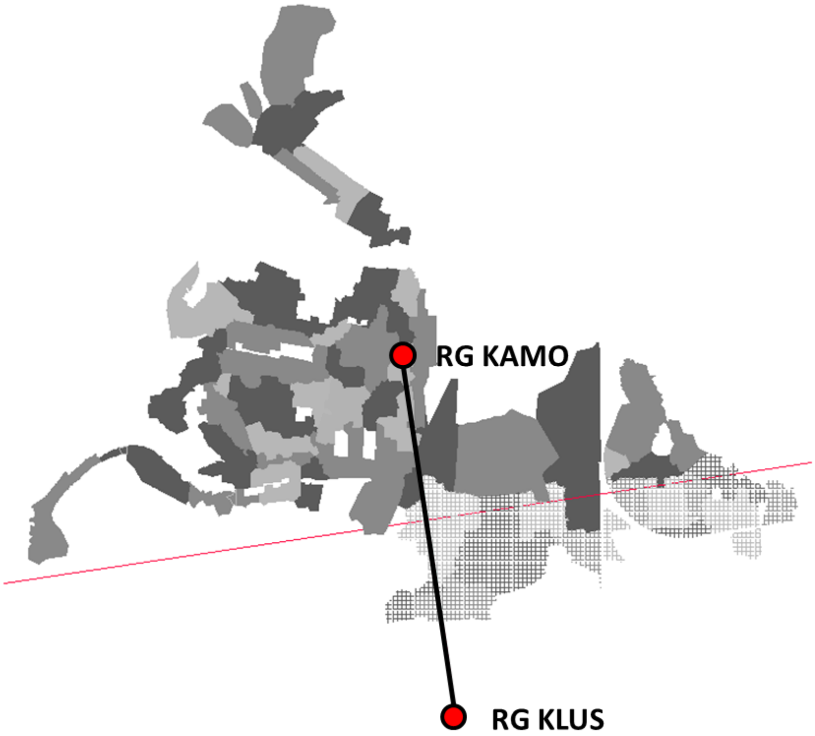

Figure 6-25: Assignment of rain gauges to subcatchments

6.6.1.2 Reference data

In addition to the rainfall data as major model input the measurement data from the online monitoring station is used as reference data in sensitivity analysis, calibration and validation of the SMUSI model.

For the SMUSI 2003 model, data and storm events that were checked and discussed in the works of Dorfer (2005) and Hochedlinger (2005) were used. For flow data, the originally recorded data was corrected based on the work of Haas (2005). Concerning water quality data from the UV/VIS probe, a local probe calibration (discussed in Gruber et al. (2005)) was used.

For the SMUSI 2009 model, the data analysed and validated in scope of this work as described in chapter 6.5 was used. Concerning water quality data, UV/VIS data from global calibration with correction by the non-linear power model described in chapter 6.3.1 was used.

In both cases the ConvertSensorData tool was used to convert the data in a format usable by SMUSI. Therefore the data had to be converted to equidistant 5-minute time steps. As the original data is not equidistant (measurement interval of 1 minute in wet and 3 minutes in dry weather conditions), data was decomposed to 1 minute by linear interpolation between the data points. From this data, 5-minute values were calculated by averaging the values over the precedent five minutes.

6.6.1.3 Model parameter grouping

The model parameters used in the SMUSI model are discussed in chapter 5.3.1. For model calibration the subcatchments were assigned to groups based on i) similar slopes based on the definition given in the German DWA A-118 guideline (DWA, 2006a) and ii) land use. Hence, in model calibration, parameters are not varied for each subcatchment separately but for each defined group, leading to a significantly lower number of calibration parameters.

In total five groups were defined for the SMUSI 2003 model (see also Schneider (2007)). For the SMUSI 2009 model, groups were re-defined, separating them for the two assigned rain gauges. This led to six groups in total (2 for the catchments in the KLUS region, 4 for the catchments in the KAMO region). An overview of the subcatchment grouping is given in the appendix 8 within the SMUSI 2009 geometry tables.

6.6.2 SWMM 5 – hydrodynamic model

The SWMM model of the Graz West R05 catchment was set up by Veit (2009), where also a detailed description of the model set up is given. After a thorough data check the complete available digital sewer map and connected subcatchments were imported to SWMM. The connected subcatchments were supplied by the municipality of Graz in a GIS system, and the degree of imperviousness was determined by overlaying and blending the subcatchments with an infrared picture.

The network as represented in the model consists of 1164 sub-catchments, 1364 nodes and 1363 links in total. Figure 6-26 shows the model of the Graz West R05 catchment as represented in SWMM.

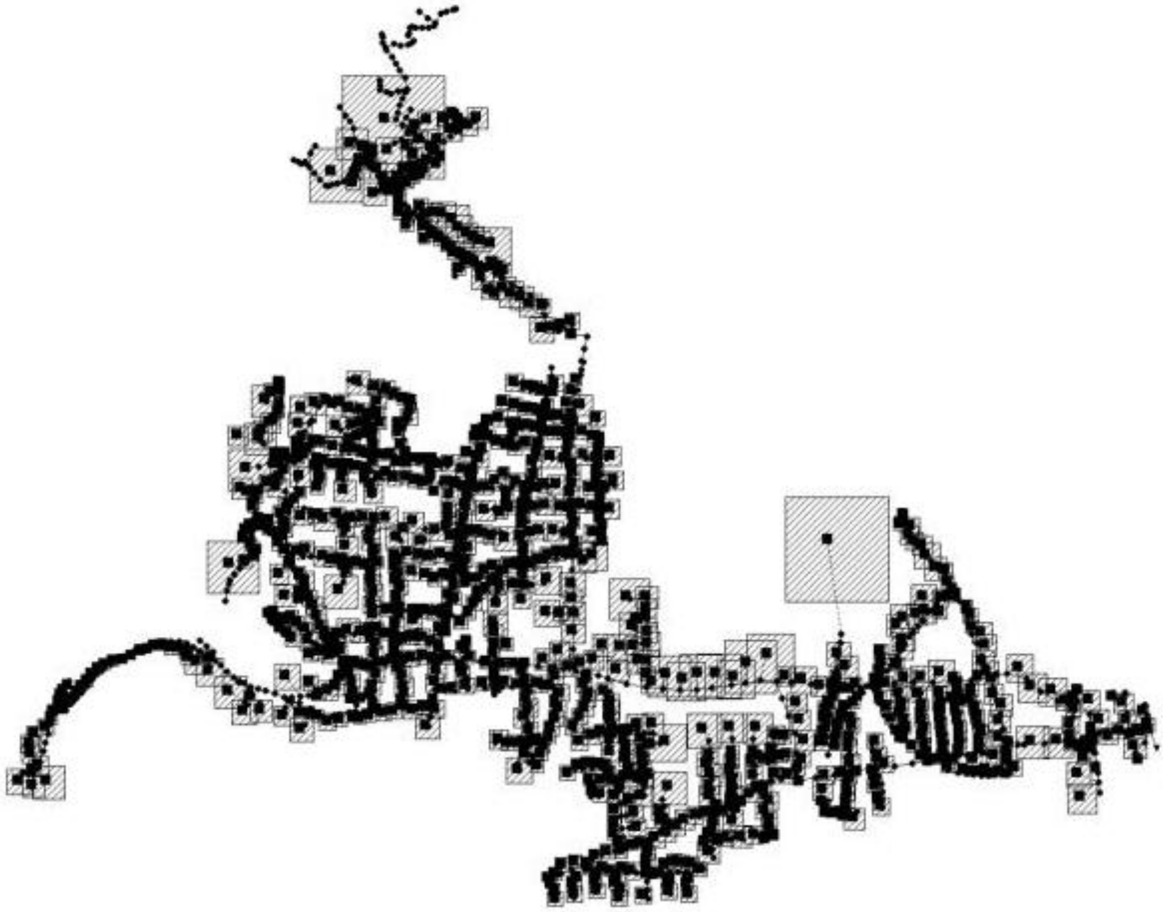

Figure 6-26: Graz West R05 catchment as represented in SWMM 5.0 (Gamerith et al., 2011, with permission from CHI Press)

The SWMM model was calibrated manually on hydraulics against the 2009 measurement data. It was also successfully linked to the BlueM.OPT framework in this work. Due to time constraints, the methods discussed below for global sensitivity analysis and automated model calibration were so far only applied to the SMUSI model. They can, however, easily be applied to the SWMM model. Currently work on this topic is under way (Muschalla et al., submitted).

6.6.3 Comparison SMUSI – SWMM (hydraulic model)[6]

In this paragraph the results obtained with a pre-calibrated SMUSI 2009 and the manually calibrated SWMM 5 models are compared, both models representing the current network status as of 2009.

The models were compared based on data from December 2008 to June 2009. Events were classified based on their peak flows as small (peak flow < 500 L/s), medium (peak flow > 500 and < 2000 L/s) and large events (peak flow > 2000 L/s). In total, 4 small, 19 medium and 11 large events were identified in the period 2009-01 to 2009-06.

Based on the prior data analysis, results from the manually calibrated SWMM model were evaluated for 12 chosen events on volume error and the Nash-Sutcliffe efficiency coefficient (Nash and Sutcliffe, 1970) E_Q described by Equation 6-1. This coefficient is a goodness-of-fit measure that describes how well the measured and simulated curves fit. Values for the efficiency coefficient range from -∞ to 1. A value of 1 means that all the simulated values fit exactly to the measured values. A value of 0 indicates that the simulation results are not better than using a mean value. The advantage of this measure compared to e.g. the sum of squared errors is that a direct interpretation of the value is possible. (Uhl, 2004) cited in (Hoppe, 2006) classifies the ranges for the Nash-Suttcliffe as follows: E > 0.75 as very good and 0.5 < E < 0.75 as good. While these limits seem to be rather arbitrary they are used as indicators also in this work.

$$E = 1 - \frac{\sum_{t=1}^{T}(Q_o^t - Q_m^t)^2}{\sum_{t=1}^{T}(Q_o^t - \bar{Q}_o)^2} \qquad \textbf{Equation 6-1}$$

With E … Nash-Sutcliffe efficiency coefficient, t… time (T), Q_o … obeserved discharge ($L^3\ T^{-1}$), Q_m … simulated discharge ($L^3\ T^{-1}$) and $\bar{Q}_o$ … mean of observed discharge (L^3T^{-1})

Events with a peak flow higher than 2500 L/s could not be evaluated due to the measurement limit for flow data discussed in chapter 6.5.2.2. With one exception volume errors were in the range of ±20%. For six of the twelve events E_Q > 0.8 is reached and the minimum E_Q is at 0.27. Details on the evaluation are given in Veit (2009).

The figures presented in the following show simulation results from both the SMUSI and SWMM model for one event of each class (small, medium and large). Discharge (L/s) is shown on the left axis and precipitation intensity (mm/5 min) on the right axis. The dotted line represents the measured values, the continuous line the SWMM results and the dashed line

[6] This chapter is taken from Gamerith et al. (2011) in slightly modified form (with permission from CHI Press) and Veit (2009)

the results from the SMUSI 2009 model. In order to make the figures legible the scales for precipitation intensity and flow vary for the different events.

In general the results obtained with both models are satisfactory for small and medium events (see Figure 6-27 and Figure 6-28). The dynamics of the runoff could be reproduced and the start and end of the events are mostly well fit.

The SMUSI model shows a higher fluctuation (more accentuated peaks) in the simulated runoff, while SWMM gives a smoother response. This can be explained by the surface runoff model where the short concentration time in the pre-calibrated SMUSI model leads to shorter response time. The dynamics observed in the measured data lie in between the two.

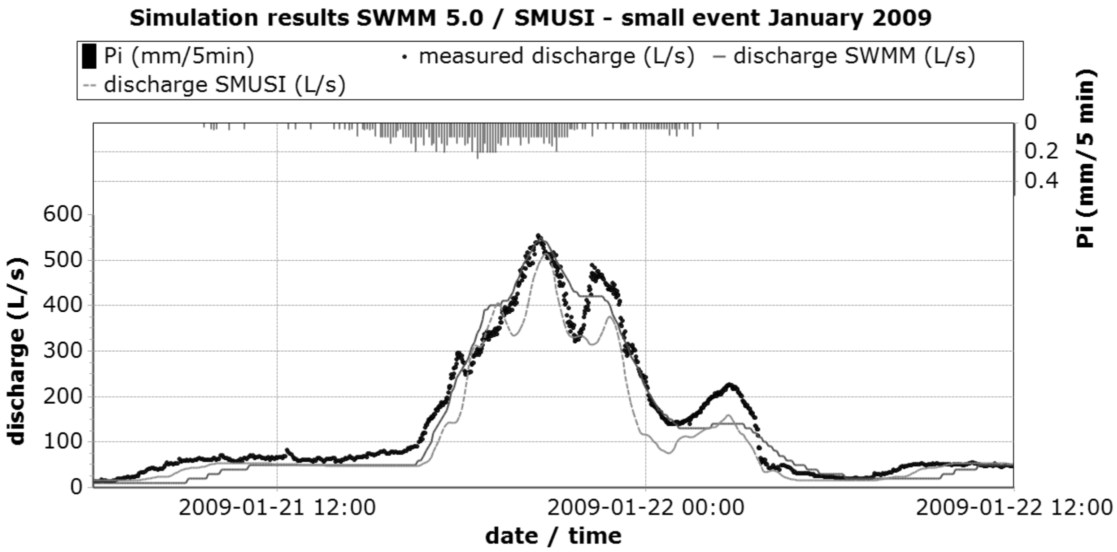

Figure 6-27: SWMM And SMUSI results for a small event in January 2009 (Gamerith et al., 2011, with permission from CHI Press)

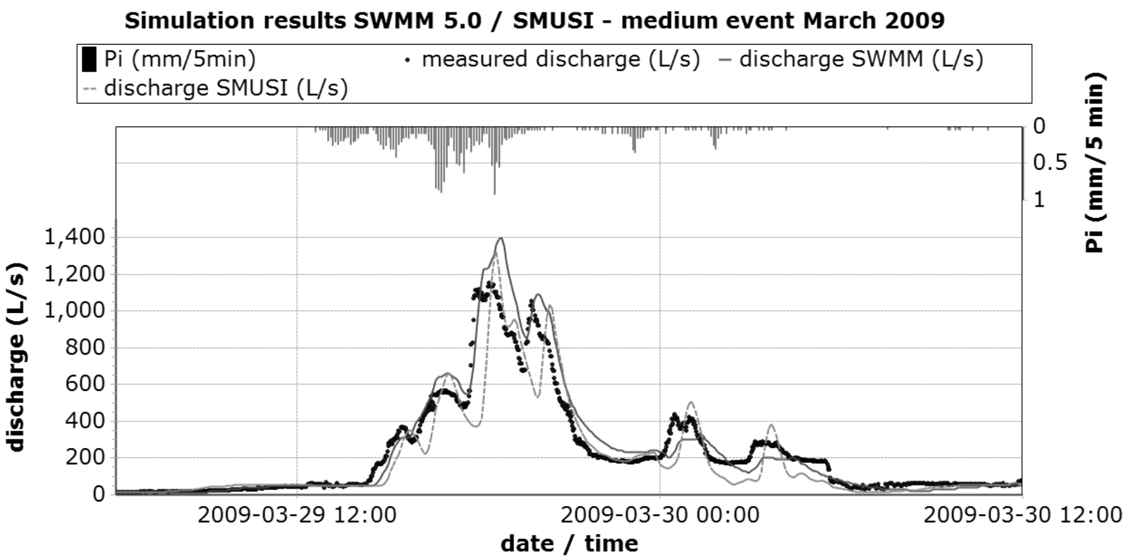

Figure 6-28: SWMM and SMUSI Results for medium event in March 2009 (Gamerith et al., 2011, with permission from CHI Press)

The results for large rainfall events (Figure 6-29) show the problem of the flow meter measurement limit discussed in chapter 6.5.2.2. The runoff peaks resulting from the SMUSI and SWMM models are at 6200 and 7000 L/s respectively. As the measurement is limited to

2500 L/s no statement about the quality of the models can be made for these large events. However, the second runoff peak of about 2200 L/s is rather well fitted. A time shift can be identified between the SWMM and SMUSI results. The source of this shift has not yet been identified, investigations are under way.

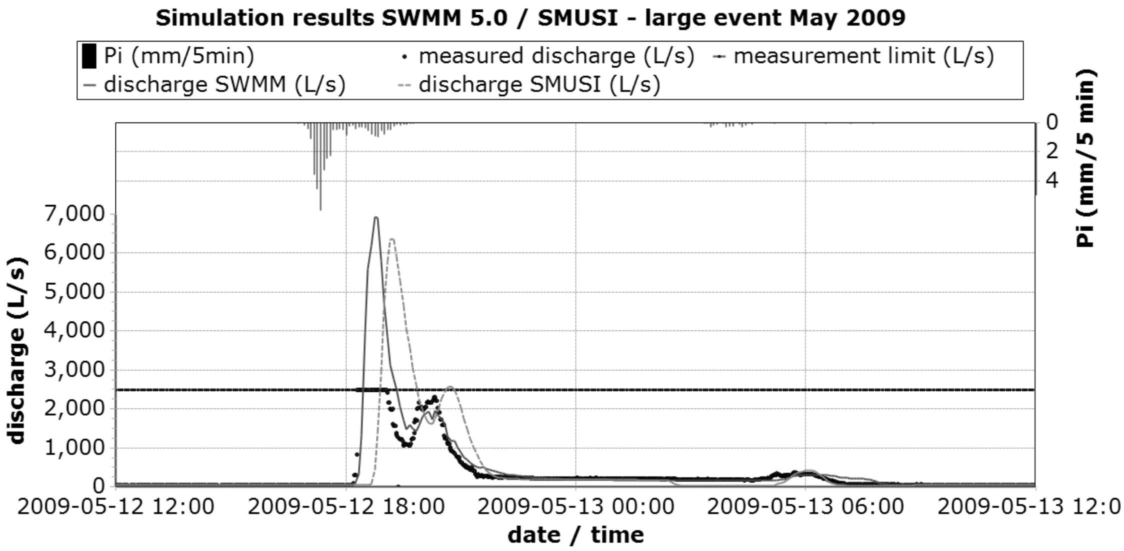

Figure 6-29: SWMM and SMUSI results for a large event in May 2009 (Gamerith et al., 2011, with permission from CHI Press)

Overall this first evaluation of the models shows that both models are able to reproduce different events quite similarly. Taking into account the computational costs of the models, the SMUSI model shows important advantages: Simulation of a one-year period takes several minutes with the SMUSI model but a couple of hours with the SWMM model (the effective computation time is dependent on the used hardware).

This is also one reason why the methods for global sensitivity analysis and automated model calibration described in the following were only applied to the SMUSI model. However, especially for the water quality simulation it would be of high interest to apply the developed methodology also on the SWMM model.

6.7 Global sensitivity analysis (SMUSI 2009 model)

Global sensitivity analysis (GSA) was performed using the SMUSI 2009 model. As methods, the evaluation of the Standardised Regression Coefficients (SRCs) and the screening method of Morris (both described in chapter 4.2.1) were used. Several aims were defined for the GSA in scope of this work for the case study Graz West R05:

- To identify the most important model parameters and rank them according to their impact on the model output (sensitivity) for the Graz West R05 SMUSI 2009 model for both the hydraulic model and two sewer water quality model approaches.
- To assess if the choice of different objectives and events effects the results from GSA.
- To identify combinations of objectives and/or events that lead to most information on the model parameters (i.e. which parameters are sensitive for which objective and/or which events).

- To assess and compare the applicability of the two methods in an urban drainage modelling context and to evaluate their limitations.
- To identify the major sources of uncertainty due to the model parameters by propagating uncertainties through the model with Monte Carlo simulations and subsequent evaluation of the SRCs.

The parameter ranking and the identification of objectives and events leading to most information on the model output should provide a sound basis for further model calibration.

In order to address these points, several runs for the different model approaches were performed. Objectives for annual statistical values and different quality criteria (objective functions) for several events were evaluated with both methods. The procedure is described in the following. First an overview of the evaluated objectives and the events chosen for GSA is given. Then the results for the hydraulic model and the water quality model approaches are presented and discussed. Based on the results, the applicability of the two GSA methods to this case study is discussed

6.7.1 Evaluated objectives and quality criteria

In order to address the questions i) if the choice of the objectives or quality criteria effects the output from the sensitivity analysis and ii) which objectives or combination of objectives can give most information on the model output, several objectives were evaluated for the hydraulic and sewer water quality models.

As discussed in chapter 4.2.1, both the Morris Screening and the evaluation of the SRCs need a scalar model output. This means that either i) statistical values as the total runoff volume, the number of overflows, etc. or ii) quality criteria measures (objective functions) from comparison of a measured and a simulated time series as e.g. the sum of squared errors, the Nash-Sutcliffe efficiency coefficient, etc. can be used for evaluation.

Table 6-8 and Table 6-9 give an overview of the evaluated model results for the hydraulic and sewer water quality models respectively. The objectives were classified in **annual values** and **values per event** as well as in **measurement independent** and **measurement dependent** values.

The *annual values* were evaluated from model output simulated with the 2009 rainfall time series. *Values per event* were evaluated for all events described in the next chapter. *Measurement independent* means that these values are calculated directly from the model output. No measured reference time series is needed for them to be calculated. *Measurement dependent,* on the other hand, describes values that are calculated from comparing the simulated time series (i.e. hydrographs or pollutographs) to a measured reference time series by calculating e.g. a goodness-of-fit measure.

Concerning the evaluation for hydraulics as given in Table 6-8, annual values were chosen that are typically used to describe the system behaviour of a combined sewer system and also used in current guidelines (as e.g. in the German *ATV Arbeitsblatt A128* (ATV, 1992) or the Austrian *ÖWAV Regelblatt 19* (OEWAV, 2007)). As measurement independent values per event the runoff and overflow volume as well as the peak flow were evaluated. For the measurement dependent values, all objective functions implemented in the BlueM.OPT framework as discussed in chapter 5.4.2 were calculated based on the simulated time series and the reference time series described in chapter 6.6.1.2.

Table 6-8: Objectives evaluated for GSA - hydraulics

Annual values (measurement independent)	
Total runoff volume	m³/year
Total overflow volume	m³/year
Number of Overflows	-/year
Overflow duration	min/year
E0 : overflow ratio as defined in the ATV A-128 guideline (ATV, 1992)	-
Values per event (measurement independent)	
Total runoff volume	m³/event
Total overflow volume	m³/event
Peak flow	m³/s
Values per event (measurement dependent)	
All objective functions implemented in BlueM.OPT	

The objectives evaluated for the water quality models are given in Table 6 9. As annual values, the total runoff load and the total overflow load were calculated. As measurement independent values per event, the peak concentration and the event mean concentration were chosen. The load per event was not considered, as this is not calculated natively by the SMUSI model without post-processing. As for hydraulics all objective functions implemented in BlueM.OPT were evaluated. Parameters for the hydraulic model were fixed based on a pre-calibration of the SMUSI 2009 model as presented in chapter 6.6.3

Table 6-9: Objectives evaluated for GSA – sewer water quality

Annual values (measurement independent)	
Total runoff load	kg/year
Total overflow load	kg/year
Values per event (measurement independent)	
Peak concentration	g/m³
Event mean concentration	g/m³
Values per event (measurement dependent)	
All objective functions implemented in BlueM.OPT	

6.7.2 Choice of events

In order to evaluate if the use of different storm events can affect the outcome of the GSA, several events were chosen for the evaluation of the *values per event*. The events were chosen from the 2009 measurement time series with the aim to cover a most broad spectrum of possible events. In addition the choice of the events was based on:

- Data availability for evaluation of the measurement dependent objectives: only events with complete data on both hydraulics and pollutant concentrations in the reference time series were chosen.
- Rainfall data: only events were rainfall data was recorded on both rain gauges KLUS and KAMO were chosen. Events with extreme spatio-temporal distributed rainfall identified from the visual data analysis were not taken into account.

- If several events showed similar characteristics in rainfall and flow, one single event was chosen from these for evaluation.

Table 6-10 gives an overview of the events meeting the criteria stated above. From these events the six events given in **bold** were chosen for GSA. For the event 2009-060 on July 07th only measurement independent values were evaluated, as the flow surpassed the measurement limit of 2.5 m³/s and evaluation of measurement dependent objectives would yield biased results.

Table 6-10: Events identified and chosen for sensitivity analysis

Event No	Date	Peak flow (approx.)	Start evaluation	End evaluation
#		L/s	yyyy-mm-dd hh:mm	yyyy-mm-dd hh:mm
002	**January 21st**	**500**	**2009-01-21 14:00**	**2009-01-22 03:00**
004	January 27th	700		
008	February 08th	1000		
013	**March 03rd**	**700**	**2009-03-06 04:30**	**2009-06-03 17:00**
015	March 29th	1200		
017	**April 04th**	**300**	**2009-04-19 20:30**	**2009-04-20 00:30**
018	April 23rd	500		
021	**April 29th**	**2200**	**2009-04-29 03:00**	**2009-04-29 18:00**
022	**April 29th**	**1300**	**2009-04-29 20:00**	**2009-04-30 10:00**
036	May 26th	600		
037	May 27th	1000		
047	June 24th	800		
048	June 24th	800		
060	**July 07th**	**> 2500****	**2009-07-07 15:00**	**2009-07-07 21:00**
065	July 15th	>>		
066	July 18th	>>		
101	November 08th	800		
106	Dezember 01st	300		
108	December 08th	1100		

** only measurement independent values evaluated

6.7.3 Settings for the GSA methods

Simulation period for the **SMUSI model** in GSA was the whole year 2009. The continuous simulation over this period allows taking into account the effects of rainfall history for both the hydraulic model (affecting the runoff from pervious areas calculated by the SCS method) and the accumulation and wash-off approaches, where the accumulation of pollutants happens during the dry periods and the wash off during storm weather conditions.

All model parameters were assumed as uniformly distributed within the parameter ranges discussed in chapter 5.3.1.5. It is important to note that the results presented in the following are only valid for this chosen parameter distribution. As exemplarily shown in this chapter, changes in the parameter limits can have significant effects on the outputs from the GSA.

For **evaluation of the SRCs,** a Monte Carlo simulation with 500 runs as proposed in a study for a waste water treatment plan model by Sin et al. (2010) with plain random sampling was used.

For the **Morris screening**, a prior evaluation of the parameterisation for the number of *r* repetitions (or trajectories), *p* levels and the grid jump (see chapter 4.2.1.2 for more information) was done. In his original publication, Morris (1991) proposed to use a setting with *r*=4, *p*=4 and a grid jump of *p*/2. Recommended values in Saltelli et al. (2004) increase the number of repetitions to *r*=10.

A first evaluation carried out in this work for the case study SMUSI 2009 model showed that the use of 4 levels was insufficient especially for the water quality model. There the parameter range is not covered satisfactorily when using 4 levels. Therefore, for the results presented in the following, a setting with *r*=20, *p*=8 and a grid jump of 4 was chosen. The increase in the repetitions allows covering the variation of the parameters when using 8 levels.

6.7.4 Non-linearity in SRC and Morris screening

As stated in chapter 4.2.1.1, a low R^2 value from a multivariate linear regression shows that assumption of linearity in evaluation of the SRCs is no longer valid. Figure 6-30 and Figure 6-31 show scatter plots of the parameter values against two objectives evaluated for the hydraulic model from the 500 Monte Carlo simulation runs.

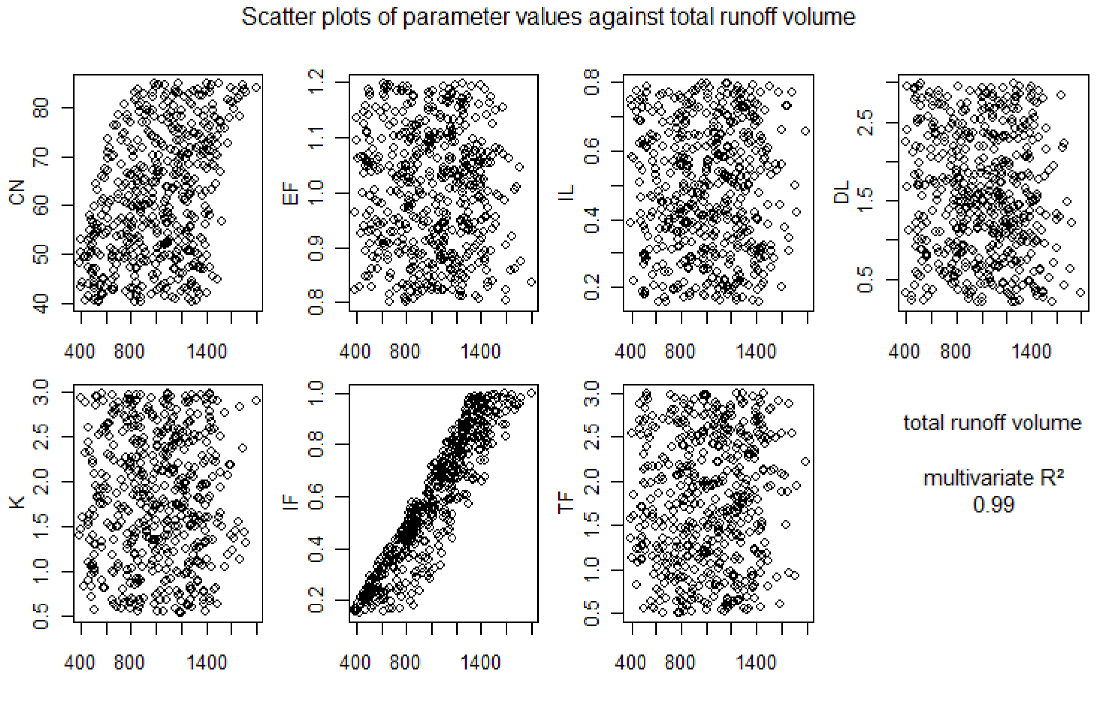

Figure 6-30: Scatter plots of parameter values against total runoff volume from 500 Monte Carlo simulations

In Figure 6-30 the evaluated objective is the total annual runoff volume. The scatter plots show that the imperviousness factor *IF* has close to linear impact on the total annual runoff volume. The curve number (*CN*) value can be interpreted as slightly less linear, having some impact in its variation range. No functional behavior can be identified for the other parameters evaporation factor (*EF*), initial losses (*IL*), depression losses (*DL*), pipe roughness (K) and concentration time factor (*TF*). The multivariate R^2 is high with a value of 0.99.

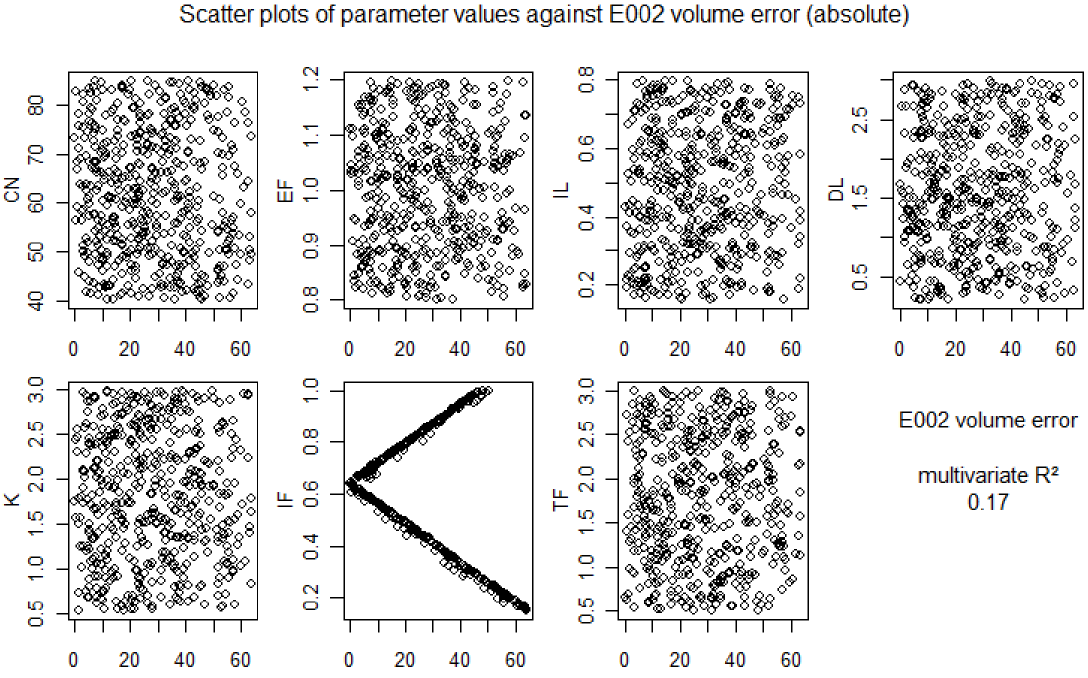

Figure 6-31: Scatter plots of parameter values against absolute volume error (event E002) from 500 Monte Carlo simulations

In Figure 6-31 the evaluated objective is the volume error (absolute value) calculated for event E002 from simulated and measured time series. A minimum of the volume error is reached for an *IF* value close to 0.6, for higher and lower *IF* values the absolute volume error increases. It is obvious that the effect of *IF* on the volume error cannot be described by a linear model. This is expressed in a low R^2 value of 0.17. The evaluation of SRC is not valid as sensitivity measure in that case. No functional behaviour for the other parameters can be identified.

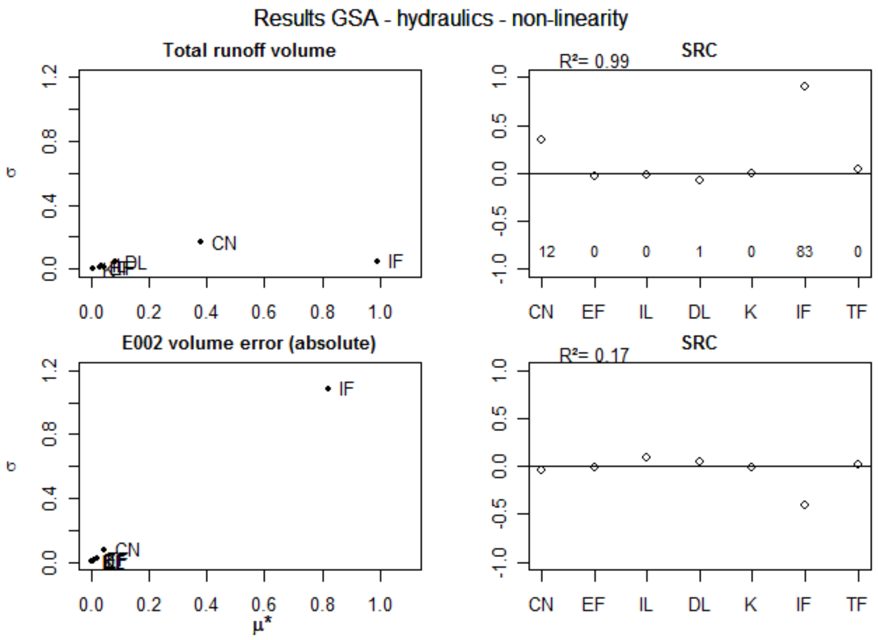

Figure 6-32: GSA results hydraulics – effect of non-linearity

An evaluation of the two objectives with Morris screening and SRCs is shown in Figure 6-32. Many of the figures presented in the following are designed in the same scheme: on the left hand side of the plot the results of the Morris Screening are shown, on the right hand side the results for SRCs evaluation. Each left-right pair corresponds to one evaluated objective. The Morris screening plots on the left hand side show: i) the evaluated objective and ii) the standard deviation σ and mean μ^* of the elementary effects on the *y* and *x*-axis respectively. The SRC plots on the right hand side show: i) the standardised regression coefficient value and the parameter name on the *y* and *x*-axis respectively, ii) the R^2 calculated from multivariate linear regression in the top left corner of the plot and iii) the squared SRCs multiplied by 100 just above the *x*-axis, provided R^2 is higher than 0.7. The scales in the Morris screening result plots can vary for better legibility.

In Figure 6-32 both methods yield similar results for the total annual runoff volume. The Morris screening indicates high linearity and a strong effect of IF and higher non-linearity or interaction for the *CN* value. The SRCs also identify *IF* as the most influential parameter, followed by the *CN* value. As approximate linearity holds (R^2 of 0.99), the squared SRCs can be interpreted as follows: approximately 80% of the output variance are due to the variation of *IF*, about 10% due to the *CN* value.

For the volume error, the high σ value for *IF* indicates high non-linearity or interactions. Compared to *IF* all other factors are negligible. For SRCs the low R^2 also indicates non linearity. The parameter ranking is different from the Morris screening results. Hence, the expected behavior identified from the scatter plots is indicated by the Morris screening method in both cases and for the SRC evaluation when R^2 is high.

6.7.5 GSA results - measurement independent objectives for the hydraulic model

In this chapter selected results from GSA of the hydraulic model with evaluation of measurement independent objectives are discussed that yield especially interesting information in interpretation. Additional results are presented in appendix 9.2.

Figure 6-33 shows the results for the annual values total overflow volume and number of overflows. The Morris screening results in Figure 6-33 for total annual overflow volume show that the imperviousness factor *IF* has the highest influence on the results, followed by the *CN* value and possibly the depression losses. All other parameters are grouped close to 0. The higher σ value for the *CN* value indicates either higher non-linearity or interaction effects of this parameter.

The results for SRC evaluation show the same parameter ranking as identified by the Morris screening. The multivariate linear regression results in a high coefficient of determination R^2 with a value of 0.98, indicating that the assumption of linearity holds for this case. As the R^2 is close to 1, the squared SRCs can be interpreted as approximate percentage of the parameters influence on the result: about 80% of the variations in total annual runoff volume result from variation of the imperviousness factor. More than 15% can be apportioned to the effect of the *CN* value. All other parameters can be considered as non-influential.

Concerning the number of overflows, the Morris screening identifies *IF* as most influential, followed by *DL* and the surface concentration time factor *TF*, both with significantly lower μ^* values. As above the same ranking can be identified by the SRC method where again a high R^2 is reached.

Interpretation in sense of model application of these results can be the following: The total annual runoff is mainly influenced by the imperviousness and to a certain degree by the proportion of pervious areas contribution during large storm events. The number of overflows, on the other hand is not influenced by the pervious areas at all. This allows the interpretation that all events where the pervious areas contribute to the runoff already lead to an overview regardless of these areas contribution.

This has consequences for model calibration: any parameter with low sensitivity for an objective cannot be identified in calibration of the model for this objective as any value within the parameter distribution would satisfy the calibration. For example the *CN* value could be set to any value within its defined ranged without influencing the number of overflows. The same is valid for initial losses *IL*, pipe roughness *K* and evaporation factor *EF* for both presented objectives.

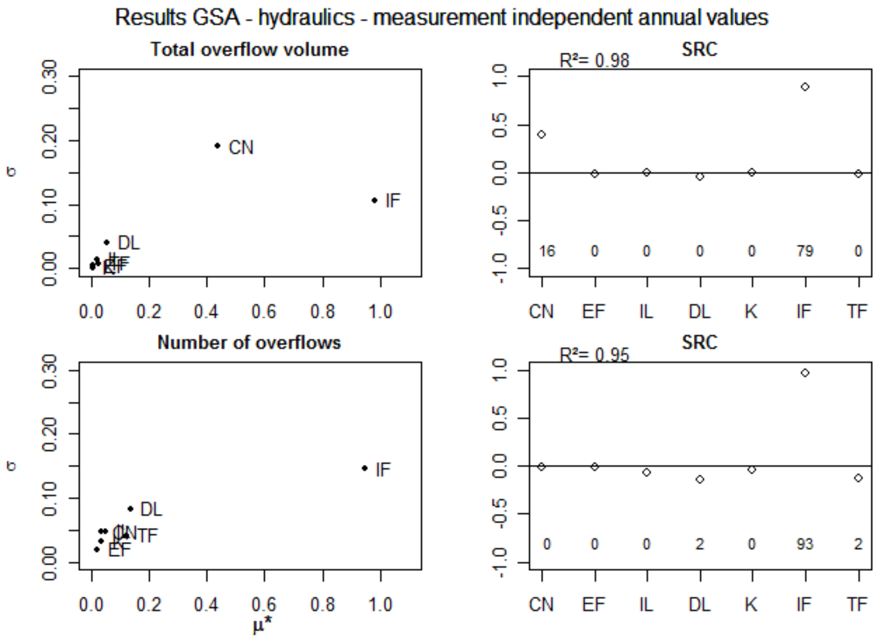

Figure 6-33: GSA results (Morris screening on the left, SRCs on the right hand side) for hydraulic model: annual values total overflow volume and number of overflows.

Figure 6-34 and Figure 6-35 show some results for the measurement independent objectives evaluated per event. In Figure 6-34 GSA results of peak flow sensitivity for a small (E017) and a large event (E060) are shown. It can be seen that in both cases *IF* is the most sensitive parameter. For the small event E017, also the depression losses have an important impact. Infiltration losses *IL* contribute to some amount. For peak flow sensitivity of the large event mainly *IF* and *CN* contribute to the output variance. Here the concentration time factor *TF* contributes to some amount. As above, high R^2 coefficients are reached for the SRC evaluation and the importance ranking of the two methods is similar. For model calibration on peak flow this implies that *DL* is better identifiable when using E017 and *CN* when using E060. In multi-event calibration (discussed in chapter 6.8 of this thesis) it is therefore appropriate to use several events for which the sensitive parameters differ in order to best exploit the measurement data.

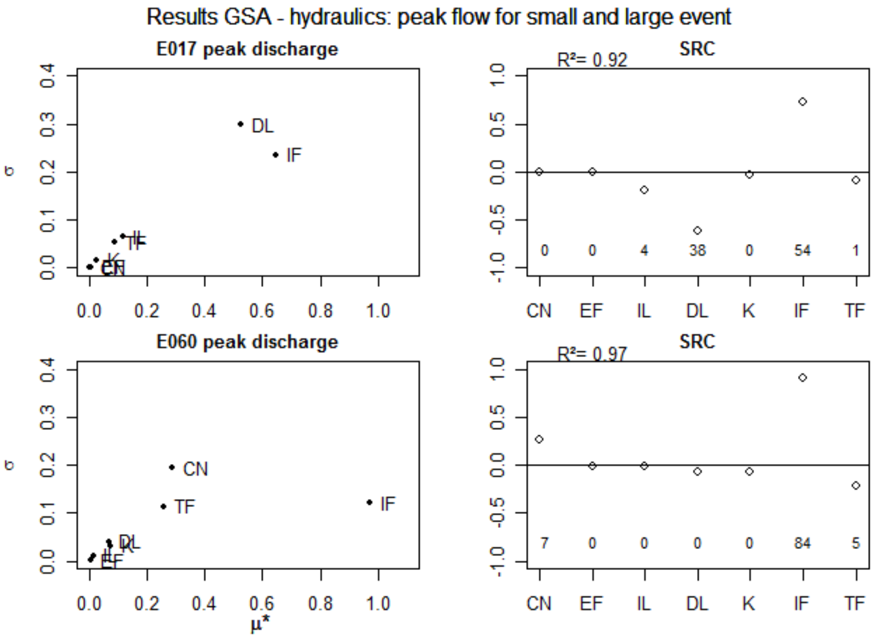

Figure 6-34: GSA results for hydraulic model: using different events – comparison of peak discharge sensitivity for a small event (E017) and a large event (E060)

This is also valid for the results presented in Figure 6-35. In this figure, the impact of using a continuous simulation can be seen based on the overflow volume of two consecutive events (E021 and E022). *CN* becomes more sensitive for the event E022 as pervious areas are already saturated by the pre-rainfall from event E021. Again, this knowledge can be used in model calibration.

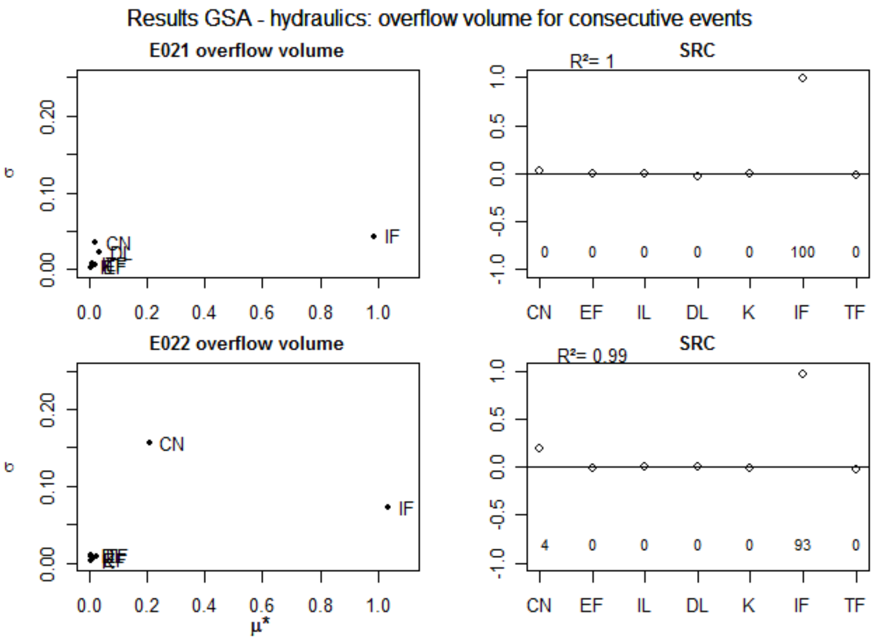

Figure 6-35: GSA results for hydraulic model: using different events – comparison of overflow volume sensitivity consecutive events to evaluate the impact of continuous simulation

While some interpretations given above are generally known in urban drainage modelling, it is shown that both GSA methods give sound results for the hydraulic model. It can be assessed that the model functions as expected. Furthermore the results allow identifying objectives and/or a set of events that yield most information in model calibration.

6.7.5.1 Impact of parameter range

As stated above, the results are only valid for the defined parameter ranges and distributions.

In order to highlight this, additional runs were carried out for the hydraulic model, reducing the range of the imperviousness factor from 0.15 to 1 to 0.6 to 1. The value of 0.6 was again based on Illgen (2009), not taking into account partly pervious surfaces. Figure 6-36 shows the results for the evaluation of the total overflow volume and the number of overflows when using these adapted limits for *IF*. While the same parameter ranking as in Figure 6-33 is obtained, especially for the number of overflow other parameters – namely *DL* and *TF* – gain significantly in importance. This behaviour is also valid for the other results discussed above. The choice of parameter limits is therefore crucial in order to obtain meaningful results.

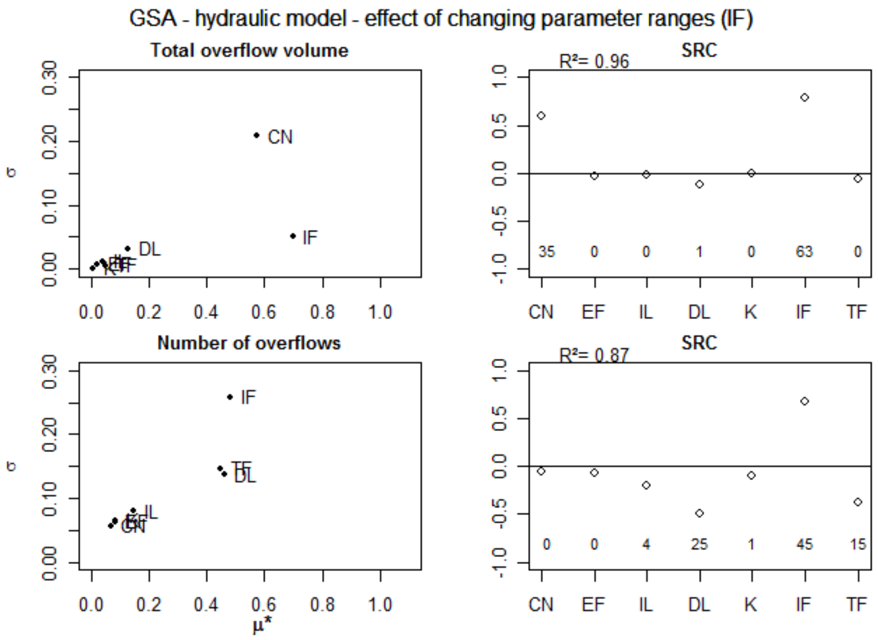

Figure 6-36: GSA results for hydraulic model: impact of changing parameter ranges (IF)

6.7.6 GSA results – measurement independent values for sewer water quality models

Sensitivity analysis for the sewer water quality model was performed for two sets of model parameters of the accumulation and wash-off approach described in 5.3.1.2: First for the basic accumulation and wash-off approach (AWO1) using the model described by Equation 5-5 and secondly for the wash-off approach (AWO2) described by Equation 5-6 including two additional parameters, namely the shape factor *W* and the limit rainfall intensity *iLim*.

Figure 6-37 shows the results from GSA for the AWO1 model for the annual values total runoff COD load and overflow COD load. As for hydraulics, both methods lead to the same parameter ranking. The maximum accumulated pollutant mass *Pmax* is ranked higher than the accumulation-removal coefficient *DISP* and the wash-off coefficient *Ke*. These three parameters show high non-linearity or interaction effect. This has also been discussed e.g. in Mourad (2005) who shows that these parameters are strongly correlated. The initial accumulated mass *Pinit* does not affect the results. This can be explained by the continuous simulation and will not hold for single-event simulation.

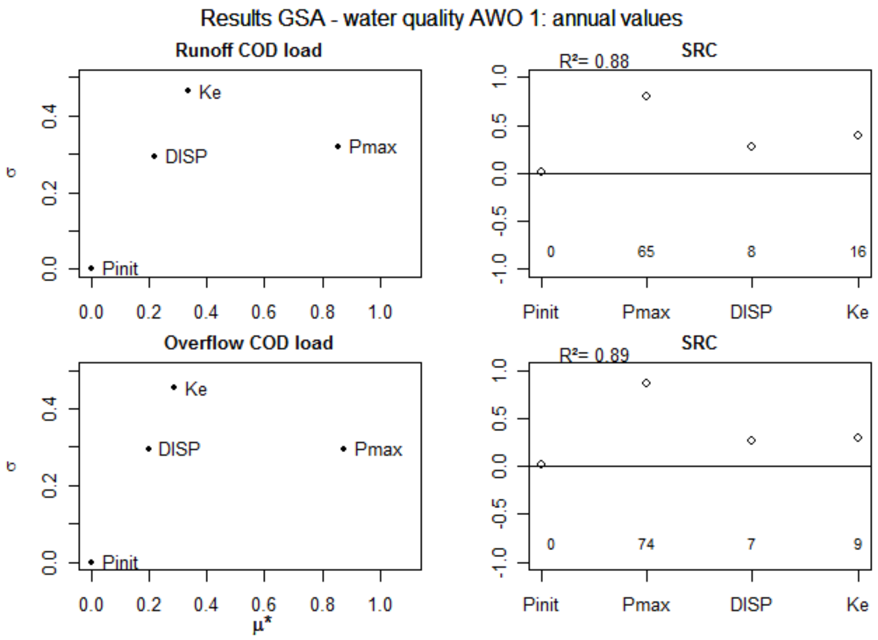

Figure 6-37: GSA results for sewer water quality model (AWO1): annual values

Appendix 9.3 shows the complete results for the evaluation of all objectives. In general the parameter ranking does not vary with the evaluated event or objective. This also implies that no identification of the objectives to use in optimisation or model calibration can be deduced.

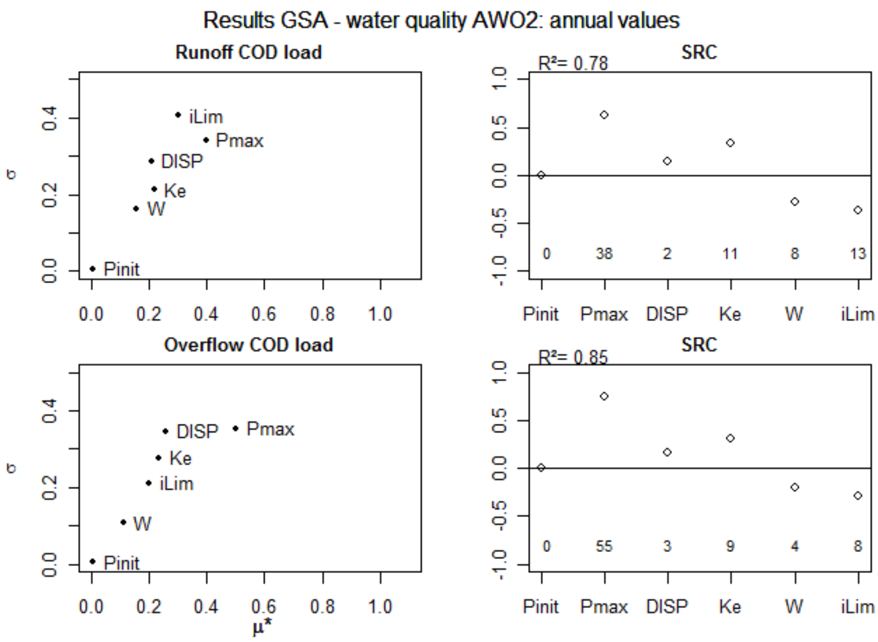

Figure 6-38: GSA results for sewer water quality model (AWO2): annual values

Figure 6-38 shows the results for the AWO2 model for the annual values total runoff COD load and overflow COD load. *Pmax* is identified as most influential parameter, for the other parameters however, ranking is different for the Morris screening and the evaluation of SRCs, even though a high R^2 is determined from the multivariate linear regression. All parameters except *Pinit* show interaction and/or non-linearity. Appendix 9.3 gives an overview of the evaluated measurement independent values. There it is shown that ranking also differs between the two methods. In general *Pmax* is identified as most influential by the SRC evaluation. For the Morris screening, the limit rainfall intensity *iLim* is the dominating parameter in some cases.

Figure 6-39 shows scatter plots for the parameter values against the annual runoff COD load from the 500 Monte Carlo simulations. It can be seen that only a very small number of parameter combinations lead to high runoff loads (i.e. parameter sets where *iLim* is small and *Pmax* is high). This allows the assumption that the parameter space cannot be sufficiently covered by the methods and that these parameter combinations lead to the difference in results from SRC and Morris screening. From the behaviour shown in Figure 6-39 it can be safely assumed that a linear regression will be successful for *Pmax,* identifying the major influence of this parameter. On the other hand, the few high values derived from low *iLim* will not impact significantly on a linear regression. Hence, the effect of this parameter will not be identified by the SRCs. With the Morris screening, apparently, it can be identified.

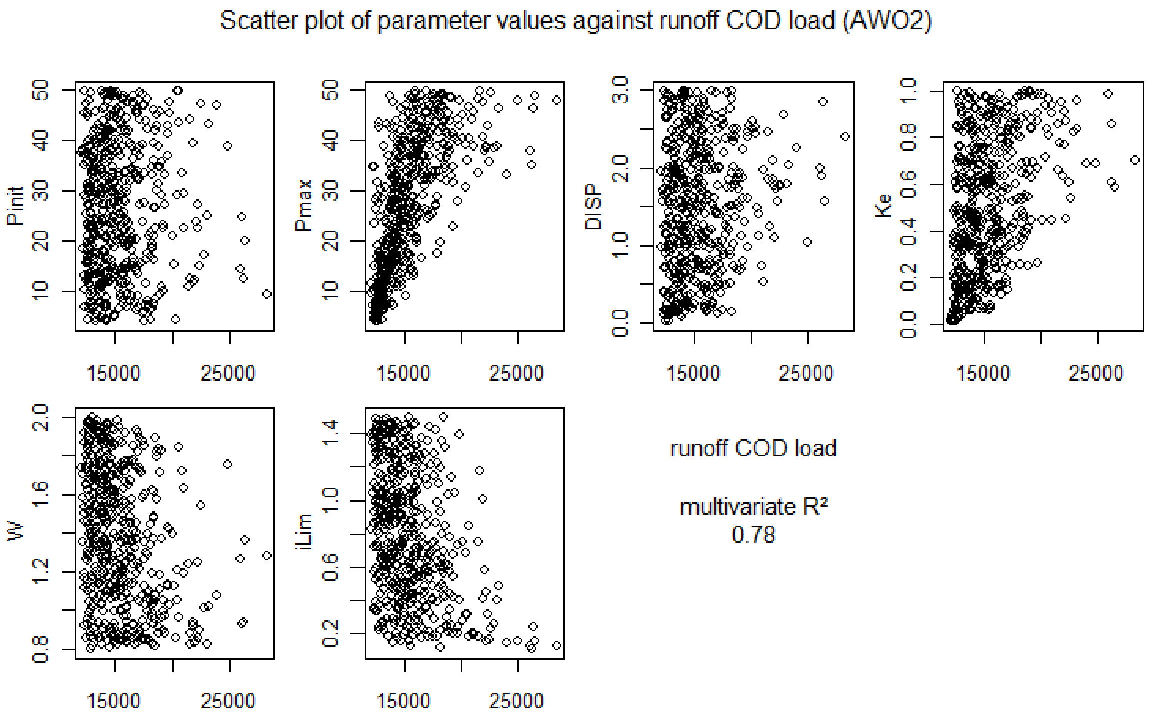

Figure 6-39: Scatter plots of parameter values against annual runoff COD load from 500 Monte Carlo simulations

Overall no clear statements can be deduced from the obtained results for the choice of events or objective function combinations to best be used in calibration of this model.

6.7.7 GSA results - impact of objective functions (measurement dependent values)

As stated above, sensitivity was also evaluated for all objective functions implemented in the BlueM.OPT framework for the hydraulic model and the sewer water quality models. The plots of the results obtained for all objective functions are given in appendix 9.2 for hydraulics and appendix 9.3 for the sewer water quality models exemplarily for one event.

The main interest of this was to evaluate if groups of objective functions can be identified that are sensitive to the same parameters. As for the event-based evaluation this would allow to define a set of objectives functions (from different identified groups) that should be evaluated in order to obtain the maximum of information about the parameters e.g. in automated model calibration. In a first step the obtained results were analysed visually to assess the major outcomes. Results from the AWO2 model were not evaluated as the results from both methods (SRCs and Morris screening) differed significantly. The following major findings can be stated for the GSA methods:

- A visual evaluation of all obtained results showed that similar ranking is obtained with both methods when R^2 is high for the hydraulic and the AWO1 model. In general the same parameter ranking is obtained for R^2 values of 0.6 and higher. R^2 of in the range of approximately 0.3 to 0.6 lead to the same parameters identified as influential but different rankings are obtained. With low $R^2 < 0.3$ no identification is possible with SRC evaluation. Non-linearity shown in low R^2 generally leads to high σ values in Morris screening.
- SRCs are not applicable (or only to a limited extent) with power functions or absolute values where non-linearity results from the objective function.
- The Morris screening proved robust for ranking the parameters as non-linearity or interactions between parameters can be identified and do not impact significantly on the ranking.

6.7.7.1 Proposed methodology for identifying informative objective functions

In scope of the analysis a first methodology was proposed for grouping the objective functions in order to determine a set of objective functions that would yield the maximum of information in a parameter estimation or model calibration.

Based on the results from the Morris Screening a grouping indicator is determined for each evaluated objective that indicates i) influential and non-influential parameters based on a user-defined threshold value for μ^* and ii) the ranking of the parameters identified as influential. The grouping indicator is then composed as a string of one ID per parameter as shown for an example in Table 6-11 (volume error for event E013): The k parameters are ranked from 1 to k in order of importance (highest to lowest μ^*). If the parameter is not influential (μ^* lower than the defined threshold value) the rank is set to 0. Then the indicator is composed by simply forming a string from the ranking vector.

Table 6-11: Exemplary determination of grouping indicator from Morris Screening results (Volume error event E013)

parameter	CN	EF	IL	DL	K	IF	TF	
ranking based on μ^*	**2**	3	6	7	5	**1**	4	
influential? (μ^* > threshold of 0.1)	**yes**	no	no	no	no	**yes**	no	
Indicator: number corresponding to rank, 0 when not influential	**2**	0	0	0	0	**1**	0	**= “2000010”**

Groups can then be defined for objectives with identical grouping indicators. Objectives within the same group yield information on the same parameter combination. It can be assumed that only limited additional information (for the same investigated value) will be obtained by using several objective functions within the same group in model calibration. An evaluation of all results from GSA for the hydraulic model identified 21 groups. Table 6-12 shows grouping results for all objective functions evaluated for event E013 for the hydraulic model. In total, 6 groups are identified. From this evaluation it can be interpreted that the proposed grouping alone is not sufficient for reasonable choice of the objective function: e.g. the volume error (PBIAS) and the peak difference (PDIFF) are classified in the same group but target different behaviours in the hydrograph. While both are influenced by the same parameters the optimum parameter values do not necessarily correspond. Currently a master thesis is prepared on this topic at the Institute.

Table 6-12: Grouping results for 34 objective functions evaluated for Event E013

Indicator	#	Objective functions names
0000010	3	Mean error (ME) Percentage Bias (PBIAS) Relative volume error (RVE)
0000012	8	Mean square derivate error (MSDE) Mean percentage error(MPE), Mean relative error (MRE) Mean absolute relative error (MARE), Mean square relative error (MSRE) Mean absolute percentage error (MAPE) Median absolute percentage error (MDAPE) Number of sign changes (NSC)
2000010	7	Volume error (Volf) Total mass balance Controller(TMC) Balance Criteria(CRBAL) Peak difference (PDIFF) Percentage error in peak (PEP) Index of agreement (IA) Mean square sorted errors (MSSE)
2000013	4	Mean squared error (MSE) Theil's coefficient (U2) Coefficient of efficiencs (Nash-Suttcliffe - CE12) Coefficient of persistence (PI)
2000031	1	Coefficient of determination (R2)0
3000012	11	Mean absolute error (MAE) Mean square logarithmic error (MSLE) Absolute maximum error (AME) Absolute relative volume error (MAER) Root mean squared error (RMSE) Fourth root mean quadrupled error (R4MS4E) Coefficient of efficiency, square root (CE122) Coefficient of efficiency, logarithmic (CELN2) Relative absolute error (RAE) RMSE standard deviation (RSR) Inertia root mean squared error (IRMSE)

6.7.8 Summary – global sensitivity analysis

To summarise the global sensitivity analysis carried out for the *Graz Sewer R05* SMUSI 2009 model, the following major findings can be stated:

The evaluation of the results from GSA showed that in general both applied methods – the Morris screening and the evaluation of the SRCs – identified the same parameters as influential and led to the same parameter ranking for the hydraulic and the AWO1 model provided approximate linearity held for SRCs. For the AWO2 model the methods yielded different results for the parameter ranking. Concerning the two methods the following findings can be stated:

- The **Morris screening** proved more robust for ranking the parameters as non-linearity and interactions between parameters do not impact significantly on the ranking.
- However, **SRCs** are a valuable measure, especially as the effect on the variance can be quantified if approximate linearity holds. In this case the squared SRCs – corresponding to the variance in the result introduced by variation of the parameter – can be interpreted as a measure for uncertainty introduced to the model by the parameters for the objective in question.

A direct comparison of the results from both methods led to identification of some limits for the case study:

- The settings proposed in Morris (1991) and Saltelli et al. (2004) for the Morris screening proved to be insufficient for a detailed evaluation especially due to the small number of levels. For a preliminary screening or narrower parameter ranges, however, they might be applicable. Based on the case study results, a setting with r=20, p=8 and a *grid jump*=4 can be recommended.
- Parameters with $\mu^* < 0.1$ in the Morris screening were generally identified as non-influential by the SRC method for the case study.
- It was shown that generally for $R^2 > 0.6$ the same parameters were identified as influential and similar ranking was obtained for the case study model.

It was confirmed that the chosen parameter range has an important impact on the results from GSA. Therefore the obtained results are only valid for the defined parameter ranges and distributions and the investigated model. This implies that using a different model requires a new analysis.

It was demonstrated how the use of different objectives or different rainfall events for assessing model sensitivity changes the importance and ranking of the parameters for both the flow and water quality model. This information is highly useful e.g. when choosing events and objectives for model calibration in order to best exploit the available information. It should also be considered when applying more sophisticated uncertainty analysis methods in order to estimate what can be identified with a chosen combination of model, event (time series) and objective function.

Concerning the GSA results for the water quality models, parameter ranking for the AWO1 model was not influenced by either the event or the objective function used in evaluation. For the AWO2 model, different rankings were obtained with the two methods. It is assumed that this is due to a small number of parameter sets that have significant impact on the model output where the parameter space is not covered satisfactorily.

A first method was proposed to use information from GSA in order to identify groups of objective functions that yield similar information. This method, however, still suffers from important drawbacks as the classification of objective functions as discussed e.g. in Hauduc (2010) is not yet considered. This surely is a field of interesting further research.

Overall it could be shown that these methods are an appropriate tool for analysing the case study catchment model. They provided valuable insights on both the hydraulic and the water quality models. In addition assumptions on the parameter distributions can be validated and GSA yields important information for further model calibration

6.8 Single- and multi objective optimisation in model calibration and validation (SMUSI 2003 model)[7]

In this chapter the application of the BlueM.OPT framework for model calibration and validation of the SMUSI model is described. Several publications that are linked directly to this work were issued on this topic, namely Muschalla et al. (2008), Gamerith et al. (2009) and Gamerith et al. (accepted). For this part of the work, data from 2003 and the SMUSI 2003 model were used.

The major aims in scope of this thesis were:

- To propose a sound calibration procedure for automated model calibration.
- To identify which sewer water quality model approach is best adapted for the case study catchment.
- To compare and assess the performance of single- and multi event optimisation for both the hydraulic and the sewer water quality model.

This chapter is organised as follows: first the choice of events and the choice of the objective functions for the 2003 model calibration are discussed. Next the calibration procedure used in this work is described. Some results for the dry weather calibration are given.

Then the results from the comparison of three sewer water quality model approaches are discussed. Based on the model approach identified as best performing, finally a comparison of single- and multi event auto-calibration is discussed.

6.8.1 Choice of calibration and validation periods/events

As discussed above, due to the expansion of the sewer network between 2004 and 2006, for the SMUSI 2003 model only a period of half a year with i) complete, continuous data on rainfall, flow and pollutant concentrations and ii) a known sewer network structure was available for modelling purposes.

Events for calibration and validation were chosen based on an evaluation of the available measurement data within the period 2003-07-01 to 2003-12-31. In this period, in total 28

[7] This chapter is compiled from Gamerith et al. (2009, with permission from IWA Publishing) and Gamerith et al. (accepted, with permission from ASCE)

events were identified. Within these i) two events surpassed the measurement limit of the flow meter ii) three events were subject to measurement gaps in either flow or pollution concentrations and iii) seven events were considered not significant based on the flow measurements (with maximum flow rates only slightly higher than the dry weather flow peak). Four events showed very similar characteristics. From these four only one was chosen for calibration/validation. Hence, in total, 13 events were used for model calibration and validation.

Table 6-13: Rainfall events and characteristics used in calibration (bold) and validation of the SMUSI 2003 model (Gamerith et al., accepted, with permission from ASCE)

Event/ Period	Start	End	Duration	precipitation sum	max. precipitation intensity	peak discharge
-	-	-	min	mm	mm/min	m^3/s
I	**2003-07-22 23:45**	**2003-07-23 01:55**	**130**	**16.9**	**4.0**	**2.73**
	2003-07-23 14:40	**2003-07-23 17:20**	**160**	**15.9**	**1.3**	**1.05**
III	2003-07-24 22:15	2003-07-25 06:35	500	7.0	1.0	1.01
IV	2003-07-28 17:45	2003-07-29 00:05	380	18.2	1.7	1.63
II	**2003-10-04 22:50**	**2003-10-05 10:05**	**675**	**21.1**	**0.6**	**2.16**
A	**2003-10-22 01:30**	**2003-10-22 09:30**	**480**	**3.6**	**0.2**	**0.15**
	2003-10-23 15:05	**2003-10-24 05:40**	**875**	**15.9**	**0.4**	**0.30**
D	2003-11-01 18:50	2003-11-02 11:45	1015	13.3	0.6	0.76
C	2003-11-26 09:00	2003-11-26 21:35	755	11.1	0.9	0.62
E	2003-11-28 10:10	2003-11-28 20:00	590	10.3	0.4	0.77
	2003-11-29 11:30	2003-11-29 18:20	410	6.0	0.3	0.28
B	**2003-12-29 09:35**	**2003-12-29 23:15**	**820**	**4.8**	**0.2**	**0.16**
	2003-12-30 03:30	**2003-12-31 21:20**	**2510**	**22.3**	**0.2**	**0.31**

An overview of the chosen events is given in Table 6-13. Eight of the events were grouped in couples in four periods (I, A, B, E). Events were classified as small, medium (A to E) and large events (I to IV) based on the peak discharge measured at the inflow of the CSO as discussed in chapter 6.6.3. The events given in **bold** (I, II and A, B) were used as calibration events (selected arbitrarily), the others for validation. For the comparison of the water quality models, events A and B were used in calibration.

6.8.2 Choice of the objective functions

As objective functions, the Nash-Sutcliffe efficiency coefficient E described in Equation 6-1 (chapter 6.6.3) and the absolute volume error (Equation 6-2) were chosen. Concerning the Nash-Sutcliffe efficiency coefficient, in the following the notation E_Q is used when addressing discharge and E_C when addressing COD concentrations. In that case the measured discharge Q_O is replaced by the measured COD concentration C_O and the simulated discharge Q_m is replaced by the simulated COD concentration C_m.

$$Volume\ Error = 100 * \frac{\sum_{t=1}^{T} |(Q_o^t - Q_m^t)| \cdot \Delta t}{\sum_{t=1}^{T} Q_o^t \cdot \Delta t}$$ **Equation 6-2**

With: Q_o … observed/measured discharge ($L^3\ T^{-1}$), Q_m … simulated discharge ($L^3\ T^{-1}$) and Δt … time step (T)

The choice was based on the interpretability and comparability of both values. Both objectives are often used in urban drainage and watershed modeling. Future runs could profit from combinations of objective functions identified by a GSA that yield most information on the model results.

6.8.3 Step-by step calibration and validation procedure

The model calibration is based on the high resolution measurement data of precipitation, discharge and COD_{eq} concentrations. All the data was thoroughly checked for errors beforehand to avoid using erroneous data in the calibration process. The calibration and validation procedure itself was subdivided into five steps.

1. Calibration of dry weather flow
   a. for discharge and
   b. COD_{eq} concentrations.
2. Wet weather discharge calibration
   a. for small and medium rainfall
   b. for large rainfall events using the best performing parameter set for small and medium events as the starting point.
3. Validation of wet weather discharge calibration with independent rainfall periods for both small/medium and large event calibration.
4. COD_{eq} calibration in wet weather conditions. The best performing parameter set for wet weather discharge calibration was used for runoff simulation.
5. Validation of wet weather COD_{eq} calibration with independent rainfall periods.

6.8.4 Single and multi-event optimisation in model calibration and validation

Single-event (SE) and multi-event (ME) optimisation was carried out for comparison of the implemented sewer water quality approaches and in order to assess the performance of these optimisation methods.

Based on the calibration procedure described above, Table 6-14 gives an overview of all the model parameters used in calibration, the type of optimisation (SE or ME) and the calibration period (according to Table 6-13).

Table 6-14: Calibration procedure for comparing single- and multi-event optimisation: calibration parameters, type and period (Gamerith et al., accepted,modified, with permission from ASCE)

Dry weather conditions			
calibration step	**calibration parameters**	**type**	**calibration period**
1-a. dry weather flow	daily production (l/(cap.d)) daily pattern (hourly distribution)	-	6 independent dry weather periods averaged after calibration
1-b. dry weather COD_{eq} concentrations	mean concentration (mg/l) daily pattern (hourly distribution)	-	
Wet weather conditions			
calibration step	**calibration parameters**	**type**	**calibration period**
2-a. discharge for small and medium rainfall events	runoff concentration time factor *TF* (min) imperviousness factor *IF** (-) evaporation factor *EF* (mm/a) initial losses *IL* (mm) depression losses *DL* (mm)	SE	A and B separately
		ME	A and B (weighted and Pareto optimization)
2-b. discharge for large rainfall events	SCS- curve number *CN**	SE	I and II separately
		ME	I and II (weighted and Pareto optimization)
4. wet weather COD_{eq} concentrations	initial mass *Pinit** (kg/ha) maximum accumulated mass *Pmax** (kg/ha) accumulation coefficient *DISP** (1/d) wash off coefficient Ke* (1/mm) shape factor *W**[1] (-) limit rainfall intensity *iLim**[1] (mm/min)	SE	A and B separately
		ME	A and B (weighted and Pareto optimization)

As described in 6.6.1, the 44 modelled subcatchments were grouped in 5 groups based on similar slopes and land use for calibration proposes. All the model parameters marked with an asterisk were applied to subcatchments groups. The other parameters are global model parameters. [1]The shape factor *W* and the limit rainfall intensity *iLim* were only used for the comparison of the sewer water quality model approaches with ME Pareto optimisation.

The following optimization strategies were applied in steps 2, 3 and 4:

- SE optimisation: The Nash Sutcliffe efficiency coefficient is minimised for one single event. This results in one optimum parameter set.
- ME - weighted objective optimisation: The Nash Sutcliffe efficiency coefficient is calculated for each event and averaged over the calibration events. The averaged Nash Sutcliffe efficiency coefficient is minimised. This results in one optimum parameter set.
- ME - Pareto optimum optimisation: The Nash Sutcliffe efficiency coefficient is calculated and minimised for each event as an independent objective. This results in a set of Pareto optimal solutions (see section 4.3.4.1).

Validation (steps 3 and 5 in the proposed calibration procedure) were carried out with the chosen events not used in calibration.

6.8.4.1 Results for dry weather calibration

Dry weather flow was calibrated first for discharge and then for COD_{eq}. As the daily flow and pollution concentration patterns vary by season, a separate calibration was carried out for several dry weather periods. The obtained optimised flow patterns and daily production (L/cap·day) for discharge as well as the COD_{eq} patterns and mean COD_{eq} concentrations were then averaged from the results for the evaluated periods. An overview of the results for the individual periods is given in appendix 10. The Nash-Sutcliffe efficiency was used as single objective for both discharge and COD_{eq} calibration.

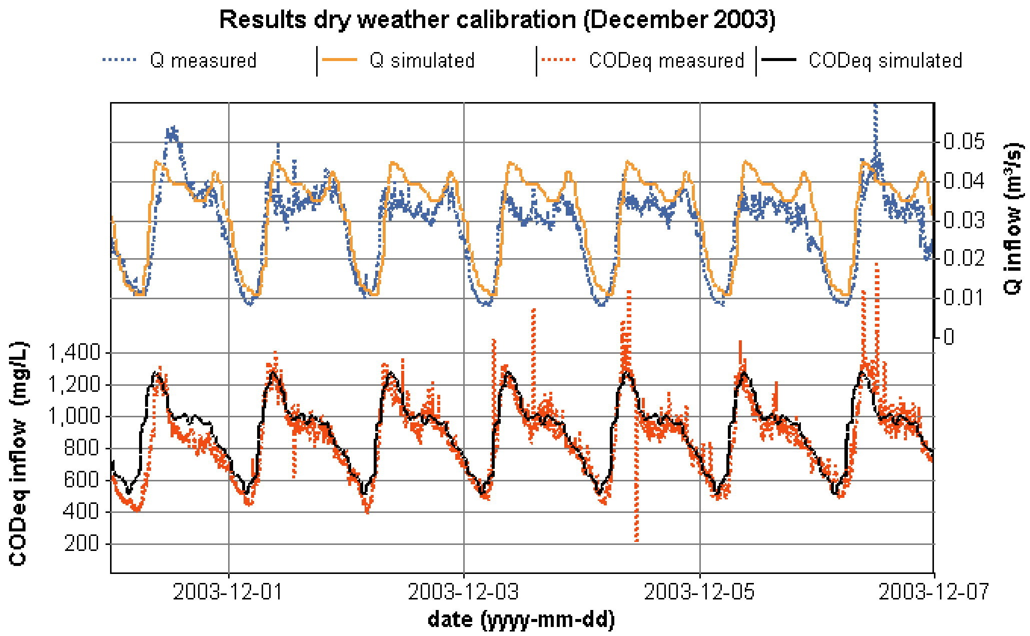

Figure 6-40: SMUSI 2003 results for dry weather calibration for Q inflow and COD_{eq} (Gamerith et al., accepted, with permission from ASCE)

Figure 6-40 exemplarily shows the calibration results for a one-week dry weather period in December 2003. Similar good results were obtained for the other dry periods. The dry weather pattern for discharge as well as COD concentration proved to be stable over the examined period with some seasonal fluctuations. These fluctuations as well as the impact of weekends on the daily patterns were not treated separately in the SMUSI model.

6.8.4.2 Results for discharge calibration in wet weather conditions

The discharge in wet weather conditions was calibrated with both SE and ME optimisation. In both cases the same set and variation range of calibration parameters were used. The Nash-Sutcliffe efficiency coefficient was used as objective function in all cases. In addition, the total percentage runoff volume error was calculated for all the periods to acquire additional information on the calibration quality. The volume error was, however, not used by the optimisation algorithm.

From the Pareto optimum multi-event calibration three optimised parameter sets are compared: the two optimum solutions for the calibration periods and the compromise optimum solution determined by the minimum L2-metric from the ideal point (see Equation 4-4 in section 4.3.4.1).

The calibration results for small and medium events are presented in Table 6-15. Calibration periods are given in bold. Regarding the Nash-Sutcliffe efficiency coefficient, the single-event optimisation fits the respective calibration periods better than the optimum solution obtained by any multi-event optimisation.

Comparing the results from SE-optimisation, the validation events are significantly better fit when using event B for calibration. Using only event A in optimisation leads to significantly worse validation results. This can also be seen in ME-Pareto optimisation where the optimum solution for period B leads to better results in the validation events. A comparison between the ME-weighted optimum solutions and the ME-Pareto optimum solution shows no significant difference. The compromise solution was judged to be the best solution. It fits well to the calibration events and fits second-best for the validation period when evaluating both the Nash-Sutcliffe efficiency and the volume error.

Table 6-15: SE and ME calibration results for small and medium events: Nash-Sutcliffe efficiency and volume error (Gamerith et al., accepted, with permission from ASCE)

SE	Event		**A**	**B**	C	D	E
Period A - optimum solution	E_Q	-	**0.91**	**0.73**	0.39	0.25	0.48
	Volume Error	%	**5**	**16**	18	46	24
Period B - optimum solution	E_Q	-	**0.65**	**0.93**	0.85	0.65	0.83
	Volume Error	%	**15**	**2**	11	28	8
ME - weighted optimum (A&B)	Event		**A**	**B**	C	D	E
optimum solution (A&B weighted)	E_Q	-	**0.75**	**0.87**	0.86	0.64	0.78
	Volume Error	%	**2**	**11**	15	38	21
ME - Pareto optimization (periods A&B)	Event		**A**	**B**	C	D	E
Optimum solution period A	E_Q	-	**0.87**	**0.86**	0.63	0.44	0.67
	Volume Error	%	**1**	**9**	15	39	19
Optimum solution period B	E_Q	-	**0.70**	**0.92**	0.86	0.66	0.83
	Volume Error	%	**7**	**0**	8	30	11
Compromise Optimum solution	E_Q	-	**0.81**	**0.90**	0.72	0.53	0.75
	Volume Error	%	**3**	**4**	11	34	15

Table 6-16 shows the calibration results for large rainfall events. The differences between the SE and ME optimum solutions for the validation events are negligible. This was to be expected as only one model parameter – namely the *CN* value – was used in the optimization process.

As for small and medium events, the compromise optimum solution provides the most stable overall results when comparing the three events for both E_Q and volume error. Again, no significant difference between the ME-weighted and ME-Pareto-optimum compromise solution can be identified.

Table 6-16: SE and ME calibration results for large events: Nash-Sutcliffe efficiency and volume error (Gamerith et al., accepted, with permission from ASCE)

SE	Event		**I**	**II**	III	IV
Event I - optimum solution	E_Q	-	**0.88**	**0.76**	0.51	0.81
	Volume Error	%	**1**	**24**	31	10
Event II - optimum solution	E_Q	-	**0.56**	**0.87**	0.65	0.81
	Volume Error	%	**42**	**2**	22	22
ME - weighted (events I & II)	Event		**I**	**II**	III	IV
optimum solution (I & II weighted)	E_Q	-	**0.86**	**0.81**	0.55	0.84
	Volume Error	%	**12**	**18**	29	1
ME - Pareto optimization (events I & II)	Event		**I**	**II**	III	IV
Optimum solution event I	E_Q	-	**0.88**	**0.75**	0.51	0.81
	Volume Error	%	**2**	**24**	31	9
Optimum solution event II	E_Q	-	**0.61**	**0.87**	0.65	0.81
	Volume Error	%	**38**	**3**	22	22
Compromise optimum solution	E_Q	-	**0.84**	**0.82**	0.56	0.85
	Volume Error	%	**15**	**17**	28	1

6.8.4.3 Comparison of sewer water quality model approaches

In order to assess which of the sewer water quality approaches implemented in SMUSI yields the most satisfying results for the case study catchment, first a comparison of the different model approaches was carried out. Therefore the performance of the three approaches i) constant stormwater concentration, ii) accumulation wash-off approach 1 (AWO1) using the basic wash-off equation (Equation 5-5) and iii) the accumulation wash-off approach 2 (AWO2) using the wash-off equation with two additional parameters *W* and *iLim* described by Equation 5-6 was compared.

Parameters for the hydraulic model were chosen as determined by the compromise optimum solution determined in ME Pareto optimisation for events A and B as discussed above.

Three ME calibrations were performed using events A and B as calibration events. Figure 6-41 shows the hydrograph from the discharge calibration and the three resulting pollutographs from the COD_{eq} calibration (compromise Pareto optimum solution). In the measured COD_{eq} data a concentration peak can be recognised at the beginning of the first event, whereas a dilution occurs during the second.

The calibrated datasets show a good correlation between measured and simulated COD concentration. Since it is not possible to consider a first flush using the first modelling approach (constant storm water concentrations), the accumulation and wash-off approaches show superior performance. They can better reproduce the concentration peak at the beginning of the first event as well as dilution during the second event.

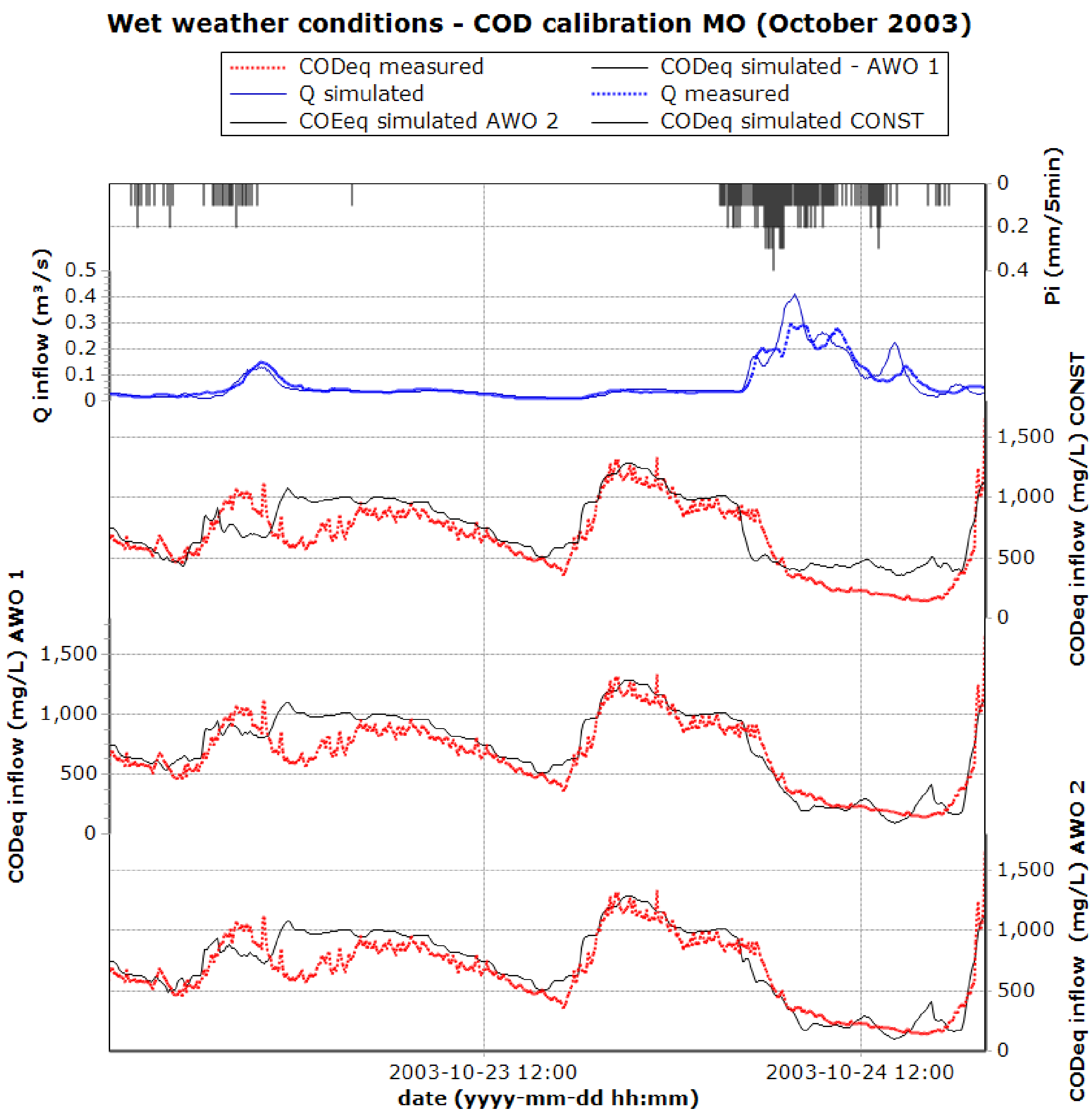

Figure 6-41: Precipitation and calibration results for wet weather condition (hydraulic and COD with 3 model approaches – constant – AWO1 and AWO2) (Gamerith et al., 2009, with permission from IWA Publishing)

Table 6-17 shows the obtained Nash-Sutcliffe coefficients for the two calibration periods and the corresponding sewer water quality model approach for the obtained Pareto-optimum solutions. Three optimal solutions are compared: the two solutions that are optimal for the events A and B respectively and the compromise optimum solution. The results for the second accumulation and wash-off approach show that in this example the additional parameters *W* and *iLim* do not add to calibration quality. Actually, for this approach the optimum parameter set for event A leads to poor results for event B (resulting in an E_C of 0.10). The first accumulation wash-off approach was therefore judged best performing. It also leads to satisfying results for the November validation resulting in a Nash-Suttcliffe coefficient of 0.63.

Table 6-17: Nash-Sutcliffe coefficients for different storm water pollution concentration approaches (ME calibration), (Gamerith et al., 2009, modified, with permission form IWA Publishing)

	Approach					
	constant		AWO 1		AWO 2	
	E_C - A	E_C - B	E_C - A	E_C - B	E_C - A	E_C - B
Optimum A	0.64	0.46	0.74	0.52	0.75	0.10
Optimum B	0.64	0.46	0.74	0.59	0.73	0.57
Compromise Optimum	0.64	0.46	0.74	0.57	0.75	0.51

6.8.4.4 Results for COD_{eq} calibration in wet weather conditions

Based on the choice of the best performing sewer water quality approach discussed above, a comparison of the performance of single- and multi event optimisation for COD_{eq} was carried out. Table 6-18 shows the calibration results for wet weather COD concentrations. Here SE and ME optimisation perform equally well regarding model fit (E_C) for the validation periods. Apparently, the validation periods chosen are not sensitive within the parameter range obtained.

Table 6-18: SE and ME calibration results for COD_{eq} calibration and validation - Nash-Sutcliffe efficiency (Gamerith et al., accepted, with permission from ASCE)

SE	Event		**A**	**B**	C	D	E
Period A - optimum solution	E_C	-	**0.75**	**0.13**	0.66	0.56	0.36
Period B - optimum solution	E_C	-	**0.16**	**0.56**	0.64	0.70	0.28
ME - weighted optimum (A&B)	Event		**A**	**B**	C	D	E
Optimum solution (A&B weighted)	E_C	-	**0.73**	**0.57**	0.64	0.70	0.29
ME - Pareto optimization (periods A&B)	Event		**A**	**B**	C	D	E
Optimum solution period A	E_C	-	**0.74**	**0.52**	0.65	0.63	0.34
Optimum solution period B	E_C	-	**0.74**	**0.58**	0.63	0.67	0.32
Compromise Optimum solution	E_C	-	**0.74**	**0.57**	0.65	0.65	0.31

A comparison of the results for events A and B show that using only data from one event (SE) leads - in this case - to significantly worse results for the other event. In ME all data from the two events is exploited. There the optimised parameter sets can explain both events with the same accuracy as the optimum set obtained in SE optimization. No preference for the compromise optimum solution over the optimum solutions for event A or event B can be deduced from the results.

Figure 6-42 shows the measured and simulated hydrographs and pollutographs (COD_{eq}) for event B. The simulated hydrograph comes from the compromise optimum of the ME discharge calibration. Simulated pollutographs are shown for the SE optimum solution for period A and the ME compromise optimum. The difference in fit indicated by the E_C value is visible in the results.

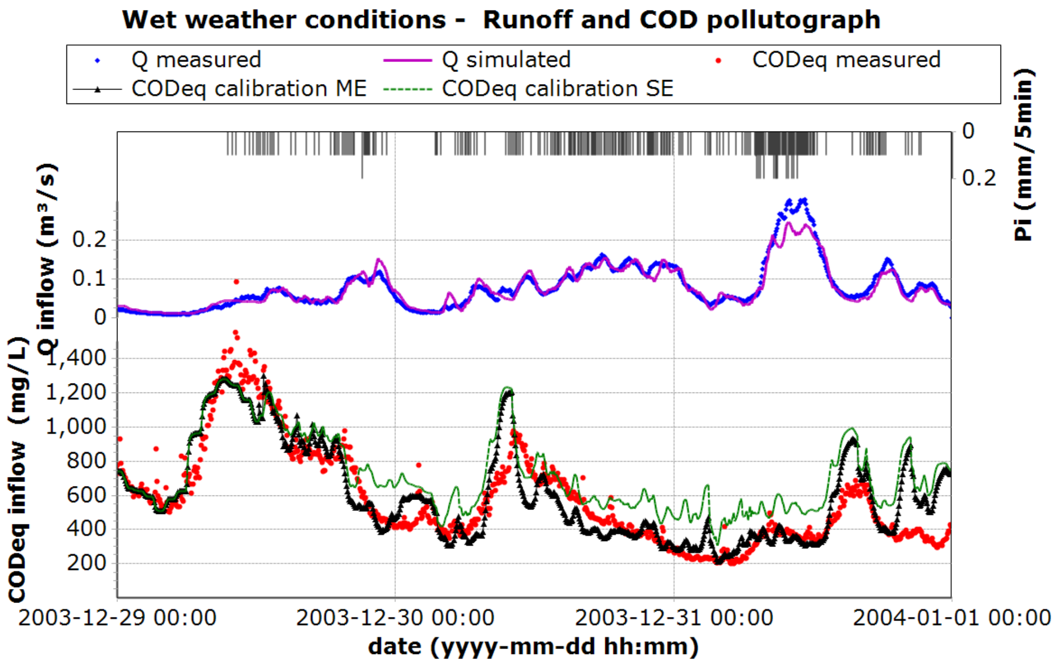

Figure 6-42: Hydrograph and COD_{eq} from SE and ME calibration results in wet weather conditions for event B (Gamerith et al., accepted, with permission form ASCE)

Figure 6-43 shows the measured and simulated hydrographs and pollutographs (ME compromise optimum solution) for validation events C and In general the dynamics in the COD concentrations can be reproduced by the model. However, the fluctuations (accentuated peaks) in the simulated concentrations are still high compared to the measured values.

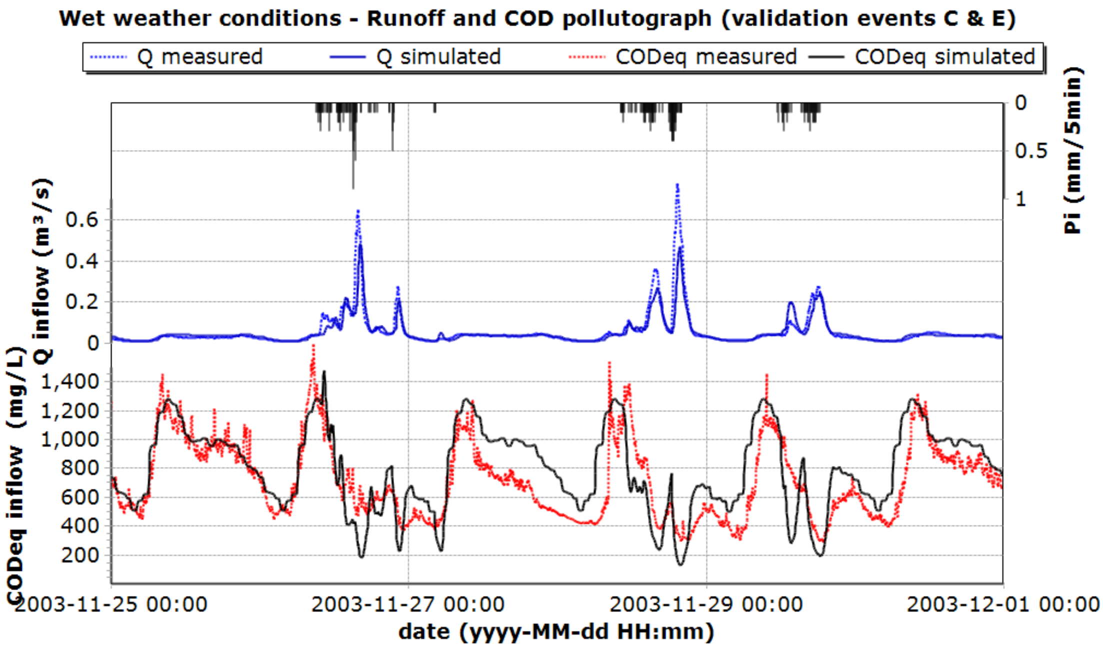

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Figure 6-43: Hydrograph and COD_{eq} from ME calibration results in wet weather conditions (events C and E) (Gamerith et al., 2011, with permission from CHI Press)

6.8.5 Summary – single- and multi-event optimisation

To summarise the results obtained from single- and multi-objective optimisation of the SMUSI 2003 catchment model, the following major findings can be stated:

- The proposed five-step calibration and validation procedure seems reasonable for the case study catchment.
- Of the three examined sewer water quality model approaches the accumulation wash-off approach using the basic wash-off equation led to the most convincing results. As concentration peaks can be observed at the beginning of several events the constant storm water concentration approach is not appropriate as it cannot reproduce this effect. The more complex wash-off equation did not lead to better results than the basic one. On the contrary, the additional calibration parameters used in this equation led to significantly worse results for validation periods in one case.
- Form a comparison of single- and multi event optimisation, the compromise optimum solution from ME optimisation proved the most stable for runoff calibration. This was not observed in sewer water quality calibration, where all the solutions from ME optimisation performed equally well.
- The results show that ME optimisation can lead to better model calibration depending on the event chosen in SE optimisation. This stresses the importance of using several events in model calibration. Based on a comparison of the validation data it is shown that the choice of the event used in SE optimisation can lead to a significant impact on the calibration quality.
- No general predominance of the ME - Pareto optimum optimisation over the ME-weighted sum optimisation could be identified. However, exploiting the Pareto front offers several advantages, as the optimum parameter sets for each event as well as intermediary parameter sets can be analysed. For instance the impact of each event used in calibration on the model results can be easily assessed by comparing the Pareto-optimum solutions.
- The results show that long term measurements in combination with the applied optimisation algorithm allow sound calibration and simulation of discharge as well as pollutant concentrations for the Graz West catchment.

Currently the proposed procedure is under way for the calibration of the SMUSI 2009 model. Based on the results from the GSA concerning the choice of event and the objective functions that yield most information on the results further improvement can be expected when moving from single-objective – multi event to a multi-objective multi-event optimisation. In addition high interest lies in the application of the optimiser to the hydrodynamic SWMM model.

7 Conclusion and outlook

Several objectives were defined for this thesis based on several challenges identified in a screening of the available high-resolution online monitoring data collected continuously over the last years at the *Graz West R05* catchment. There, flow and pollutant concentrations for several target parameters are monitored in-situ by flow metres and an ultraviolet-visible spectrometer probe. The identified challenges are mainly linked to the management and quality assurance of the measured data and the application of the data in sewer flow and water quality models.

Therefore this work aimed at i) developing tools that allow the management and quality assessment (validation) of the measured data, ii) setting up and test state-of-the-art tools for global sensitivity analysis, model calibration and assessment of model performance and link them to existing sewer water quality models and iii) applying the developed tools to the measured data and sewer models set up for the *Graz West R05* case study.

These developments should then allow i) estimating the uncertainties in the measurements – with focus on the performance of the UV/VIS probe in wet weather conditions, ii) analysing and validating the data by semi-automated data validation tools, iii) performing a global sensitivity analysis to identify the most sensitive model parameters, estimate their influence on model output uncertainties and identify combinations of events and/or objective functions leading to most information on the system and iv) evaluating the performance of single- and multi-objective optimisation in model calibration.

Eventually the performance of the developed methods should be discussed and a framework proposed that allows following a step-by-step procedure *from data to validated model output* that is transferable to other case studies.

In order to address these aims, first a literature review of the state-of-the-art in the management of combined sewer systems, measurement and data as well as modelling, sensitivity and uncertainty analysis and automated model calibration was carried out. From this, several promising methods could be identified. Many of them have not yet – or only to a limited extent – been applied in sewer modelling. Therefore, besides the organisation of the presented methods in a common framework, one major contribution of this work is the application and evaluation of these methods in an urban drainage context.

Concerning the implementation of the developed tools and methods the following work was done in scope of this thesis: Tools – coded and realised in Visual Basic .NET and [R] – were developed and applied for data analysis and validation. For UV/VIS probe calibration, global sensitivity analysis and optimisation, the BlueM.OPT framework (coded in .NET) developed at TU Darmstadt and Université Laval was used and expanded: An additional class for UV/VIS probe calibration was implemented; two global sensitivity analysis methods – the screening method of Morris and the evaluation of the standardised regression coefficients – were implemented via a link to [R] and coded; several objective functions were added and a stand-alone tool for evaluation of these quality criteria with pre-calculated time series was developed. In addition, some minor adaptions for the internal time series management and the time series visualisation tool were coded.

Basically two models were set-up for the case study catchment, one in the hydrodynamic software SWMM, the other in the conceptual hydrological software SMUSI. The actual model set-up was not part of this thesis but carried out in closely related works (co-)supervised by the author. The models were then linked via the BlueM.OPT framework to the GSA methods and an already available optimiser based on evolutionary strategies, allowing multi-objective optimisation based on the concept of Pareto-optimality. Due to the significantly lower computational costs, the developed methods were so far only applied to the SMUSI catchment model. Within this model, one model approach for hydraulics and three different model approaches for sewer water quality were available, namely i) a constant stormwater concentration approach, ii) a basic accumulation and wash-off approach (AWO1) and iii) an extended accumulation wash-off approach using two additional parameters (AWO2).

While the results from the case study are not directly transferable to other catchments, the proposed methodology itself is transferable. It is possible to apply the proposed methods e.g. to measurement data in standardised CSV format or any SWMM model available.

Overall, the presented methods could only be usefully applied due to the availability of high resolution measurement data. However, especially the water quality data is obtained at significant costs: the costs for the UV/VIS probe itself are elevated compared to simpler measurement devices as e.g. turbidity probes and the relatively complex in-situ installation and required regular maintenance of the device lead to non-negligible overall costs. In addition, absolute concentration values can only be obtained with limited accuracy. The relative changes in the concentrations, however, can be assessed satisfactorily. Especially for smaller operators the costs for material and personal are demanding. However, the costs of such an installation have to be seen in relation to standard procedures: depending on the required number of data, taking manual samples and subsequent lab analysis might be significantly more expensive. Summarising, the probes seem especially suited

- To understand the dynamics of pollutants in the investigated system and assess phenomena linked to pollution transport. Effectively this is only possible with high resolution measurements.
- To validate or develop models for pollutant transport: Until now most models were developed based on grab samples. Even if taken over longer periods and with high frequency, data density as obtained with online-measurements cannot be reached.
- For real time control applications, the probes seem a useful tool to detect variations in the pollutant concentrations. However caution is advised when using absolute values for control strategies as they can only be measured with limited accuracy.

Based on the experiences from the case study installation it is advised here that installing such devices should be well thought through:

- Use such probes where the data is needed: e.g. when the understanding of the full dynamics of pollutant concentrations is crucial (i.e. in especially sensitive environments) or for the development of model approaches.
- While several target parameters can be derived with UV/VIS probes it is advised to check if simpler probes can lead to similar results for the defined objective.
- Keep in mind that local probe calibration is required with a sufficient database of calibration data in order to obtain relatively reliable measurements.

7.1 Measurements, data analysis and validation

Concerning the **calibration of the UV/VIS probe**, an evaluation of a global calibration provided by the manufacturer highlighted the importance of local probe calibration as significant errors of about 50% for COD and up to 100% for TSS were identified. For local probe calibration a class was implemented in the BlueM.OPT framework that allows using the available optimisation algorithms. Based on the obtained results, however, caution is advised when calibrating UV/VIS probes locally to samples from one single rainfall event or events with similar concentration ranges. In that case not all possible effects and variations in the wastewater matrix can be assessed. This might effectively lead to higher errors than using the provided global calibration. Without proper calibration or an insufficient data base, resulting errors might easily reach 100% or more. With local probe calibration using all available data no significant amelioration of the results compared to a correction by simple regression could be identified. Also, as already highlighted in previous studies, the validation of the raw spectra is crucial to avoid errors in the averaged spectrum used for calculation of the derived concentration value. Overall, with local probe calibration errors in an order of magnitude of 25% to 30% over the whole measurement range were obtained for COD concentrations in wet weather conditions.

To summarise the **data analysis and validation procedure** of the *Graz Sewer R05* data, a **visual data analysis** is strongly advocated. It allows identifying obvious measurement gaps and errors and helps to understand the behaviour and overall functioning of the system. The analysis is, however, a laborious process and takes up a non-negligible amount of time.

Several tests for **semi-automated data validation,** namely a min-max test, a cross validation test and the evaluation of the residuals from the moving average were implemented, flagging measured values as either valid (A), not valid (C) or subject to additional analysis (B). The currently implemented tests proved sufficient for the purpose of this work as they allowed identifying major parts of erroneous data. The min-max and cross validation test were especially useful for validation of the hydraulics. The evaluation of the residuals from the moving average showed good performance for the noisy water quality data. From the experiences in this work, the use of relative and not absolute residuals is advocated. However, while this method is appropriate for measurements in dry weather conditions (i.e. for substituting noisy data values by the moving average) it is not fully recommended for highly dynamic storm weather conditions where abrupt changes can occur.

In addition it is proposed here to add a (D) category to the validation routines, as some values might be correctly measured but might not useful in a special context or to treat the problem in question.

In near future it should be possible to carry out the proposed tests within the OpenSDM framework currently being developed at the institute.

7.2 Global sensitivity analysis and objective functions

Two methods for GSA – the **Morris screening** and the evaluation of the **standardised regression coefficients** (SRCs) were implemented in the BlueM.OPT framework and applied to the SMUSI catchment model in this thesis. Both methods have been proposed in different scientific fields but until now only found limited application in urban drainage. Compared to other methods, they are rather easy to implement and especially the Morris screening is designed to work at low computational costs. In order to assess the impact of the choice of the objective function on the parameter sensitivities, additional objective functions were implemented in the BlueM.OPT code. The evaluation presented in this thesis is novel as these methods have not yet been applied in the context of sewer water quality modelling and high-resolution data. Especially for the sewer water quality models the high-resolution data allows a comprehensive evaluation of goodness-of-fit measured between simulated and measured data.

The evaluation of the obtained results for the case study catchment showed that in general both methods identified the same parameters as influential and lead to the same parameter ranking for the hydraulic model and the basic accumulation and wash-off approach provided approximate linearity held for SRCs. For a more complex accumulation and wash-off model approach the methods yielded different results in the parameter ranking. Overall the Morris screening proved more robust for ranking the parameters. With this method, non-linearity and interactions between parameters can be identified and do not impact significantly on the ranking. The SRCs on the other hand, are a valuable measure, especially as the effect on the output variance can be quantified if approximate linearity holds. In this case the SRCs can be interpreted as a measure for uncertainty introduced to the model by the parameters for the objective in question.

It was confirmed that the chosen parameter ranges have an important impact on the results from GSA. Hence the obtained results are only valid for the defined parameter distributions and the investigated model.

In addition it was demonstrated how the use of different objectives or different rainfall events for assessing model sensitivity changes the importance and ranking of the parameters for both the flow and water quality model. This information can be used e.g. when choosing events and objectives for model calibration in order to best exploit the available information.

7.3 Single- and multi-event optimisation

An optimisation algorithm based on evolutionary strategies that was available in the BlueM.OPT framework was used to assess the performance of the different sewer water quality approaches and to compare the performance of single- and multi-objective optimisation. While the application of multi-objective optimisation has already been discussed and proposed in an urban drainage context, the work in this thesis provides novel insights in the performance of these methods and their applicability especially with high-resolution data. As for the GSA, the detailed evaluation of goodness-of-fit measured between simulated and measured data is only possible due to the high resolution data.

With the used optimisation algorithm multi-objective optimisation results either in i) one optimum solution based on an aggregated objective from each event or ii) in a set of Pareto-optimal solutions. The optimised solutions obtained from SE optimization are compared to the optimised solutions obtained from ME optimization: the two solutions that are optimal for the two calibration periods respectively and a compromise optimum solution determined by the minimum L2-metric as well as the aggregated solution.

In this work a five-step calibration and validation procedure is proposed that showed to work well for the case study catchment. In a comparison of the three sewer water quality model approaches, the basic accumulation wash-off approach led to the most convincing results.

The comparison of single- and multi-event optimisation shows that ME optimisation can lead to better model calibration depending on the event chosen in SE optimisation. This stresses the importance of using more than one event in model calibration. Based on a comparison of the validation data it is shown that the choice of the event used in SE optimisation can lead to a significant impact on the calibration quality. No general predominance of the ME - Pareto optimum optimisation over the ME-weighted sum optimisation could be identified. However, exploiting the Pareto front offers several advantages, as the optimum parameter sets for each event as well as intermediary parameter sets can be analysed. For instance the impact of each event used in calibration on the model results can be easily assessed by comparing the Pareto-optimum solutions.

The results show that long term measurements in combination with the applied optimisation algorithm allow sound calibration and simulation of discharge as well as pollutant concentrations for the Graz West R05 catchment model: Concerning the hydraulic model, calibration events could be fitted with volume errors under 10% for small and medium events and about 15% for large events with Nash-Sutcliffe efficiency values ranging from 0.75 to 0.9. For validation events volume errors range in an order of magnitude of 15 to 20% and Nash-Sutcliffe efficiency coefficients from 0.5 to 0.8. For COD concentrations, a percentage bias of 10 to 15% was obtained for calibration and validation events, Nash-Sutcliffe efficiency coefficients range with one exception between 0.5 and 0.8.

7.4 Outlook

This work treats a broad topic linked to data management, data treatment, sensor calibration, model analysis and optimisation. An overall procedure is proposed and developed that can be applied to facilitate the steps to get *from data to validated model results*. However, while several issues are addressed and novel insights are obtained, also many interesting questions for future research are raised. Some of them are currently treated in woks in preparation at the Institute.

The UV/VIS measurements run stable at the measurement site. However, costs for maintenance and operation are non-negligible. Hence, this method will most likely not be used as day-to-day technology in near future. It is however strongly advocated if assessing the full dynamics of pollution concentrations in a system is crucial. Further research and efforts could be focused on simpler installation and maintenance requirements.

Concerning data validation, only a limited number of tests is implemented so far. A refinement and implementation of additional tests is strongly recommended, a demand also highlighted in several publications issued over the last years.

Uncertainty analysis is a topic of major importance in current research in urban drainage. From the proposed methodology only limited information on uncertainties can be obtained in the global sensitivity analysis. Hence, the implementation of state-of-the-art methodologies for uncertainty analysis can only be recommended.

In this work, a first method is proposed to use information from GSA in order to identify groups of objective functions that yield similar information. This method, however, still suffers from important drawbacks as the classification of objective function type cannot yet be considered. A refined definition on this would help identifying sets of objective functions to apply in optimisation and model calibration and is a field of interesting future research.

As the discussed GSA methods showed to give important insight in the model functioning and allow confirming or detecting obvious errors in the model structure they can be assumed to prove especially useful when setting up new models. Therefore it would be of high interest to test the procedure on newly developed models.

Concerning the use of multi-objective optimisation algorithms in model calibration further improvement can be expected when moving from single-objective – multi-event to a multi-objective multi-event optimisation based on the results from the GSA concerning the choice of events and objective functions that yield most information. In addition high interest lies in the application of the optimiser to the available hydrodynamic SWMM model.

It should also be stated here that while the work is rather focused on the implementation and theoretical comparison of the methods, the developed methodology does not focus solely on research but also the application in practice is strongly advocated: the methods are readily available and can be used to address real-world problems.

For instance, in a global sensitivity analysis any model parameter can be varied. This can include e.g. storage tank volumes, site specific reduction of impervious areas, change in throttle diameters etc. With the presented methods, sensitivity can be assessed over the multitude of possible variations rather than varying one parameter at a time and evaluating the impacts separately.

Also the use of the optimisation algorithm is advocated for practice: First, compared to manual model calibration (that is still the method of choice in practice) it bases model calibration on objective measures and reduces subjectivity. Secondly, as for GSA it can be used to determine optimised combinations of measures in the sewer system e.g. for the reduction of overflow loads, determination of optimised control strategies etc.

Nonetheless, it is advised to apply the presented methods with care and with a critical eye on the results, heeding engineering knowledge. The methods can only provide results within the defined settings and limits and over-confidence in the results just because of the use of sophisticated methods should be avoided.

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Author: Valentin Gamerith, Guenter Gruber, Dirk Muschalla

Publication: Journal of Environmental Engineering

Publisher: American Society of Civil Engineers

Date: 01/05/2011

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Sincerely,
Valentin Gamerith

****

:: DI Valentin GAMERITH
:: Graz University of Technology
:: Inst. of Urban Water Management and Water Landscape Engineering
:: Stremayrgasse 10/I, A-8010 Graz
****
:: Tel.: +43-(0)316-873-8883 Office: +43-(0)316-873-8371
:: FAX: +43-(0)316-873-8376
:: Email: gamerith@sww.tugraz.at
:: Web: http://www.sww.tugraz.at

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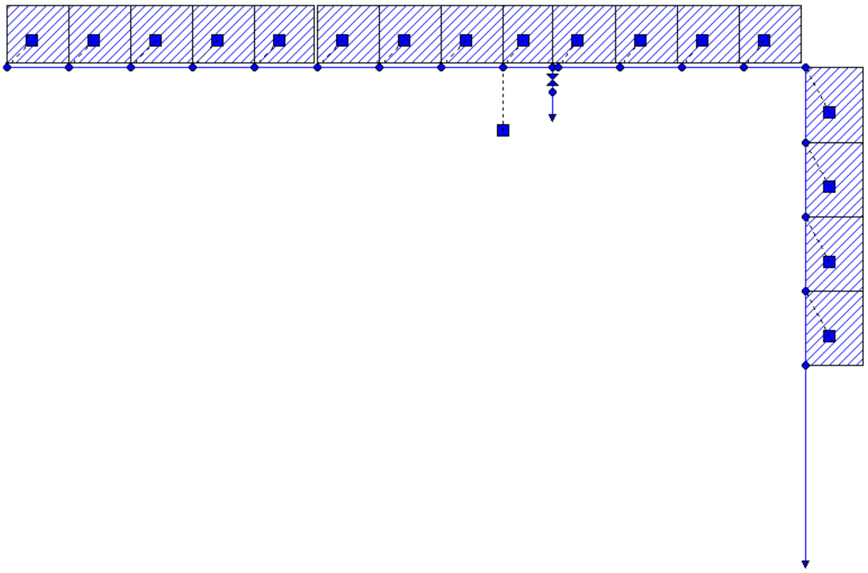
Appendix

1. Exemplary calculation of sensitivity measures

For the exemplary evaluation of the standardised regression coefficients and the Morris screening method, a SWMM model was set up for the example catchment described in the ÖWAV guideline 11 (OEWAV 2009) for the rational method. For details on the model geometry please refer to the guideline document. Three model parameters (see below) were varied and sensitivity measures for the maximum flow at the catchment outlet were calculated based on simulations with a block rainfall.



Model parameters that were varied:

parameter	description	Min	max
IMP	percentage of imperviousness	15	90
MAn	Mannings "n" (pipe roughness)	0.01	0.03
SLP	subcatchment slope	0.001	0.1

All parameters were assumed uniformly distributed

Evaluated objective:

maximum flow at outlet

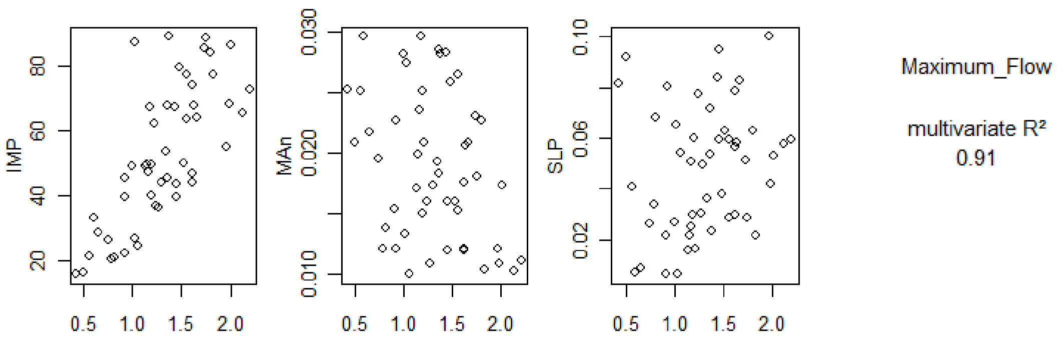
1.1. Standardised regression coefficients

For the presented example, 50 Monte Carlo simulations with the SWMM model were performed. The low number of simulations (recommended value ~ 500) was chosen for better readability, the results should therefore be regarded with care.

Monte Carlo Simulations				
	input parameter			model output
	Θ_1	Θ_2	Θ_3	y
Sim_ID	IMP	MAn	SLP	Maximum_Flow
1	40.000	0.015	0.030	1.188
2	67.916	0.021	0.058	1.634
3	36.717	0.016	0.078	1.239
4	16.051	0.025	0.082	0.431
5	68.178	0.011	0.042	1.985
6	79.696	0.026	0.038	1.485
7	87.146	0.027	0.007	1.026

8	86.217	0.017	0.053	2.006
9	72.533	0.011	0.060	2.199
10	50.153	0.016	0.063	1.521
11	63.587	0.015	0.029	1.554
12	77.235	0.026	0.059	1.552
13	88.957	0.028	0.023	1.378
14	67.134	0.030	0.025	1.174
15	55.040	0.012	0.100	1.964
16	65.713	0.010	0.058	2.123
17	22.504	0.012	0.080	0.924
18	36.336	0.011	0.030	1.270
19	43.651	0.016	0.095	1.456
20	88.487	0.018	0.029	1.745
21	27.033	0.013	0.065	1.021
22	45.755	0.018	0.072	1.365
23	39.465	0.023	0.022	0.918
24	28.951	0.022	0.009	0.648
25	49.348	0.028	0.027	0.995
26	73.891	0.018	0.030	1.620
27	83.953	0.023	0.063	1.802
28	47.134	0.012	0.057	1.612
29	67.086	0.028	0.084	1.440
30	16.697	0.021	0.092	0.506
31	47.270	0.024	0.051	1.169
32	53.530	0.019	0.036	1.338
33	45.363	0.015	0.007	0.915
34	33.288	0.030	0.007	0.598
35	44.272	0.017	0.049	1.295
36	26.675	0.019	0.026	0.748
37	62.156	0.021	0.016	1.215
38	85.391	0.023	0.051	1.730
39	44.285	0.012	0.079	1.619
40	49.473	0.025	0.060	1.196
41	77.455	0.010	0.022	1.825
42	20.546	0.012	0.034	0.785
43	24.619	0.010	0.054	1.058
44	64.279	0.021	0.083	1.660
45	21.142	0.014	0.068	0.811
46	49.066	0.017	0.016	1.132
47	67.830	0.029	0.053	1.358
48	21.723	0.025	0.041	0.557
49	49.641	0.020	0.022	1.145
50	39.730	0.012	0.059	1.448
mean $m_x = \frac{1}{n} \cdot \sum_{i=1}^{n} x_i$	52.406	0.019	0.048	1.308
Standard deviation $s_x^2 = \frac{1}{n-1} \cdot \sum_{i=1}^{n} (x_i - m_x)^2$	21.398	0.006	0.025	0.432

Scatter plots of parameter values against maximum flow



From the results, a **multivariate linear regression is performed in [R]:**

where: $y_{reg} = a + b_1 \cdot \theta_1 + b_2 \cdot \theta_2 + \ b_3 \cdot \theta_3$

```
Call:
lm(formula = unlist(MC_OBJ_SS[1]) ~ MC_PAR_SS$IMP + MC_PAR_SS$MAn +
    MC_PAR_SS$SLP)

Residuals:
     Min       1Q   Median       3Q      Max
-0.41917 -0.05410  0.03609  0.07945  0.22411

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)    7.769e-01  8.966e-02   8.665 3.16e-11 ***
MC_PAR_SS$IMP  1.851e-02  9.262e-04  19.985  < 2e-16 ***
MC_PAR_SS$MAn -3.562e+01  3.293e+00 -10.815 3.18e-14 ***
MC_PAR_SS$SLP  4.895e+00  7.831e-01   6.251 1.22e-07 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1332 on 46 degrees of freedom
Multiple R-squared: 0.9109,     Adjusted R-squared: 0.9051
F-statistic: 156.7 on 3 and 46 DF,  p-value: < 2.2e-16
```

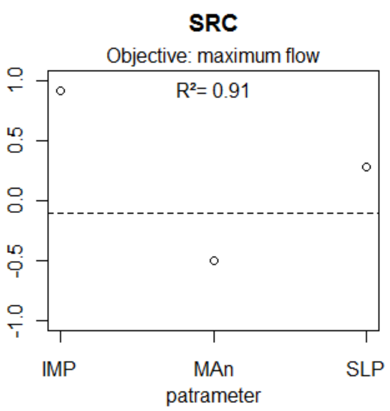
The **SRCs are then calculated** as follows:

$$\beta_i = \frac{\sigma_{\theta_i}}{\sigma_y} \cdot b_i$$

	Θ_1 IMP	Θ_2 MAn	Θ_3 SLP
b_i	0.019	-35.620	4.895
σ_{θ_i}	21.398	0.006	0.025
σ_y	0.432	0.432	0.432
SRCs $\boldsymbol{\beta_i}$	**0.916**	**-0.499**	**0.284**

This procedure is implemented in the [R] package *sensitivity* used in this work with the function *src:*

```
Call:
src(X = MC_PAR_SS, y = MC_OBJ_SS[, 1])

Standardized Regression Coefficients (SRC):
      original
IMP  0.9159695
MAn -0.4990161
SLP  0.2845190
> |
```



1.2. Morris Screening

For the presented example, a Morris screening run with 9 repetitions, 4 levels and a grid jump of 2 was chosen. The 9 trajectories were composed using the *morris* function from the [R] package *sensitivity*

		input parameters						output	elementary effects		
		original			scaled (0 – 1)			y			
					Θ_1	Θ_2	Θ_3				
Trajectory	SimID	IMP	MAn	SLP	IMP	MAn	SLP	Maximum Flow	$d(\Theta_1)$	$d(\Theta_1)$	$d(\Theta_1)$
1	1	40	0.015	0.03	0.33	0.00	0.67	1.593			
	2	90	0.01	0.067	1.00	0.00	0.67	2.603	1.51		
	3	90	0.0233	0.067	1.00	0.67	0.67	1.862		-1.11	
	4	90	0.0233	0.001	1.00	0.67	0.00	0.64			1.83
2	5	40	0.0233	0.1	0.33	0.67	1.00	1.117			
	6	90	0.0233	0.1	1.00	0.67	1.00	1.98	1.29		
	7	90	0.01	0.1	1.00	0.00	1.00	2.835		-1.28	
	8	90	0.01	0.034	1.00	0.00	0.33	2.208			0.94
3	9	15	0.03	0.034	0.00	1.00	0.33	0.346			
	10	65	0.03	0.034	0.67	1.00	0.33	1.201	1.28		
	11	65	0.0167	0.034	0.67	0.33	0.33	1.581		-0.57	
	12	65	0.0167	0.1	0.67	0.33	1.00	1.925			0.52
4	13	90	0.0233	0.034	1.00	0.67	0.33	1.632			
	14	40	0.0233	0.034	0.33	0.67	0.33	0.978	0.98		
	15	40	0.01	0.034	0.33	0.00	0.33	1.429		-0.68	
	16	40	0.01	0.1	0.33	0.00	1.00	1.687			0.39
5	17	90	0.01	0.001	1.00	0.00	0.00	0.712			
	18	40	0.01	0.001	0.33	0.00	0.00	0.597	0.17		
	19	40	0.0233	0.001	0.33	0.67	0.00	0.497		-0.15	
	20	40	0.0233	0.067	0.33	0.67	0.67	1.067			0.85
6	21	65	0.03	0.1	0.67	1.00	1.00	1.389			
	22	15	0.03	0.1	0.00	1.00	1.00	0.361	1.54		
	23	15	0.0167	0.1	0.00	0.33	1.00	0.519		-0.24	
	24	15	0.0167	0.034	0.00	0.33	0.33	0.49			0.04
7	25	90	0.03	0.001	1.00	1.00	0.00	0.611			
	26	40	0.03	0.001	0.33	1.00	0.00	0.466	0.22		
	27	40	0.0167	0.001	0.33	0.33	0.00	0.531		-0.10	
	28	40	0.0167	0.067	0.33	0.33	0.67	1.274			1.11
8	29	65	0.0233	0.001	0.67	0.67	0.00	0.585			
	30	15	0.0233	0.001	0.00	0.67	0.00	0.305	0.42		
	31	15	0.01	0.001	0.00	0.00	0.00	0.417		-0.17	
	32	15	0.01	0.067	0.00	0.00	0.67	0.688			0.41
9	33	65	0.0233	0.034	0.67	0.67	0.33	1.37			
	34	15	0.0233	0.034	0.00	0.67	0.33	0.402	1.45		
	35	15	0.01	0.034	0.00	0.00	0.33	0.654		-0.38	
	36	15	0.01	0.1	0.00	0.00	1.00	0.705			0.08

	Mean of elementary effects μ	$\mu = \frac{1}{9} \cdot \sum_{i=1}^{9} d_i$	0.99	-0.52	0.69
	Mean of absolute elementary effects μ*	$\mu^* = \frac{1}{9} \cdot \sum_{i=1}^{9} \lvert d_i \rvert$	0.99	0.52	0.69
	Standard deviation	$\sigma = \frac{1}{9-1} \cdot \sum_{i=1}^{9} (d_i - \mu^{(*)})^2$	0.57	0.43	0.57

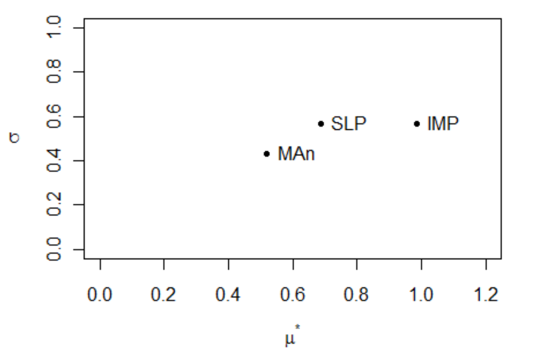
The elementary effects are calculated by $d_i(\theta) = \frac{y(\theta_1,\dots,\theta_{i-1},\theta_i+\Delta,\theta_{i+1},\dots,\theta_k) - y(\boldsymbol{\theta})}{\Delta}$. I.e. for $d_1(\Theta_1)$ this would read $d_1(\theta_1) = \frac{2.603 - 1.593}{1.00 - 0.33} = 1.51$

The sensitivity measures are $\mu^{(*)}$ and σ are the mean and the standard deviation of the elementary effect for the parameters.

The results obtained with the [R] package *sensitvity* are given below.

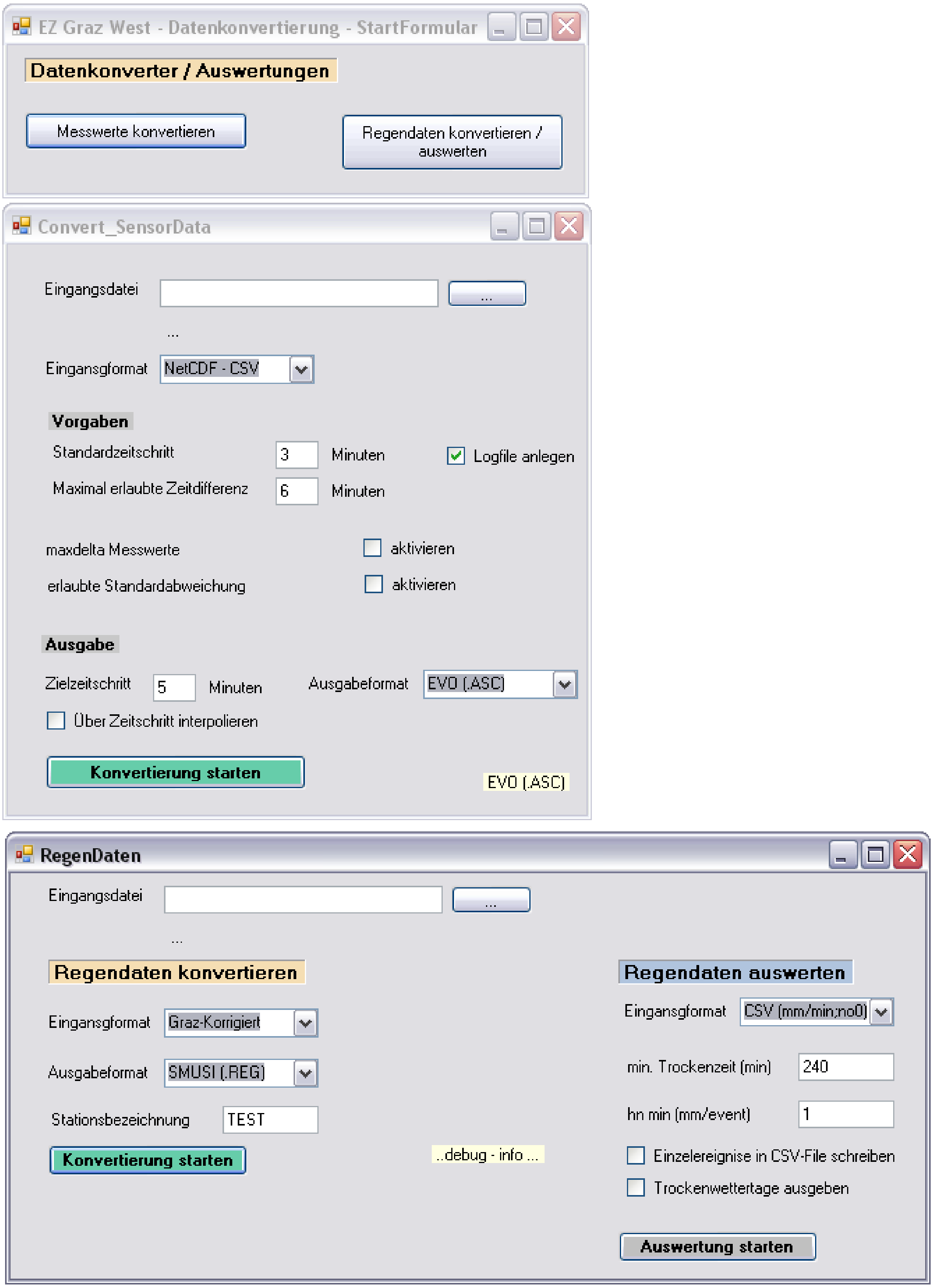
```
Call:
morris(model = NULL, factors = MS_factors, r = MS_rep, design = list(type = MS_type,

Model runs: 36
           mu   mu.star     sigma
IMP  0.9863333 0.9863333 0.5659033
MAn -0.5190000 0.5190000 0.4326987
SLP  0.6858333 0.6858333 0.5671497

> >
> MorrisResult <- tell(XMorris2, modeloutput_MAT[,1])
> MorrisResult$ee
        IMP     MAn    SLP
 [1,] 1.5150 -1.1115 1.8330
 [2,] 1.2945 -1.2825 0.9405
 [3,] 1.2825 -0.5700 0.5160
 [4,] 0.9810 -0.6765 0.3870
 [5,] 0.1725 -0.1500 0.8550
 [6,] 1.5420 -0.2370 0.0435
 [7,] 0.2175 -0.0975 1.1145
 [8,] 0.4200 -0.1680 0.4065
 [9,] 1.4520 -0.3780 0.0765
```

Morris screening results (3 parameter model)

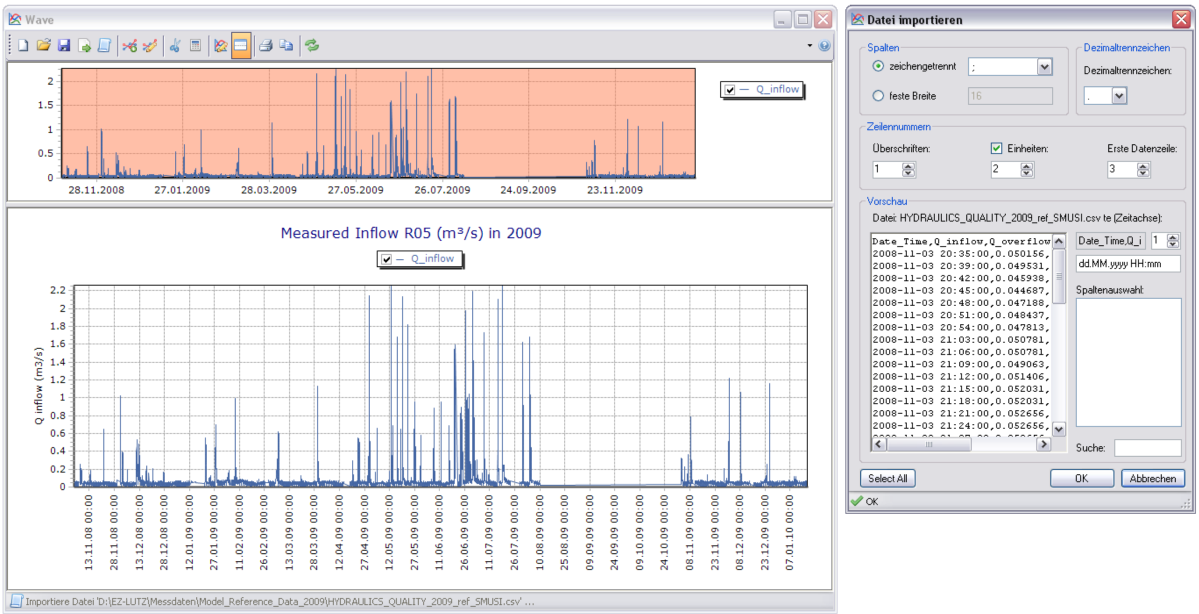


2. GUI screenshots

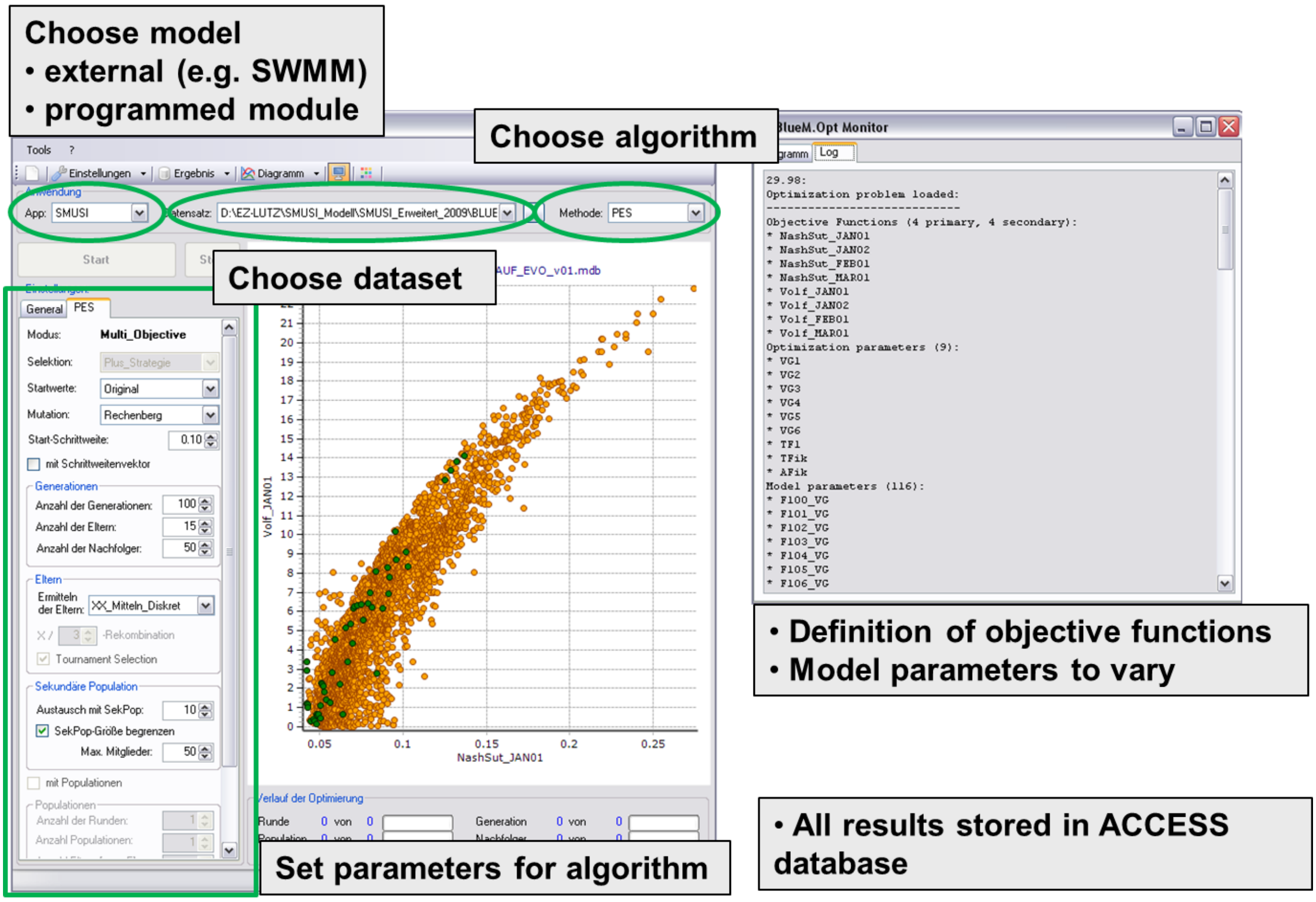
2.1. ConvertSensorData: Toolkit GUI



2.2. WAVE: GUI for file import



2.3. BlueM.OPT GUI



3. BlueM.OPT

3.1. Implemented Objective functions

Legend:

(green)	Implemented and tested
(purple)	Not implemented, possible to calculate in Post-Processing from results

Abbreviation **BOLD: as used in code & input files**	Equation	Min	Max	Tar	Adaption for optimization
ME Bias, E_1	Mean error $ME = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)$	-∞	∞	0	Use absolute value and minimize **ME_OPT**
MAE $=E'_1$	Mean absolute error (' : abs) $MAE = \frac{1}{n}\sum_{i=1}^{n}\lvert O_i - P_i\rvert$	0	∞	min	OK
MSE $=E_2$	Mean Square Error $MSE = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2$	0	∞	min	OK
MSSE $=E(sorted)_2$	Mean Square Sorted Errors (j pairs) $MSSE = \frac{1}{n}\sum_{j=1}^{n}(O_j - P_j)^2$	0	∞	min	OK
MSLE $=E(ln)_2$	Mean Square Logarithme Error $MSLE = \frac{1}{n}\sum_{i=1}^{n}(ln\,O_i - ln\,P_i)^2$	0	∞	min	OK
MSDE $=E(deriv)_2$	Mean Square Derivative Error $MSDE = \frac{1}{n-1}\sum_{i=1}^{n}((O_i - O_{i-1}) - (P_i - P_{i-1}))^2$	0	∞	min	OK
AME $=E_\infty$	Absolute Maximum Error $AME = max(\lvert O_i - P_i\rvert)$	0	∞	min	OK
MPE $=100.RE_1$	Mean percent error $MPE = \frac{100}{n}\sum_{i=1}^{n}\left(\frac{O_i - P_i}{O_i}\right)$	-∞	∞	0	Use absolute value and minimize **MPE_OPT**
MRE $=RE_1$	Mean relative error $MRE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{O_i - P_i}{O_i}\right)$	-∞	∞	0	Use absolute value and minimize **MRE_OPT**
MARE $=RE'_1$	Mean absolute relative error $MARE = \frac{1}{n}\sum_{i=1}^{n}\frac{\lvert O_i - P_i\rvert}{O_i}$	0	∞	min	OK
MSRE $=RE_2$	Mean square relative error $MSRE = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{O_i - P_i}{O_i}\right)^2$	0	∞	min	OK

Abbreviation **BOLD: as used in code & input files**	Equation	Min	Max	Tar	Adaption for optimization
MAPE ~MARE	Mean absolute percent error $MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{\lvert O_i - P_i \rvert}{\lvert P_i \rvert}$	0	∞	min	OK
MDAPE ~MARE	median absolute error percentage $MdAPE = Médiane\left(\left\lvert\frac{O_i - P_i}{O_i}\right\rvert \times 100\right)$	0	∞	min	OK
PBIAS γ=1	Percent Bias $PBIAS_{\gamma} = 100 \cdot \frac{\sum_{i=1}^{n}(O_i - P_i)^{\gamma}}{\sum_{i=1}^{n} O_i^{\gamma}}$	-∞	∞	0	Use absolute value and minimize **PBIAS_OPT**
RVE =PBIAS/100	Relative volume error $RVE = \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n} O_i}$	-∞	∞	0	Use absolute value and minimize **RVE_OPT**
MAER =PBIAS'/100	MAER=absolute RVE $RVE = \frac{\sum_{i=1}^{n}\lvert O_i - P_i \rvert}{\sum_{i=1}^{n} O_i}$	0	∞	min	OK
U2 Theil's coefficient =PBIAS2/100	Theil's inequality coefficient $U^2 = \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n} O_i^2}$	0	∞	min	OK
RMSE	Root mean square $RMSE = \sqrt{\frac{\sum_{i=1}^{n}(O_i - P_i)^2}{n}}$	0	∞	min	OK
R4MS4E	Fourth root mean quadrupled error $R4MS4E = \sqrt[4]{\frac{\sum_{n}^{i=1}(O_i - P_i)^4}{n}}$	0	∞	min	OK
TMC	Total Mass Balance Controller $TMC = 100 \cdot \left\lvert \frac{\sum_{i=1}^{n} O_i}{\sum_{i=1}^{n} P_i} - 1 \right\rvert$	0	100	0	OK
CRBAL , Bilan	Balance Criteria $Bilan = 1 - \left\lvert \sqrt{\frac{\sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} O_i}} - \sqrt{\frac{\sum_{i=1}^{n} O_i}{\sum_{i=1}^{n} P_i}} \right\rvert$	∞	1	1	Remove term (1-) **CRBAL_OPT**

Abbreviation **BOLD: as used in code & input files**	Equation	Min	Max	Tar	Adaption for optimization
PDIFF	Peak difference $PDIFF = max(O_i) - max(P_i)$	-∞	∞	0	Use absolute value and minimize **PDIFF_OPT**
PEP	Percent error in peak $PEP = \frac{max(O_i) - max(P_i)}{max(O_i)} \times 100$	-∞	∞	0	Use absolute value and minimize **PEP_OPT**
CE12 $CE_{1,2}$	Coefficient of efficiency (Nash-Sutcliffe) $CE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2}$	-∞	1	1	Remove term (1-) **CE12_OPT, NashSutt**
CE122 $CE_{1/2,2}$	$CE_{1/2,2} = 1 - \frac{\sum_{i=1}^{n}\left(\sqrt{O_i} - \sqrt{P_i}\right)^2}{\sum_{i=1}^{n}\left(\sqrt{O_i} - \overline{\sqrt{O}}\right)^2}$	-∞	1	1	Remove term (1-) **CE122_OPT**
CELN2 $CE_{ln,2}$	$CE_{ln,2} = 1 - \frac{\sum_{i=1}^{n}\left(ln(O_i) - ln(P_i)\right)^2}{\sum_{i=1}^{n}\left(ln(O_i) - \overline{ln(O)}\right)^2}$	-∞	1	1	Remove term (1-) **CELN2_OPT**
RAE =CE1,abs	Relative Absolute Error $RAE = \frac{\sum_{i=1}^{n}\lvert O_i - P_i\rvert}{\sum_{i=1}^{n}\lvert O_i - \overline{O}\rvert}$	0	∞	min	OK
RSR	RMSE-observations standard deviation ratio $RSR = \frac{\sqrt{\sum_{i=1}^{n}(O_i - P_i)^2}}{\sqrt{\sum_{i=1}^{n}(O_i - \overline{O})^2}}$	0	∞	min	OK
PI	coefficient of persistance $PI = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - O_{i-1})^2}$	∞	1	1	Remove term (1-) **PI_OPT**
IRMSE	Inertia Root Mean Squared Error $IRMSE = \frac{RMSE}{\sigma_\Delta}$ $\sigma_\Delta = \sqrt{\frac{\sum_{i=1}^{n}\left(\Delta_i - \overline{\Delta}\right)^2}{n-1}}$ $\overline{\Delta} = \frac{1}{n}\sum_{i=1}^{n}\Delta_i$ $\Delta_i = O_i - O_{i-1}$	0	∞	min	OK
IA$_\gamma$ γ=2	index of agreement $IA_\gamma = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^\gamma}{\sum_{i=1}^{n}\left(\lvert P_i - \overline{O}\rvert + \lvert O_i - \overline{O}\rvert\right)^\gamma}$	0	1	1	Remove term (1-) **IA_OPT**

Abbreviation **BOLD: as used in code & input files**	Equation	Min	Max	Tar	Adaption for optimization
NSC	Number of sign changes of residuals (Oi-Pi)	0	n-1	max	
R2	Coefficient of determination $R^2 = \left[\frac{\sum_{i=1}^{n} (O_i - \overline{O}) \times (P_i - \overline{P})}{\sqrt{\sum_{i=1}^{n} (O_i - \overline{O})^2 \sum_{i=1}^{n} (P_i - \overline{P})^2}} \right]$				

AIC	Akaike Information criterion n data, k parameters $AIC = n \times \ln(RMSE) + 2 \times k$				Based on RMSE – additional information needed (n and k)
BIC	Bayesian Information criterion n data, k parameters $BIC = n \times ln(RMSE) + k \times ln(n)$				Based on RMSE – additional information needed (n and k)
undermodelling	$Under\,mod\,elling = \frac{RMSE}{n} - (\hat{\sigma}^2 + \frac{k}{n}\hat{\sigma}^2)\frac{n-k}{n+k}$				Based on RMSE – additional information needed (n and k)
F-Test	compare the RMSE of model $F = \frac{(RMSE_i - RMSE_j)/(P_j - P_i)}{RMSE_j/(N - P_j)}$				Based on RMSE – additional information needed

3.2. Residual statistics

Abbreviation BOLD: as used in code & input files	Equation Definition: $R_i = O_i - P_i$	Min	Max	Tar	
RES_MIN	$RES\_MIN = \min_{i=1\,to\,n} (R_i)$	-∞	∞		Minimum of residuals
RES_MAX	$RES\_MAX = \max_{i=1\,to\,n} (R_i)$	-∞	∞		Maximum of residuals
RES_MEAN	$RES\_MEAN = \frac{1}{n}\left(\sum_{i=1}^{n}(R_i)\right)$	-∞	∞		Mean of residuals
RES_MED	$RES\_MED = \underset{i=1\,to\,n}{median}(R_i)$ If n = even: upper and lower of n/2 are interpolated	-∞	∞		Median of residuals
RES_SD	$RES\_SD = \sqrt{\frac{1}{n-1}\left(\sum_{i=1}^{n}(R_i - \bar{R}_i)^2\right)}$	0	∞		Residuals standard deviation
RES_SKEW	$RES\_SKEW = \frac{\frac{1}{n}\sum_{i=1}^{n}(R_i - \bar{R}_i)^3}{\left(\frac{1}{n}\sum_{i=1}^{n}(R_i - \bar{R}_i)^2\right)^{3/2}}$				Residuals sample skewness
RES_KURT	$RES_{KURT} = \frac{\frac{1}{n}\sum_{i=1}^{n}(R_i - \bar{R}_i)^4}{\left(\frac{1}{n}\sum_{i=1}^{n}(R_i - \bar{R}_i)^2\right)^{2}} - 3$				Residuals sample kurtosis

3.3. Exemplary input files for BlueM.OPT (Example GSA hydraulic model)

.ZIE file: Definition of objectives

```
*Optimierungsziele
*=================
*
*Values
*------
*
*  -----  ---------------  -------  ------------  ---------  ------------------  ----------------  ---------  ---------
*  Opt    Bezeichnung      Datei    SimGr□e       ZielFkt    Zielgr□e            OptGr□e                      IstWert
*                                                            (Block)             (Spalte)          RefWert
*  -----  ---------------  -------  ------------  ---------  ------------------  ----------------  ---------  ---------
    P     TotalRunoffVol     SUM    Summ          Diff       RunoffVolume        SumVol            0
    S     TotalOverflowVol   SUM    Summ          Diff       OverflowVolume      SumVol            0
    S     NoOverflow         SUM    B100          Diff       NoOverflows         No                0
    S     OverflowDuration   SUM    B100          Diff       OverflowDuration    Duration          0
    S     E0                 SUM    Summ          Diff       E0                  E0                0
*   S     RunoffLoad_COD     SUM    B100          Diff       RunoffLoad          COD_TOT           0
*   S     RunoffLoad_TSS     SUM    B100          Diff       RunoffLoad          TSS_TOT           0

*   S     OverflowLoad_COD   SUM    B100          Diff       OverflowLoad        COD_TOT           0
*   S     OverflowLoad_TSS   SUM    B100          Diff       OverflowLoad        TSS_TOT           0
*  -----  ---------------  -------  ------------  ---------  ------------------  ----------------  ---------  ---------
*
*ValueFromSeries
*---------------
*
*  -----  ---------------  -------  ------------  ---------  -----------------  -----------------  -----------  ---------
*  Opt    Bezeichnung      Datei    SimGr□e       ZielFkt    EvalZeitraum       Referenzwert                    IstWert

*                                                            Start              Ende               WertTyp      RefWert
*  -----  ---------------  -------  ------------  ---------  -----------------  -----------------  ---------    ---------
    S     E002_TOT_VOL       WEL    B100_Qzu      Diff       21.01.2009 14:00   22.01.2009 03:00   Summe        0
    S     E002_OF_VOL        WEL    B100_QKu      Diff       21.01.2009 14:00   22.01.2009 03:00   Summe        0
    S     E002_PEAK_Qzu      WEL    B100_Qzu      Diff       21.01.2009 14:00   22.01.2009 03:00   MaxWert      0
*   S     E002_PEAK_Czu      WEL    B100_czu      Diff       21.01.2009 14:00   22.01.2009 03:00   MaxWert      0

*   S     E002_AVERAGE_C     WEL    B100_czu      Diff       21.01.2009 14:00   22.01.2009 03:00   Average      0
    S     E013_OF_VOL        WEL    B100_QKu      Diff       06.03.2009 05:30   06.03.2009 18:00   Summe        0
    S     E013_PEAK_Qzu      WEL    B100_Qzu      Diff       06.03.2009 05:30   06.03.2009 18:00   MaxWert      0
    S     E013_TOT_VOL       WEL    B100_Qzu      Diff       06.03.2009 05:30   06.03.2009 18:00   Summe        0
*   S     E013_PEAK_Czu      WEL    B100_czu      Diff       06.03.2009 05:30   06.03.2009 18:00   MaxWert      0

*   S     E013_AVERAGE_C     WEL    B100_czu      Diff       06.03.2009 05:30   06.03.2009 18:00   Average      0
    S     E017_OF_VOL        WEL    B100_QKu      Diff       19.04.2009 21:30   20.04.2009 01:30   Summe        0
    S     E017_PEAK_Qzu      WEL    B100_Qzu      Diff       19.04.2009 21:30   20.04.2009 01:30   MaxWert      0
    S     E017_TOT_VOL       WEL    B100_Qzu      Diff       19.04.2009 21:30   20.04.2009 01:30   Summe        0
*   S     E017_PEAK_Czu      WEL    B100_czu      Diff       19.04.2009 21:30   20.04.2009 01:30   MaxWert      0

*   S     E017_AVERAGE_C     WEL    B100_czu      Diff       19.04.2009 21:30   20.04.2009 01:30   Average      0
    S     E021_OF_VOL        WEL    B100_QKu      Diff       29.04.2009 04:00   29.04.2009 19:00   Summe        0
    S     E021_PEAK_Qzu      WEL    B100_Qzu      Diff       29.04.2009 04:00   29.04.2009 19:00   MaxWert      0
    S     E021_TOT_VOL       WEL    B100_Qzu      Diff       29.04.2009 04:00   29.04.2009 19:00   Summe        0
*   S     E021_PEAK_Czu      WEL    B100_czu      Diff       29.04.2009 04:00   29.04.2009 19:00   MaxWert      0

*   S     E021_AVERAGE_C     WEL    B100_czu      Diff       29.04.2009 04:00   29.04.2009 19:00   Average      0
    S     E022_OF_VOL        WEL    B100_QKu      Diff       29.04.2009 21:00   30.04.2009 11:00   Summe        0
    S     E022_PEAK_Qzu      WEL    B100_Qzu      Diff       29.04.2009 21:00   30.04.2009 11:00   MaxWert      0
    S     E022_TOT_VOL       WEL    B100_Qzu      Diff       29.04.2009 21:00   30.04.2009 11:00   Summe        0
*   S     E022_PEAK_Czu      WEL    B100_czu      Diff       29.04.2009 21:00   30.04.2009 11:00   MaxWert      0
*   S                        WEL    B100_czu      Diff       29.04.2009 21:00   30.04.2009 11:00   Average      0
```

		E022_AVERAGE_C							
	S	E060_OF_VOL	WEL	B100_QKu	Diff	07.07.2009 16:00	07.07.2009 22:00	Summe	0
	S	E060_PEAK_Qzu	WEL	B100_Qzu	Diff	07.07.2009 16:00	07.07.2009 22:00	MaxWert	0
	S	E060_TOT_VOL	WEL	B100_Qzu	Diff	07.07.2009 16:00	07.07.2009 22:00	Summe	0
*	S	E060_PEAK_Czu	WEL	B100_czu	Diff	07.07.2009 16:00	07.07.2009 22:00	MaxWert	0
*	S	E060_AVERAGE_C	WEL	B100_czu	Diff	07.07.2009 16:00	07.07.2009 22:00	Average	0
*	-----	---------------	-------	------------	---------	-----------------	-----------------	---------	---------
*									
*									
*Series									
*------									
*									
*	-----	---------------	-------	------------	---------	-------------------	------------------		---------
						Evaluierungs			
*	Opt	Bezeichnung	Datei	SimGr□e	ZielFkt	Zeitraum	Referenzreihe	IstWert	
*						Start	Ende	RefGr□e	Datei
*	-----	---------------	-------	------------	---------	-------------------	------------------		
*HYDRUALICS									
	S	E002_Q_Volf	ASC	B100_Qzu	Volf	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_ME	ASC	B100_Qzu	ME	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MAE	ASC	B100_Qzu	MAE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MSE	ASC	B100_Qzu	MSE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MSLE	ASC	B100_Qzu	MSLE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MSDE	ASC	B100_Qzu	MSDE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_AME	ASC	B100_Qzu	AME	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MPE	ASC	B100_Qzu	MPE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MRE	ASC	B100_Qzu	MRE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MARE	ASC	B100_Qzu	MARE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MSRE	ASC	B100_Qzu	MSRE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MAPE	ASC	B100_Qzu	MAPE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_PBIAS	ASC	B100_Qzu	PBIAS	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_RVE	ASC	B100_Qzu	RVE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MAER	ASC	B100_Qzu	MAER	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_U2	ASC	B100_Qzu	U2	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_RMSE	ASC	B100_Qzu	RMSE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
									R.ASC
	S	E002_Q_R4MS4E	ASC	B100_Qzu	R4MS4E	21.01.2009 14:00	22.01.2009 03:00	Q	
	S	E002_Q_TMC	ASC	B100_Qzu	TMC	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_CRBAL	ASC	B100_Qzu	CRBAL	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_PDIFF	ASC	B100_Qzu	PDIFF	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_PEP	ASC	B100_Qzu	PEP	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_CE12	ASC	B100_Qzu	CE12	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_CE122	ASC	B100_Qzu	CE122	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_CELN2	ASC	B100_Qzu	CELN2	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_RAE	ASC	B100_Qzu	RAE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_RSR	ASC	B100_Qzu	RSR	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_PI	ASC	B100_Qzu	PI	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_IRMSE	ASC	B100_Qzu	IRMSE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_IA	ASC	B100_Qzu	IA	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MSSE	ASC	B100_Qzu	MSSE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_MDAPE	ASC	B100_Qzu	MDAPE	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_NSC	ASC	B100_Qzu	NSC	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC
	S	E002_Q_R2	ASC	B100_Qzu	R2	21.01.2009 14:00	22.01.2009 03:00	Q	R.ASC

Model parameter assignement

```
*ModellParameter
*=====================
*   ---------          --------------     -------     -------     --------     -------   -----   -----   --------

*   OptParameter   Bezeichnung   Einh.       Datei       Elem. /o       Zeile     von      bis      Faktor
*   -<---------->-     -<---------->-     -<--->-     -<--->-     -<---->-     -<--->-   -<->-   -<->-   -<---->-
*LOSSES AND EVAPORATION  #
    EF      VPFaktor     ALL      66   38   41   1
    IL      Benetz       ALL      30   38   41   1
    DL      NG1          ALL      29   38   43   1
    DL      NG2          ALL      29   45   50   0.667
    DL      NG3          ALL      29   52   57   0.333
    DL      NG3          ALL      29   59   64   0.333
*IMPERVIOUSNESS  #########
    IF      F100_VG      FKA      10   17   20   0.57
    IF      F101_VG      FKA      11   17   20   0.72
    IF      F102_VG      FKA      12   17   20   0.53
    IF      F103_VG      FKA      13   17   20   0.65
    IF      F104_VG      FKA      14   17   20   0.6
    IF      F105_VG      FKA      15   17   20   0.66
    IF      F106_VG      FKA      16   17   20   0.32
    IF      F107_VG      FKA      17   17   20   0.3
    IF      F108_VG      FKA      18   17   20   0.39
    IF      F109_VG      FKA      19   17   20   0.44
    IF      F10C_VG      FKA      20   17   20   0.39
    IF      F10D_VG      FKA      21   17   20   0.51
    IF      F10E_VG      FKA      22   17   20   0.29
    IF      F10F_VG      FKA      23   17   20   0.33
    IF      F10G_VG      FKA      24   17   20   0.44
    IF      F10H_VG      FKA      25   17   20   0.36
    IF      F10I_VG      FKA      26   17   20   0.25
    IF      F10J_VG      FKA      27   17   20   0.33
    IF      F110_VG      FKA      28   17   20   0.2
    IF      F111_VG      FKA      29   17   20   0.38
    IF      F112_VG      FKA      30   17   20   0.15
    IF      F114_VG      FKA      31   17   20   0.26
    IF      F115_VG      FKA      32   17   20   0.24
    IF      F116_VG      FKA      33   17   20   0.24
    IF      F117_VG      FKA      34   17   20   0.39
    IF      F118_VG      FKA      35   17   20   0.21
    IF      F120_VG      FKA      36   17   20   0.33
    IF      F121_VG      FKA      37   17   20   0.21
    IF      F122_VG      FKA      38   17   20   0.25
    IF      F123_VG      FKA      39   17   20   0.38
    IF      F124_VG      FKA      40   17   20   0.35
    IF      F125_VG      FKA      41   17   20   0.38
    IF      F126_VG      FKA      42   17   20   0.29
    IF      F127_VG      FKA      43   17   20   0.45
    IF      F128_VG      FKA      44   17   20   0.37
    IF      F129_VG      FKA      45   17   20   0.35
    IF      F130_VG      FKA      46   17   20   0.11
    IF      F131_VG      FKA      47   17   20   0.21
    IF      F132_VG      FKA      48   17   20   0.07
    IF      F133_VG      FKA      49   17   20   0.17
    IF      F200_VG      FKA      50   17   20   0.38
    IF      F201_VG      FKA      51   17   20   0.25
    IF      F202_VG      FKA      52   17   20   0.19
    IF      F203_VG      FKA      53   17   20   0.38
    IF      F301_VG      FKA      54   17   20   0.18
    IF      F304_VG      FKA      55   17   20   0
    IF      F305_VG      FKA      56   17   20   0.06
```

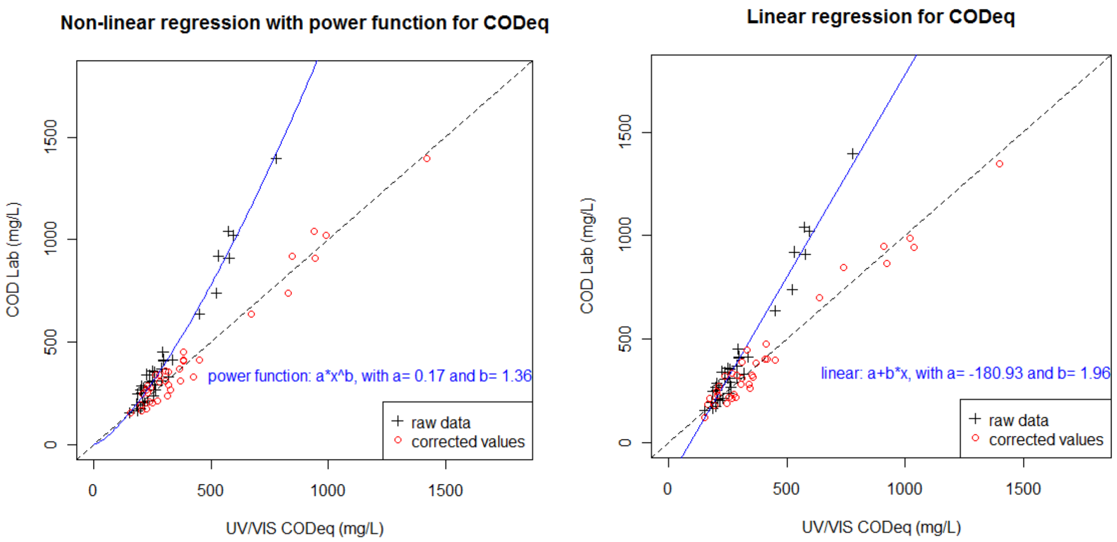
IF	F306_VG	FKA	57	17	20	0.13
IF	F307_VG	FKA	58	17	20	0.32
IF	F308_VG	FKA	59	17	20	0.11
IF	F309_VG	FKA	60	17	20	0.26
IF	F310_VG	FKA	61	17	20	0.33
IF	F311_VG	FKA	62	17	20	0.15
IF	F312_VG	FKA	63	17	20	0.36
IF	F313_VG	FKA	64	17	20	0.46
IF	F314_VG	FKA	65	17	20	0.45
IF	F315_VG	FKA	66	17	20	0.03
*CONCENTRATION TIME #########						
TF	F100_TF	FKA	10	30	33	6.1
TF	F101_TF	FKA	11	30	33	6.9
TF	F102_TF	FKA	12	30	33	7.3
TF	F103_TF	FKA	13	30	33	6.2
TF	F104_TF	FKA	14	30	33	5.7
TF	F105_TF	FKA	15	30	33	6.9
TF	F106_TF	FKA	16	30	33	6
TF	F107_TF	FKA	17	30	33	5.7
TF	F108_TF	FKA	18	30	33	5.4
TF	F109_TF	FKA	19	30	33	10.1
TF	F10C_TF	FKA	20	30	33	5.7
TF	F10D_TF	FKA	21	30	33	6
TF	F10E_TF	FKA	22	30	33	5.4
TF	F10F_TF	FKA	23	30	33	5.2
TF	F10G_TF	FKA	24	30	33	6
TF	F10H_TF	FKA	25	30	33	5.4
TF	F10I_TF	FKA	26	30	33	5.8
TF	F10J_TF	FKA	27	30	33	5.5
TF	F110_TF	FKA	28	30	33	5.5
TF	F111_TF	FKA	29	30	33	6
TF	F112_TF	FKA	30	30	33	7.6
TF	F114_TF	FKA	31	30	33	7
TF	F115_TF	FKA	32	30	33	9.7
TF	F116_TF	FKA	33	30	33	6
TF	F117_TF	FKA	34	30	33	6
TF	F118_TF	FKA	35	30	33	5.6
TF	F120_TF	FKA	36	30	33	5.8
TF	F121_TF	FKA	37	30	33	5.8
TF	F122_TF	FKA	38	30	33	5.6
TF	F123_TF	FKA	39	30	33	6.3
TF	F124_TF	FKA	40	30	33	5.1
TF	F125_TF	FKA	41	30	33	5.7
TF	F126_TF	FKA	42	30	33	7.8
TF	F127_TF	FKA	43	30	33	6.3
TF	F128_TF	FKA	44	30	33	5.9
TF	F129_TF	FKA	45	30	33	6.4
TF	F130_TF	FKA	46	30	33	6
TF	F131_TF	FKA	47	30	33	5.3
TF	F132_TF	FKA	48	30	33	5.5
TF	F133_TF	FKA	49	30	33	5.6
TF	F200_TF	FKA	50	30	33	10.7
TF	F201_TF	FKA	51	30	33	7.6
TF	F202_TF	FKA	52	30	33	9.7
TF	F203_TF	FKA	53	30	33	6.4
TF	F301_TF	FKA	54	30	33	5.8
TF	F304_TF	FKA	55	30	33	6.5
TF	F305_TF	FKA	56	30	33	5.6
TF	F306_TF	FKA	57	30	33	6.4
TF	F307_TF	FKA	58	30	33	5.9
TF	F308_TF	FKA	59	30	33	6.2
TF	F309_TF	FKA	60	30	33	8
TF	F310_TF	FKA	61	30	33	7.5

TF	F311_TF	FKA	62	30	33	6.2
TF	F312_TF	FKA	63	30	33	7.8
TF	F313_TF	FKA	64	30	33	6.6
TF	F314_TF	FKA	65	30	33	6.9
TF	F315_TF	FKA	66	30	33	6.7
*CN VALUE ##############						
CN	F100_CN	FKA	10	25	28	1
CN	F101_CN	FKA	11	25	28	1
CN	F102_CN	FKA	12	25	28	1
CN	F103_CN	FKA	13	25	28	1
CN	F104_CN	FKA	14	25	28	1
CN	F105_CN	FKA	15	25	28	1
CN	F106_CN	FKA	16	25	28	1
CN	F107_CN	FKA	17	25	28	1
CN	F108_CN	FKA	18	25	28	1
CN	F109_CN	FKA	19	25	28	1
CN	F10C_CN	FKA	20	25	28	1
CN	F10D_CN	FKA	21	25	28	1
CN	F10E_CN	FKA	22	25	28	1
CN	F10F_CN	FKA	23	25	28	1
CN	F10G_CN	FKA	24	25	28	1
CN	F10H_CN	FKA	25	25	28	1
CN	F10I_CN	FKA	26	25	28	1
CN	F10J_CN	FKA	27	25	28	1
CN	F110_CN	FKA	28	25	28	1
CN	F111_CN	FKA	29	25	28	1
CN	F112_CN	FKA	30	25	28	1
CN	F114_CN	FKA	31	25	28	1
CN	F115_CN	FKA	32	25	28	1
CN	F116_CN	FKA	33	25	28	1
CN	F117_CN	FKA	34	25	28	1
CN	F118_CN	FKA	35	25	28	1
CN	F120_CN	FKA	36	25	28	1
CN	F121_CN	FKA	37	25	28	1
CN	F122_CN	FKA	38	25	28	1
CN	F123_CN	FKA	39	25	28	1
CN	F124_CN	FKA	40	25	28	1
CN	F125_CN	FKA	41	25	28	1
CN	F126_CN	FKA	42	25	28	1
CN	F127_CN	FKA	43	25	28	1
CN	F128_CN	FKA	44	25	28	1
CN	F129_CN	FKA	45	25	28	1
CN	F130_CN	FKA	46	25	28	1
CN	F131_CN	FKA	47	25	28	1
CN	F132_CN	FKA	48	25	28	1
CN	F133_CN	FKA	49	25	28	1
CN	F200_CN	FKA	50	25	28	1
CN	F201_CN	FKA	51	25	28	1
CN	F202_CN	FKA	52	25	28	1
CN	F203_CN	FKA	53	25	28	1
CN	F301_CN	FKA	54	25	28	1
CN	F304_CN	FKA	55	25	28	1
CN	F305_CN	FKA	56	25	28	1
CN	F306_CN	FKA	57	25	28	1
CN	F307_CN	FKA	58	25	28	1
CN	F308_CN	FKA	59	25	28	1
CN	F309_CN	FKA	60	25	28	1
CN	F310_CN	FKA	61	25	28	1
CN	F311_CN	FKA	62	25	28	1
CN	F312_CN	FKA	63	25	28	1
CN	F313_CN	FKA	64	25	28	1
CN	F314_CN	FKA	65	25	28	1
CN	F315_CN	FKA	66	25	28	1

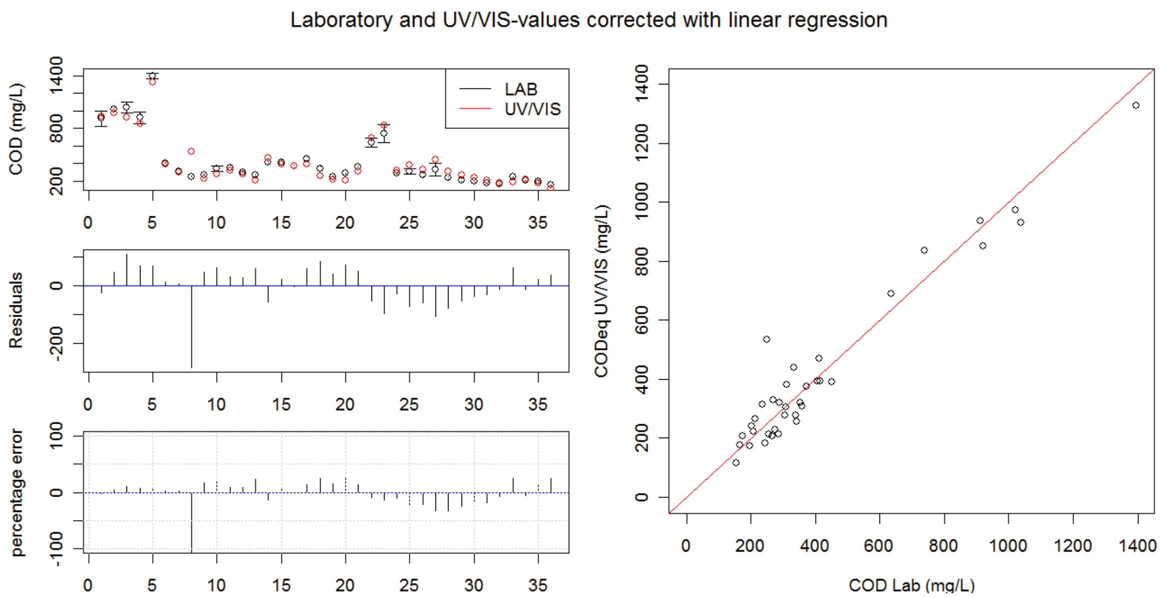
Optimisation parameters

```
*Optimierungsparameter
*====================
*
*   --------------      -------   -----------   --------   --------   -----------   ----------   -----------
*   Bezeichnung         Einh.     Anfangsw.     Min        Max        Beziehung     Objekt       Zeitpunkt
*   -<---------->-      -<--->-   -<------->-   -<---->-   -<---->-   -<------->-   -<------>-   -<------->-
    CN                  -         60            40         85
    EF                  -         1             0.8        1.2
    IL                  -         0.5           0.15       0.8
    DL                  -         1.5           0.2        3
    K                   -         1.5           0.5        3
    IF                  -         0.5           0.15       1
*   VG2                 -         0.5           0.2        1
*   VG3                 -         0.5           0.2        1
*   VG4                 -         0.5           0.2        1
*   VG5                 -         0.5           0.2        1
*   VG6                 -         0.5           0.2        1
    TF                  -         1             0.5        3
*   Pinit               -         10            4          50
*#  Pinit2              -         1             0.5        50
*#  Pinit3              -         1             0.5        50
*#  Pinit4              -         1             0.5        50
*#  Pinit5              -         1             0.5        50
*   Pmax                -         1             4          50
*#  Pmax2               -         1             0.5        50
*#  Pmax3               -         1             0.5        50
*#  Pmax4               -         1             0.5        50
*#  Pmax5               -         1             0.5        50
*   DISP                -         1             0.01       3
*#  DISP2               -         1             0.01       3
*#  DISP3               -         1             0.01       3
*#  DISP4               -         1             0.01       3
*#  DISP5               -         1             0.01       3
*   Ke                  -         1             0.01       1
*#  Ke2                 -         1             0.01       1
*#  Ke3                 -         1             0.01       1
*#  Ke4                 -         1             0.01       1
*#  Ke5                 -         1             0.01       1
*   --------------      -------   -----------   --------   --------   -----------   ----------   -----------
```

4. UV/VIS calibration: linear- and non-linear regression for global calibration



Results from power regression and linear regression: black dots corresponding to global calibration values, blue line to regression function. Red dots show the values corrected be the obtained regression function. Dashed line indicates the bisector.



Results from [R]-script evaluation of correction of the global calibration by linear regression

5. Rain gauges

5.1. Measurement periods and registered data loss

Graz West catchment - overview rain gauges and rainfall data							
Rain gauge	**Klusemanngasse (KLUS)**			**Lutz (LUTZ)**		**Karl Morre (KAMO)**	
Abbr.	RG_KLUS		RG_KLUS_B	RG_LUTZ		RG_KAMO	
Type	tipping bucket		weighing	tipping bucket		tipping bucket	
Year	measuring period	calibration	measuring period	measuring period	calibration	measuring period	calibration
2003	11.07.2003 31.12.2003		26.03.2003 31.12.3003	-		-	
2004	01.01.2004 15.01.2004		01.01.2004 28.10.2004	09.04.2004 12.07.2004	-	-	
2005	01.01.2005 31.12.2005*	02.09.2004	01.01.2005 17.10.2005	-		-	
2006	01.01.2006 31.12.2006		28.01.2006 31.12.2006	01.01.2006 31.12.2006*	06.05.2004	-	
2007	01.01.2007 31.12.2007		-	01.01.2007 31.12.2007	19.07.2007	-	
2008	01.01.2008 31.12.2008*	07.07.2008	-	01.01.2008 31.12.2008		28.11.2008 31.12.2008*	-
2009	01.01.2009 31.08.2009		-	01.01.2009 31.08.2009	not calibrated	01.01.2009	summer

* registered data loss

Graz West catchment - rain gauges - registered data loss						
Rain gauge	**Klusemann (KLUS)**		**Lutz (LUTZ)**		**Karl Morre (KAMO)**	
Code	RG_GW01_A		RG_GW02		RG_GW03	
Type	tipping bucket		tipping bucket		tipping bucket	
Year	start	end	start	end	start	end
2004	-	-	-	-	-	-
2005	21.01.2005	-	-	-	-	-
	18.04.2005	26.04.2005				
	19.07.2005	22.07.2005				
	25.07.2005	-				
	03.08.2005	-				
	02.09.2005	-				
	13.09.2005	-				
	23.10.2005	-				

	16.11.2005	-				
	26.12.2005	30.12.2005				
2006	-	-	04.03.2006	05.03.2006	-	-
			16.05.2005	01.06.2006		
			25.07.2006	08.09.2006		
2007	-	-	23.01.2007	29.01.2007	-	-
			05.02.2007	08.02.2007		
			07.03.2007	18.03.2007		
			29.04.2007	04.05.2007		
2008	10.07.2008	13.07.2008	-	-	07.12.2008	10.12.2008

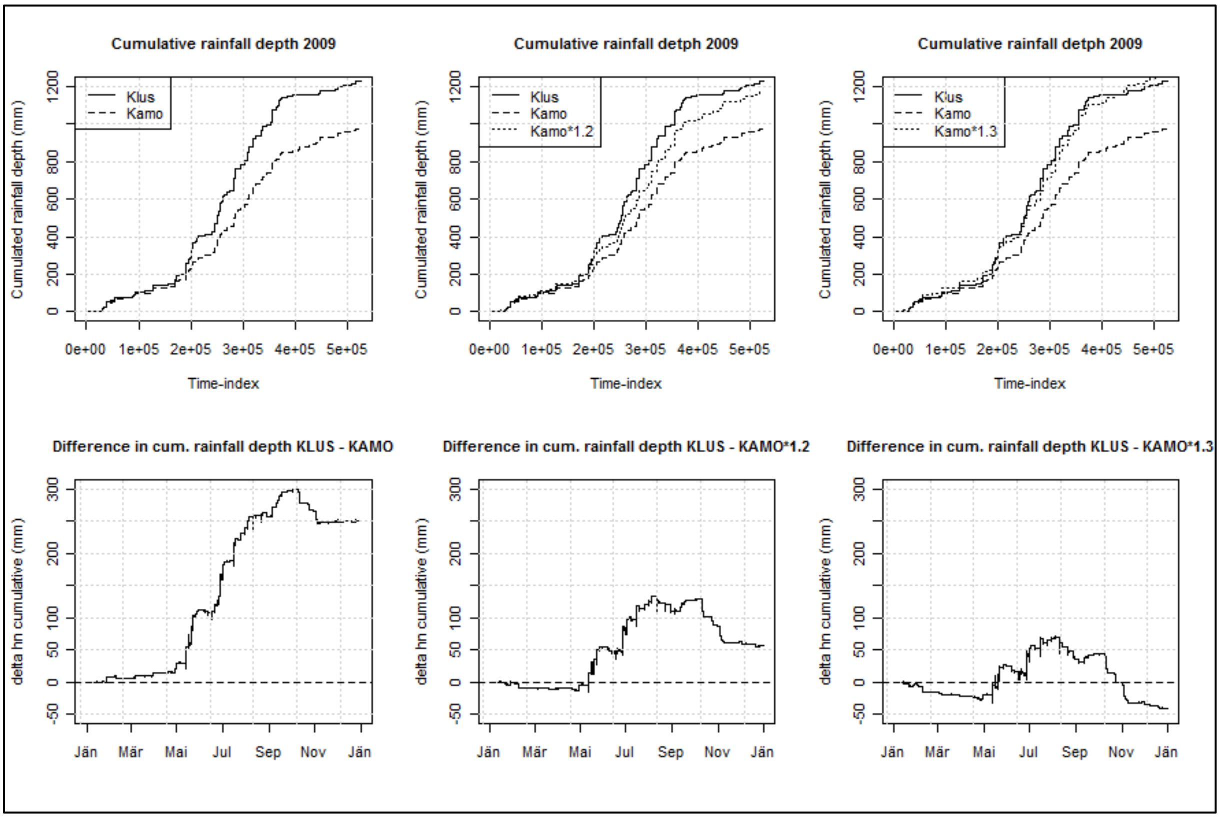
5.2. Identified events by the ConvertSensorData tool for 2009

Event	Start (earliest)	End (latest)	No.	duration (min)			Sum Hn (mm)			Max Hn (mm/min)		
-	date/time	date/time	-	KAMO	KLUS	LUTZ	KAMO	KLUS	LUTZ	KAMO	KLUS	LUTZ
2009_1	14.01.2009 06:54	15.01.2009 14:02	3	660	279	1476	4.95	4.86	5.81	0.09	0.12	0.20
2009_2	21.01.2009 09:30	22.01.2009 02:18	3	954	1005	994	12.41	11.98	15.22	0.09	0.12	0.20
2009_3	23.01.2009 20:24	24.01.2009 00:58	3	171	196	272	3.21	4.22	4.21	0.09	0.12	0.09
2009_4	27.01.2009 04:11	28.01.2009 00:59	3	1215	1226	1248	20.21	28.54	30.17	0.09	0.12	0.20
2009_5	01.02.2009 17:19	03.02.2009 11:53	3	450	520	2407	2.08	1.76	14.74	0.09	0.11	0.09
2009_6	02.02.2009 07:31	03.02.2009 10:10	2	1591	1494	0	9.11	9.08	0.00	0.09	0.12	0.00
2009_7	03.02.2009 21:57	04.02.2009 04:13	3	358	362	371	1.91	2.07	2.66	0.09	0.11	0.09
2009_8	07.02.2009 19:13	08.02.2009 12:24	3	1017	1029	992	16.56	14.20	18.52	0.09	0.12	0.18
2009_9	21.02.2009 19:26	22.02.2009 08:56	2	779	0	810	1.22	0.00	1.65	0.09	0.00	0.09
2009_10	02.03.2009 16:47	03.03.2009 02:46	3	582	526	506	1.48	1.39	1.58	0.09	0.10	0.20
2009_11	04.03.2009 19:00	05.03.2009 00:42	3	336	328	330	2.60	2.68	2.84	0.09	0.11	0.09
2009_12	05.03.2009 09:09	05.03.2009 22:57	3	828	803	799	6.94	8.47	8.42	0.09	0.11	0.09
2009_13	06.03.2009 02:34	06.03.2009 14:16	3	572	520	700	12.23	14.25	16.13	0.09	0.12	0.09
2009_14	19.03.2009 15:13	19.03.2009 22:15	3	344	107	420	4.08	4.01	4.03	0.09	0.13	0.09
2009_15	29.03.2009 12:32	30.03.2009 10:47	3	935	1334	362	22.62	28.57	16.45	0.17	0.40	0.28
2009_16	17.04.2009 11:17	17.04.2009 13:47	1	0	0	150	0.00	0.00	1.10	0.00	0.00	0.18
2009_17	19.04.2009 20:33	20.04.2009 04:59	3	428	475	506	4.25	5.53	5.32	0.09	0.12	0.09
2009_18	23.04.2009 03:24	23.04.2009 06:56	3	146	157	208	5.02	4.46	5.78	0.26	0.12	0.09
2009_19	23.04.2009 17:44	23.04.2009 23:43	2	0	359	311	0.00	1.20	1.10	0.00	0.12	0.09
2009_20	24.04.2009 21:07	25.04.2009 06:45	1	578	0	0	1.04	0.00	0.00	0.09	0.00	0.00
2009_21	28.04.2009 19:20	30.04.2009 10:52	3	1746	1130	1175	27.22	19.43	12.12	0.51	1.48	0.37
2009_22	29.04.2009 19:30	30.04.2009 09:57	2	0	867	656	0.00	22.19	21.74	0.00	0.55	0.85
2009_23	30.04.2009 19:44	30.04.2009 20:26	1	0	0	42	0.00	0.00	1.37	0.00	0.00	0.09
2009_24	03.05.2009 15:24	03.05.2009 15:54	1	0	0	30	0.00	0.00	2.67	0.00	0.00	0.28
2009_25	04.05.2009 12:21	04.05.2009 16:24	3	136	171	198	2.69	4.61	4.58	0.17	0.25	0.09
2009_26	05.05.2009 11:24	05.05.2009 11:25	1	1	0	0	1.50	0.00	0.00	1.42	0.00	0.00
2009_27	11.05.2009 21:16	11.05.2009 23:54	1	158	0	0	1.56	0.00	0.00	0.09	0.00	0.00
2009_28	12.05.2009 16:44	12.05.2009 19:43	3	171	167	137	22.99	47.33	31.61	1.64	2.86	2.39
2009_29	13.05.2009 03:18	13.05.2009 07:43	2	190	257	0	2.08	2.79	0.00	0.17	0.13	0.00
2009_30	13.05.2009 16:43	13.05.2009 17:58	3	72	70	28	3.90	4.52	2.57	0.17	0.25	0.18
2009_31	13.05.2009 22:15	14.05.2009 06:35	2	459	491	0	2.17	2.36	0.00	0.09	0.11	0.00
2009_32	16.05.2009 13:32	16.05.2009 18:30	3	282	298	287	22.60	25.18	14.63	2.87	1.89	1.45
2009_33	18.05.2009 18:49	18.05.2009 20:59	3	124	130	85	3.11	5.81	5.59	0.51	0.90	0.95
2009_34	19.05.2009 16:52	19.05.2009 22:24	3	313	314	175	24.78	49.95	42.97	0.85	2.09	1.86
2009_35	22.05.2009 16:14	22.05.2009 17:35	3	81	62	34	12.29	29.62	15.22	1.72	3.32	2.07
2009_36	26.05.2009 17:41	26.05.2009 23:21	2	331	328	0	5.11	8.38	0.00	0.26	0.56	0.00

Event	Start (earliest)	End (latest)	No.	duration (min)			Sum Hn (mm)			Max Hn (mm/min)		
-	date/time	date/time	-	KAMO	KLUS	LUTZ	KAMO	KLUS	LUTZ	KAMO	KLUS	LUTZ
2009_37	27.05.2009 04:25	27.05.2009 17:09	2	618	762	0	11.44	16.12	0.00	0.17	0.26	0.00
2009_38	30.05.2009 05:15	30.05.2009 16:05	3	601	632	61	7.11	8.32	1.47	0.09	0.12	0.09
2009_39	05.06.2009 22:11	06.06.2009 01:07	3	140	171	149	1.39	1.31	1.74	0.09	0.11	0.09
2009_40	06.06.2009 20:07	07.06.2009 08:21	3	108	727	58	3.89	3.23	2.86	0.26	0.11	0.37
2009_41	07.06.2009 19:00	07.06.2009 23:10	3	192	237	4	4.46	2.09	2.65	1.41	0.11	1.15
2009_42	11.06.2009 14:12	12.06.2009 04:17	3	32	830	22	5.15	4.28	4.65	0.76	0.11	0.56
2009_43	16.06.2009 14:16	16.06.2009 22:24	2	488	0	18	10.57	0.00	2.39	0.26	0.00	0.28
2009_44	17.06.2009 08:44	17.06.2009 08:45	1	0	1	0	0.00	12.57	0.00	0.00	8.71	0.00
2009_45	19.06.2009 21:43	20.06.2009 13:17	3	934	909	45	32.72	41.81	14.09	0.43	1.00	1.05
2009_46	22.06.2009 15:30	22.06.2009 19:32	3	204	229	204	2.26	1.18	1.46	0.09	0.11	0.09
2009_47	23.06.2009 07:38	25.06.2009 02:26	2	2545	608	0	35.36	13.74	0.00	0.26	0.26	0.00
2009_48	24.06.2009 00:06	25.06.2009 04:02	1	0	1676	0	0.00	30.15	0.00	0.00	0.26	0.00
2009_49	26.06.2009 18:17	26.06.2009 20:56	3	159	146	15	12.34	18.50	8.75	1.17	1.95	1.77
2009_50	27.06.2009 12:25	27.06.2009 16:51	3	238	260	20	1.13	34.61	4.30	0.17	2.71	1.05
2009_51	27.06.2009 20:57	27.06.2009 23:53	2	176	32	0	4.41	1.40	0.00	0.34	0.26	0.00
2009_52	28.06.2009 07:48	29.06.2009 05:21	3	1222	1293	3	12.57	15.63	1.11	0.17	0.26	0.47
2009_53	29.06.2009 11:13	29.06.2009 16:51	3	237	338	9	1.13	2.08	1.85	0.09	0.26	0.47
2009_54	30.06.2009 11:47	30.06.2009 13:34	2	89	0	59	9.67	0.00	9.31	0.34	0.00	1.26
2009_55	01.07.2009 10:00	01.07.2009 11:30	2	7	90	0	2.65	17.66	0.00	0.68	1.78	0.00
2009_56	01.07.2009 18:38	01.07.2009 20:13	3	71	95	3	3.02	10.20	1.68	0.51	1.10	0.66
2009_57	02.07.2009 11:42	02.07.2009 13:39	2	0	100	10	0.00	2.47	3.73	0.00	0.40	0.75
2009_58	03.07.2009 13:42	03.07.2009 14:19	2	26	37	0	1.21	4.26	0.00	0.09	0.40	0.00
2009_59	06.07.2009 11:43	06.07.2009 14:27	3	158	164	139	1.56	2.77	2.29	0.09	0.12	0.09
2009_60	07.07.2009 15:34	07.07.2009 17:52	3	105	132	58	14.61	13.20	4.25	1.56	1.46	0.37
2009_61	08.07.2009 00:38	08.07.2009 04:39	2	232	241	0	1.74	1.77	0.00	0.09	0.11	0.00
2009_62	08.07.2009 23:32	09.07.2009 00:41	2	59	67	0	1.13	1.64	0.00	0.09	0.12	0.00
2009_63	10.07.2009 02:07	10.07.2009 11:41	2	464	574	0	2.34	3.67	0.00	0.09	0.11	0.00
2009_64	13.07.2009 09:43	13.07.2009 09:46	1	0	0	3	0.00	0.00	1.60	0.00	0.00	0.87
2009_65	15.07.2009 19:06	16.07.2009 00:52	3	346	300	65	40.50	69.18	57.10	1.64	3.06	3.53
2009_66	18.07.2009 08:54	18.07.2009 13:44	3	290	268	183	42.83	47.45	36.89	1.57	1.83	2.00
2009_67	24.07.2009 23:18	25.07.2009 05:53	3	329	371	45	12.55	21.50	8.91	0.34	1.06	0.75
2009_68	30.07.2009 16:09	31.07.2009 00:02	3	473	367	324	18.24	26.39	9.37	0.51	0.97	0.28
2009_69	03.08.2009 15:51	04.08.2009 21:36	3	1581	1779	509	53.78	72.23	11.65	0.34	1.30	0.95
2009_70	04.08.2009 07:18	04.08.2009 14:11	1	0	0	413	0.00	0.00	1.65	0.00	0.00	0.18
2009_71	10.08.2009 16:31	10.08.2009 22:53	3	382	298	65	35.89	37.52	30.48	1.65	3.03	3.54
2009_72	13.08.2009 18:13	14.08.2009 05:16	3	663	657	314	18.79	19.65	5.33	0.26	0.39	0.37
2009_73	14.08.2009 12:24	14.08.2009 12:51	1	27	0	0	1.04	0.00	0.00	0.09	0.00	0.00
2009_74	21.08.2009 19:55	21.08.2009 21:37	3	75	90	41	23.69	25.98	47.94	1.01	1.31	3.20
2009_75	22.08.2009 16:05	23.08.2009 01:03	3	538	288	87	17.32	19.69	7.47	0.26	0.41	0.95
2009_76	28.08.2009 23:42	29.08.2009 00:46	3	64	54	49	14.87	10.15	19.85	1.87	1.11	1.56
2009_77	29.08.2009 09:42	29.08.2009 22:47	2	785	429	0	5.80	3.28	0.00	0.34	0.12	0.00
2009_78	04.09.2009 00:18	05.09.2009 07:27	3	1827	1865	206	62.99	77.56	9.24	0.43	0.55	0.47
2009_79	04.09.2009 17:04	04.09.2009 17:22	1	0	0	18	0.00	0.00	1.47	0.00	0.00	0.28
2009_80	11.09.2009 13:02	11.09.2009 16:58	3	235	131	115	7.69	14.15	11.88	0.43	0.70	1.10
2009_81	12.09.2009 05:41	12.09.2009 08:36	2	37	169	0	1.04	1.08	0.00	0.09	0.12	0.00
2009_82	12.09.2009 15:03	12.09.2009 16:23	2	0	72	16	0.00	4.00	2.95	0.00	0.40	0.37
2009_83	13.09.2009 14:50	14.09.2009 05:09	2	859	848	0	14.39	20.09	0.00	0.17	0.27	0.00
2009_84	14.09.2009 09:25	14.09.2009 20:21	2	656	651	0	5.55	6.42	0.00	0.17	0.69	0.00
2009_85	15.09.2009 01:41	15.09.2009 05:43	3	241	239	89	4.92	5.24	2.41	0.43	0.70	0.56
2009_86	16.09.2009 20:37	17.09.2009 03:04	2	387	337	0	4.34	5.69	0.00	0.17	0.56	0.00
2009_87	17.09.2009 14:15	18.09.2009 03:21	3	628	772	26	5.12	10.73	15.55	0.17	0.70	1.65
2009_88	25.09.2009 13:48	25.09.2009 14:17	2	0	29	13	0.00	1.83	4.08	0.00	0.41	0.47
2009_89	01.10.2009 17:51	01.10.2009 23:16	3	325	93	93	3.88	5.73	3.71	0.43	0.97	0.46
2009_90	02.10.2009 07:23	02.10.2009 10:33	3	127	190	95	3.29	4.12	1.48	0.26	0.40	0.28
2009_91	09.10.2009 13:32	09.10.2009 19:31	1	359	0	0	3.27	0.00	0.00	0.68	0.00	0.00
2009_92	10.10.2009 03:02	10.10.2009 10:31	2	405	0	449	2.43	0.00	4.67	0.09	0.00	0.09
2009_93	10.10.2009 19:58	11.10.2009 03:38	2	460	0	228	10.23	0.00	6.14	0.17	0.00	0.09
2009_94	12.10.2009 00:02	12.10.2009 08:33	2	511	0	24	6.83	0.00	1.20	0.43	0.00	0.28
2009_95	12.10.2009 08:14	12.10.2009 08:20	1	0	0	6	0.00	0.00	1.86	0.00	0.00	0.56

Event	Start (earliest)	End (latest)	No.	duration (min)			Sum Hn (mm)			Max Hn (mm/min)		
-	date/time	date/time	-	KAMO	KLUS	LUTZ	KAMO	KLUS	LUTZ	KAMO	KLUS	LUTZ
2009_96	22.10.2009 14:20	22.10.2009 18:15	1	235	0	0	1.99	0.00	0.00	0.09	0.00	0.00
2009_97	23.10.2009 17:53	24.10.2009 11:10	1	1037	0	0	8.50	0.00	0.00	0.09	0.00	0.00
2009_98	30.10.2009 05:03	30.10.2009 05:40	1	37	0	0	1.39	0.00	0.00	0.09	0.00	0.00
2009_99	02.11.2009 14:51	03.11.2009 16:23	1	1532	0	0	13.01	0.00	0.00	0.09	0.00	0.00
2009_100	04.11.2009 13:15	04.11.2009 23:02	1	587	0	0	5.29	0.00	0.00	0.09	0.00	0.00
2009_101	06.11.2009 11:15	07.11.2009 06:11	2	1133	1120	0	8.85	8.51	0.00	0.09	0.12	0.00
2009_102	08.11.2009 12:46	09.11.2009 05:08	2	978	891	0	13.44	13.94	0.00	0.17	0.25	0.00
2009_103	18.11.2009 15:06	18.11.2009 18:31	1	0	205	0	0.00	1.11	0.00	0.00	0.12	0.00
2009_104	28.11.2009 07:17	28.11.2009 10:15	2	133	175	0	1.65	3.05	0.00	0.09	0.12	0.00
2009_105	30.11.2009 01:35	30.11.2009 04:01	2	111	146	0	1.30	1.54	0.00	0.09	0.11	0.00
2009_106	01.12.2009 00:48	01.12.2009 09:32	2	515	524	0	4.68	6.57	0.00	0.09	0.13	0.00
2009_107	01.12.2009 14:13	01.12.2009 18:27	3	254	226	194	7.97	5.67	1.11	0.17	0.21	0.28
2009_108	08.12.2009 11:36	08.12.2009 14:29	2	155	173	0	8.49	10.48	0.00	0.17	0.13	0.00
2009_109	14.12.2009 13:30	14.12.2009 22:32	1	542	0	0	1.48	0.00	0.00	0.09	0.00	0.00
2009_110	19.12.2009 08:12	19.12.2009 20:21	2	630	535	0	3.82	4.51	0.00	0.09	0.11	0.00
2009_111	20.12.2009 10:20	20.12.2009 12:23	1	123	0	0	2.00	0.00	0.00	0.09	0.00	0.00
2009_112	23.12.2009 23:31	24.12.2009 01:32	2	117	113	0	1.82	2.78	0.00	0.09	0.12	0.00
2009_113	25.12.2009 09:03	25.12.2009 17:14	3	483	295	127	9.35	11.37	2.50	0.26	0.41	0.47

5.3. Substituting missing values for the KLUS rain gauge



Visual evaluation of cumulative rainfall residuals for substituting missing values from KLUS rain guage by KAMO rain gauge

6. Visual data analysis

6.1. Hydraulics and water quality 2003-2006

127_CSO_Lutt Hydraulics - Visual Data Analysis		
Hydraulics - FLOW - general remarks		
Overflow measurement sometimes negative Values -> Pre-Validation!		
for night minima: sometimes measured value values = 0. ? Problem of probe measuring very low flow?		
how to explain abrupt changes in DWF (min. - and max. value) in Q and h?		
Measurement limits		
Limits for Q:	2400	l/s
Measurement gaps and errors / visual analysis		
2003	from 01.04.2003: based on corrected flow data (Hochedlinger)	
09.05.2003	13.05.2003	failure
14.05.2003	17.05.2003	failure
21.08.2003	02.09.2003	failure
2004	based on corrected flow data (Hochedlinger)	
	from August: no corrected data available	
29.03.2004 09:00	30.03.2004 15:00	failure
15.04.2004	22.04.2004	no corrected flow data
06.05.2004	13.05.2004	failure
14.09.2004 14:00	20.09.2004 18:00	failure
2005		
01.01.2005	23.02.2005	"unsteady" measurements (DWF, many values = 0)
2006		
23.06.2006	28.06.2006	measuerment failure for night minimum. Remark: after very strong rainfall event

127_CSO_Lutz Parameters s:can - Visual Data Analysis		
s:can - general remarks		
visual comparison of COD, CODf and TSS		
CODf: high peaks do not react as with TSS and COD		
generally 2004: drifts clearly visible		
how to interpret differences as in November 2005? ("stability" of measurements?)		
s:can - measurement limits		
CODeq	1500	up to August 2003; from March 2004
	1800	from August 2003 - to March 2004
CODf,eq		
TSSeq	1200	up to August 2003
	1450	from August 2003 to March 2004
SAC254*		
SAC436*		
N03-N*	16	mg/l

*not checked in visual comparison		
Measurement gaps and errors / visual analysis		
2003		
11.10.2003	onwards	drift?
09.05.2003	13.05.2003	failure
14.05.2003	17.05.2003	failure
21.08.2003	02.09.2003	failure
16.12.2003	20.12.2003	failure
2004		
27.01.2004 12:00	28.01.2004 12:00	failure
29.03.2004 09:00	30.03.2004 15:00	failure
07.04.2004 17:00	08.04.2004 10:00	failure
11.04.2004	23.04.2004	TSS concentrations erroneous
29.04.2004 12:00	01.05.2004 13:00	failure
06.05.2004	13.05.2004	failure
22.06.2004 20:00	23.06.2004 11:00	failure
10.07.2004	onwards	drift?
14.08.2004 00:00	17.08.2004 16:00	failure
21.08.2004	05.10.2004	drift, wrong measurements? - TSS / COD >>
14.09.2004 14:00	20.09.2004 18:00	failure
01.11.2004 18:00	02.11.2004 09:00	failure
2005		
04.04.2005 12:00	05.04.2005 18:00	failure
18.04.2005 23:00	19.04.2005 17:00	failure
27.04.2005 22:00	30.04.2005 17:00	failure
28.05.2005 12:00	30.05.2005 00:00	failure
17.07.2005 12:00	18.07.2005 12:00	failure
03.08.2005 21:00	11.08.2005 04:00	failure
13.08.2005 17:00	14.08.2005 22:00	failure
10.10.2005 13:00	13.10.2005 15:00	failure
15.11.2005 07:00	17.11.2005 15:00	failure
17.11.2005 00:00		change in behaviour
2006		
23.01.2006 14:00	13.02.2006 18:00	failure
16.05.2006 18:00	18.05.2006 15:00	failure
14.06.2006		change in behaviour - nothing noted in Log

6.2. Hydraulics and water quality 2009

Visual analysis Q inflow								
measurement failure			**Measurement limit reached**			**in-sewer storage - retained flow**		
Begin	End		Begin	End	remark	Begin	End	remark
29.11.2008 12:00	01.12.2008 12:00		12.05.2009 18:00	12.05.2009 19:00		01.12.2008 14:00	01.12.2008 18:00	
18.12.2008 12:00	19.12.2008 02:00		16.05.2009 16:45	16:05.2009 17:15		28.01.2009 03:00	28.01.2009 05:30	
12.01.2009 00:00	21.01.2009 00:00		19.05.2009 18:45	19.05.2009 20:00		08.02.2009 15:00	08.02.2009 20:00	
05.02.2009 14:00	06.02.2009 02:00		22.05.2009 17:45	22.05.2009 18:30		29.04.2009 14:00		strong event, several follow up events - between event
26.02.2009 09:00	28.02.2009 10:00		19.06.2009 23:45	19.06.2009 23:45	*some minutes only	12.05.2009 21:30	13.05.2009 05:00	Follow up event - end not exact
04.03.2009 23:00	05.03.2009 14:00		26.06.2009 19:30	26.06.2009 20:00	*2 peaks cut off	13.05.2009 19:30	13.05.2009 21:00	? Check with rainfall. Possibly: event on 12. 05
14.04.2009 14:00	18.04.2009 04:00		30.06.2009 15:45	03.06.2009 16:00		16.05.2009 18:00		Follow up event - end not exact
20.06.2009 12:00	22.06.2009 00:00		07.07.2009 18:00	07.07.2009 18:45		16.05.2009 21:00	17.05.2009 04:30	
13.07.2009 16:15	13.07.2009 18:00		15.07.2009 21:15	15.07.2009 22:00	*2 peaks cut off	19.05.2009 23:00	20.05.2009 12:00	
15.07.2009 06:00	15.07.2009 21:00		18.07.2009 10:45	18.07.2009 13:45	*3 peaks, very strong event!	22.05.2009 20:00	23.05.2009 04:30	
23.07.2009 09:00	28.07.2009 23:00					26.05.2009 20:15	25.05.2009 21:15	Small event (Qmax = 600 l/s)
05.08.2009 08:00	02.11.2009 17:00	cable defect				27.05.2009 12:00	27.05.2009 15:30	
09.11.2009 19:00	11.11.2009 03:00					07.06.2009 21:30	07.06.2009 23:00	
14.12.2009 06:00	16.12.2009 04:00	*marked in log				11.06.2009 17:00	11.06.2009 20:15	
						20.06.2009 02:00		Measurement Failure and follow up events-
						23.06.2009		Follow up event - cannot be evaluated
						26.06.2009 22:00	27.06.2009 06:30	
						27.06.2009 00:30	28.06.2009 04:00	*interesting: event 27.06. 14:00 with same peak flow = no visible effect
						28.06.2009 23:00	29.06.2009 02:00	
						30.06.2009 16:00	01.07.2009 10:30	Follow up event - perhaps not exact
						07.07.2009 20:00	08.07.2009 06:00	Follow up event - perhaps not exact
						16.07.2009 00:30	16.07.2009 10:00	
						18.07.2009 16:00	19.07.2009 12:00	
						31.07.2009 02:00	31.07.2009 07:30	
						04.08.2009 20:00	05.08.2009 03:30	
						08.12.2009 15:30	08.12.2009 19:00	
						25.12.2009 18:30	25.12.2009 21:00	

Visual analysis - CODeq_TSSeq_inflow					
measurement failure			**other**		
Begin	End		Begin	End	
28.11.2008 02:00	01.12.2008 12:00		05.05.2009 10:00	12.05.2009 00:00	inconsistent values
18.12.2008 12:00	19.12.2008 02:00		17.06.2009 00:00	19.06.2009 00:00	inconsistent values
10.01.2009 09:00	21.01.2009 00:00		08.07.2009 00:00	13.07.2009 00:00	inconsistent values
05.02.2009 14:00	06.02.2009 02:00		04.12.2009 00:00		shift -> significantly higher

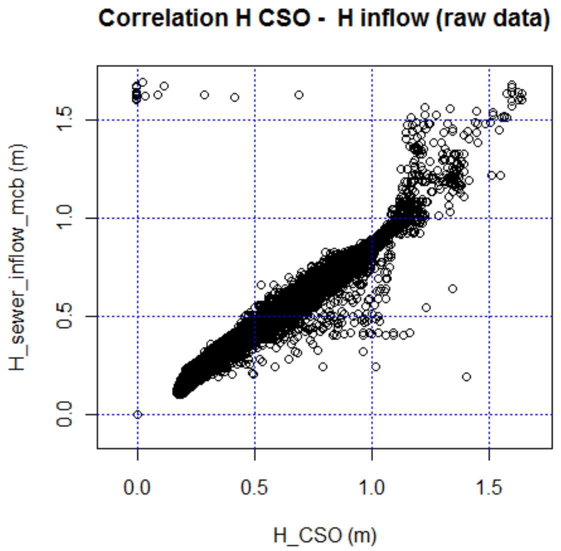
					COD/TSS values
26.02.2009 09:00	28.02.2009 10:00				
04.03.2009 23:00	05.03.2009 14:00				
14.04.2009 14:00	18.04.2009 04:00				
20.06.2009 12:00	22.06.2009 00:00				
15.07.2009 06:00	15.07.2009 21:00				
23.07.2009 09:00	28.07.2009 23:00				
05.08.2009 08:00	02.11.2009 17:00				
09.11.2009 19:00	11.11.2009 03:00				
14.12.2009 06:00	16.12.2009 04:00				

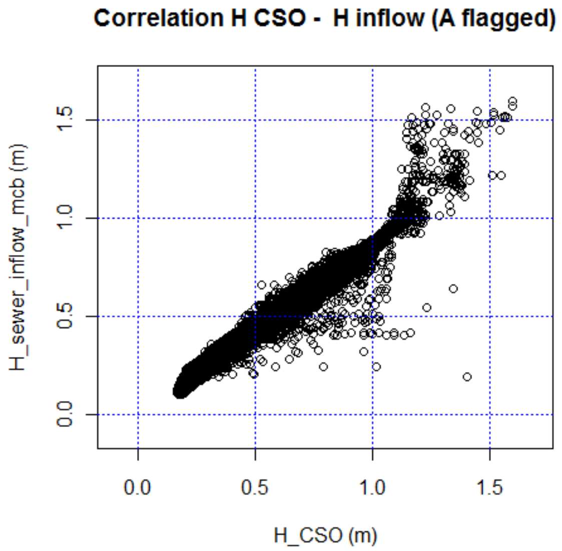
7. Data validation:

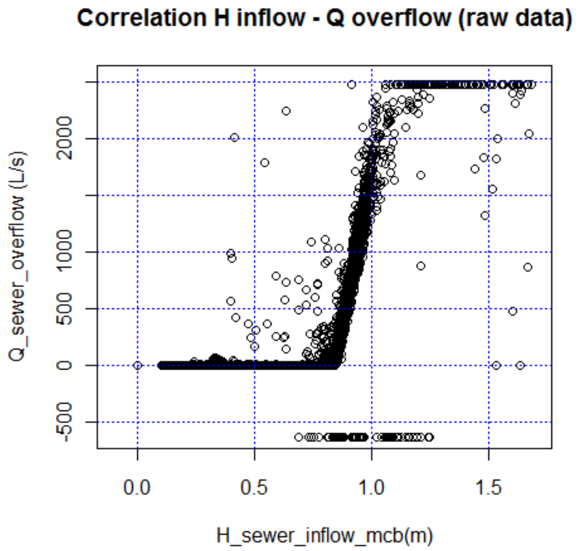
7.1. Settings for semi-automated data validation

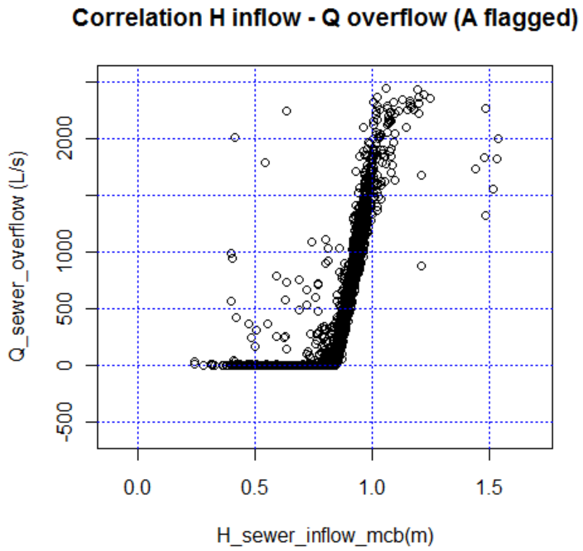
Variable	**Unit**	**Test settings**					
		min - max				cross validation	moving average residuals
		min A	max A	min B	max B		percentage error
H_CSO	m	0	2.5	-	-	-	-
H_sewer_inflow	m	0.03	1.6	-	1.7	-	-
H_sewer_overflow	m	0.03	1.6	-	1.7	-	-
Q_sewer_inflow_mcb	m³/s	0	2450	-	2500	if (Q_sewer_overflow - Q_sewer_inflow) < 0 then Q_sewer_inflow = B	-
Q_sewer_overflow	m³/s	1	2450	-	2500	if H_CSO > 1 and Q_sewer_overflow <10 then Q_sewer_overflow=B if (Q_sewer_overflow - Q_sewer_inflow) < 0 then Q_sewer_overflow = B if H_CSO<0.6 and Q_sewer_overflow>0 then Q_sewer_overflow =B	-
CODeq_inflow	mg/L	5	1250	1300	-	-	(+-) 25% = B
TSSeq_inflow	mg/L	5	2200	2300	-	-	(+-) 25% =B
Delta_t	min	1	3	1	12	-	-

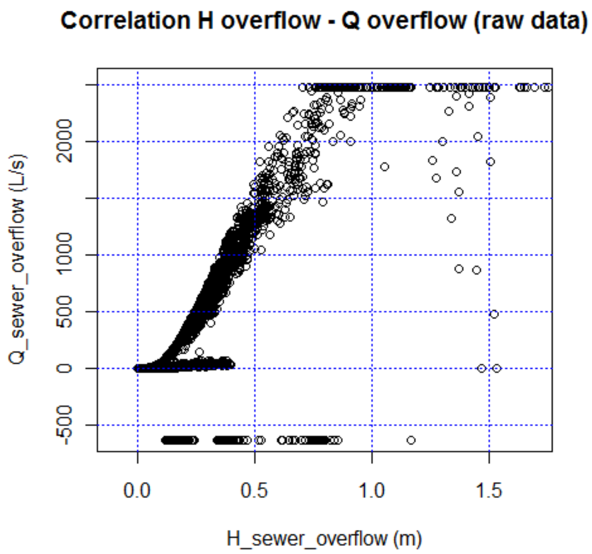
7.2. Correlation plots for hydraulics

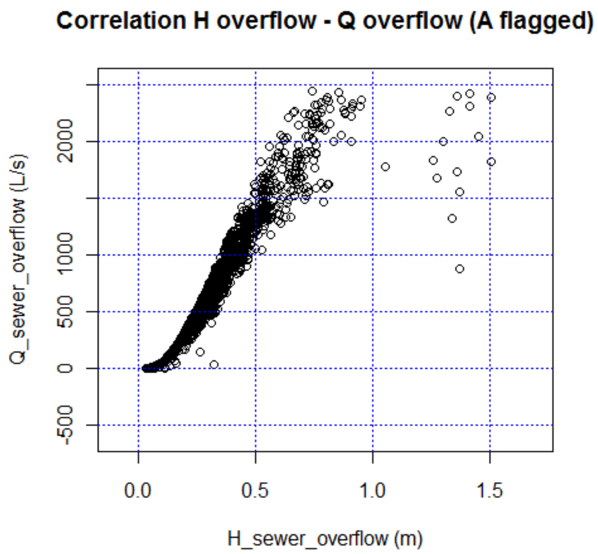


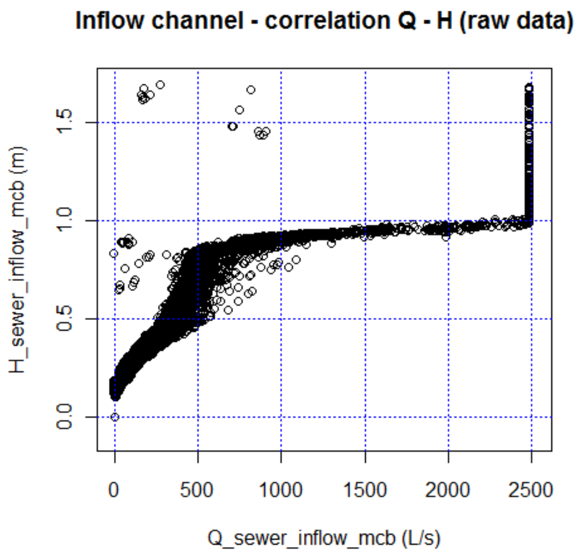


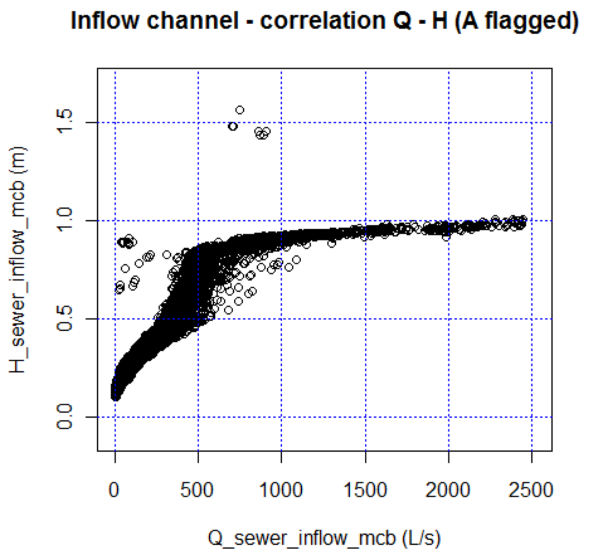


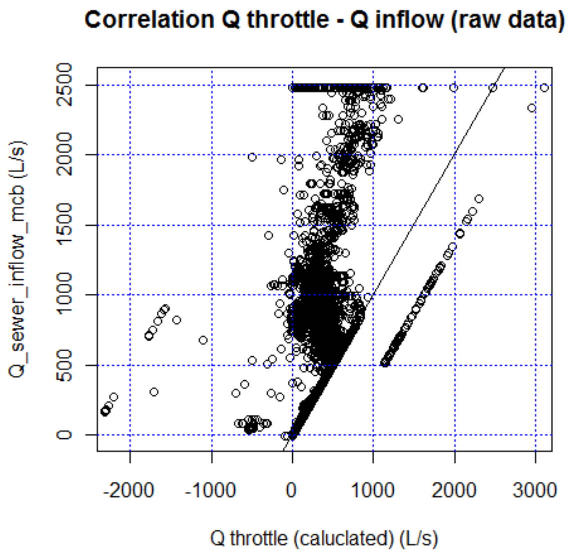


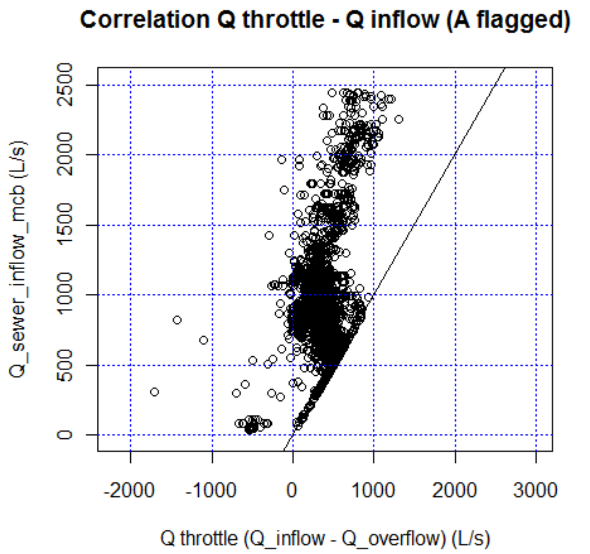






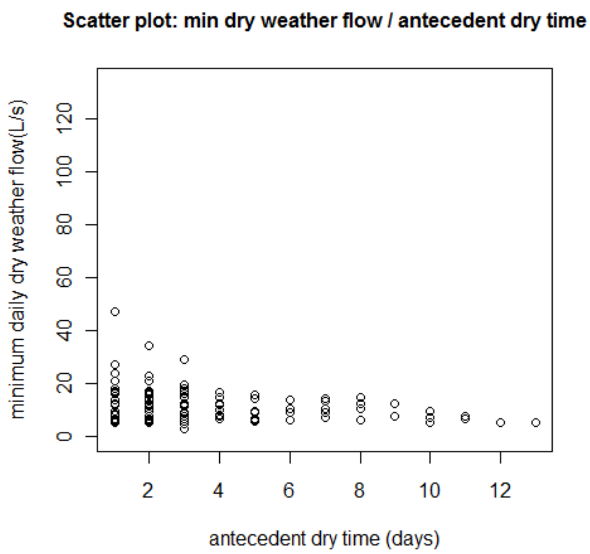


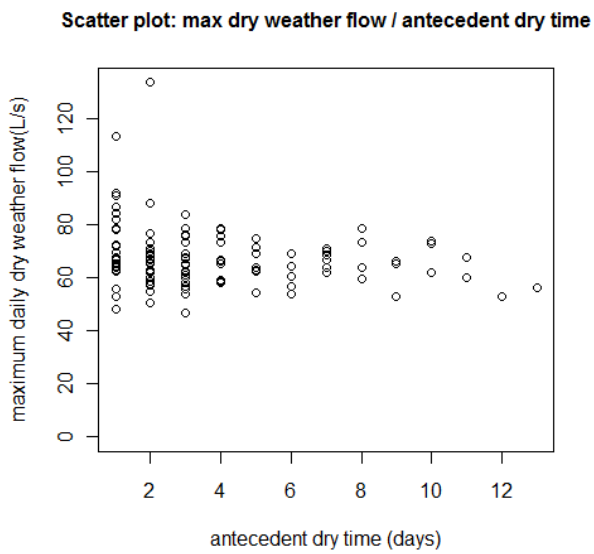




7.3. Dry weather evaluation

Effect of antecedent dry weather days on minimum and maximum daily DWF





8. SMUSI 2009 model – geometry data

Main sewer collectors

Bez.	dtf	Typ	L	D,maxB	Avoll	kb	H_unten	H_oben	Typ
-	min	-	m	m	qm	mm	mueNN	mueNN	
S121	0	2	5	0.6		1.424	365.55	365.8	2
S124		5	4.6			1.424	362.99	365.55	2
S132		1	410.8	0.5		1.424	382.8	419.88	2
S131		1	483.6	0.5		1.424	359.02	382.8	2
S10I		5	205.3			1.424	357.85	359.02	2
S10H		1	120.7	0.25		1.424	361.4	362.61	2
S129		5	317.7			1.424	359.69	361.4	2
S10F		1	132	0.25		1.424	361.13	362.99	2
S10G		5	159.5			1.424	358.94	359.69	2
S123		5	577.3			1.424	357.06	361.13	2
S127		2	200	0.7		1.424	358.06	358.94	2
S10E		1	409.4	0.4		1.424	361.59	365.55	2
S120		2	457.9	0.7		1.424	358.98	361.59	2
S125		5	329.9			1.424	357.06	358.06	2
S13H	0	1							1
S122		2	131.2	0.9		1.5	356.73	357.06	2
S12H	0	1							1
S117		2	375.9	0.7		1.424	359.71	361.78	2
S119		2	47.5	1.2		1.424	356.57	356.73	2
S116		2	118	0.7		1.424	357.24	357.85	2
S10D		2	213.9	0.9		1.424	356.54	357.24	2
S17H	0	2							1
S115		2	567.9	1.3		1.424	354.85	356.54	2
S114		5	300.3			1.424	354.28	354.85	2
S201		1	96.1	0.8		1.424	353.25	353.32	2
S112		5	272.4			1.424	353	354.28	2
S200		2	386.3	0.9		1.424	350.45	353.25	2
S111		5	412.3			1.424	350.31	353	2
S20H	0	1							1
S10B		5	17.8			1.424	350.2	350.31	2
S10C		1	302	1.7		1.424	348.1	350.2	2
S107		5	383.8			1.424	345.5	347.52	2
S07H	0	1							1
S110		5	235.5			1.424	345.5	348.09	2
S106		5	316.7			1.424	342.98	345.46	2
S10J		5	2.6			1.424	342.97	342.98	2
S103		5	315.7			1.424	342.71	344.87	2
S10A		5	59.027			1.424	342.71	342.97	2
S102		5	339.8			1.424	341.34	342.68	2
S100		5	198.28			1.424	340.57	341.34	2
SSKA		5	1			1.424	340.56	340.57	2
Stra	0	1							1
Sfik	0	1							1
DV12		1	4	0.3726		1.424	365.49	365.55	
S300		5	99			0.8	368.64	369.42	2
S301		1	485	0.35		0.8	363.75	368.64	2
S302		5	207			0.8	362.44	363.75	2
S303		2	422.3	1.2		0.8	359.86	362.44	2
S304		2	266.7	1.5		0.8	358.25	359.86	2
S305		2	120	1.5		0.8	357.96	358.25	2
S306		5	240			0.8	358.25	359.26	2
S307		5	555			0.8	356.87	357.96	2
S308		5	248			0.8	355.89	356.87	2
S309		5	210			0.8	355.04	355.89	2
S310		5	202			0.8	356.87	357.69	2

S311		5	315			0.8	357.69	358.31	2
S312		5	172			0.8	357.69	358.05	2
S31H	0	1							1
S32H	0	1							1
SK1H	0	1							1
DVK1		1	0.72	0.25		1.42			1
SK2H	0	1							1
DVK2		1	3.15	0.25		1.42			1
SK3H	0	1							1
DVK3		1	1.67	0.25		1.42			1
R30		1	10	0.25		1.42	368.5	368.64	1

Subcatchments (incl. grouping)

	A	VG	Ng	CN	tf	Einw.	BWN	R	P	Qh	group
-	ha	-	-	-	min	-	-	-	-	l/Ed	
F100	2.4545	0.12	1	60	18.3	230	n	4	1	130	VG1
F101	6.1717	0.16	1	60	20.7	473	n	4	1	130	VG1
F102	8.0232	0.12	1	60	21.9	682	n	4	1	130	VG1
F103	2.8082	0.14	1	60	18.6	23	n	4	2	130	VG1
F104	3.9772	0.18	2	60	17.1	68	n	4	2	130	VG2
F105	17.044	0.2	2	60	20.7	798	n	4	2	130	VG2
F106	7.3702	0.07	2	60	18	220	n	4	2	130	VG1
F107	4.8084	0.07	2	60	17.1	196	n	4	2	130	VG1
F108	1.7079	0.12	2	60	16.2	25	n	4	2	130	VG2
F109	28.792	0.13	2	60	30.3	287	n	4	2	130	VG2
F10C	4.6573	0.09	2	60	17.1	132	n	4	2	130	VG1
F10D	1.8491	0.51	1	60	18	20	n	4	3	130	VG3
F10E	5.4229	0.28	3	60	16.2	228	n	4	5	130	VG5
F10F	1.193	0.32	3	60	15.6	164	n	4	5	130	VG5
F10G	1.9243	0.44	1	60	18	268	n	4	3	130	VG3
F10H	0.86569	0.35	2	60	16.2	34	n	4	5	130	VG5
F10I	5.53	0.24	2	60	17.4	250	n	4	4	130	VG4
F10J	2.0367	0.07	2	60	16.5	27	n	4	2	130	VG1
F110	2.6076	0.04	2	60	16.5	89	n	4	2	130	VG1
F111	7.3479	0.08	2	60	18	225	n	4	2	130	VG1
F112	23.557	0.04	2	60	22.8	101	n	4	2	130	VG2
F114	17.85	0.26	1	60	21	343	n	4	3	130	VG3
F115	18.79	0.24	1	60	29.1	1063	n	4	3	130	VG3
F116	1.9538	0.24	1	60	18	24	n	4	3	130	VG3
F117	2.0156	0.39	1	60	18	96	n	4	3	130	VG3
F118	8.1469	0.21	3	60	16.8	233	n	4	5	130	VG5
F120	5.0697	0.31	2	60	17.4	173	n	4	4	130	VG4
F121	12.906	0.21	3	60	17.4	302	n	4	5	130	VG5
F122	0.23321	0.25	1	60	16.8	9	n	4	3	130	VG3
F123	10.704	0.36	2	60	18.9	575	n	4	4	130	VG4
F124	0.85146	0.34	3	60	15.3	83	n	4	5	130	VG5
F125	4.381	0.36	2	60	17.1	310	n	4	4	130	VG4
F126	10.196	0.29	1	60	23.4	507	n	4	3	130	VG3
F127	3.5163	0.45	1	60	18.9	417	n	4	3	130	VG3
F128	6.8149	0.35	2	60	17.7	649	n	4	4	130	VG4
F129	12.008	0.33	2	60	19.2	628	n	4	4	130	VG4
F130	15.952	0.11	3	60	18	477	n	4	5	130	VG5
F131	3.0368	0.21	3	60	15.9	148	n	4	5	130	VG5
F132	7.3087	0.07	3	60	16.5	83	n	4	5	130	VG5
F133	9.5387	0.17	3	60	16.8	87	n	4	5	130	VG5
F200	23.798	0.38	1	60	32.1	565	n	4	3	130	VG6
F201	8.9705	0.25	1	60	22.8	285	n	4	3	130	VG6
F202	18.376	0.19	1	60	29.1	369	n	4	3	130	VG6
F203	3.7927	0.38	1	60	19.2	118	n	4	3	130	VG6

F301	12.71	0.18	3	60	17.4	953	n	4	5	130	VG5
F304	24.31	0	3	60	19.5	10	n	4	5	130	VG5
F305	3.22	0.06	2	60	16.8	210	n	4	4	130	VG4
F306	11.83	0.12	2	60	19.2	318	n	4	4	130	VG4
F307	6.08	0.3	2	60	17.7	228	n	4	4	130	VG4
F308	2.98	0.11	1	60	18.6	285	n	4	3	130	VG3
F309	11.04	0.26	1	60	24	1710	n	4	3	130	VG3
F310	8.91	0.33	1	60	22.5	359	n	4	3	130	VG3
F311	2.77	0.15	1	60	18.6	493	n	4	3	130	VG3
F312	9.87	0.36	1	60	23.4	1735	n	4	3	130	VG3
F313	4.62	0.46	1	60	19.8	386	n	4	3	130	VG3
F314	6.25	0.45	1	60	20.7	650	n	4	3	130	VG3
F315	4.93	0.03	1	60	20.1	90	n	4	3	130	VG3

System logic

Beschreibung	Nr.	1	2 3	1	2
F130	F130			B2BB	
Becken 2	B2BB	F130		S10H	
F121	F121			S121	
Hilfssammler vor V	S121	F121		V121	
V121	V121	S121		S124	S10E
F124	F124			B1BB	
S124	S124	V121		B1BB	
Becken 1	B1BB	F124	S124	S10F	
F133	F133			S132	
F132	F132			S131	
S132	S132	F133		S131	
F131	F131			S10I	
S131	S131	F132	S132	S10I	
F10I	F10I			B3BB	
S10I	S10I	F131	S131	B3BB	
Becken 3	B3BB	F10I	S10I	S116	
F10H	F10H			S129	
S10H	S10H	B2BB		S129	
F128	F128			S10G	
F129	F129			S10G	
S129	S129	F10H	S10H	S10G	
F10F	F10F			S123	
S10F	S10F	B1BB		S123	
F10G	F10G			S127	
S10G	S10G	F128	F129 S129	S127	
F123	F123			S13H	
S123	S123	F10F	S10F	S13H	
F126	F126			S125	
F127	F127			S125	
S127	S127	F10G	S10G	S125	
F10E	F10E			S120	
S10E	S10E	V121		S120	
F120	F120			S12H	
S120	S120	F10E	S10E	S12H	
F125	F125			S122	
S125	S125	F126	F127 S127	S122	
Nullsammler nach S1	S13H	F123	S123	S122	
F122	F122			S119	
S122	S122	F125	S125 S13H	S119	
Nullsammler nach S1	S12H	F120	S120	S119	
F118	F118			S117	
F116	F116			S10D	
S116	S116	B3BB		S10D	
F117	F117			S17H	
S117	S117	F118		S17H	
S119	S119	F122	S122 S12H	S17H	
F10D	F10D			S115	
S10D	S10D	F116	S116	S115	
Nullsammler nach S1	S17H	F117	S117 S119	S115	
F115	F115			S114	
S115	S115	F10D	S10D S17H	S114	
F202	F202			S201	

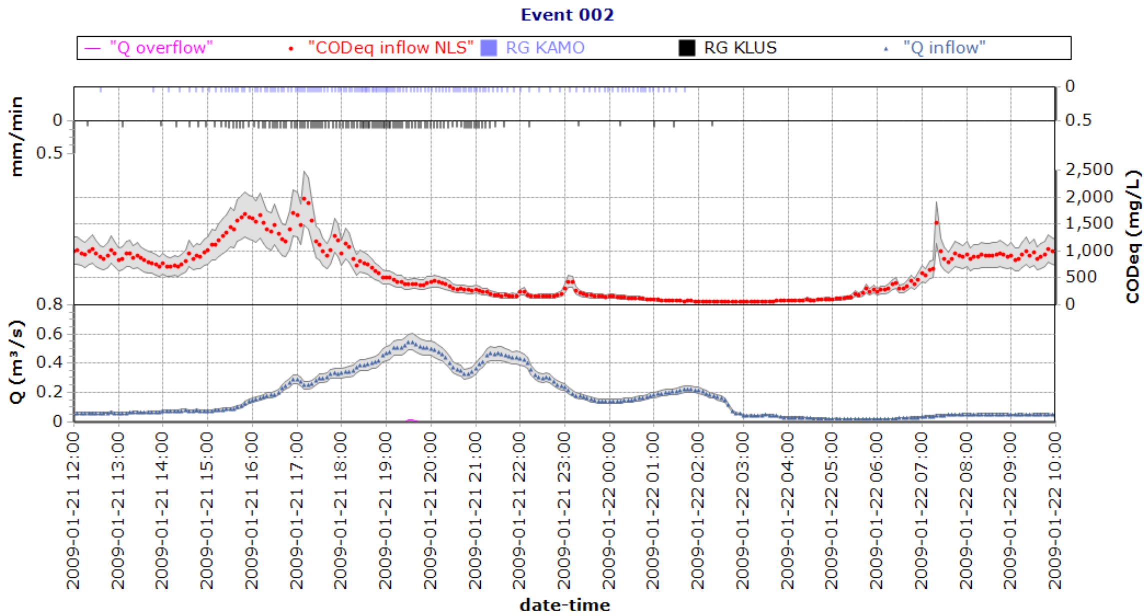
F203	F203			S201	
F114	F114			S32H	
S114	S114	F115	S115	S32H	
F301	F301			S300	
F304	F304			S300	
F305	F305			S302	
F306	F306			S302	
F307	F307			S304	
F308	F308			S305	
F309	F309			S306	
F310	F310			S307	
F311	F311			S31H	
F312	F312			S311	
F313	F313			S310	
F314	F314			S312	
F315	F315			S309	
S311	S311	F312		S310	
S312	S312	F314		S310	
S310	S310	F313	S311 S312	S31H	
S300	S300	F301	F304	R301	
Regenüberlauf	R301	S300		S301	
S301	S301	R301		S302	
S302	S302	F305	F306 S301	S303	
S303	S303	S302		S304	
S304	S304	F307	S303	S305	
S306	S306	F309		S305	
S305	S305	F308	S304 S306	S307	
S307	S307	S305	F310	VK11	
VK11	VK11	S307		S308	SK1H
Nullsammler nach VK	SK1H	VK11		S308	
Nullsammler nach S3	S31H	F311	S310	S308	
S308	S308	S31H	SK1H VK11	VK21	
VK21	VK21	S308		S309	SK2H
Nullsammler nach VK	SK2H	VK21		S309	
S309	S309	F315	VK21 SK2H	VK31	
VK31	VK31	S309		S112	SK3H
Nullsammler nach VK	SK3H	VK31		S112	
F201	F201			S200	
S201	S201	F202	F203	S200	
F112	F112			S111	
Nullsammler nach S1	S32H	F114	S114	S112	
S112	S112	S32H	SK3H VK31	S111	
F200	F200			S20H	
S200	S200	F201	S201	S20H	
F111	F111			S10B	
S111	S111	F112	S112	S10B	
Nullsammler nach S2	S20H	F200	S200	S10B	
F108	F108			S107	
F109	F109			S107	
S10B	S10B	F111	S111 S20H	S10C	
F10C	F10C			S110	
S10C	S10C	S10B		S110	
F107	F107			S07H	
S107	S107	F108	F109	S07H	
F110	F110			S106	
Nullsammler nach S1	S07H	F107	S107	S106	
S110	S110	F10C	S10C	S106	
F106	F106			S10J	
S106	S106	F110	S07H S110	S10J	
F104	F104			S103	
F105	F105			S103	
F10J	F10J			S10A	
S10J	S10J	F106	S106	S10A	
F103	F103			S102	
S103	S103	F104	F105	S102	
S10A	S10A	F10J	S10J	S102	
F101	F101			S100	
F102	F102			S100	
S102	S102	F103	S103 S10A	S100	
F100	F100			SSKA	
S100	S100	F101	F102 S102	SSKA	
Nullsammler nach S1	SSKA	F100	S100	Stra	
Fiktiver Translatio	Stra	SSKA		Sfik	

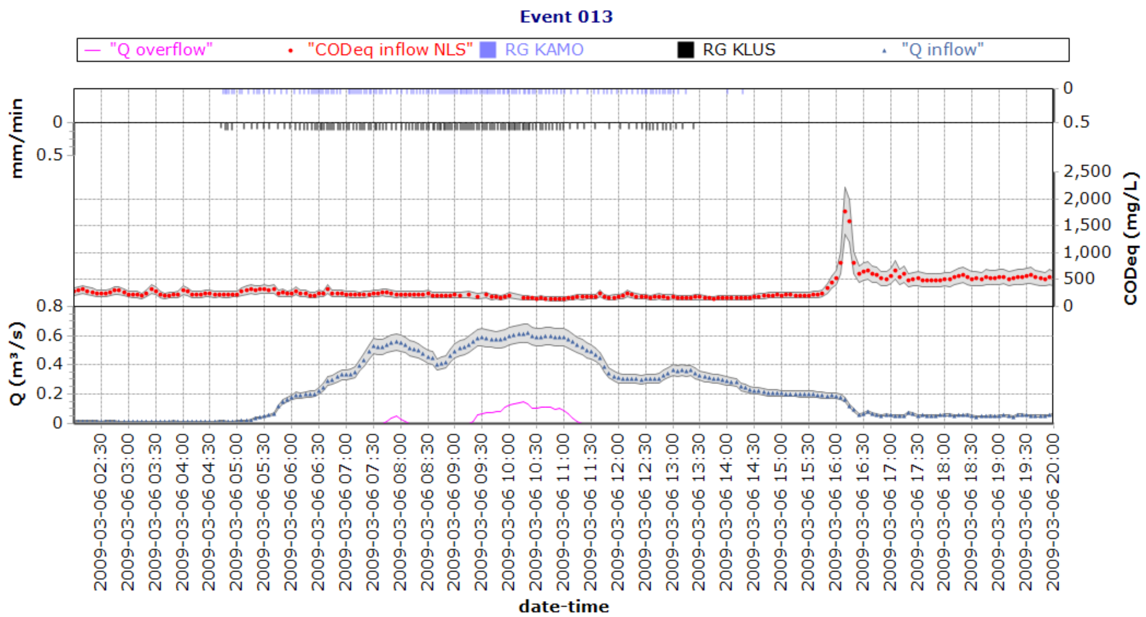
Fiktiver Translatio	Sfik	Stra		B100	
SKU anstelle des RU	B100	Sfik		KLA	
Kläranlage	KLA	B100			

9. Global Sensitivity Analysis

9.1. Chosen events

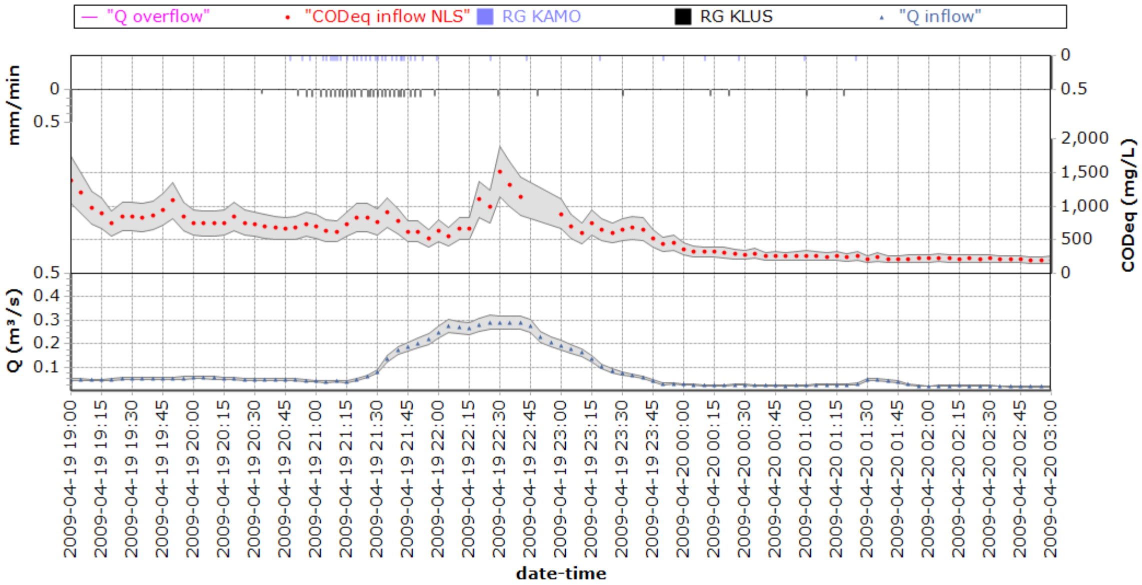
Figures indicating COD_{eq} with a 25% error bound and Q with an estimated 10% error bound



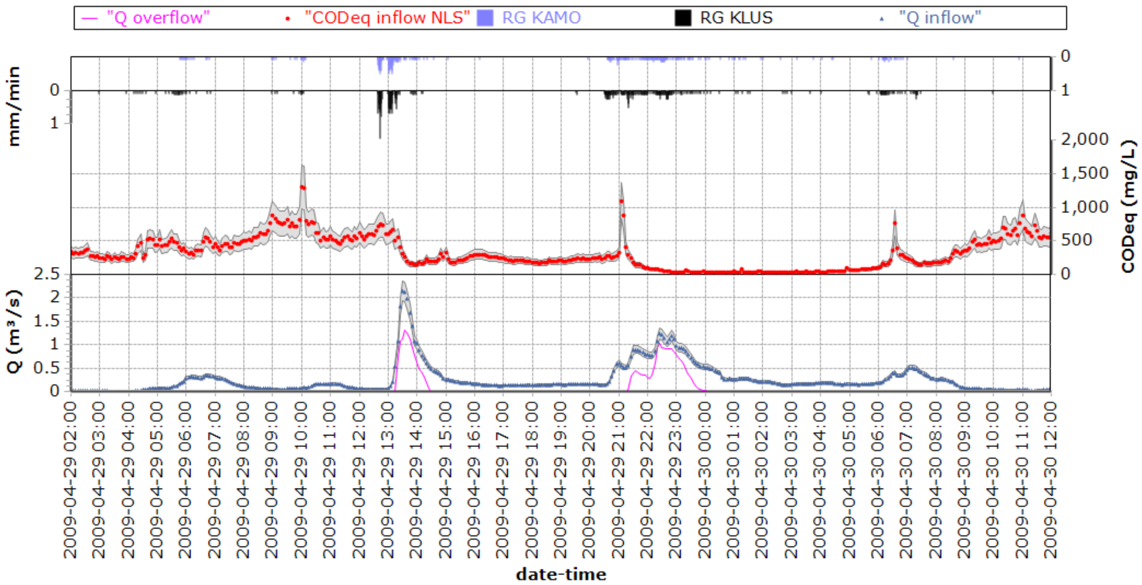


Appendix

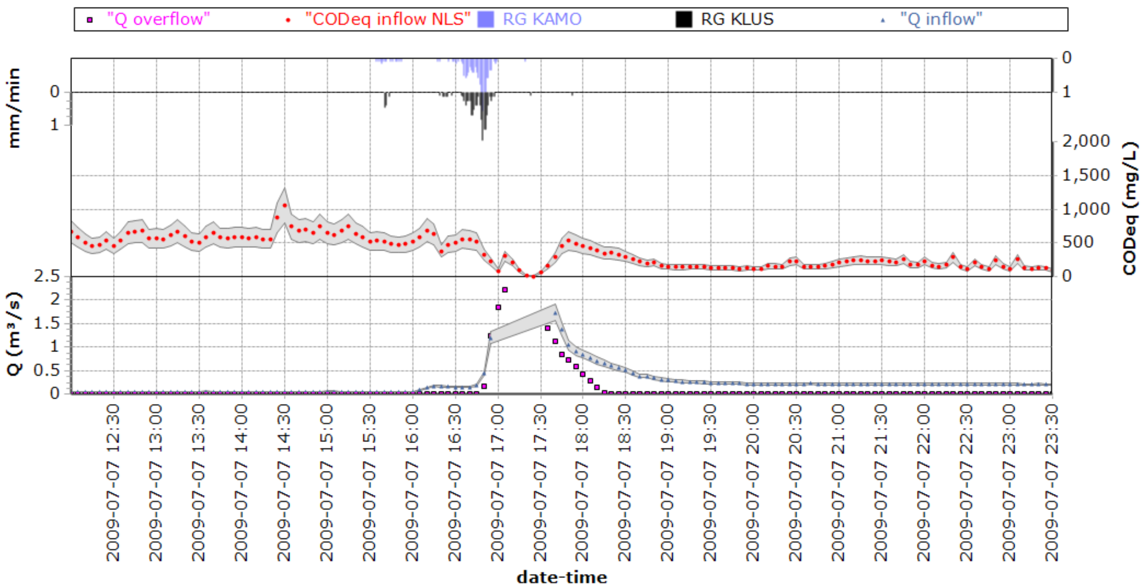
Event 017



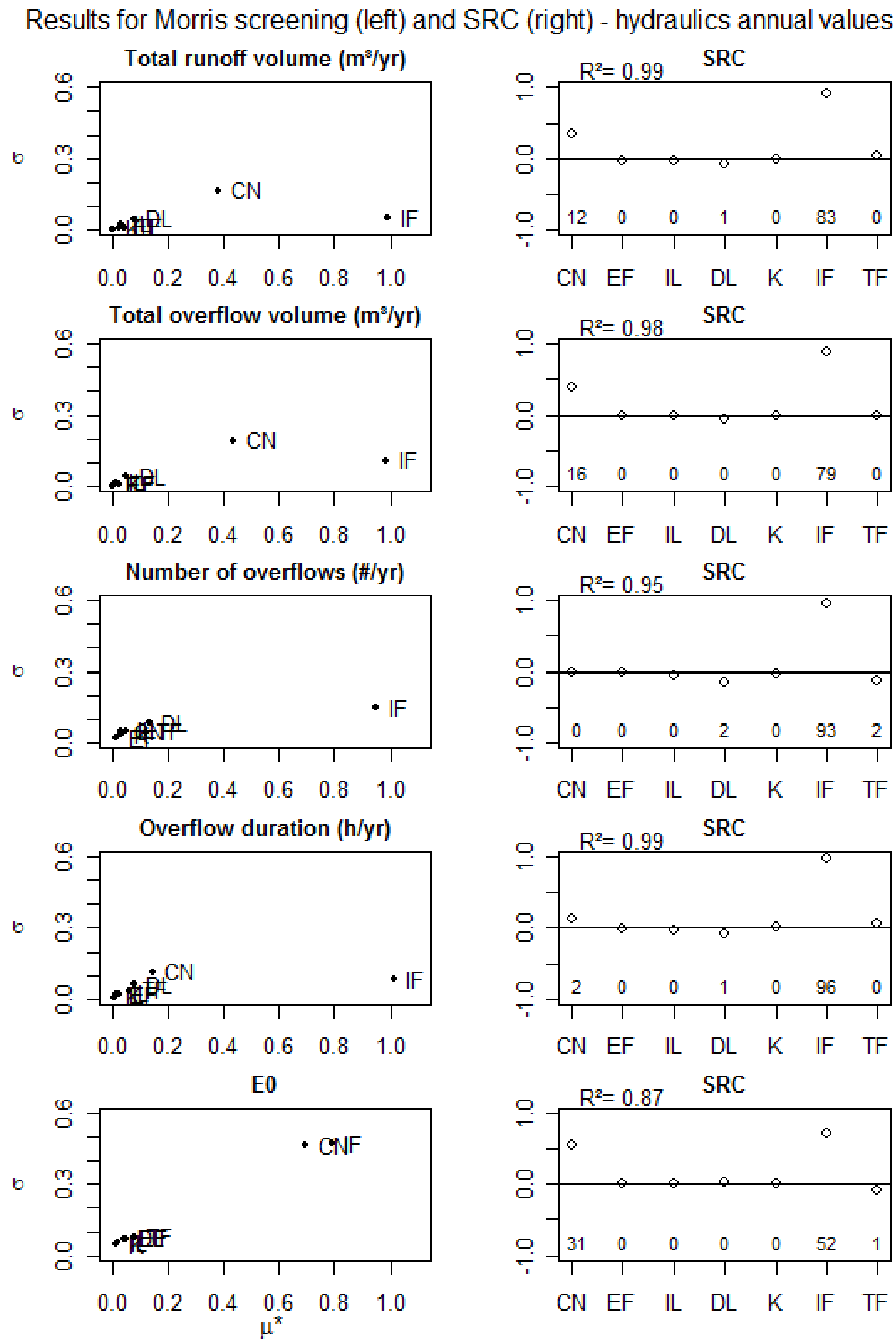
Event 021 & 022

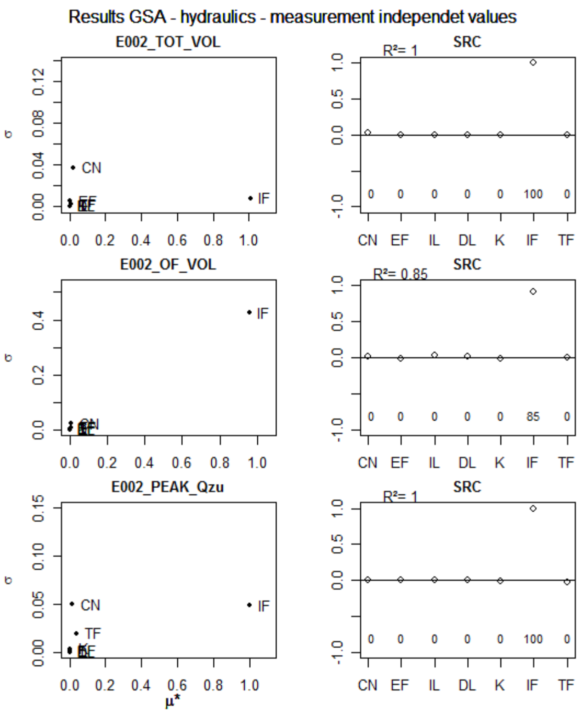


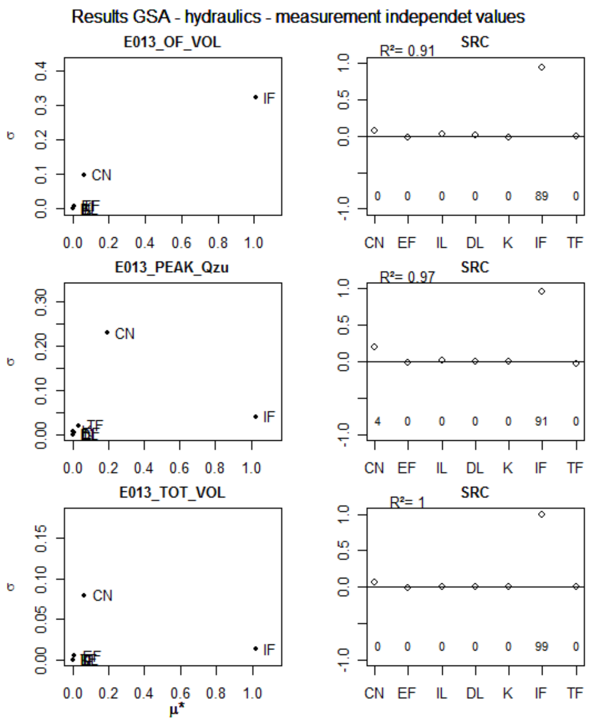
Event 060

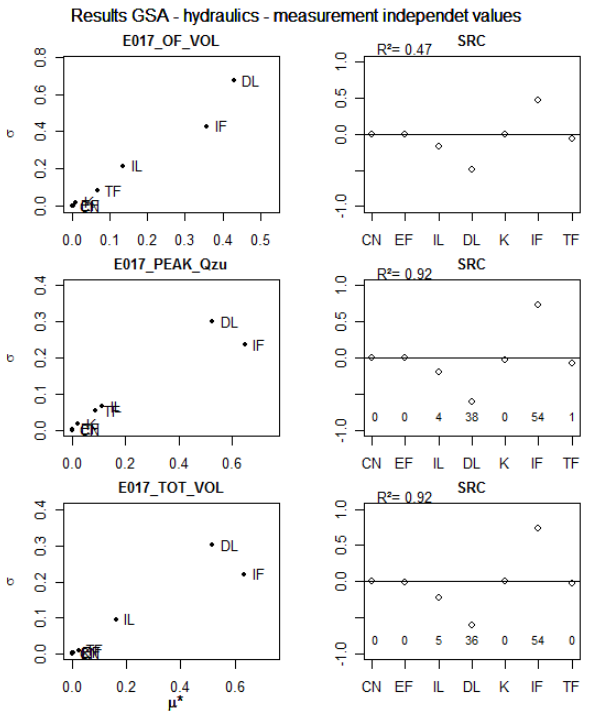


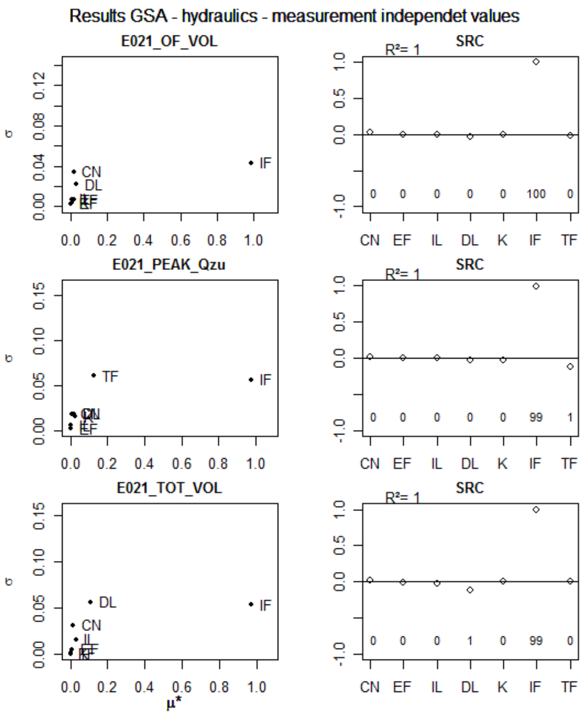
9.2. GSA results – hydraulics

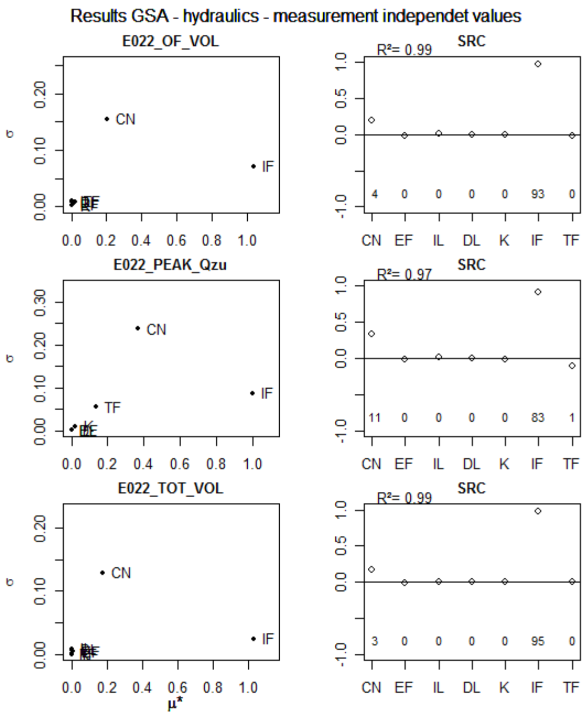


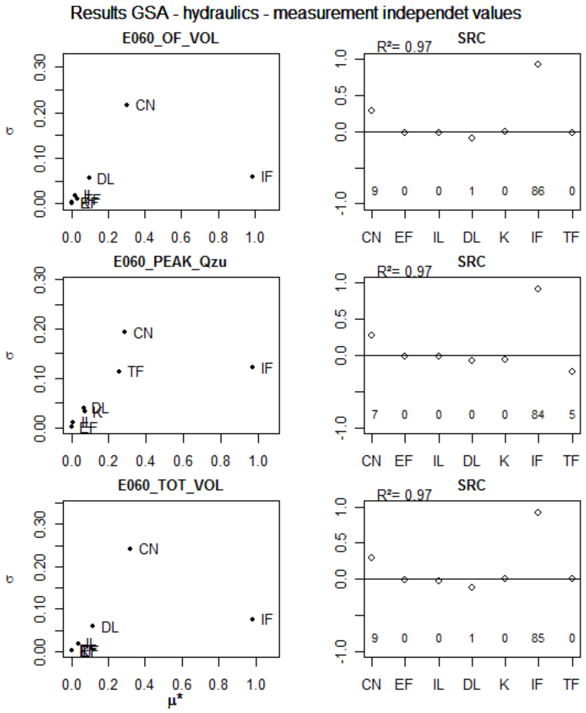

Results GSA - hydraulics - measurement independet values
E002_TOT_VOL
SRC
E002_OF_VOL
SRC
E002_PEAK_Qzu
SRC
σ
μ*

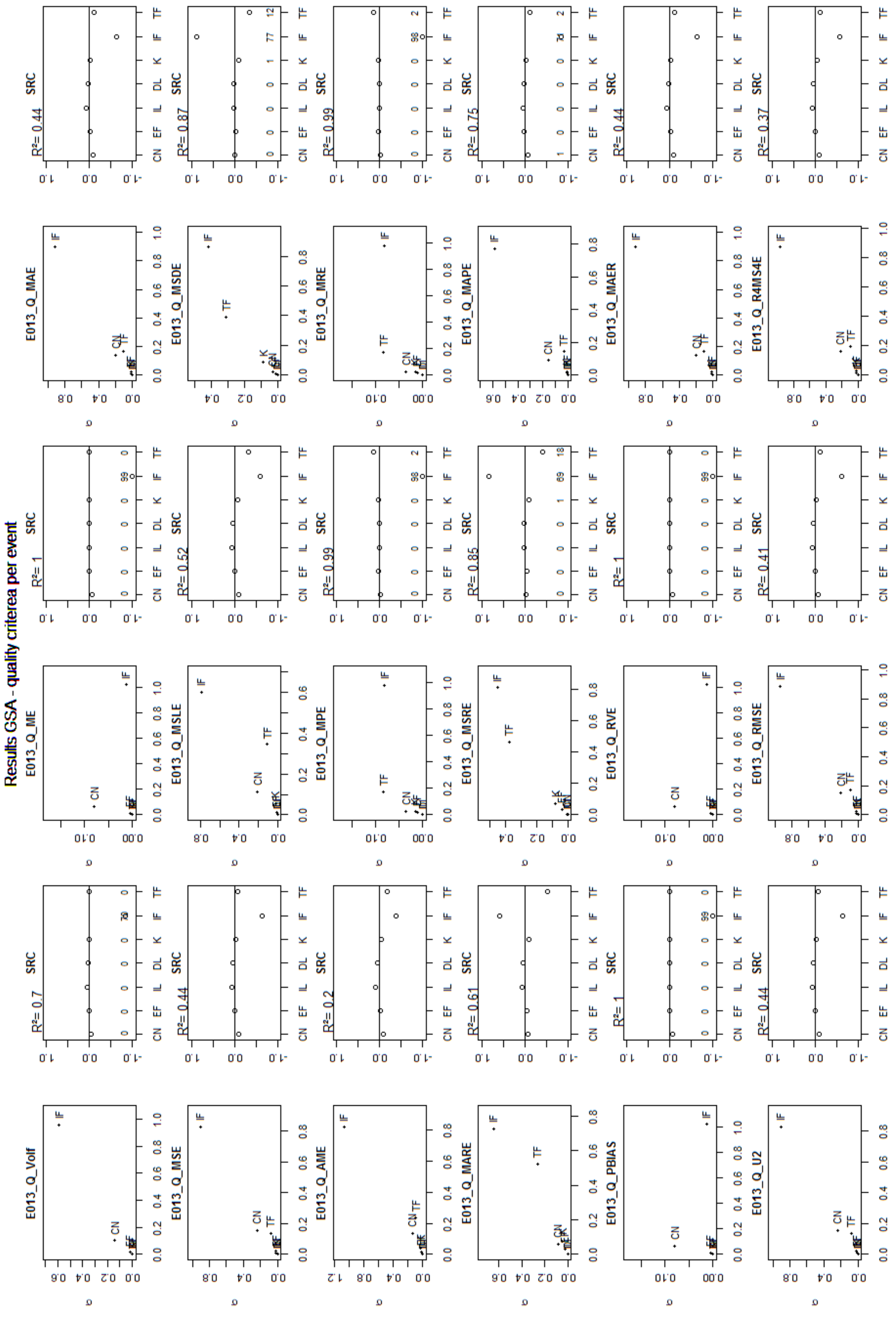

Results GSA - hydraulics - measurement independet values
E013_OF_VOL
SRC
E013_PEAK_Qzu
SRC
E013_TOT_VOL
SRC
σ
μ*

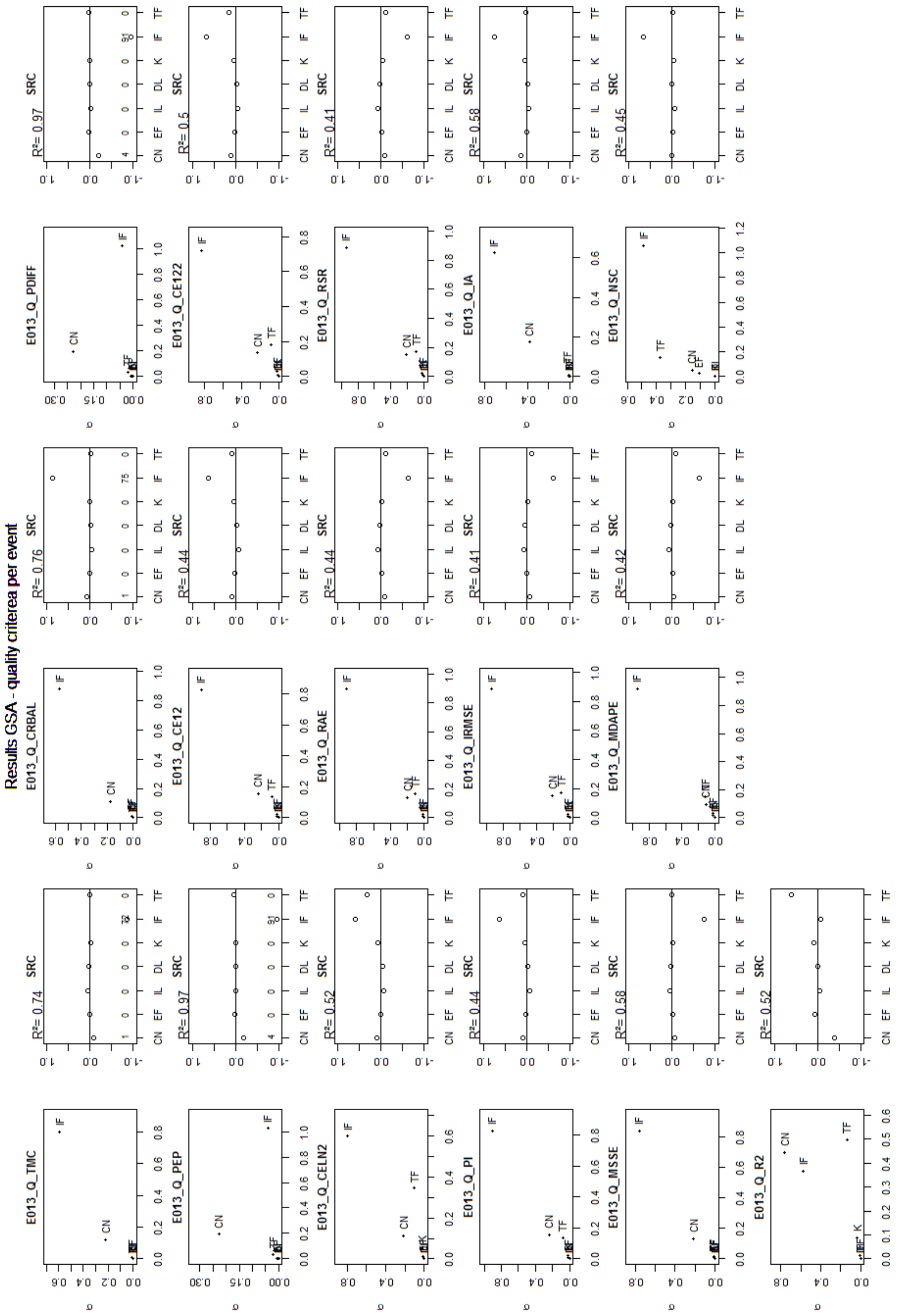

Results GSA - hydraulics - measurement independet values
E017_OF_VOL
SRC
E017_PEAK_Qzu
SRC
E017_TOT_VOL
SRC
σ
μ*


Results GSA - hydraulics - measurement independet values
E021_OF_VOL
SRC
E021_PEAK_Qzu
SRC
E021_TOT_VOL
SRC
σ
μ*


Results GSA - hydraulics - measurement independet values
E022_OF_VOL
SRC
R²= 0.99
4 0 0 0 0 93 0
E022_PEAK_Qzu
SRC
R²= 0.97
11 0 0 0 0 83 1
E022_TOT_VOL
SRC
R²= 0.99
3 0 0 0 0 95 0
CN EF IL DL K IF TF
σ
μ*

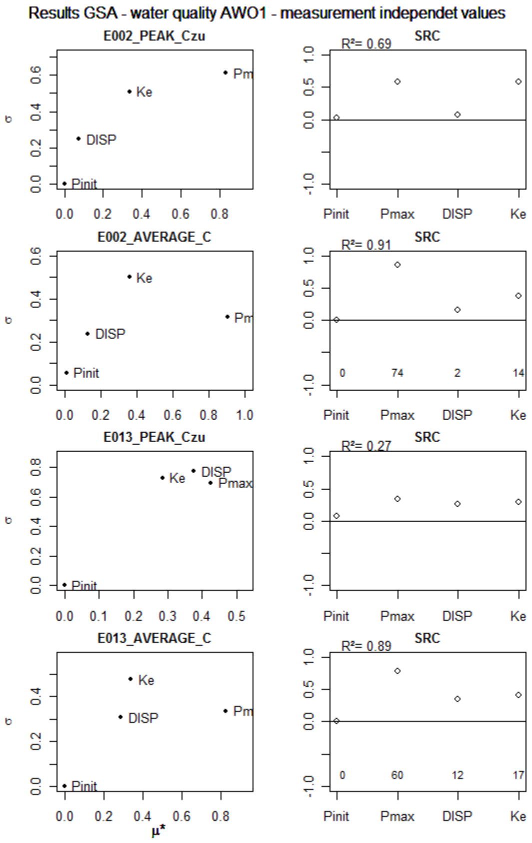

Results GSA - hydraulics - measurement independet values
E060_OF_VOL
SRC
R²= 0.97
9 0 0 1 0 86 0
E060_PEAK_Qzu
SRC
R²= 0.97
7 0 0 0 0 84 5
E060_TOT_VOL
SRC
R²= 0.97
9 0 0 1 0 85 0
CN EF IL DL K IF TF
σ
μ*

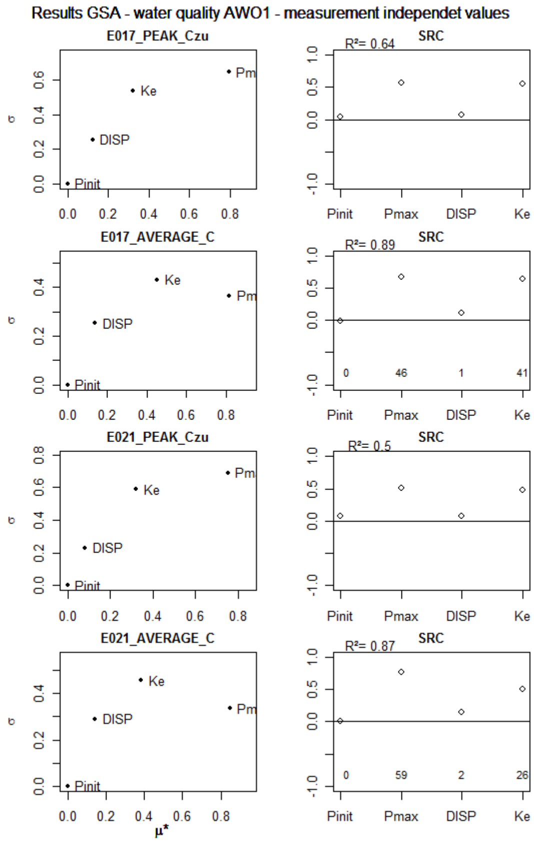

Results GSA - quality criterea per event
E013_Q_VolF
E013_Q_ME
E013_Q_MAE
E013_Q_MSE
E013_Q_MSLE
E013_Q_MSDE
E013_Q_AME
E013_Q_MPE
E013_Q_MRE
E013_Q_MARE
E013_Q_MSRE
E013_Q_MAPE
E013_Q_PBIAS
E013_Q_RVE
E013_Q_MAER
E013_Q_U2
E013_Q_RMSE
E013_Q_R4MS4E
SRC

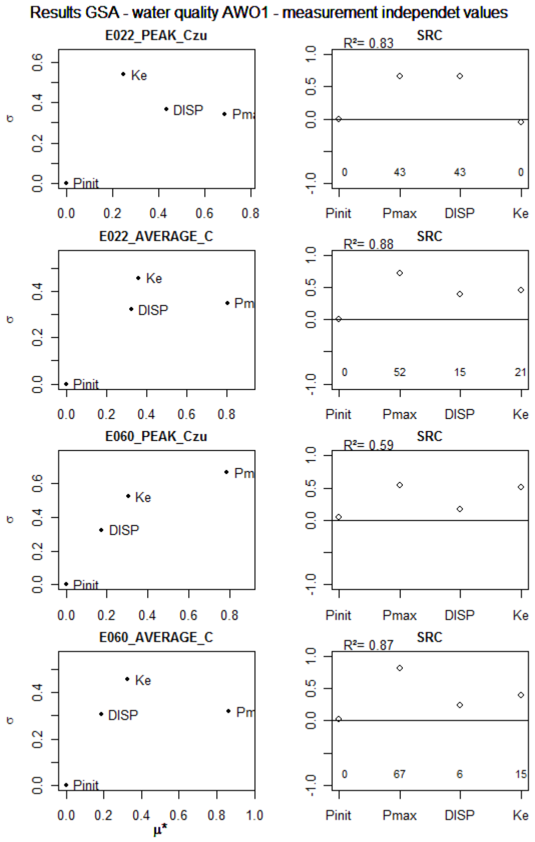

Results GSA - quality criterea per event
E013_Q_TMC
E013_Q_PEP
E013_Q_CELN2
E013_Q_PI
E013_Q_MSSE
E013_Q_R2
E013_Q_CRBAL
E013_Q_CE12
E013_Q_RAE
E013_Q_IRMSE
E013_Q_MDAPE
E013_Q_PDIFF
E013_Q_CE122
E013_Q_RSR
E013_Q_IA
E013_Q_NSC

9.3. GSA results – sewer water quality models

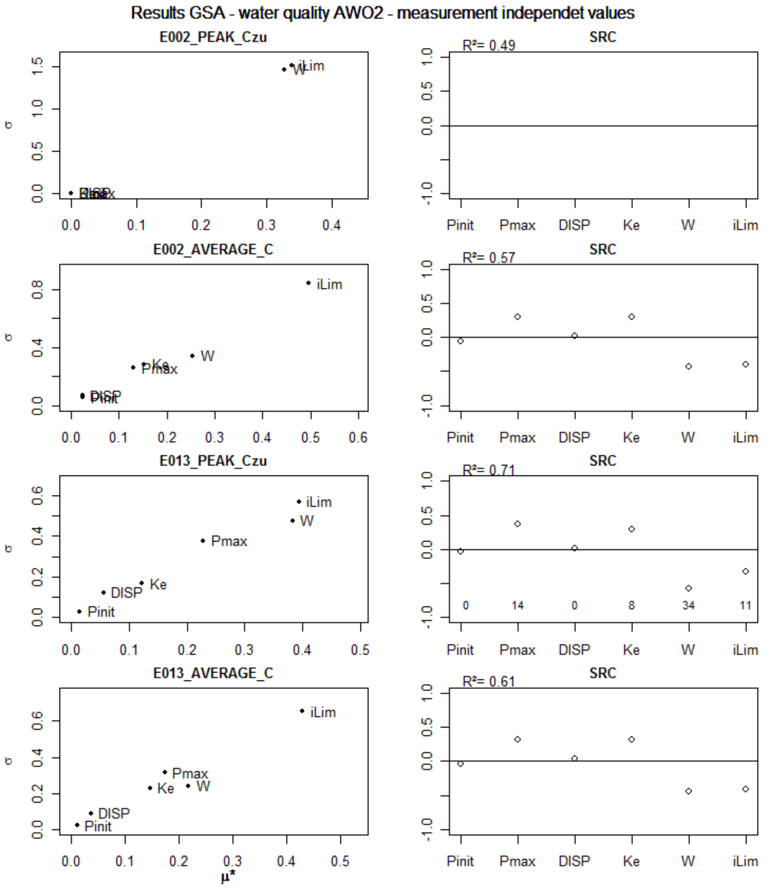
AWO1 – measurement independent values

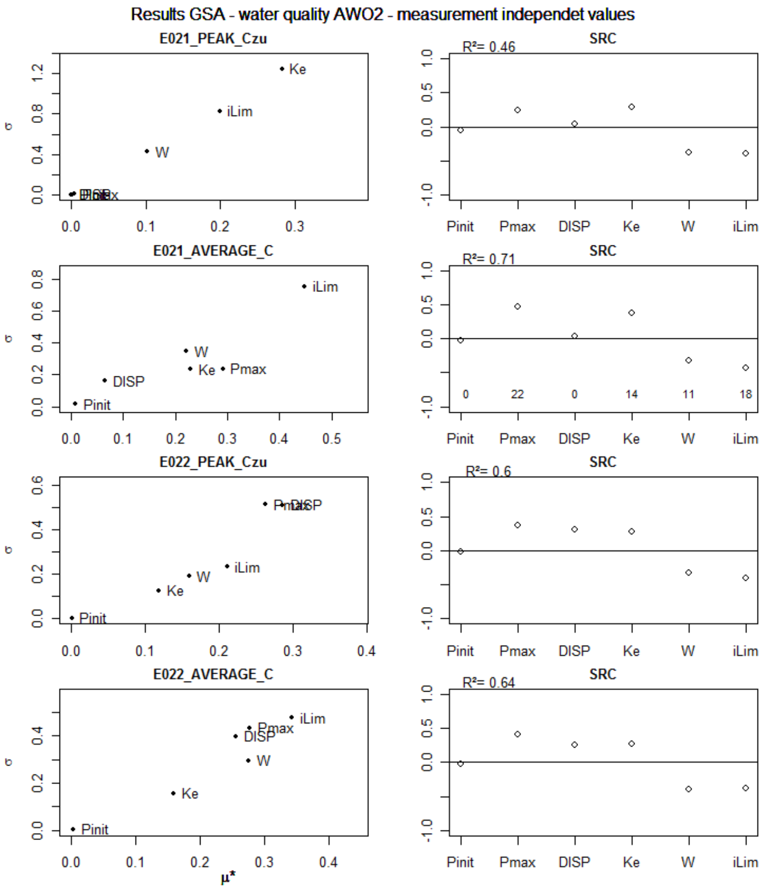


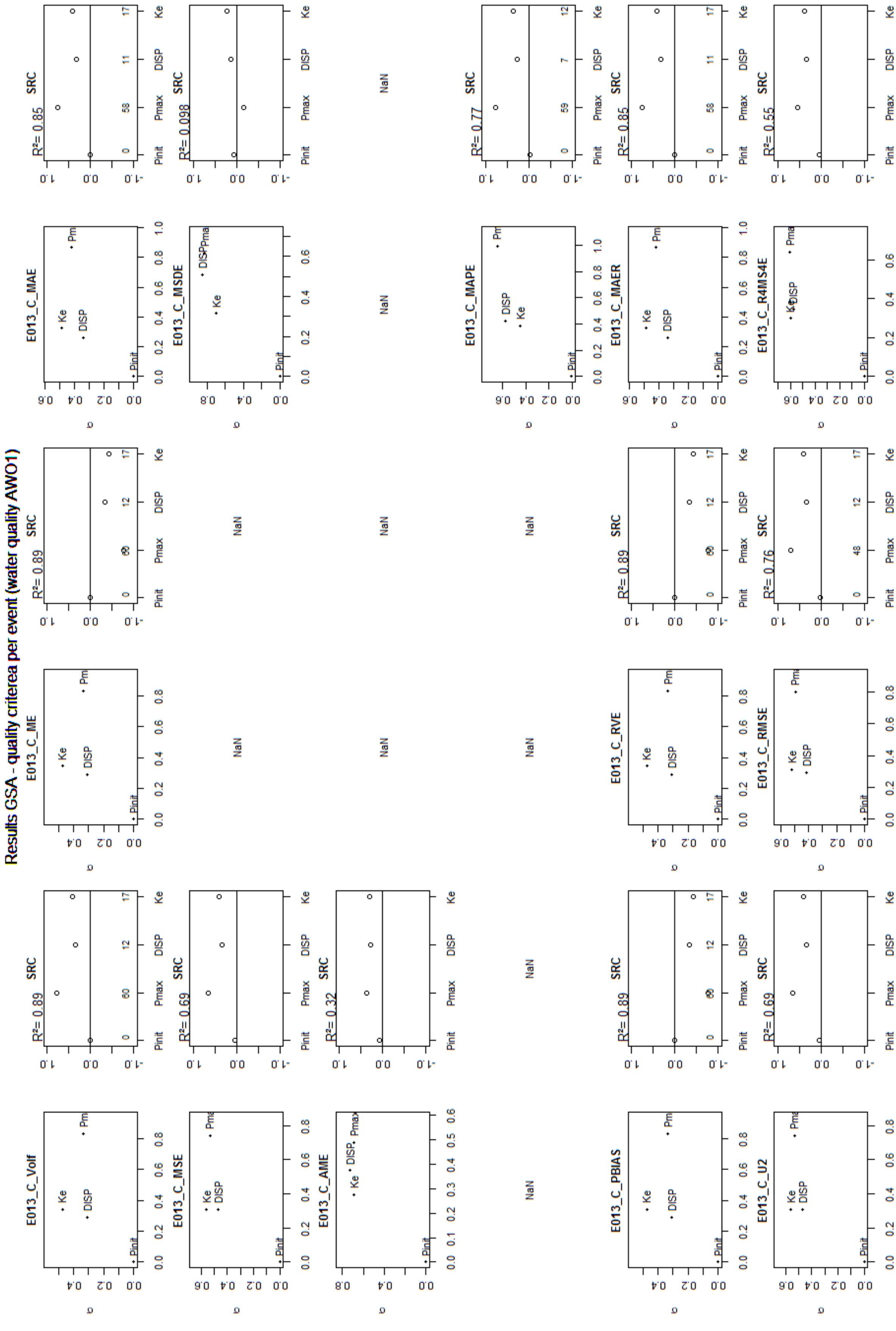




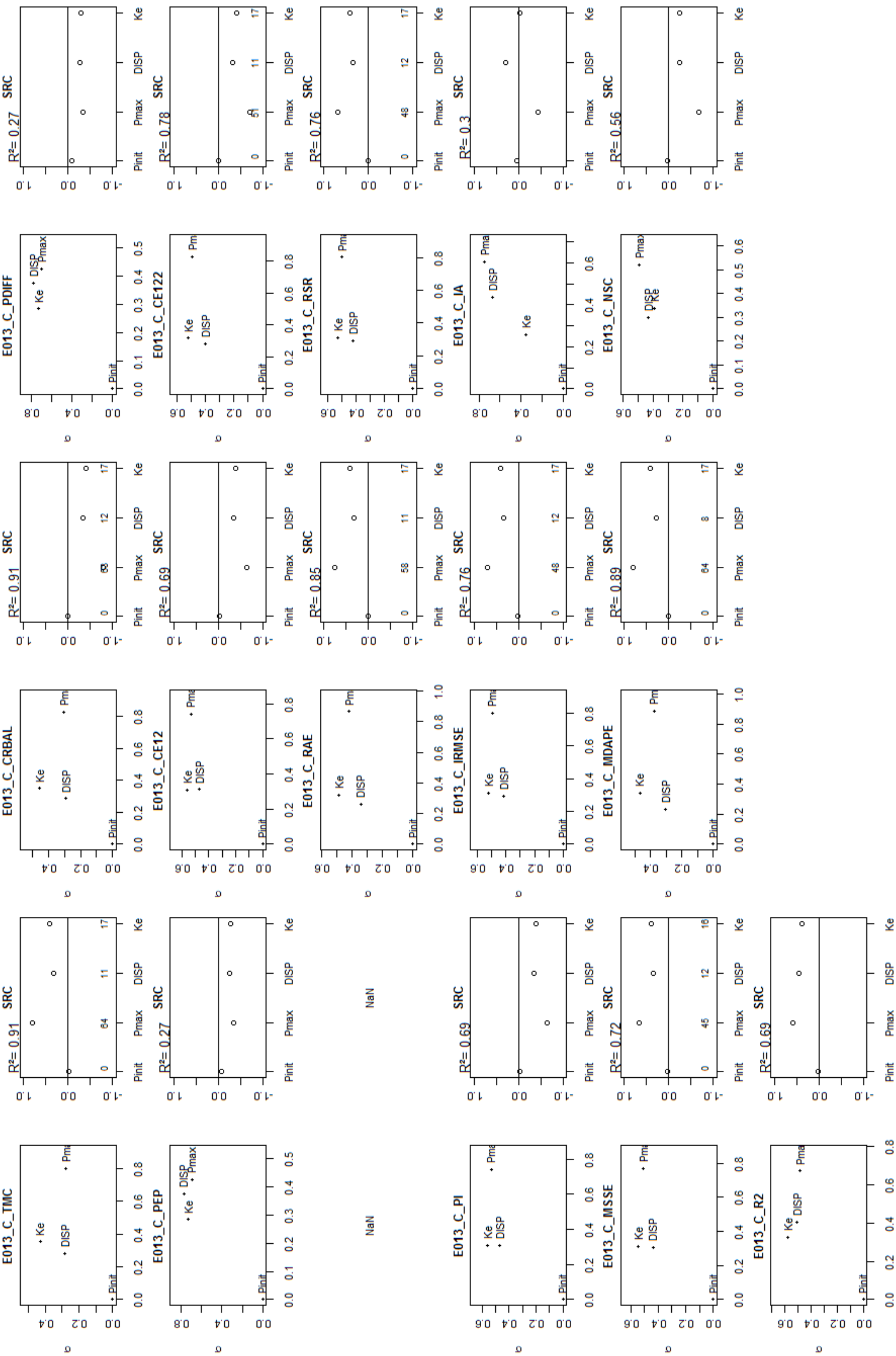
AWO2 – measurement independent values

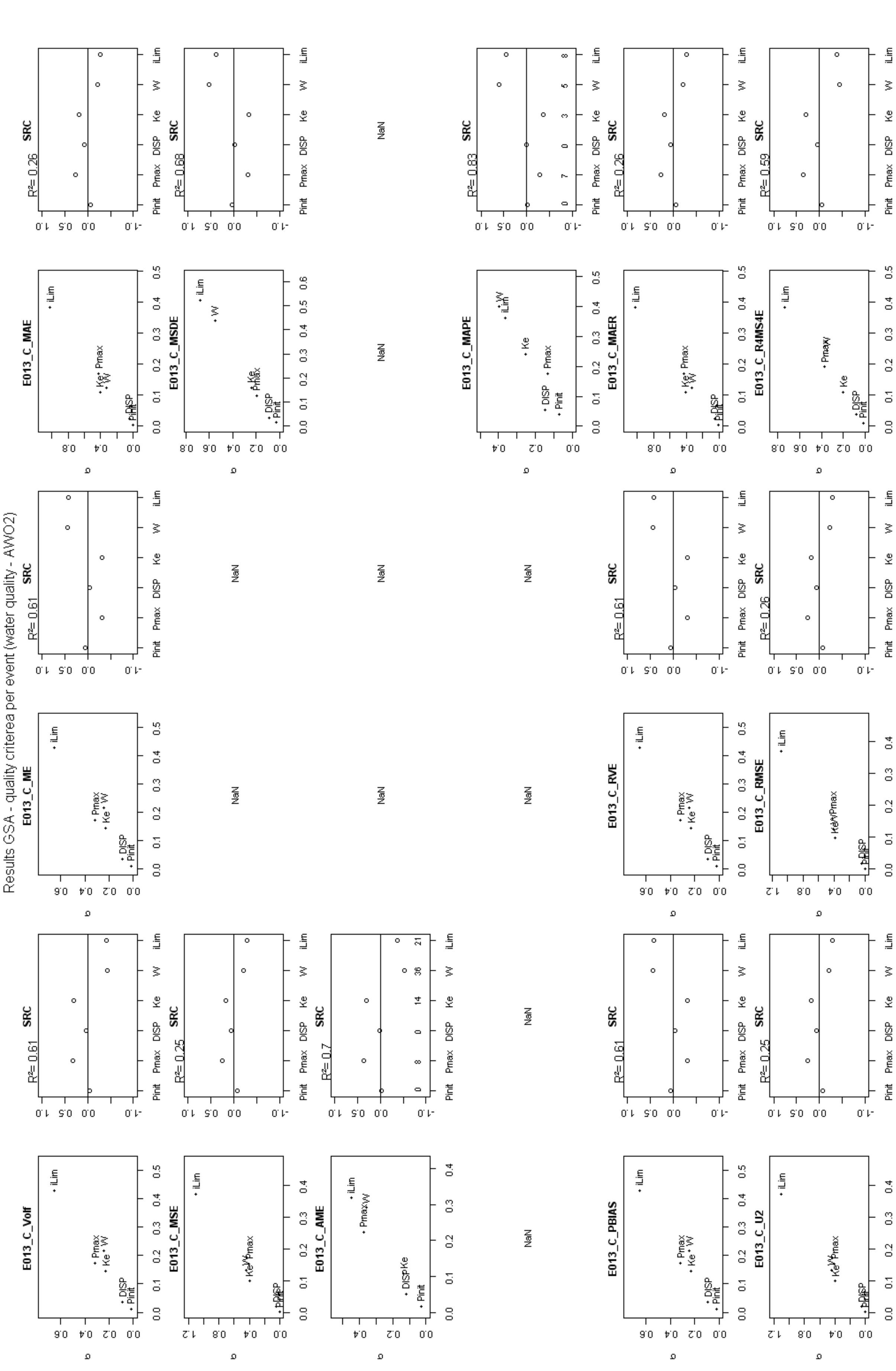


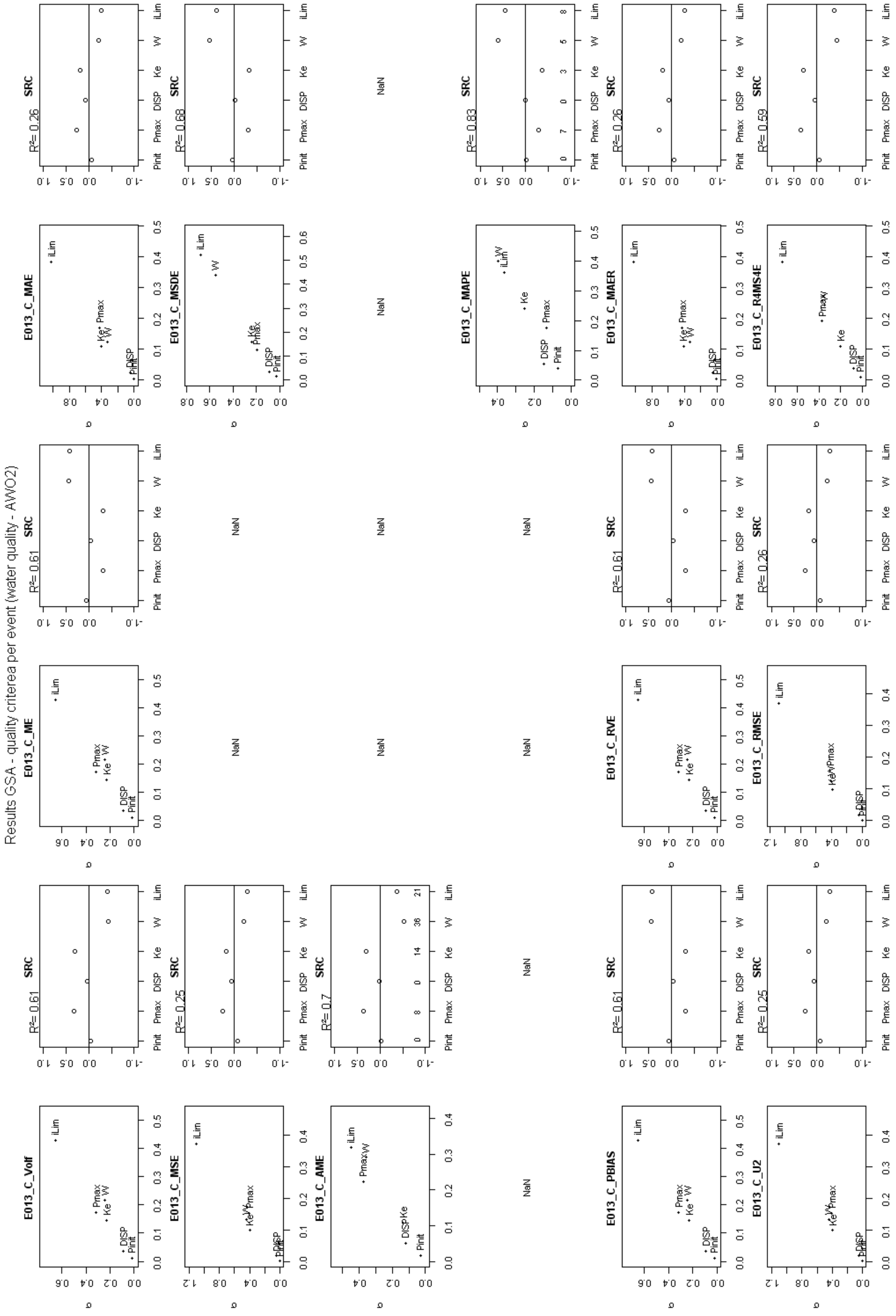



Results GSA - quality criterea per event (water quality AWO1)

Results GSA - quality criterea per event (water quality AWO1)




Results GSA - quality criterea per event (water quality - AWO2)
E013_C_Volf
E013_C_MSE
E013_C_AME
E013_C_ME
E013_C_MAE
E013_C_MSDE
E013_C_MAPE
E013_C_MAER
E013_C_R4MS4E
E013_C_RVE
E013_C_RMSE
E013_C_PBIAS
E013_C_U2
SRC
NaN


Results GSA - quality criterea per event (water quality - AWO2)
E013_C_Volf
E013_C_MSE
E013_C_AME
E013_C_PBIAS
E013_C_U2
E013_C_ME
E013_C_RVE
E013_C_RMSE
E013_C_MAE
E013_C_MSDE
E013_C_MAPE
E013_C_MAER
E013_C_R4MS4E

10. SMUSI 2003 model dry weather calibration

Period	**July**	**August**	**September**	**October**	**November**	**December**	**Average**
Start	2003-07-14 00:00	2003-08-07 00:00	2003-09-15 00:00	2003-10-13 00:00	2003-11-19 00:00	2003-12-08 00:00	
End	2003-07-15 23:55	2003-08-08 23:55	2003-09-18 23:55	2003-10-18 04:00	2003-11-21 23:55	2003-13-12 23:55	
L/cap.d	167.7	188.5	162.9	197.7	195	170.1	180.32
Daily patter							
00:00	0.67	0.65	0.59	0.57	0.53	0.6	0.60
01:00	0.42	0.46	0.4	0.44	0.35	0.36	0.41
02:00	0.26	0.29	0.25	0.33	0.27	0.09	0.25
03:00	0.33	0.2	0.22	0.19	0.21	0.21	0.23
04:00	0.28	0.16	0.17	0.15	0.3	0.05	0.19
05:00	0.29	0.14	0.18	0.16	0.15	0.21	0.19
06:00	0.47	0.47	0.53	0.51	0.47	0.34	0.47
07:00	1.12	1	1.37	1.26	1.18	1.08	1.17
08:00	1.45	1.68	1.6	1.42	1.63	1.45	1.54
09:00	1.56	1.62	1.46	1.33	1.43	1.57	1.50
10:00	1.47	1.45	1.27	1.27	1.48	1.81	1.46
11:00	1.27	1.49	1.22	1.28	1.45	1.41	1.35
12:00	1.24	1.29	1.21	1.34	1.38	1.38	1.31
13:00	1.26	1.44	1.27	1.27	1.33	1.39	1.33
14:00	1.23	1.25	1.25	1.26	1.26	1.48	1.29
15:00	1.22	1.31	1.28	1.16	1.17	1.24	1.23
16:00	1.15	1.09	1.19	1.21	1.21	1.11	1.16
17:00	1.06	1.04	1.19	1.23	1.13	1.14	1.13
18:00	1.12	1.17	1.1	1.17	1.32	1.11	1.17
19:00	1.25	1.08	1.36	1.36	1.31	1.31	1.28
20:00	1.36	1.2	1.64	1.65	1.35	1.52	1.45
21:00	1.32	1.31	1.36	1.42	1.24	1.36	1.34
22:00	1.2	1.23	1.02	1.07	0.92	0.99	1.07
23:00	1.05	1	0.87	0.95	0.93	0.8	0.93
	24.05	24.02	24	24	24	24.01	24.01