Quantification of Exfiltration from Sewers with Tracers

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First, you see your data
for what they seem to be.
Then, you ask them for the truth
- are you what you seem to me?

You see with broad expanse
you ask with narrowed power,
you see and ask and see
and ask and see... and ask.

With brush you paint the possibilities
with pen you scribe the probabilities.
For in pictures we find insight
while in numbers we find strength.

FORREST W. YOUNG

I asked Hanna why she does not believe in statistics but instead in fate and such things. ‘You with your statistics’, she says. ‘If I had one hundred daughters, all bitten by a viper, then yes! Then I would lose only three to ten daughters. Amazingly few! You are perfectly right.’

MAX FRISCH, Homo Faber

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A final hug goes to a little tree at the slopes of the Roten. May you grown tall and green for a long long while.
Abstract

Introduction

Although sewers present a convenient solution to transport and dispose sewage they cannot be considered watertight. In the recent decades, considerable effort has been undertaken to assess the environmental and health hazard potential of exfiltration from sewers (into the ground), although the magnitude of sewer leakage is not fully known.

Aim of this thesis

Quantitative information on sewer leakage is mainly scarce because the available methods are too costly (e.g., pressure testing of an entire sewer network) or too involved (e.g., groundwater contaminant modelling) for urban water managers and practical engineers. The aim of this thesis was to investigate the quantification of exfiltration from sewers measurement with tracers.

As tracer experiments are cost-effective, generally applicable, environmentally safe and convenient to use it was supposed that they have the potential to become a routine measurement method.

Methodology

The main investigations for the development of the methods were performed in main sewers in the surroundings of Zurich, Switzerland. First, a pulse dosing strategy with a single tracer was investigated and then a method with a continuous dosing of two different tracer substances was tested.

In parallel, the behavior and analysis of tracers in wastewater was tested and a framework for the statistical assessment of uncertainty was developed.

Furthermore, data analysis techniques have been developed to design the optimal tracer experiment and to calculate absolute exfiltration rates from tracer experiment data.

The practical applicability of the method was also tested by partners of an European research project (APUSS) who applied the methods in a variety of different conditions in different European cities.

Tracer methods

The basic idea of the QUEST (Quantification of Exfiltration from Sewers with Tracers) and the QUEST-C is that exfiltration measurement is feasible by a mass balance of a tracer substance over the investigated sewer line. A known mass of tracer is dosed to the reach under investigation and the tracer is passed through the sewer line with the wastewater flow. If exfiltration occurs, tracer substance is lost with the seeping wastewater. From the remaining tracer mass at the end of the reach, exfiltration can be determined as a ratio relative to the labelled flow.

The key feature of the methods is that a reference signal is dosed a the end of the investigated reach, which serves as an in-situ calibration and increases the measurement accuracy by avoiding absolute flow measurements.
The data analysis includes an assessment of uncertainty of the measurement result, for which statistical techniques as bootstrap and regression analysis have been applied.

**Experimental design**

The QUEST and QUEST-C tracer methods have a high degree of freedom with regard to the choice of tracer and the dosing strategy. The application of any of these techniques requires the investigator to make a number of decisions regarding experimental design which influence the extent of uncertainty in the final estimate of exfiltration. We propose a procedure for optimal experimental design which is based on the analysis of uncertainty.

One important finding is that the best experimental design depends on how much the investigator is willing to spend on the monitoring process (in terms of effort and financial resources) and how these expenditures compare with the consequences of an incorrect estimation of exfiltration.

**Dispersion in sewers**

In order to thoroughly plan an experiment in practice, the mixing of tracer in the sewer under investigation have to be predicted correctly.

In cooperation with the APUSS partners, a large dataset of tracer experiments under a variety of conditions was analyzed for longitudinal dispersion and suitable equations were identified to: i) deduce dispersion coefficients from tracer data and ii) predict reasonable dispersion coefficients in sewers.

One interesting conclusion was that dispersion coefficients of sewers are two to three orders of magnitude smaller than those measured in rivers and do not differ much from system to system.

**Learning from tracer data**

Bayesian data analysis was used to convert the relative information from tracer test into absolute exfiltration rates. This is possible if available prior knowledge (e.g., elevation of groundwater table, water level in the pipe, etc.) is incorporated in the analysis.

The results from a conceptual study show that most information is gained from tracer experiments if the knowledge on exfiltration is incomplete and many iterative measurements can be performed. As the tracer methods are far less expensive than CCTV analysis or remediation measures, this is a promising result for the usefulness of the tracer methods, because comparatively more measurements could be performed on a restricted budget.

**Conclusions**

Exfiltration from sewer can be quantified with tracers. However, no general statement is possible whether this is generally the case for all sewers because this largely depends on the necessary accuracy, which again is conditional on the magnitude of defects and on the preference of the investigator.

Although the concept is simple and the experimental procedures are documented thoroughly, the application of the tracer methods might also lead to false results if not great care is taken.

However, as there is considerable ignorance on sewer leakage in general, the proposed tools will improve the understanding of leakage and provide valuable information on transport processes in sewers.
Zusammenfassung

Einleitung

Obwohl die Schwemmkanalisation eine bequeme Lösung für den Transport und die Ableitung von Abwasser darstellt, kann sie nicht als wasserdichte Lösung betrachtet werden. In den letzten Jahrzehnten wurden beträchtliche Anstrengungen unternommen, um die Umwelt- und Gesundheitsgefährdung durch undichte Kanäle abzuschätzen. Trotzdem ist das Wissen über die Größenordnung von Abwasserverlusten aus Kanalleckagen, was eine Grundvoraussetzung darstellt, immer noch unsicher.

Ziel dieser Arbeit

Quantitative Informationen über Kanalleckagen sind hauptsächlich deshalb knapp, weil die vorhandenen Methoden zu konstenintensiv (z.B., Druckprüfung eines gesamten Kanalnetzes) oder zu schwierig (z.B., der Modellierung von Grundwasserverunreinigungen) für Wasserwirtschaftler und praktische Ingenieure sind. Das Ziel dieser Arbeit war, die quantitative Bestimmung von Exfiltration aus Kanalsystemen mit Markierungsstoffen (Tracern) zu untersuchen.

Da Tracerexperimente kostengünstig, allgemein anwendbar, aus ökologischer Sicht unbedenklich und leicht anzuwenden sind, könnten sie das Potential für eine Routinemessmethode aufweisen.

Methode


Außerdem wurden Techniken zur Datenanalyse entwickelt, um ein optimales Experiment zu entwerfen und absolute Exfiltrationsraten aus den experimentellen Ergebnissen zu schätzen.

Die praktische Anwendbarkeit der Methoden wurde auch von den Partnern eines europäischen Forschungsprojektes (APUSS) geprüft, die die Methoden unter unterschiedlichen Bedingungen in den verschiedenen europäischen Städten anwendeten.

Tracer methoden

Die grundlegende Idee der QUEST Methode (Quantification of Exfiltration from Sewers with Tracers) und QUEST-C (Continuous dosing) Methode ist, dass die Exfiltration über eine Massenbilanz einer Tracersubstanz in der zu untersuchenden Kanalstrecke gemessen werden kann.

Eine bekannte Masse des Tracers wird dem Abwasser zudosiert und fliesst mit dem Abwasser durch die zu untersuchende Leitung. Wenn Exfiltration auftritt, geht mit dem versickernden Abwasser auch Tracersubstanz verloren.
ZUSAMMENFASSUNG

Von der am Ende der Strecke gemessenen, restlichen Tracermasse kann die Exfiltration in der Leitung als Anteil des markierten Durchflusses berechnet werden.

Eine wesentlicher Bestandteil der Methoden ist, dass ein Referenzsignal am Ende der untersuchten Leitung zudosiert wird, das wie eine in-situ Kalibrierung wirkt. Es bewirkt eine erhöhte Maßgenauigkeit erhöht, weil unter anderem auf eine genaue Durchflussmessung verzichtet werden kann.

Die Datenanalyse schließt eine Abschätzung der Unsicherheit des Messresultats ein. Hierfür wurden statistische Techniken wie bootstrap und Regressionsanalysen entwickelt.

Experimentelles Design

Die QUEST und QUEST-C Tracermethoden haben viele Freiheitsgrade hinsichtlich der Wahl des Tracers und der Dosierungsstrategie. Die Anwendung dieser Techniken macht es erforderlich, Entscheidungen in Bezug auf das experimentelle Design zu treffen, die schliesslich die Unsicherheit in den Messresultaten beeinflussen. Wir schlagen ein Verfahren für optimales experimentelles Design vor, das auf den Resultaten der entwickelten Unsicherheitsanalyse aufbaut.

Ein wichtiges Ergebnis ist, dass das optimale experimentelle Design davon abhängt, wie viel der Anwender bereit ist für die Tracermessung zu investieren (hinsichtlich Betriebsaufwand und finanziellen Mitteln) und wie diese Kosten in Relation zu den Konsequenzen aus falsch bestimmt Kanalleckagen stehen.

Dispersion in Abwasserkanälen


Es zeigte sich, dass Dispersionskoeffizienten in Abwasserkanälen zwei bis drei Größenordnungen kleiner sind als die, die in Flüssen gemessen werden. Zudem unterscheidet sich die Dispersion nicht wesentlich von System zu System.

Aus Tracerdaten lernen

Mit Bayesischer Datenanalyse wurden absolute Verlustraten aus der gemessenen Information über Leckagen ermittelt. Für die Anwendung der Tracertests in Netzwerken ist das in der Regel nur möglich, wenn vorhandenes vorheriges Wissen (z.B., Lage des Grundwasserspiegels, Wasserstand im Kanalrohr, usw.) in die Analyse miteinbezogen wird.

Die Resultate einer konzeptionellen Studie zeigen, dass die Tracerexperimenten die meisten Informationen liefern, wenn i) das Wissen über Abwasserverluste unvollständig ist und ii) viele Experimente durchgeführt werden können. Da die Anwendung der Tracermethoden wesentlich kostengünstiger ist als Kamerabefahrungen oder Sanierungsmaßnahmen, ist das ein vielversprechendes Resultat für deren Anwendbarkeit, da mit einem limitierten Budget können vergleichsweise mehr Tracermessungen durchgeführt werden können als mit den anderen Verfahren.
Schlussfolgerungen


Obgleich das zugrundeliegende Konzept einfach ist und die experimentellen Verfahren gründlich dokumentiert wurden, ist deren Anwendung nicht trivial. Verlässliche Resultate werden nur erhalten, wenn eine gewisse Erfahrung vorhanden ist und die Experimente mit der gebotenen Sorgfalt durchgeführt werden.

Im Allgemeinen besteht jedoch immer noch beträchtliche Unsicherheit über die Größenordnung von Abwasserverlusten aus undichten Kanälen, und es ist zu erwarten, dass die vorgeschlagenen Methoden zum besseren Verständnis der Exfiltration beitragen. Zusätzlich können mit Tracerexperimenten wertvolle Informationen über Transportprozesse in Abwasserkanälen gewonnen werden.
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Chapter 1.
Seeking certainty on sewer leakage

Although sewers present a convenient solution to transport and dispose sewage they have many shortcomings, one of which is their leakiness. Cracks, fissures and gaps occur during the normal aging process and lead to exfiltration (of wastewater into the ground) if the sewer pipe is located above the groundwater table. And, what is also important, many of today’s sewer lines have been laid in times where the construction of watertight pipe connections had simply not been feasible.

1.1. Current problems

The compromised structural integrity of sewer networks and the threat of health and environmental hazards from untreated wastewater seeping into the soil beneath our cities raised growing concern in the preceding decades. Recently emerging knowledge on the behavior and fate of micropollutants (pharmaceuticals, synthetic or natural hormones) in the environment added another dimension to this discussion.

With the high investment cost for sewer rehabilitation in mind, considerable effort has been made to assess the quantity and consequences of sewer leakage. However, no general available methods for their assessment have been found. Rutsch et al. (2005) give a comprehensive overview on the actual state of research, which is not included in this thesis. We found that current knowledge on sewer leakage is still incomplete, although many promising approaches have been investigated.

Interestingly, experts still dispute whether sewer leakage is critical at all. One position is that sewer leakage is not of major concern, because i) exfiltration is generally supposed to be so small that it cannot be detected by discharge measurements and ii) possible pollutants could largely be eliminated by biological degradation or adsorption (Rauch and Stegner, 1994; Vollertsen and Hvitved-Jacobsen, 2003; Hua et al., 2003). In opposition to that, a number of cases are reported (Deutsch, 1963; Eiswirth and Hötzl, 1997; Wolf et al., 2004; Wakida and Lerner, 2005; Fenz et al., 2005) where elevated concentrations of pollutants suggest a diffuse groundwater contamination by leaky sewers. Apparently, a lack of understanding subsists because

- sewers are buried in the ground and difficult to access. This makes seepage difficult to investigate and is a major reason for the present uncertainty on its magnitude,

- sewer leakage is a complex process which is spatially heterogeneous and dynamic. It is assumed that leakage rates depend on the characteristics of the individual defect (e.g., discharge, wastewater composition, soil) and vary over time (e.g., clogging by biofilm growth, seasonal variations in groundwater table, flow variations and erosion of sewer sediment),

- the proposed tools are either too involved for urban water managers (e.g., groundwater modelling) or do not allow for a realistic assessment of exfiltration (e.g., test rigs, pressure testing).
Chapter 1. Seeking certainty on sewer leakage

In this thesis, certainty on sewer leakage is sought in such as an innovative experimental approach to quantify exfiltration with tracers is investigated. Applying tracers should have certain advantages over existing methods:

- direct measurements over clearly defined reaches are possible,
- tracer experiments are quick and cost-effective (e.g., compared to groundwater monitoring and modelling),
- tracer experiments are generally applicable,
- exfiltration is assessed under realistic flow conditions (e.g., dry weather flow, undisturbed conditions of the sewer environment),
- instantaneous values can be obtained, not averaged over years as from groundwater studies.

1.2. Goals and questions

This thesis was embedded in the European research project APUSS (Assessing infiltration and exfiltration on the Performance of Urban Sewer Systems). In the project, it was intended to develop methods and tools for the assessment of infiltration and exfiltration on a more serious and scientific basis than before, and to help cities and operators to define better investment and rehabilitation strategies (appendix A).

The primary goal of this thesis is to investigate the suitability of tracers to quantify exfiltration. This includes an experimental procedure that is applicable by practitioners, corresponding algorithms for data analysis including an assessment of uncertainty as well as a framework for optimal experimental design.

In particular, the following questions should be answered:

- Can exfiltration from sewers be identified using tracer experiment data?
- What tracer systems (substance and analytics) are suited for wastewater applications?
- What statistical methods for error analysis should be applied?
- Can systematic errors be reduced by a clever dosing strategy?
- Can the use of multiple tracers improve the accuracy of the method?
- Do transport processes (e.g. wave propagation) affect the obtained results?
- How accurately can leakage be estimated from tracer measurements?
- What would be appropriate methods of data analysis to infer exfiltration rates from exfiltration ratios?
- Can the results from tracer experiments be improved when available knowledge on the location and gravity of sewer defects is incorporated in the analysis?

In addition, detailed guidelines on the preparation, the performance and data analysis of the tracer experiments should be provided to the APUSS partners and practising engineers.
1.3. Outline of this thesis

In the following two chapters, the developed tracer methods will be presented. First, the QUEST method (Quantification of Exfiltration from Sewers with Tracers) will be presented that uses pulse injections of a single tracer to quantify exfiltration relative to the labelled flow. The next chapter gives details on the QUEST-C method that applies a continuous dosing strategy of two different tracer substances. Chapter 4 concentrates on the experimental design of a tracer experiment and suggests how to find the optimal dosing strategy. In chapter 5 suitable models are suggested to predict dispersion in sewers, which is crucial for the planning and exact performance of a tracer experiment. This investigation is largely based on the experimental data collected in the course of this thesis, but complementary data from tracer experiments have been collected and incorporated in the analysis. In chapter 6 a conceptual approach is presented how to obtain absolute exfiltration rates from tracer experiment data, when available a priori information is considered. This work ends with conclusions and an outlook.

My thesis is structured as a paper dissertation. It is indicated which of the chapters have been submitted for publication.
Chapter 2.  

Exfiltration Measurements with Pulse Dosing of Tracers


2.1. Introduction

Due to advanced age, inadequate maintenance, or poor construction, most sewer systems are not completely watertight. The potential for groundwater infiltration is a widely recognized problem (Weiss et al., 2002; White et al., 1997; Abdel-Latif and El-Hosseiny, 1995), but exfiltration of wastewater can pose a greater risk to human health and the environment (Eiswirth and Hötzel, 1997; Bishop et al., 1998; Reynolds and Barrett, 2003). Various methods for quantification of exfiltration have been developed, including indirect methods such as groundwater monitoring (Deutsch, 1963; Kreitler et al., 1978) and contaminant transport modelling, (Härig, 1991) and direct methods such as pressure testing (Decker, 1998), georadar inspection (Fritzsche, 1994), and water balance accounting (Härig, 1991; Trauth et al., 1995).

Unfortunately, the indirect methods are generally too involved for widespread application by urban water managers, and results may not be sufficiently reliable for practical use. On the other hand, direct methods can yield relatively accurate estimations for single leaks, but extrapolation to larger sections of the sewer network is questionable due to the non-uniformity of defects. As a result, hardly any urban water managers can provide estimates of exfiltration in their systems for use in rehabilitation planning.

In hydrological research, the interactions of streams with subsurface waters are often characterized by tracer studies (Fernald et al., 2001; Harvey et al., 1996; Worman et al., 2002; Zaramella et al., 2003). However, in sewers tracer tests are hardly ever performed. In this paper, we introduce a novel method for the QUantification of Exfiltration from Sewers using artificial Tracers (QUEST method). The objectives underlying the development of this method were as follows:

1. To propose a conceptual framework for accurate estimation of exfiltration based on measurements of an introduced tracer,

2. To design and test a field experiment implementing the proposed concept with a tracer that is convenient to use and environmentally safe,

3. To investigate, and develop as necessary, statistical techniques for analyzing the resulting data,

4. To rigorously assess the accuracy of the method using reliable methods of uncertainty analysis.
The detailed analysis of uncertainty was a particularly important objective of our study. While current methods for exfiltration measurement are known to be unreliable, quantitative estimates of uncertainty have not been made. Uncertainty estimation is not simply a scientific exercise in describing how well we know a particular quantity, but rather is the first step towards reaching a rational decision about the need for sewer rehabilitation with regard to exfiltration. Informally, uncertainty estimates allow one to assess the potential for undesirable outcomes, such as health hazards or environmental harm, and adopt a decision strategy that depends on the magnitude of this potential (Reckhow, 1994). More formally, uncertainty expressed in the form of a probability distribution about an outcome can be used to determine the "expected cost" for decision options (e.g., sewer restoration), calculated through integration of cost functions over the probability distribution (Pratt et al., 1964). While the process for reaching a decision is the responsibility of elected officials, urban water managers, and other stakeholders, it is the responsibility of scientists and engineers to provide the quantitative information upon which the decision is based.

2.2. Methods

Conceptual overview

If an artificial tracer is introduced into a well-mixed sewer system and exfiltration occurs downstream, then it can be expected that the tracer will be lost at the same rate as the wastewater. Therefore, if the amount of tracer remaining at the end of an investigated reach can be determined, it can be compared with the amount introduced to estimate exfiltration over the reach as,

\[
E = 1 - \frac{\text{mass}_{\text{out}}}{\text{mass}_{\text{in}}}
\]

(2.1)

where \(E\) = exfiltration, expressed as a proportion of wastewater discharge, and \(\text{mass}_{\text{in}}\) and \(\text{mass}_{\text{out}}\) = upstream and downstream mass of tracer, respectively.

Determination of the downstream tracer mass requires integration of the product of instantaneous tracer concentration and wastewater discharge. However, discharge measurement in sewers may not be very accurate, especially if portable flow meters are used (Bertrand-Krajewski et al., 2000). For this reason, we propose using one or more downstream reference inputs, in addition to the upstream indicator input (Figure 2.1) to eliminate the need for accurate discharge measurement. This occurs because only the mass of the indicator tracer is lost over the investigation reach, and the reference input is unaffected. Therefore, changes in the relative mass of tracer between the points of introduction and the point of measurement can be used to estimate exfiltration over the investigation reach according to,

\[
E = 1 - \frac{\text{mass}_{\text{REF,in}}}{\text{mass}_{\text{IND,in}}} \cdot \frac{\text{mass}_{\text{IND, out}}}{\text{mass}_{\text{REF, out}}} = 1 - \frac{\text{mass}_{\text{REF,in}}}{\text{mass}_{\text{IND,in}}} \cdot \frac{\int Q(t)C_{\text{IND}}(t)dt}{\int Q(t)C_{\text{REF}}(t)dt}
\]

(2.2)

where \(\text{mass}_{\text{REF,in}}\) and \(\text{mass}_{\text{IND,in}}\) = introduced mass of reference and indicator tracer, \(\text{mass}_{\text{REF,out}}\) and \(\text{mass}_{\text{IND,out}}\) = downstream mass of reference and indicator tracer, \(C_{\text{REF}}\) and \(C_{\text{IND}}\) = downstream concentration of reference and indicator tracer, and \(Q(t)\) = downstream discharge.

The computed exfiltration ratio is even not affected by water losses downstream the addition of the reference tracer (Figure 2.1), because it can be assumed that it affects both signals equally:

\[
\frac{\text{mass}_{\text{REF, eir}}}{\text{mass}_{\text{REF, out}}} = \frac{\text{mass}_{\text{IND, eir}}}{\text{mass}_{\text{IND, out}}}
\]

(2.3)
2.3. Experimental design

Figure 2.1.: Conceptual sketch of the experimental set-up of the QUEST method

where \( \text{mass}_{\text{REF},\text{eir}} \) and \( \text{mass}_{\text{IND},\text{eir}} \) = mass of reference and indicator tracer at the end of investigation reach (\( \text{mass}_{\text{REF},\text{eir}} = \text{mass}_{\text{REF},\text{in}} \)). Under steady flow conditions, equation 2.2 simplifies to:

\[
E = 1 - \frac{\text{mass}_{\text{REF},\text{in}}}{\text{mass}_{\text{IND},\text{in}}} \cdot \frac{\int C_{\text{IND}}(t) dt}{\int C_{\text{REF}}(t) dt}
\]  

(2.4)

Thus, when the masses of introduced tracer are known and constant discharge during the experiment is assumed, only downstream concentration measurements are required, not discharge. If additional information on the discharge should be available, the reference tracer can be used to correct for systematic errors in the discharge measurements. The QUEST method recommends slug injections for indicator and reference tracers, which makes it possible to use a single tracer substance. This has the major advantage of only requiring measurement of one state variable, instead of two.

This substantially decreases measurement uncertainty because the calculation of exfiltration is made robust against any systematic errors that apply equally to both signals, such as variation in the wastewater matrix, the sensors, or the measuring chain (Bertrand-Krajewski et al., 2003).

In a typical experimental setup, reference and indicator concentration peaks can be easily distinguished at the point of measurement because the indicator pulse is much more dispersed due to its greater travel distance (Figure 2.2). However, depending on the tracer substance used, the natural background concentration in the wastewater might confound the correct identification of the downstream tracer signals.

2.3. Experimental design

2.3.1. Tracer selection

An ideal tracer for implementing the QUEST method would be one that is readily available, conservative in wastewater, easy to measure, easily mixed, and environmentally safe. While no single tracer is ideal, we found that NaCl more closely meets our criteria than other tracers such as fluorescent dyes, specific ions, and radioactive substances.

First, NaCl is inexpensive and readily available in the form of road salt. This makes it possible for urban water managers to conduct repeated experiments on a limited budget.

Second, NaCl behaves conservatively in wastewater and is not pH sensitive. Adsorption to organic matter or biofilm has not been reported in the literature and is considered unlikely
due to the natural background of Na\(^+\) in sewage, which suggests that available adsorption sites are already occupied. Unfortunately, this advantage is also the biggest disadvantage because the natural background concentration is non-negligible and can be dynamic, thus disturbing measurement of introduced tracer. However, an appropriate experimental design can minimize this effect, as discussed below.

Third, convenient techniques for measuring NaCl are available for sewer applications. The dynamic nature of tracer signals requires in-line measurement technology with a frequency of at least one per second. Grab sampling (with a maximum frequency in the order of one per ten seconds) is seldom acceptable due to the risk of truncating tracer peaks. NaCl concentrations can be continuously monitored by modern conductivity sensors, which show a linear calibration against NaCl concentration (in the range 0.3 mS\(\text{cm}^{-1}\) to 10 mS\(\text{cm}^{-1}\)), are automatically temperature corrected, can be adapted for sewer applications, and exhibit a response time of less than one second.

Fluorescent dyes, which can also be measured in-line by filter-fluorometers, may present an interesting alternative to NaCl. However, in preliminary trials we found that the optical measurement technique employed was sensitive to sewerage properties such as grease, particulates, and turbidity. Other ions which could be measured by ion-specific detection, such as Li\(^+\) and Br\(^-\), were also considered, but were found to be inferior to NaCl because of dissatisfactory sensor properties as slow measurement response times, sensitivity to temperature, fouling of the ion-selective membranes, and considerable cross-sensitivity to other ions.

Unfortunately, a second disadvantage of using NaCl as a tracer is the considerable density difference between NaCl solution and fresh water. Especially in sewers with low slopes and low velocities this may require the use of additional measures to guarantee mixing (e.g., sewerage pumps). However, mixing can be verified during the experiment by the installation of multiple probes in the cross section. The extent to which the interpretation of measurement results will be complicated by imperfect mixing in the investigation reach will be discussed below.

Finally, NaCl is an environmentally safe tracer and will not contaminate the surrounding soil or groundwater in the case of exfiltration. Also, there is not a risk of disturbing groundwater tracing experiments that may be occurring, as may be the case with fluorescent dyes.
2.3.2. Dosing technique

As mentioned above, NaCl (respectively conductivity) is naturally present in wastewater at non-negligible concentrations. Therefore, to minimize variation in the background concentration, experiments should be conducted during the period of least human activity, usually in the middle of the night. A sufficient mass of tracer should be added to result in downstream concentrations that are substantially higher than the fluctuations in natural background concentration. Also, care should be taken to assure that a precise mass of tracer is added, through careful mixing of NaCl solution and complete addition. Finally, accurate integration of the concentration peaks requires careful quantification of the baseline signal of NaCl. We found that by partially overlapping the reference and indicator pulses, maximum information on the baseline could be obtained for a fixed measurement time. Furthermore, the replication of reference and indicator pulses will also improve the accuracy of exfiltration estimation and it is recommendable to dose series of reference pulses per indicator pulse during an experimental campaign. Details on optimal experimental design will be described by Rieckermann et al. (2005c).

2.3.3. Site suitability

The QUEST method is conceptually applicable to any section of the sewer system where exfiltration estimates are desired. However, the interpretation of estimated tracer mass loss as "loss of a proportion of discharge" is considerably more difficult in a reach where discharge is non-uniform due to inflows or extensive infiltration/exfiltration. Therefore, we can expect that the most reliable estimates of exfiltration will occur where the assumptions inherent in the method are most closely satisfied. For example, reaches in which the tracer and wastewater are well mixed will provide more accurate estimates. With hydrodynamic simulation studies, we found that the interpretation of measurement results might not be trivial as it will often be site-specific and sensitive to the location of leaks relative to inflows.

2.4. Data analysis

The goal of analysis of tracer data from a QUEST experiment is the accurate deconvolution of the concentration time series into the baseline, the reference signals and the indicator signal. This is necessary for the correct determination of each tracer mass.

We identified the three signals by statistically fitting two forms of parameterized peak functions (one form for the indicator peak and one for the reference peaks) simultaneously with a baseline function. A variety of peak functions are available for this purpose, including analytical solutions of the advection-dispersion equations, statistical distribution functions, analytical functions used in chromatography and powder diffraction analysis or combinations of these (Marco and Bombi, 2001). While analytical solutions of advection-dispersion equations would allow for a physical interpretation of model parameters, such an interpretation is not necessary for our purposes. The primary criterion for selection of a peak function is a close fit to the data, as measured by the standard deviation of model residuals. Options for fitting the baseline might include all types of globally parameterized functions (e.g., linear, exponential, logarithmic, polynomial).

Commercially available software packages are available for fitting peak functions to data (e.g., PeakFit, SPSS). However, we found that more general functions were required than those provided with these packages, particularly locally parameterized spline functions. Therefore, we performed data analysis using the statistical programming language R (R Development Core Team, 2004). A nonlinear least-squares algorithm included with R was used for parameter estimation.

Problems may arise from the frequentist approach to parameter estimation, in which over-parameterized models can lead to singular covariance matrices that do not allow for parameter
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estimation. This is mostly due to low sensitivity of the model results to problematic parameters or collinearity in the parameter space. To diagnose such critical situations, sensitivity measures and collinearity indices can be used (Brun et al., 2001).

During the development of the method we found that identifiability problems with the reference peak model could be partly solved by dosing a series of reference pulses in one experiment. As all peaks of this class undergo the same transport process to the measuring point the measured signals have similar shapes. This enables us to substantially reduce the number of peak model parameters by jointly fitting common shape parameters for all peaks of the series instead of individually estimating the shape parameters for each peak. Also, this allowed for the fitting of flexible functions such as locally parameterized splines which would not be possible otherwise. When a combination of two or more peak functions is used to describe a signal, it proved useful to fix identical parameters (e.g., amplitude or location parameters) at reasonable values.

Once appropriate peak functions are identified and fitted, the integrals needed for equation 2.2 can be calculated for each peak by numerical integration (Piessens et al., 1983).

2.5. Uncertainty analysis

Even after careful selection and fitting of peak functions, uncertainty remains in the final estimation of exfiltration. We identified the following possible sources of uncertainty (Figure 2.3):

1. Inaccuracy in the dosing of tracer mass
2. Incomplete mixing of tracer over the sewer cross-section
3. Tracer measurement error
4. Error in peak model parameters
5. Error in model structure and baseline representation
6. Error in simultaneous discharge measurements, when available

In contrast to this, uncertainties due to variations in the wastewater matrix, transmission errors in the measurement chain and numerical computation errors are considered negligible.

The uncertainty introduced by the former sources should be minimized whenever possible through careful experimental technique. However, when uncertainty cannot be eliminated, the effect on final results should be carefully estimated. Guidance for how to consider each of the above uncertainty sources will be presented first. This is followed by a description of methods for propagating uncertainty to final results.

Inaccuracy in the dosing of tracer mass Tracers were added to the sewer using a dosing tube and funnel to avoid gross errors caused by splashes of tracer on the sewer wall. However, dosing errors may occur due to spillage or adherence to the tube or funnel. As the practical dosing procedure is very site specific, it has to be evaluated for each experimental campaign.

Incomplete mixing of tracer over the sewer cross-section Mixing in the sewer can be achieved by locating the tracer dosing points upstream of large drops in the sewer or by creating additional turbulence by external means (e.g., sewerage pumps). Furthermore, mixing can be verified by using multiple measurement probes located around the sewer cross-section. Generally, mixing can be considered complete when the coefficient of variation of concentration in the cross-section is less than 2% (Rutherford, 1994). Finally, a smooth appearance in the tracer curves indicates adequate mixing. We expect that these checks will make errors caused by incomplete mixing negligible.
Tracer measurement error Measurements of conductivity are reported to be accurate to 0.5%, after lab verification of accurate temperature correction (Niesel, 2003). To convert measured conductivity to NaCl concentration, calibration curves must be developed for each sensor. Errors in the calibration curve can be estimated using the outputs of linear regression analysis, including the resulting distribution of residuals and parameter standard errors.

Error in peak model parameters The nonlinear least-squares regression algorithm employed for fitting the peaks provides estimates of residual and parameter error. These can easily be used to assess the error in the model parameters. However, unless the assumptions of regression are strictly met, these estimates may be unreliable (Bates and Watts, 1988). Depending on the sensor quality (signal-to-noise ratio of the conductivity electrodes), the assumption that is likely to be most problematic for the QUEST method when NaCl is used as a tracer is that of independently, identically distributed residuals. We have found that even after careful peak fitting, some autocorrelation in the residuals remains.

Autocorrelation is problematic with regard to the estimated standard errors of peak parameters, which are likely to be underestimated. This is because the autocorrelation in the residuals implies that the information content of the data is overestimated by the regression algorithm. In some peak fitting applications (Berar and Baldinozzi, 1993; Altomare et al.,
1995), this situation has been handled by manipulating the data (e.g., lumping data points together or leaving out inconvenient data points). However, we believe that the correct way to deal with models that are too simple to fit the data is not to manipulate the data but to look for a more appropriate (i.e. more highly parameterized) model (Bates and Watts, 1988). Unfortunately, this may increase problems with parameter identifiability.

This appears to be a general dilemma in environmental modelling and uncertainty analysis. The more accurate and frequent measurements become, the more often frequentist statistical inference fails. Simple models show systematic errors, while complex models have too many parameters to be identifiable. In our case we chose a spline approach to implement a highly flexible locally parameterized model which results in a residual pattern with a minimally systematic structure. However, as one has to carefully select and tune the initial values of the model parameters, this task relies heavily on identifiability analysis to overcome convergence problems (Brun et al., 2001).

For the reasons described above, in addition to non-normality of model residuals, the uncertainty of the model parameters was estimated using a bootstrap approach (Efron and Tibshirani, 1993) rather than a local curvature method. In the bootstrap procedure, a virtual dataset is created by first fitting the model to the data and drawing a random sample from the obtained residuals which is then added to the best fitting model function. Refitting the model on the virtual dataset yields a new set of model parameters, and an estimate of the uncertainty of the model parameters is obtained by repeating this process a large number of times.

Error in model structure and baseline representation The nature of the tracer baseline is an important factor in the analysis, as it influences the accuracy of peak parameter estimates and can lead to model structural errors. This is because a small peak in the background concentration that occurs simultaneously with the passage of a tracer peak can be mistaken as part of the dosed tracer mass. Experimental design (such as nighttime dosing) can minimize such effects, but they can never be completely eliminated.

As it is impossible to know the true shape of the baseline during passage of tracer, we also used a bootstrap resampling method to estimate the possible range of effects of the baseline on peak shape estimation. This was done by recording background concentration alone for a length of time at least as long as the duration of the actual experiment (alternatively, segments of baseline occurring between measured peaks could be pieced together). Synthetic baselines of length equal to the experiment are then created by subsampling from the measured baseline, maintaining the time order of measurements but randomly determining the starting point (continuous looping can be used as necessary). This synthetic baseline is then added to the fitted peak functions, and the peak and baseline models are refitted. This is done repeatedly, computing the resulting exfiltration for each iteration. The result is a distribution of exfiltration estimates that only reflect the uncertainty due to baseline variation in the investigation reach, regardless of other sources of uncertainty. The procedure is valid so long as it can be assumed that the background concentration patterns during the actual experiment are sufficiently similar to those used to generate the synthetic datasets.

Error in simultaneous discharge measurement If the assumption on steady discharge does not hold, or passing times of the reference pulses are large, it is advisable to provide a simultaneous discharge measurement with a high time resolution. In our framework, we consider area-velocity measurements based on the Doppler principle because they are standard in most engineering applications. Systematic and random errors are considered for the sewer diameter, velocity, and water level.
2.6. Case study

2.6.1. Site description

To demonstrate the feasibility of QUEST, we applied the method to a section of sewer in Rümlang, Switzerland. Rümlang is a community of 5,600 people with a sewer system that dates back to the 1950s and that was subsequently extended and renovated. We chose an investigation reach of 2130 m that included sewers of different diameters, slopes, and shapes, as well as retention tanks and a combined sewer overflow structure.

The measurement point was located 100 m downstream of the investigation reach, after a drop in the sewer line that ensured complete cross-sectional mixing. This was tested in a preliminary experiment in which conductivity was measured with six probes equally distributed over the entire cross section, yielding a coefficient of variation less than 2%. The mean dry weather flow at the measuring point is 25 l s⁻¹, and the average baseline conductivity of the wastewater is 0.8 mS cm⁻¹. At the dosing point of the indicator tracer, located in an upstream branch of the sewer system, discharge was estimated at 2 l s⁻¹. No information was available on the structural condition of the investigated sewer reach or on the groundwater level.

2.6.2. Experimental Design

Tracer addition consisted of three indicator pulses (each 5481 g NaCl, added over 30-40 seconds) that were dosed together with twelve reference pulses (either 942 or 754 g NaCl). We used a tracer solution with a concentration of 200 g NaCl⁻¹, prepared using common road salt and tap water. To minimize baseline effects, the tracer study was carried out from 0:00 to 4:00 at night. Additionally, background conductivity alone was measured for two subsequent days.

Electrical conductivity was recorded downstream with a time resolution of one second, which allowed for a smooth monitoring of the tracer pulses. Conductivity was measured with two spade-shaped probes (TetraCon 325S, WTW) installed on a model boat. Preliminary testing showed that mounting the probes on this type of streamlined floating device or on metal rings avoids clogging, even in heavily particle-laden wastewater. A series of ten standard additions was used for calibration, yielding a linear relationship between conductivity and tracer concentration (slope = 0.54 gl⁻¹/(mS cm⁻¹) for both sensors). As the assumption of steady discharge did not always hold at our measuring site, a simultaneous flow measurement based on the Doppler ultrasonic area-velocity principle (SIGMA 950, American Sigma) was made.

2.6.3. Data Analysis

The mean of the indicator signal between the dosing and measurement points was 78 minutes, and the time of passage at the measurement point was approximately 20 minutes (Figure 2.4). Due to the greater influence of longitudinal dispersion, the indicator pulses are much broader.
than the reference pulses and the skewness indicates the presence of dead zones in the flow where tracer was delayed. The non-equidistant intervals of the reference peaks reflect practical difficulties in achieving regularly spaced dosing but do not affect the results of analysis.

The third indicator signal can be seen to have perturbations in the tail which most probably originate from variations in the background conductivity. For this reason, we decided to eliminate this indicator peak and its adjoining reference peaks from further analysis.

A variety of peak functions was fitted to the tracer data. A combination of a Pearson IV (PIV) distribution function and a spline was found to provide the best fit to the reference peaks, and a combination of Gaussian and Pearson IV distribution functions was found to provide the best fit to the indicator peak (Figure 2.5, left). These peak functions led to the smallest residuals with the weakest time structure. To ensure parameter identifiability, we chose to fix the height of one distribution function at approximately half the total peak height and only fit the value of the other. This means that the two functions contribute approximately equally to the overall shape of the peak model. A locally linear baseline model was found to be most appropriate.

2.6.4. Uncertainty analysis

Inaccuracies in dosing of tracer mass: We assessed these errors in laboratory tests for the equipment used in our experiments and found that they were well represented by an exponential distribution with a mean loss of 2.2 g.

Incomplete mixing of tracer over the sewer cross-section: As mentioned above, in a previous experiment mixing was evaluated not critical. During the experiment, the two sensors showed a very good agreement, with an average coefficient of variation of 1.7%. Therefore, errors caused by incomplete mixing were considered negligible.

Tracer measurement error: The standard error of the calibration constants of the two sensors were estimated as 0.002 and 0.004 g/l/(mScm⁻¹) respectively.

Error in peak model parameters: It was observed that the model fits the data very well and that the magnitude of the residuals is in the order of a few percent of the measured data.

Figure 2.4.: Measured time series of conductivity (black) and discharge (grey).
2.6. Case study

Figure 2.5.: Fitting of different models to the first tracer peak. Top: identification of individual components. Bottom: residual plot. Left: highly parameterized model with linear baseline, spline and a combination of Pearson IV (PIV) and Gaussian peaks. Right: surrogate model for baseline error evaluation with bootstrap procedure (linear baseline, Pearson IV and a combination of Pearson IV and Gaussian peaks).

Consequently, the bootstrap method for estimation of uncertainty in the model parameters yielded narrow distributions (not shown) with a mean coefficient of variation of 0.033.

**Error in model structure and baseline representation** The error caused by variation in the baseline was assessed using a set of 1000 bootstrapped background segments. However, as the computational demand for fitting a locally parameterized spline is very high, it was computationally very demanding to perform the bootstrap using the best fit model. Instead, we used a simpler surrogate model with a linear baseline, a Pearson IV distribution for the reference peaks and a combination of Pearson IV and Gaussian distributions for the indicator peak. This model fit the data nearly equally well, but did not meet the assumption of independent, identically distributed residuals (Figure 2.5, right). While this may affect estimates of parameter standard errors, it should not affect the estimated parameter values themselves. To show that using a simpler model to assess baseline error provides reasonable estimates, we compared the bootstrap results for the best fitting model with the surrogate model for the first peak and found a discrepancy of only 1.48% for the baseline error which was considered to be not significant.

Experimental data sets that have clearly recognizable problems in the background pattern would normally be removed from further analysis (e.g., the third indicator peak in our study). However, a typical bootstrap procedure would include synthetic datasets that have such problems. Therefore, to achieve more representative error estimates, we decided to apply a "filter" to these datasets that approximates the manual filtering that normally occurs. We found the standard deviation of model residuals to be a suitable statistic for filtering. Based on a visual inspection, we chose to exclude synthetic data sets which led to residuals with a standard deviation greater than or equal to 0.012 mScm⁻¹. This procedure eliminated the most extreme errors and led to a distribution of the baseline error with a mean of -3.7% and a standard deviation of 5.9% what we believe are more representative uncertainty estimates.

**Error in simultaneous discharge measurement:** The Doppler ultrasonic area-velocity principle computes the discharge from information on the wetted cross-sectional area and the mean flow velocity. Therefore, we considered uncertainty in these two components. From field
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experience it was assumed that the diameter of the sewer has a systematic normally-distributed measurement error term with a mean of zero and a standard deviation of 0.015m. It was estimated in laboratory tests that the water level measurement has a random normally-distributed error with zero mean and standard deviation of 0.003 m. Furthermore, we assumed a random normally-distributed measurement error for velocity with a standard deviation of 5% of the measured value.

**Full error propagation:** To conduct the full error propagation, 2000 filtered bootstrap and Monte Carlo samples were used. Distributions of exfiltration were first determined for each indicator peak separately by combining the results of two probes (Figure 2.6). Assuming that the errors in the two peaks are mostly independent, a single distribution was achieved by multiplying the probability densities given by the two curves at corresponding values.

To determine the relative importance of the various sources of uncertainty, five error propagations were performed, each of which excluded the error from one source. This procedure yields very narrow distributions for the exclusion of the most important error sources and has the advantage that correlated effects of the other sources are taken into account.

### 2.7. Results

The best-fit peaks, baseline, and resulting integration led to point estimates of exfiltration for the two indicator peaks of 12.5 and 8.2%. Propagation of all sources of uncertainty for each indicator peak resulted in slightly skewed probability distributions with standard deviations of 5.9 and 3.1% respectively (Figure 2.6).
2.8. Discussion

Multiplying the two distributions gives a single distribution for exfiltration with a mean of 9.9 and a standard deviation of 2.7% (Figure 2.7). Other appropriate summaries of this distribution might include the median (10.0) or mode (10.2), together with a credible interval (e.g., 95%: [5.4, 14.0]). We can conclude from these results that exfiltration is significantly greater than zero, yet is most probably less than 15%.

Uncertainty analysis indicates that the overwhelming source of uncertainty is variation in the baseline pattern (Figure 2.8), despite the fact that the study was performed at night to minimize this effect. Interestingly, we observed a slight bias in exfiltration when the baseline error is not considered. This is a site-specific effect that results from the temporal pattern of the natural background concentration at the Rümlang sewer, which was used to estimate the baseline error component. In our case we found that the baseline naturally contains more "peak" patterns than recesses, which leads more often to an overestimation of the indicator signal. Consequently, exfiltration is underestimated. Another slight bias is caused by the dosing error due to incomplete addition of tracer, however it is of minor magnitude and like all other sources practically negligible in this situation.

2.8. Discussion

Our case study suggests that the QUEST method is a convenient way of estimating exfiltration without requiring accurate discharge measurements. However, the results of the analysis must be interpreted carefully.

First, it must be kept in mind that exfiltration losses are expressed as a proportion of the labelled flow, which can be difficult to interpret when there are substantial inflows downstream of the tracer addition. At our study site for example, discharge increased from approximately 2 to 20 l s⁻¹ between the points of dosing and measurement, and the losses are expressed for the entire reach. This implies that the exact location and magnitude of specific leaks can only be detected with subsequent studies conducted in smaller sub-reaches. With regard to absolute exfiltration rates, which might be most valuable for urban water managers, one has to be very careful with the interpretation of the results, if the flow conditions in a reach are not uniform. At the current state of development we can only state with certainty that over the whole 2 km reach a minimum of approximately 10% of the labeled flow (here: 0.2 l s⁻¹) was lost, which is also only valid for the time of the experimental campaign. As sewer exfiltration could be a
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Figure 2.8: Uncertainty analysis of a QUEST experiment. Boxes represent the median and interquartile range of estimated values. The whiskers extend to the most extreme data point which is no more than 1.5 times the interquartile range. Each boxplot was produced by excluding one source of uncertainty, as indicated by the horizontal axis label.

Very dynamic process, which might depend heavily on hydrostatic pressure and the presence of sewer sediments, any extrapolation of the result must be handled with great care. From this we conclude that the method should preferably be performed in short reaches without much inflow, where the interpretation of the measurement results is straightforward.

For sewer rehabilitation planning, more detailed analysis using CCTV will be necessary in any case, because decision makers have to consider structural failure above the water level that can not be detected by our method. Nevertheless, we demonstrated that the method is suited for the quick screening of large reaches and catchments. Even in cases where the interpretability might be difficult or exfiltration ratios are regarded too uncertain, the method can be used to comparatively assess similar reaches with regard to a rehabilitation priority ranking.

There is no single criterion for determining whether the QUEST method is sufficiently accurate for practical use. In fact, representation of the results as a full probability distribution gives a full picture of the relative likelihood of different values for exfiltration, as measured by the method. Decision makers can then use this information to decide whether sewer rehabilitation is necessary. This decision should depend not only on the magnitude of exfiltration, but also on the potential for leaks to cause undesirable outcomes such as disease or environmental damage. This will be a function of factors such as the quality of the wastewater, the depth of groundwater, and the proximity to surface waters. Clearly, exfiltration estimation is just one component of the integrated assessment that is required for urban water management decisions.
Monte Carlo Simulation is a convenient method of uncertainty analysis because uncertainty from different sources can be easily integrated in one procedure. Additionally, individual contributions to error can be easily assessed. In our study, variation in the background conductivity was the most important source of error, and we expect this to generally be the case when using NaCl as a tracer. NaCl is present at non-negligible concentrations in wastewater, and variations can confound identification of tracer peaks. Tracers that are not naturally present in wastewater may be preferable, if they meet the other criteria of the QUEST method.

In many engineering applications, it is not possible to meet all assumptions employed in regression analysis. For example, systematic patterns in model residuals will be present in most cases. Even more flexible models might avoid this problem, but we expect that practical identifiability will become a problem as the number of model parameters increases. As described above, the use of a bootstrap approach to estimating parameter uncertainty would be an improvement over regression-based estimates. However, such a procedure requires a model that is sufficiently simple to be fitted to the data in a time that allows for thousands of such fits to be performed. In any case, it seems that the computed exfiltration is relatively insensitive to parameter uncertainty of the magnitude found in our study. This is because of the good representation of the data by the model and a low random noise component in the measurements.

Estimates of the magnitude of uncertainty caused by baseline variation are conditional on the choice of threshold used in the data filtering process of the bootstrap procedure. We chose a threshold that seemed to reasonably approximate the visual inspection process we employed. However, this threshold may depend on the quality of the data and the experience of the analyst. A more or less stringent threshold will directly influence estimates of uncertainty.

The potential for improving the QUEST method through modification of experimental design is currently being investigated (Rieckermann et al., 2005c). Opportunities exist to optimize the number of tracer pulses and the temporal dosing strategy of the indicator and reference pulses. Other possibilities, which are focused on the application of more specific tracers are also being tested. For tracers that do not permit in-line measurement, continuous dosing strategies and the simultaneous use of two different substances may be an option (Rieckermann et al., 2005a). However, at this stage of development, further experience also has to be gained from applications to other systems under a variety of conditions.

2.9. Conclusions

Our goal was to develop an exfiltration estimation method that is convenient and accurate enough to be applied in engineering practice. It seems that the QUEST method can meet this goal when implemented using NaCl as a tracer. The use of both an indicator and reference pulse of tracer eliminates the need for discharge measurement when discharge is constant, thereby removing a potentially important source of uncertainty. NaCl is a conservative, easily measured, and environmentally safe tracer. However, it is also naturally present in wastewater, leading to potential errors in tracer signal detection - the major remaining source of uncertainty in the method. In a case study that was conducted over a two-kilometer-long reach of unknown condition, this error was estimated at ±2.7% exfiltration. Future development should concentrate on the development of detailed guidelines for an optimal experimental design to further reduce this uncertainty and indicate possible limitations.
Chapter 3.
Exfiltration measurements with continuous dosing of tracers


3.1. Introduction

In current research on soil and water contamination, the interaction of open channel flows with the surrounding soil is an important issue. In natural systems, the exchange of groundwater and surface water can play a key role in the evaluation of the ecological integrity of streams and compare different watershed management strategies (Schwarzenbach et al., 1983; Dahm et al., 1998). In engineering systems, leakage from irrigation channels and urban drainage structures can have a major impact on the surrounding soil and groundwater (Ellis and Revitt, 2002; Wolf et al., 2004; Wakida and Lerner, 2005; Halden and Pauli, 2005).

Unfortunately, the assessment of transboundary fluxes of water and solutes is complex and the understanding of groundwater recharge is still considered a major research need in natural systems (Dahm et al., 1998; Sophocleous, 2002). In technical systems (e.g., sewers), the knowledge on leakage and related processes is also sparse (Reynolds and Barrett, 2003; Hua et al., 2003). This is to one extent, because exfiltration of wastewater from sewers (into the groundwater) has often only been investigated in pilot studies (Ellis et al., 2003; Vollertsen and Hvitved-Jacobsen, 2003; Rauch and Stegner, 1994), which cannot fully account for the heterogeneity of real-world systems.

Apparently the in-situ measurement of exfiltration is difficult, for which we see two major reasons. First, leakage is often small compared to the actual discharge. This implies that losses are often not detectable from upstream-downstream discharge measurements, which are difficult to perform with sufficient precision in open channels. Second, discharge measurements alone are often inappropriate for this task, because exfiltration can be masked by hidden inflows. The application of tracers could help to overcome these shortcomings. However, only few tracer studies for leakage detection have been reported (Zellweger, 1994; Jensen and Madsen, 1996; Knudsen et al., 1996).

In this paper, we will propose an innovative tracer method to directly quantify leakage from open channels, considering as example exfiltration from sewers. In comparison to previous studies, we will discuss the uncertainty of exfiltration measurements with tracers and present the following innovations:

1. the QUEST-C method (QUantification of Exfiltration from Sewers using artificial Tracers with Continuous dosing), that reduces systematic errors by an improved experimental design,
Chapter 3. Exfiltration measurements with continuous dosing of tracers

2. a comprehensive framework to rigorously assess the accuracy of this method using reliable methods of uncertainty analysis,

3. a new approach for data analysis that accounts for dynamic flow.

A brief overview about the methodology is presented together with two different models for data analysis and the error analysis framework. Finally, we will demonstrate the usefulness of this approach on a case study and discuss important benefits and limitations of our approach.

3.2. Methods

3.2.1. Conceptual outline

The basic principle of exfiltration measurements with tracers is to dose a well-known amount of tracer to the sewer under investigation and apply a mass balance on the investigation reach (Rieckermann et al., 2005b). Given conservative behavior of the substance and full mixing, the tracer loss is directly related to the leakage in the reach.

Losses of the so-called indicator tracer (Figure 3.1) are generally identified relative to a reference tracer which is not affected by leakage. Exfiltration \( E \) is expressed as a ratio relative to the labelled flow:

\[
E = 1 - \frac{\text{mass}_{\text{REF,in}}}{\text{mass}_{\text{IND, out}}} - \frac{\text{mass}_{\text{IND, out}}}{\text{mass}_{\text{REF, out}}} = 1 - \frac{\int c_{\text{REF}}q_{\text{REF}}(t)dt}{\int c_{\text{IND}}q_{\text{IND}}(t)dt} \cdot \frac{\int Q(t)C_{\text{IND}}(t)dt}{\int Q(t)C_{\text{REF}}(t)dt}
\]  

(3.1)

where \( c_{\text{REF}} \) and \( c_{\text{IND}} \) are the tracer concentrations of the dosing solution, \( q_{\text{REF}} \) and \( q_{\text{IND}} \) are the dosing rates, and \( C_{\text{REF}} \) and \( C_{\text{IND}} \) are the tracer concentrations in the sample. \( Q(t) \) is the discharge at the measuring point.

Rieckermann et al. (2005b) used slug injections of tracers, which has the advantage that only one tracer substance is needed and only one single measurement error has to be considered. In other studies (Jensen and Madsen, 1996; Knudsen et al., 1996; Ohlsen and Genders, 1993) a continuous dosing strategy is applied, which requires different substances for indicator and reference input. In this case no inline measurements are necessary and a single discrete sample would allow to measure exfiltration if the discharge in the channel were to be steady.
3.2. Methods

3.2.2. Experimental design

Important improvements of the experimental design with regard to previous studies are:

1. using gravimetric measurements rather than volumetric measurements
2. measuring the ratio of tracer concentrations in the sample relative to the concentration ratio of the same tracers in a working standard produced from the two dosing solutions
3. systematic checks for gross errors (e.g., additional discharge measurements)

Tracer selection Ideal tracers for our method would be those that are readily available, conservative in wastewater, easy to measure, easily mixed and environmentally safe. Obviously, the computed exfiltration ratio \( E \) (equation 3.1) is systematically wrong if the tracer concentrations are reduced or magnified in the sewer reach (e.g., adsorption or natural tracer background in the wastewater). It might be for those reasons that early studies chose very specific tracer substances which are unlikely to be present in wastewater. Ohlsen and Genders (1993) used radioactive isotopes, whereas Vollertsen et al. (2002) report the use of fluorescent dyes. While no single tracer is ideal, we found that specific ions more closely met our criteria than the traces mentioned above. We obtained satisfactory results using Lithium as indicator and Bromide as reference tracer, which will be discussed in detail further below.

Dosing technique Both containers with tracer dosing solution were placed on balances with data acquisition facilities. This is more precise than volumetric measurements and allows for a continuous recording of the tracer input (Figure 3.2).

Working standard We prepared a working standard by mixing definite amounts of both tracer dosing solutions on an analytical balance. Then, the mixture was diluted to meet the concentration range of the tracers in the samples. In doing so, systematic errors from pipettes

Figure 3.2.: Setup of the QUEST-C experiment with field equipment (balances, data acquisition units and peristaltic pumps for dosing and sampling)
and graduated flasks, which might well be in the order of a few percent, are avoided. In addition, this is a convenient procedure to compute the dosed tracer masses, when the inputs of tracer solution are recorded from gravimetric measurements. To provide redundant information, a second working standard was prepared directly after the experiment by pumping from both tracer solutions into a single container for a defined time.

**Sampling strategy** We performed a time-proportional continuous composite sampling (Smith, 2001) instead of time-proportional discrete sampling. This minimizes random errors, because eventual fluctuations in tracer concentrations are integrated out. Although monitoring by ion-selective electrodes would be recommendable, we found that available devices for Lithium and Bromide performed unsatisfactory in the sewer environment.

**Additional discharge measurements** We installed a discharge measurement device at the sampling point. This provides additional information to check the tracer data for systematic errors. Depending on the reach characteristics, it can be also used for a more complex data analysis that accounts for dynamic flow effects, as presented below.

**Site suitability** The QUEST-C method is conceptually applicable to any section of the sewer system where exfiltration estimates are desired. However, Rieckermann et al. (2005a) point out that the interpretation of estimated tracer mass loss as "loss of a proportion of discharge" is more difficult in a reach with considerable inflows, infiltration/exfiltration or non-uniform discharge. With hydrodynamic simulation studies, it was found that the interpretation of measurement results will often be site-specific and sensitive to the location of leaks relative to inflows.

### 3.2.3. Data analysis

In the following we present two approaches to data analysis of a QUEST-C experiment: the simplified approach assuming steady discharge and the dynamic approach. For each method we develop an uncertainty analysis framework.

**A) Simplified approach**

**Model**

In the simplified approach, the discharge is assumed to be steady during the experiment. This modifies equation 3.1 to:

\[
E = 1 - \left( \frac{c_{Br}}{c_{Li}} \frac{w_{Li}}{w_{Br}} \right) \cdot \frac{m_{Br}}{m_{Li}} \cdot \frac{C_{Li}}{C_{Br}}
\]

(3.2)

where \(c_{Br}\) and \(c_{Li}\) are the tracer concentrations of the working standard, \(w_{Br}\) and \(w_{Li}\) are the masses of tracer solutions in the working standard, \(m_{Li}\) and \(m_{Br}\) are the dosing rates of the tracer solution and \(C_{Li}\) and \(C_{Br}\) are the tracer concentrations in the sample.

**Uncertainty analysis**

For the simplified approach, we identified seven major sources of uncertainty which will be presented below. Uncertainty due to variations in the wastewater matrix, adsorption on sewer slimes, transmission errors in the measurement chain and numerical computation errors were considered negligible (Figure 3.3).

**Inaccuracy in the dosing rates** As dosing rates are recorded continuously, they can be checked for gross errors easily. In case that no irregularities occur, a linear model describes the decrease in weight adequately. Parameter standard errors are estimated by linear regression analysis.
3.2. Methods

Indicator and Reference Signal

Figure 3.3.: Framework of uncertainty analysis for the QUEST-C method with major error contributions. Dotted ellipses indicate errors that are eliminated by the experimental setup or are assumed to cross out in equation 3.2. Note that discharge information is only considered explicitly in the dynamic model. For the simplified model, the impact of the transport error must be considered as a black box.

Incomplete mixing of tracer over the sewer cross-section (2) Generally, mixing can be considered complete when the coefficient of variation of concentration in the cross-section is less than 2% (Rutherford, 1994). In case that mixing by natural turbulence is found to be insufficient, it is recommended to improve it by external means (e.g., sewerage pumps).

Natural background concentration of tracer (3) The expected natural background of each tracer in the investigation reach must be tested beforehand and in case of significant background of the indicator tracer, a different substance should be chosen. Background concentrations of the reference tracer can be corrected through additional background sampling at the dosing point.

Adsorption of tracer to wastewater solids (4) Any significant adsorption of tracer to wastewater solids would introduce a bias in the computed exfiltration ratio. Tracer behavior should be assessed by laboratory batch tests.

Concentration measurement error in samples and standards (5) The measurement error is estimated from repetitive measurements on the analytic device. Systematic errors are avoided by the preparation of the working standard.

Error of analytical balance (6) The analytical balance is used to produce the laboratory standard with a high accuracy. Information on its expected precision can be obtained from the manufacturer.
Chapter 3. Exfiltration measurements with continuous dosing of tracers

Error from transport phenomena due to unsteady flow (\(\square\)) The separation of wave and fluid might cause variations of the tracer ratio in the samples (here: transport error). It has to be considered that discharge fluctuations in time result in waves which travel at a higher celerity than the main water body (Huisman et al., 2000). Henderson (1966) estimated that kinematic waves travel with a speed of 5/3 of the mean velocity under the assumptions of a wide rectangular channel and a constant friction coefficient. For the QUEST-C method, this would mean that the two tracer substances that have been dosed to the same water element were diluted differently at their dosing points. The magnitude of this error fundamentally depends on the flow during the experiment and the transport characteristics of the investigation reach (length, roughness, slope, etc.). When the simplified model is applied, this effect is to some extent inherent in the captured data, but the overall magnitude cannot be assessed without additional discharge information Figure 3.3.

Full error propagation As equation 3.2 is linear in the parameters, the overall random error is assessed by Gaussian error propagation.

B) Dynamic approach

Model

When additional discharge measurements \((Q(t))\) are available, the exfiltration is computed from the ratio of tracer loads instead of concentration ratios:

\[
E = 1 - \left( \frac{c_{Br} \cdot w_{La}}{c_{La} \cdot w_{Br}} \right) \cdot \frac{m_{Br}}{m_{La}} \cdot \frac{\int Q(t)C_{La(t)}dt}{\int Q(t)C_{Br(t)}dt}
\]  

(3.3)

where \(Q(t)\) is the discharge.

Uncertainty analysis

Although from a conceptual point of view further information should lead to more accurate exfiltration estimates, additional errors to those mentioned above are also introduced (Figure 3.3):

Errors in discharge measurement (\(\bigcirc\)) Standard flow measurement devices compute the flow from area-velocity measurements. Systematic errors in the area stem from the installation procedure of the device and the sewer diameter estimate \((d_{sewer})\). Random errors affect the water level \((h)\) and velocity \((v)\).

Integration error by limited time resolution of flow monitoring and sampling Discharge measurements generally have a higher time resolution than composite samples. For the computation of the load, the samples concentration is assumed to be representative for the whole sampling interval. Although this seems reasonable because of the constant tracer dosing, it causes some error in the computed exfiltration. In the data analysis procedure, this uncertainty is considered when the suggested bootstrap resampling is performed.

In addition, the available discharge information allows to estimate the full distribution of the transport error. For this purpose, we suggest hydrodynamic transport modelling in combination with bootstrap resampling (Efron and Tibshirani, 1993):

First, the continuous tracer concentrations at the measuring point should be simulated with a numeric model that uses the discharge recorded during the experiment. Synthetic samples are then created according to the experimental sampling scheme by drawing from the simulated concentrations, maintaining the time order of measurements but randomly.
determining the starting point (continuous looping can be used as necessary). The synthetic samples are then analyzed with equation 3.3. This is done repeatedly, computing the resulting exfiltration for each iteration.

The result is a distribution of exfiltration estimates that reflect the uncertainty due to transport phenomena in the investigation reach. As time-proportional composite samples are taken, the result is conditional on the sampling interval and number of samples.

The procedure is valid so long as it can be assumed that the model is sufficiently calibrated to represent realistic transport characteristics of the reach. For this purpose, additional tracer experiments with inline measurements would be essential.

**Full error propagation** We propose a Monte Carlo approach, which makes it possible to assess error contributions from field and laboratory measurements together with errors from transient transport phenomena and sampling scheme in one framework.

Values of the tracer concentration in the samples \((C_{eq, Li}, C_{eq, Br})\) and the working standard \((c_{eq, Li}, c_{eq, Br})\) are drawn from the specified distributions. Similarly, values are drawn from distributions of the dosing rates \((m_{Li}, m_{Br})\), which are obtained from regression analysis on the balance data. Also masses of tracer solutions in the laboratory standard \((w_{Li} and w_{Br})\) are drawn, considering the error of the analytical balance. The error of the velocity readings \((v)\) can also be assessed with information from the manufacturer, whereas the systematic and random error contributions in the water level and sewer diameter \((h_{syst}, h_{rand}, d_{sewer})\) should be assessed from practical experience.

Values of the error due to the transport phenomena and the composite sampling scheme are drawn from the error distribution resulting from the bootstrap resampling process. For each parameter set, an exfiltration estimate considering measurement errors is first computed with equation 3.3. Then, it is corrected for the transport error to obtain a final estimate (Figure 3.3).

This process can be repeated several hundred of times to yield a distribution of final exfiltration estimates.

In the following section we present a case study to evaluate the practical applicability of the method and to determine the accuracy of the computed results with regard to precision and eventual bias.

### 3.3. Case study

#### 3.3.1. Site description

A QUEST-C experiment was performed in a trunk sewer connecting the village of Rümlang to Oberglatt (CH). The investigation reach is 643 m long and the total length of the section amounted to 760 m. In the whole reach, the sewer has a circular profile with a diameter of 0.9 m. The average discharge during dry weather is 24.4 l s\(^{-1}\) with an average water depth of 0.11 m and a mean velocity of 0.48 m s\(^{-1}\). The investigation reach has no lateral inflows and is in very good structural condition, which was confirmed by CCTV investigations. As the sewer is expected to be watertight, it is possible to check the obtained results for bias and to validate the procedure.

#### 3.3.2. Experimental design

Lithium Chloride was used as indicator tracer and a 15 g l\(^{-1}\) Li\(^+\) dosing solution was prepared to obtain the desired concentration in the sample. The reference tracer was a 25 g l\(^{-1}\) Br\(^-\) solution...
of Sodium Bromide. Samples were filtered immediately in the field and later analysed by ion chromatography (IC). The analysis (performed on a Metrohm Compact IC) showed a very good reproducibility of 1.2% of the measured value for Li⁺ and 0.5% for Br⁻. For data analysis we used the raw peak areas of the IC measurements units, as exfiltration is computed relative to a standard. In the following, we will therefore we will use the notation $C_{eq}$ to indicate the use of concentration equivalents instead of absolute concentrations.

Batch test results suggest a conservative behavior of the tracers in wastewater and in the sample bottles. The natural background of Lithium in this sewer was negligible, which was the reason why it was applied as the indicator tracer. Fluctuations of Bromide were considered by additional background sampling (Figure 3.2). During the development of the method, we found that analysis of lithium in wastewater on ICP-OES (Spectro CIROS VISION) performed unsatisfactory. Lithium concentrations were overestimated by 45-47%, which was eventually due to cross-sensitivities with wastewater components.

Peristaltic dosing pumps (ISMATEC BVK, ISMATEC MV-CA4) were used for the dosing of the tracer solutions. Both containers with tracer solution were placed on balances (OHAUS DP150) to record the dosing rates. The discharge during the experiment was measured with two flow meters based on the Doppler Ultrasonic Area-Velocity principle (SIGMA 950, American Sigma) which were installed upstream and downstream of the sewer reach.

To ensure complete cross-sectional mixing of the tracers, additional turbulence was created with sewerage pumps. Mixing was tested in a preliminary experiment with slug injections of NaCl: Six conductivity probes were equally distributed over the entire cross section and yielded a coefficient of variation less than 2%.

The experiment was conducted from 11:00 - 13:30 hrs which was identified as a period of almost steady flow from previous flow measurements. Time-proportional continuous composite sampling over 10 minutes was performed with peristaltic pumps. At the measuring point two series of 10 samples were taken in parallel. Upstream the Bromide dosing point 10 samples were taken for background correction. The sampling at the different locations was synchronized with wooden floats.

After the experiment, the laboratory standard was prepared by mixing 1.0108 g of LiCl solution and 1.7980 g of NaBr solution on an analytical balance (Mettler Toledo AB-S).

### 3.3.3. Data analysis

#### A) Simplified approach

From two series of samples, the average exfiltration ratio was calculated to 1.1% (Figure 3.4). For series 1 1.2% for and series 2 1.0% were computed, which is in good accordance with the expected result of zero exfiltration.

#### Assessment of uncertainty

All uncertainty contributions for the individual model parameters are summarized in Table 3.1. Considering all 20 samples we obtained a total standard error of 2.6% for the exfiltration estimate. The largest uncertainty contributions are those of the Bromide and Lithium concentration equivalents in the samples ($C_{eq, Li}$ and $C_{eq, Br}$) (Table 3.1, column 5).

This is due to different error contributions: errors of the analytical procedure and the sampling as well as wave separation during the experiment. However, these effects cannot be separated and from the discrete set of samples it is not possible to assess whether the transport error could lead to considerable bias.
3.3. Case study

Figure 3.4.: Averaged discharge, concentration equivalents (Li⁺, Br⁻) and computed exfiltration ratio from the QUEST-C experiment. Exfiltration was computed from the average of two series.

Table 3.1.: Parameters of the simplified model, parameter uncertainties and corresponding error contributions from Gaussian error propagation. The sample concentration uncertainties consider the uncertainty of the IC and the variability of the 10 samples.

<table>
<thead>
<tr>
<th>Parameter (θi)</th>
<th>Unit</th>
<th>Description</th>
<th>μθi</th>
<th>σθi,random</th>
<th>∂E/∂θi</th>
<th>(∂E/∂θi)²σ²θi</th>
</tr>
</thead>
<tbody>
<tr>
<td>wₗi</td>
<td>g</td>
<td>analytical balance</td>
<td>1.011</td>
<td>2.00E-04</td>
<td>0.034</td>
<td>4.74E-11</td>
</tr>
<tr>
<td>wBr</td>
<td>g</td>
<td>analytical balance</td>
<td>1.798</td>
<td>2.00E-04</td>
<td>-0.562</td>
<td>1.27E-08</td>
</tr>
<tr>
<td>mLi</td>
<td>g s⁻¹</td>
<td>reference mass input to sewer</td>
<td>1.77</td>
<td>3.67E-05</td>
<td>-379.21</td>
<td>1.93E-10</td>
</tr>
<tr>
<td>mBr</td>
<td>g s⁻¹</td>
<td>indicator mass input to sewer</td>
<td>3.37</td>
<td>8.94E-05</td>
<td>300.077</td>
<td>7.20E-10</td>
</tr>
<tr>
<td>cₑq,Li</td>
<td>IC units</td>
<td>tracer concentration, standard</td>
<td>16.79</td>
<td>0.033</td>
<td>-0.06</td>
<td>3.89E-06</td>
</tr>
<tr>
<td>cₑq,Br</td>
<td>IC units</td>
<td>tracer concentration, standard</td>
<td>29.049</td>
<td>0.069</td>
<td>0.035</td>
<td>5.79E-06</td>
</tr>
<tr>
<td>Cₑq,Li</td>
<td>IC units</td>
<td>tracer concentration, sample</td>
<td>11.125</td>
<td>0.15</td>
<td>0.091</td>
<td>1.85E-04</td>
</tr>
<tr>
<td>Cₑq,Br</td>
<td>IC units</td>
<td>tracer concentration, sample</td>
<td>20.868</td>
<td>0.333</td>
<td>-0.048</td>
<td>2.61E-04</td>
</tr>
</tbody>
</table>
Table 3.2.: Parameter uncertainties for the dynamic exfiltration model (equation 3.3). All error contributions were considered normally distributed with the specified mean values and standard deviations ("n.c." = not considered, "-" = not required).

<table>
<thead>
<tr>
<th>Parameter ( (\theta_i) )</th>
<th>Unit</th>
<th>Description</th>
<th>( \mu_{\theta_i} )</th>
<th>( \sigma_{\theta_i,\text{random}} )</th>
<th>( \sigma_{\theta_i,\text{systematic}} )</th>
</tr>
</thead>
<tbody>
<tr>
<td>( h )</td>
<td>[m]</td>
<td>waterlevel measurement</td>
<td>( h_{\text{meas}} )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>( d_{\text{sewer}} )</td>
<td>[m]</td>
<td>sewer diameter</td>
<td>0.9</td>
<td>-</td>
<td></td>
</tr>
<tr>
<td>( v )</td>
<td>[m s(^{-1})]</td>
<td>velocity measurement</td>
<td>( v_{\text{meas}} )</td>
<td>0.05( v_{\text{meas}} )</td>
<td>n.c.</td>
</tr>
<tr>
<td>( w_{Li} )</td>
<td>[g]</td>
<td>analytical balance</td>
<td>1.011</td>
<td>2.00E-04</td>
<td>-</td>
</tr>
<tr>
<td>( w_{Br} )</td>
<td>[g]</td>
<td>analytical balance</td>
<td>1.798</td>
<td>2.00E-04</td>
<td>-</td>
</tr>
<tr>
<td>( m_{Li} )</td>
<td>[g s(^{-1})]</td>
<td>peristaltic dosing pump</td>
<td>1.77</td>
<td>3.67E-05</td>
<td>n.c.</td>
</tr>
<tr>
<td>( m_{Br} )</td>
<td>[g s(^{-1})]</td>
<td>peristaltic dosing pump</td>
<td>3.37</td>
<td>8.94E-05</td>
<td>n.c.</td>
</tr>
<tr>
<td>( c_{eq,Li} )</td>
<td>[IC units]</td>
<td>tracer concentration, standard</td>
<td>16.79</td>
<td>0.033</td>
<td>-</td>
</tr>
<tr>
<td>( c_{eq,Br} )</td>
<td>[IC units]</td>
<td>tracer concentration, standard</td>
<td>29.049</td>
<td>0.069</td>
<td>-</td>
</tr>
<tr>
<td>( C_{eq,Li} )</td>
<td>[IC units]</td>
<td>tracer concentration, sample</td>
<td>( C_{eq,Li,\text{meas}} )</td>
<td>0.012( C_{eq,Li,\text{meas}} )</td>
<td>n.c.</td>
</tr>
<tr>
<td>( C_{eq,Br} )</td>
<td>[IC units]</td>
<td>tracer concentration, sample</td>
<td>( C_{eq,Br,\text{meas}} )</td>
<td>0.005( C_{eq,Br,\text{meas}} )</td>
<td>n.c.</td>
</tr>
<tr>
<td>( \sigma_{\text{exf transport}} )</td>
<td>[-]</td>
<td>transport error</td>
<td>assessed separately</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### B) Dynamic approach

We obtained an exfiltration ratio of 0.3% of the labeled flow for the average of the two sample series (Figure 3.5), which again is in accordance with our expectations.

#### Assessment of uncertainty

**Exfiltration estimate considering measurement errors** All error contributions for the individual model parameters are summarized in Table 3.2. Uncertainty estimates that reflect practical knowledge were considered to be normally distributed in order to not over-predict the influence of uniform error distributions. After Evans et al. (2000) the standard deviation of a uniform distribution with \([-a, +a]\) is transformed into the standard deviation of a normal distribution by

\[
\sigma_{\text{rect}} = \frac{a}{\sqrt{3}}
\]

Note that the tracer measurement uncertainties \(\sigma_{C_{eq}}\) consider the uncertainty of the ion chromatograph. Therefore, they are smaller than the corresponding values in Table 1 which additionally reflect the variability of the 10 samples which is not captured by the simple model structure.

2000 simulations of equation 3.3 were performed for the Monte Carlo error propagation. The samples were drawn from the joint distribution of the model parameters without considering correlation of parameters or autocorrelation in time. For the average of the two series, the mean exfiltration ratio is computed to -0.3% with a standard deviation of 0.5% (Figure 3.7, left).
Chapter 3. Exfiltration measurements with continuous dosing of tracers

Figure 3.6.: The impact of transient transport phenomena on the exfiltration ratio, investigated by hydrodynamic modelling; Top: measured and simulated discharge, simulated tracer concentrations; Bottom: exfiltration computed progressively from ratio of tracer concentrations (grey dots) and loads (black line).

Transport error To assess the error from transient transport phenomena, a numeric model of the Rümlang sewer reach was implemented in AQUASIM (Reichert, 1994) using the upstream discharge measurements, data of pumping rates and the concentrations of the dosing solutions. It was calibrated to concentration and discharge data of two previous experiments, for which inline data of conductivity were recorded. The grid space was chosen very narrow ($\Delta x = 0.33$ m) to reduce numerical dispersion, which allowed for the estimation of a dispersion coefficient ($K = 0.02$ m$^2$s$^{-1}$) together with a Manning-Strickler roughness coefficient ($k_{st} = 54.5$ m$^{1/3}$s$^{-1}$). The very good agreement of modelled and observed discharge during the experiment (Figure 3.6, upper graphs) provides validation.

It can be seen, that Lithium and Bromide are affected differently by the dynamic flow pattern. In this specific constellation the magnitude of error by discrete sampling can be in the order of several percent (Figure 3.6). Note that the short-time fluctuations in the Lithium concentration (upper graph) are due to scatter in the upstream discharge measurements (not shown), which is propagated through the hydrodynamic model. As the water level readings are rather stable, this stems mostly from turbulence scattering the velocity readings. As we had no additional information on the velocity in the reach we chose to perform the simulation on the recorded data and discuss the consequences, instead of arbitrarily smoothing out the data.

From the bootstrap resampling analysis, the transport error is computed to -0.8% with a standard deviation of 1.1% (Figure 3.7, center).
3.4. Discussion

Final corrected exfiltration estimate The final estimate is assessed by combining the measurement and transport errors (Figure 3.7). A mean exfiltration of 0.5% is obtained with a standard deviation of 1.2%. The 95% confidence interval is estimated as [-0.027%; 0.024%].

To determine the relative importance of the various sources of uncertainty, sixteen error propagations were performed, each of which excluded the error from one source. This procedure has the advantage that correlated effects of the other sources are taken into account. The largest single error contribution was found to be the transport error, despite the fact that the study was performed at a time of steady discharge.

3.4. Discussion

The dynamic analysis of this QUEST-C experiment at the sewer system of Rümlang yielded a substantially lower uncertainty (1.2%) than the simplified analysis (2.6%). In general, this is a very promising result. However, two aspects must be discussed in more detail:

First, we must recall that the results of the hydrodynamic model are also uncertain because of model structure and parameter uncertainty. Therefore, the sensitivity of the transport error to parameter uncertainty was investigated. As parameter standard errors from the estimation procedure were considered inconclusive because of systematic patterns in the residuals, a scenario analysis was performed rather than an error propagation. We chose two extreme settings for the parameters $K$ and $k_{st}$, which lead to particularly smooth ($K_1 = 0.04 \text{ m}^2\text{s}^{-1}$, $k_{st,1} = 50 \text{ m}^{1/3}\text{s}^{-1}$) or pronounced ($K_2 = 0 \text{ m}^2\text{s}^{-1}$, $k_{st,2} = 60 \text{ m}^{1/3}\text{s}^{-1}$) tracer concentrations in comparison to the calibrated model. Computing the transport error for all three scenarios, it was found that they differed only by 0.2% in their standard deviations. Therefore, we considered the hydrodynamic model sufficiently calibrated in this particular case.

Second, it must be considered that the uncertainty analysis for the dynamic model is only feasible if all significant inflows into a reach can be monitored, which might be impractical in a sewer network. Furthermore, this would require in most cases additional tracer experiments and investments. Nevertheless, the information of an independent flow meter at the measuring point is always recommendable as it allows to compute a best exfiltration estimate from tracer loads instead of concentration ratios, even when no uncertainty analysis is performed.
With regard to the general applicability of the QUEST-C method, our findings and experience suggest that it is applicable in all sewers of interest where good mixing can be guaranteed.

The uncertainty of the computed exfiltration ratio is to a large extent dependent on the data quality and a careful performance of the experiment. However, it also depends on the characteristics of the reach (baseline of tracer, flow properties). For this reason, a general statement about the uncertainty of the methodology as suggested by Knudsen et al. (1996) does not seem realistic. Instead, we propose to perform an individual error assessment for each experiment according to the procedures discussed herein.

In our study, discharge variations were the most important source of error, and we expect this to generally be the case when a continuous dosing procedure is applied. To a certain degree this can be counteracted by a prolonged sampling scheme. However, the duration of an experiment depends on many objectives: the location of the investigation reach in the network, the daytime of the experiment, the financial budget and, which is often overlooked, the desired accuracy of the method. Although the QUEST-C method is not intended to replace traditional CCTV inspections, urban water managers could use the information on sewer losses to elaborate optimal sewer rehabilitation strategies, efficient detection of extreme leaks or a cost-effective long-term monitoring of leakage.

In natural systems, discharge variations are considered less serious, because hydrological processes are often much slower. Yet, this is clearly a question of scale and might depend on the individual case. In contrast, when our method is applied to a river or stream, insufficient mixing is to be seen much more critical, because it can hardly be influenced technically. This might make the application of the method difficult in channels with a number of tributaries, highly irregular cross-sections or low velocities. Nevertheless, we believe that our tracer method can be a useful tool to investigate the spatial and temporal variations of surface- and groundwater interactions in-situ. Complementary information might be gained compared to other investigation methods (e.g., groundwater monitoring, remote sensing coupled with GIS). Furthermore, the estimation of uncertainty in the obtained result allows for quantitative risk assessment.

### 3.5. Conclusions

- In this paper, we propose a robust experimental procedure to accurately measure losses from open channels with artificial tracers. Leakage is identified relative to the labelled flow which makes the uncertainty in the result dependent on the reach characteristics and the applied model for data analysis.

- In a case study the exfiltration from a 760 m long sewer reach of very good structural condition was investigated and no significant leakage was detected. The uncertainty was estimated to 2.6% of total flow with a simplified model. Analyzing the data with a dynamic approach, the standard error in the result could be reduced to 1.2%. The method was found to have no significant bias. As a general statement about the uncertainty of the methodology is not realistic, we suggest an individual error assessment for each experiment.

- For technical systems, transient discharge phenomena were found to be the largest source of uncertainty, which indicates that the time of the experiment should be chosen carefully. This also suggests that the use of a very specific tracer does not necessarily improve the accuracy of the estimated exfiltration. Applying the method to natural systems, we expect inappropriate mixing of tracer to be most critical.
3.5. Conclusions

- Future improvement of the tracer method should concentrate on the development of detailed guidelines for an optimal experimental setup and to indicate possible limitations.
Chapter 3. Exfiltration measurements with continuous dosing of tracers
4.1. Introduction

We have recently proposed a number of techniques for determining exfiltration rates in sewers using tracers (Rieckermann et al., 2005a,b) that were developed within the scope of the European project APUSS (Assessing exfiltration and infiltration on the Performance of Sewer Systems). The application of any of these techniques requires the investigator to make a number of decisions regarding experimental design. These include the number of tracer additions to use, the mass of tracer used in each addition, the relative timing of additions, and the starting time of the experiment. These choices influence the amount of uncertainty in the final estimate of exfiltration. However, there is no universal answer to the question what is the optimal choice of options. The best experimental design depends on how much the investigator is willing to spend on the monitoring process (in terms of effort and financial resources) and how these expenditures compare with the consequences of an incorrect determination of exfiltration. The goal of this paper is to address these issues using the formal framework of decision analysis (Clemen, 1996).

Decision analysis is a method for selecting among alternatives based on formal axioms of human preference. The basic principle is that a decision-maker can state his/her preferences for the possible outcomes of a decision, expressed as the levels of a selected set of measurable attributes, as well as his/her attitude towards risk. Additionally, he/she can obtain estimates of the likelihood of all possible outcomes of each decision alternative, expressed using probability distributions of attribute levels. The decision-maker should then prefer the alternative that maximizes a mathematical combination of the stated preferences and probabilities. This approach differs from purely statistical methods such as power analysis because it accounts not only for the probabilities of making "correct" and "incorrect" decisions but also for the relative consequences of these decisions.

We demonstrate the decision analytic approach to experimental design using the QUEST method of exfiltration estimation (Rieckermann et al., 2005b), as applied to a stretch of a main sewer in Rümlang, Switzerland. For the sake of clarity, we limit our analysis to one particular variant: QUEST with NaCl as tracer.

4.2. Material and methods

4.2.1. Exfiltration estimation using the QUEST method

The QUEST method is described in detail by Rieckermann et al. (2005b). We will only provide sufficient information here to set the context for the experimental design decisions being investigated. Briefly, the method uses two sets of pulsed tracer additions straddling the investigation...
reach: an upstream indicator addition and one or more downstream reference additions (Figure 4.1, left). Exfiltration is then estimated by performing a mass balance on the indicator addition by comparing the total mass passing the sampling cross section with the mass added. The mass lost is then a direct indication of the loss of wastewater over the investigation reach. The reference addition serves as a type of internal calibration, eliminating the effect of systematic proportional errors. This improves the accuracy of exfiltration estimates. In a typical situation, the signals of the indicator and reference additions are clearly distinguishable at the sampling cross section because of the differing degree of longitudinal dispersion caused by different travel times (Figure 4.1, right).

The precision of estimated exfiltration is influenced by the dosing strategy (number of pulses, timing, etc.) and could be improved through experimental design optimization. Alternately, it is possible that in some cases a less precise estimate would be appropriate, accompanied by some savings in cost and effort. In general, it would be beneficial to have a formal framework for considering the role of uncertainty in the decision process. Addressing these issues is the goal of decision analysis, as described in the next section.

4.2.2. Decision analysis

Reichert et al. (2005) describe a general procedure of how decision analysis techniques can be used to support environmental decisions. The procedure is divided into seven steps:

Step 1: Definition of the decision problem
Step 2: Identification of objectives and attributes
Step 3: Identification and pre-selection of alternatives
Step 4: Prediction of outcomes
Step 5: Quantification of preferences for outcomes
Step 6: Ranking of alternatives
Step 7: Assessment of results

In the following case study, we will first give a brief description of the investigated system and then develop the optimal experimental design, providing details on the seven step decision analysis procedure as we proceed.
4.3. Case study

4.3.1. System description

We applied our methodology at an investigation reach of 980 m length on a trunk sewer between the villages of Rümlang and Oberglatt, Switzerland. The circular sewer has a diameter of 0.9 m and a slope of 0.9 per mil, and the mean flow in the reach is 25 ls⁻¹ with an average depth of 0.12 m.

Rieckermann et al. (2005b) discuss the choice of possible tracers, suggesting the use of NaCl, as measured by conductivity, because it is the cheapest and easiest tracer to apply in comparison with fluorescent dyes and radioactive tracers. The difficulty however is that conductivity is present at non-negligible background levels in the sewer due to the presence of NaCl and other solutes. Variability in this baseline can confound accurate estimation, because peaks in the background can occur simultaneously with the passage of a tracer peak and be mistaken for part of the dosed tracer mass. Careful experimental design (such as nighttime dosing) can minimize such effects, but they can never be completely eliminated.

Preliminary field tests: As the design of the experiment depends critically on the sewer characteristics, the discharge and conductivity baseline were first monitored over several days. Dispersion in the reach determines the shape and duration of the tracer peaks at the measurement point. We assessed dispersion from preliminary tracer experiments with single indicator and reference pulses. Estimating sewer dispersion from empirical formulae is also possible (Rieckermann et al., 2005d), but experiments lead to more reliable estimates of peak shapes.

4.3.2. Experimental design using the decision analytic framework

Step 1: Definition of the decision problem. The premise of the case study is that a decision has already been made to use QUEST to estimate exfiltration in the Rümlang reach and that the resulting estimates will be used to decide whether or not to rehabilitate the sewer. Given this situation, the investigator would like to know: "What is the best QUEST layout for this particular reach?"

We believe it is relevant to approach this question as a decision problem, rather than to perform the experiment spontaneously, because:

- Evaluation of the consequences of sewer leakage is site-specific; therefore the optimal balance of experimental cost and accuracy should be site-specific,
- Uncertainty in measurement of exfiltration is site- and method-specific, therefore it should be considered explicitly,
- The attitudes of the decision-maker toward cost and risk should be considered.

Step 2: Identification of objectives and attributes. An objective is something a decision maker would like to achieve, and attributes are measurable system properties that can be used to quantify the degree of fulfillment of the objectives. These form the basis for both the preference and likelihood evaluations.

In our case study, the objectives are relatively straightforward: The investigator would like to minimize the costs associated with an incorrect determination of exfiltration, as well as to minimize the cost of the tracer experiment itself. An incorrect determination of exfiltration may be costly for one of two reasons: either sewer rehabilitation is undertaken unnecessarily (when exfiltration is over-estimated), or sewers are allowed to continue to leak (when exfiltration is under-estimated) causing undesirable surface or ground water pollution. We define these as avoidable costs. The experimental costs include the cost of the tracer material, equipment costs,
labour costs, and the added costs of working at night. Costs, in units of Euro, are the appropriate attribute for assessing each of the objectives.

**Step 3: Identification and pre-selection of alternatives.** The next step in applying decision theory is to select the set of alternatives to be considered. In the present context, this means choosing all the components of a dosing strategy (e.g., the time of the investigation, the number of tracer pulses, etc.). As these options imply an impractically large number of combinations, we define some representative scenarios for further analysis, based on the peak shapes estimated from the preliminary field tests:

First, we define experiments, which indicate the different dosing strategies with respect to how many tracer pulses are dosed at what time-intervals, using the following parameters: tracer masses of reference and indicator additions (MR and MI in [g]), number of reference pulses per indicator peak (NR) and three timing parameters (T1, T2, T3 in [s]) (Figure 4.2). Second, we define layouts, which are composed of one or more experiments, using the starting time of the experiment (t0 in [h]) and the total number of indicator additions (NI).

In total, 42 different experiments were analysed by randomly sampling from a range of values for MR [10, 2000], MI [100, 5000], NR [1, 5], T1 [50, 1000], T2 [400, 3000], and T3 [2, 800]. Further considering NI to take all values from 1 to 4 and t0 to take hourly values from 0:00 to 23:00, we obtain 4032 different layouts, which form the full set of alternatives considered.

**Step 4: Prediction of outcomes.** Determination of the probability distributions of each attribute for each decision alternative is the next task in the analysis. We predict the outcomes for the different QUEST layouts with a two-component model: (1) a technical sub-model which predicts the error in exfiltration estimates and (2) an economic sub-model that computes the experimental cost and expected pollution and rehabilitation costs for each layout.

Technical sub-model: A method for performing a full uncertainty analysis of the QUEST method is described by Rieckermann et al. (2005b). As it was found that errors from dosing, sensor calibration and discharge measurements can be practically neglected, only the error contribution from the baseline is considered. The baseline error, which does not necessarily follow a statistical probability distribution, is random and conditional on the dosing strategy. We assessed it using a bootstrap resampling approach (Efron and Tibshirani, 1993), as described by Rieckermann et al. (2005b). This was done by performing a large number of simulations for each experiment and determining the distribution for the underlying baseline error for each possible
starting time. In our case the error is time-dependent and specific for each experiment. Our calculations are based on 750 bootstrap samples from two days of baseline and flow measurements. Second order sampling uncertainty was found to be negligible for sample sizes larger than 700. The errors were lumped together in bins of hourly intervals, to match the time resolution of $t_0$. As we are interested in the error of each layout, we use Monte Carlo Simulation to propagate the error from each experiment to the corresponding layouts. When a certain layout starts at $t_0$, samples from the baseline error of the underlying experiment are drawn from the bin $t_0$ according to the number of indicator pulses used. If multiple indicator pulses are injected, the duration of this layout might extend over $n$ hours. In this case, the baseline error is also sampled at the following starting times $t_0+1, \ldots, t_0+n$. Finally, all samples of the baseline error are averaged to compute one error of this certain layout. In order to obtain a realistic probability distribution of the exfiltration error estimate for each alternative, this procedure is repeated 5000 times for each layout.

**Economic sub-model:** The determination of the cost functions is a matter of engineering economics, and we follow a rather simple approach (Table 4.1). The experimental cost associated with a specific layout follows directly from the layout’s definition. For example, the starting time and duration of the experiment determine the labour costs. The avoidable costs are either caused by unnecessary surface or ground water pollution (underestimation of exfiltration) or unnecessary rehabilitation (overestimation of exfiltration). In the Rümlang case study, we assume a rehabilitation cost of 550 € m$^{-1}$ (Berger et al., 2002), which leads to a rehabilitation cost for the 980m long reach of about 0.54 Mio. €. The cost of pollution (e.g., soil remediation) is assumed to be directly proportional to the percent exfiltration. For simplicity, we assume an expected long-term pollution cost of 0.2 Mio. € percent$^{-1}$ (Figure 4.3, left). If we assume that the sewer operator will make an economically sensible decision when given accurate information on exfiltration, then he/she would choose to rehabilitate the sewer when the exfiltration is known to be greater than 2.7% and would not rehabilitate when exfiltration is less than this value. When uncertainty exists, incorrect decisions are most likely to occur when exfiltration is near this breakpoint. In such a situation, the costs of errors in exfiltration are symmetric about the mean estimate, with a cost slope of 0.2 Mio. € percent$^{-1}$ in either direction. In this way, the most uncertain estimation methods are the most penalized in terms of cost.

**Step 5. Quantification of preferences for outcomes.** The preferences of the decision-maker for the possible outcomes must next be quantified. This is done by constructing value or utility functions over the range of each attribute. Value functions describe the preference structure of the decision-maker with respect to the attribute (i.e., whether more or less of the attribute
Table 4.1.: Parameter values of the cost function.

<table>
<thead>
<tr>
<th>Category</th>
<th>Description</th>
<th>Value</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labour cost</td>
<td>Worker salary</td>
<td>50 € per hr</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Engineer salary</td>
<td>70 € per hr</td>
<td></td>
</tr>
<tr>
<td></td>
<td>No. of workers</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Night-time supplement factor</td>
<td>1.33</td>
<td>Increase in salary from 21:00 to 05:00; Variable cost, depending on starting time of layout</td>
</tr>
<tr>
<td>Labour hours</td>
<td>Preparation</td>
<td>8 hrs</td>
<td>4 hrs worker, 4 hrs engineer; Fixed cost</td>
</tr>
<tr>
<td></td>
<td>Execution</td>
<td></td>
<td>Variable cost</td>
</tr>
<tr>
<td></td>
<td>Data analysis</td>
<td>4 hrs</td>
<td>4 hrs engineer; Variable cost</td>
</tr>
<tr>
<td></td>
<td>Reporting</td>
<td>4 hrs</td>
<td>2 hrs worker, 2 hrs engineer, Fixed cost</td>
</tr>
<tr>
<td>Consumables</td>
<td>Cost for consumables during experiment: tracer, car, tools, water, etc.</td>
<td>1 € per kg NaCl</td>
<td>Includes overhead. Retail price for NaCl is about 0.3 € per kg; Variable cost</td>
</tr>
<tr>
<td>Equipment</td>
<td>Flow meter</td>
<td>20 € per campaign</td>
<td>Standard ultrasonic Doppler device; Fixed cost</td>
</tr>
<tr>
<td></td>
<td>Conductivity device</td>
<td>10 € per campaign</td>
<td>Fixed cost</td>
</tr>
<tr>
<td></td>
<td>No. of flow meters</td>
<td>1</td>
<td>Fixed cost</td>
</tr>
<tr>
<td></td>
<td>No. of conductivity devices</td>
<td>2</td>
<td>Fixed cost</td>
</tr>
</tbody>
</table>
is better; whether there is decreasing, increasing, or constant marginal value associated with increases in the attribute level), while utility functions include additional information on the decision-maker’s risk attitudes. Both value and utility functions are subjective entities, generally determined through the performance of elicitation interviews with the decision-maker (Clemen, 1996). When the decision-maker is assumed to have a risk-neutral, marginally-constant (i.e., linear) preference structure and all attributes can be expressed using monetary units, then preferences can be described using financial costs or benefits directly. This is the situation we assume in this case study, and thus use costs, rather than value or utility as the measure of relative preference.

**Step 6: Ranking of alternatives.** The technical model developed in step 4 leads to probability distributions of the error in exfiltration for each layout, based on the Monte Carlo samples. Applying the economic model then leads to an experimental cost for each layout and an avoidable cost for each value of the exfiltration error. The total expected cost for each layout is then calculated as the fixed experimental cost plus the expected value of the avoidable cost (calculated as the integrated product of the cost function and the probability distribution).

Decision theory dictates that the layout with the minimal total expected cost should be preferred.

In our analysis, the layout with minimal expected cost is one with a starting time of 23:00 that uses three repetitions of the indicator pulse, each with two reference pulses, and leads to an overall experimental time of approximately 2.25 h. The optimal masses of NaCl for the reference and indicator additions are 500 and 300 g, respectively. This layout leads to a total expected cost of 7262 €, of which 2220 € are experimental costs for preparation, measurements, data analysis, and reporting. The remainder are the expected costs of pollution and/or unnecessary rehabilitation.

**Step 7: Assessment of results.** When the total expected cost for all 4032 layouts is plotted against the parameters describing the layout alternatives (Figure 4.4), we observe that the cost is most sensitive to the mass of added tracer (MR and MI). This is because increased mass generally leads to reduced uncertainty in exfiltration estimation. It is also clearly beneficial to perform the measurement campaign in the night hours 22:00-3:00 when baseline variation is low. Additionally, uncertainty decrease substantially with the dosing of several indicator pulses.

Analyzing the 100 top-ranked layouts (not shown), we found that they all start between 13:00 to 2:00, and in 96% of the cases multiple indicator pulses are dosed. Further, all the top-ranked layouts are created from only 8 different experiments (Figure 4.5).
4.4. Discussion

The described decision analytic procedure leads to an optimal design of a QUEST experiment. However, the result is based on assumptions (e.g., details of the cost model) which may be rather simplistic. Therefore, the sensitivity of the final ranking of layouts should be analysed with respect to technical and economic model uncertainty. Although this is important to gain insight into the power of the results, we must omit it here for the sake of brevity.

Our results suggest that a separation of indicator and reference peaks would result in lower expected cost (see Figure 4.4, far right), due mostly to more precise exfiltration estimates. This would also lead to a simpler data analysis procedure (Rieckermann et al., 2005b). However, previous studies (Rieckermann et al., 2005b) have suggested that peak overlap is preferable. It must be noted that in the present study this issue could not be precisely addressed, as all experimental parameters were varied simultaneously, confounding the effects of peak overlap and relative timing. We plan to examine this issue in more detail in the future.

During the original development of our procedure, we took the identifiability of peak parameters to be a measure for the quality of experimental design. However, we found that identifiability measures, which are often based on sensitivity functions (Brun et al., 2001), are useful tools for data analysis but are not conclusive for experimental design. Therefore, we recommend the more "holistic" decision analytic procedure described here.

4.5. Conclusions

We have demonstrated a decision analytic method for selecting an optimal experimental design for exfiltration estimation using tracer methods, such as those developed in the APUSS project. Decision analysis accounts for uncertainty in estimation and its associated costs. Results will depend on site-specific technical and economic models, but we believe that it can generally be concluded that, when NaCl is used as the tracer, accuracy in exfiltration estimation is most sensitive to the amount of tracer used and the starting time of the experiment. Our analysis is particularly relevant for engineers who are interested in applying the tracer methods, but the decision analytic framework described here is transferable to other applications in urban hydrology as well.
Chapter 5.
Dispersion in sewers


5.1. Introduction

Taylor (1954) was the first to relate longitudinal mixing of solutes in flow to a Fickian-Type dispersion. In sewer transport modelling the 1D Advection-Dispersion equation (ADE) is generally applied as

\[
\frac{\partial Ac}{\partial t} + \frac{\partial Qc}{\partial x} = \frac{\partial}{\partial x}(AK \frac{\partial c}{\partial x}) + AJ
\]  

(5.1)

where \( A \) = wetted area, \( c \) = cross-sectional mean concentration, \( Q \) = discharge, \( K \) = longitudinal dispersion coefficient, \( J \) = sum of reaction rates of transformation processes, \( t \) = time, \( x \) = direction of mean flow.

Theoretically, the ADE is only valid in the equilibrium zone, where an equilibrium has become established between the effects of velocity shear and cross-sectional turbulent diffusion. In order to properly represent mixing in the so called initial zone, more complex models have to be applied (Fischer et al., 1979; Rutherford, 1994; Reichert and Wanner, 1991). In spite of the rigorous framework that restricts its practical application, the ADE often proves useful for a wide range of applications such as integrated modelling (Langeveld et al., 2003; Meirlaen et al., 2001), sewer process modelling (Almeida et al., 1999; Huisman, 2001) stochastic forecasting of specific substances (Ort et al., 2005) and the experimental design of tracer experiments (Rieckermann et al., 2005b).

Although the choice of a proper dispersion coefficient is often crucial to obtain reliable results, sewer-specific data have only very recently been published (Garsdal et al., 1995; Huisman et al., 2000; Boxall et al., 2003) and (Langeveld et al., 2003). However, no established equation for the prediction of dispersion coefficients for urban sewer applications is presently available and in most cases predictions are questionable as will be explained further below. The aim of this study is to suggest optimal methods for the analysis of tracer experiments and to propose a simple formula to rapidly predict dispersion coefficients from bulk data. We will first describe the data base, then comment on the choice of models for data analysis and finally discuss the results with special regard to their uncertainty and possible limitations.

5.2. Material and methods

In this section we discuss the data on which the study is based and present appropriate models for the estimation of dispersion coefficients.
Chapter 5. Dispersion in sewers

Figure 5.1.: Top: Longitudinal profile of a sewer section. 0 = dosing point of tracer (slug injection), 1 = first monitoring point (outside the initial zone), 2 = second measuring point at the end of the reach; Bottom: tracer curves at dosing and monitoring stations

5.2.1. Data base

A total of 60 experiments, which were all performed under dry weather conditions, was analyzed with regard to dispersion. Mostly, sewers with diameters smaller than 2m were investigated in different European cities under a variety of flow conditions. We distinguish between two classes of data:

The first class contains all experiments which were conducted with the explicit intention of measuring dispersion coefficients. As mixing in the initial zone is not represented by the ADE, the tracer concentrations were measured at two points downstream from the injection point (Figure 5.1). These data are herein referred to as type "0-1". In our study we have 25 such datasets from 8 reaches with mostly constant diameters and stable flow conditions.

The second class contains tracer experiments which were not originally been designed for dispersion measurements. These datasets, which were mostly collected in the APUSS\(^1\) project to quantify exfiltration with tracers (Rieckermann et al., 2005b), contain concentration profiles from the downstream measuring point but not from point and will be referenced by "0-2". For a better representativeness, well-documented data from literature (Johnson, 1944) was incorporated to give a total of 35 type 0-2 investigations from 29 different sewer sections.

All experiments (type 1-2 and 0-2 ) were performed with slug injections of the tracer and in the majority of experiments the tracer curves were monitored using inline devices with a time resolution of a few seconds. Most experiments were performed with NaCl using electric conductivity measurements. Different fluorescent dyes were also used as tracers, but from a number of experiments only 8 of these datasets were identified as suitable for this study (Rhodamin

\(^1\)APUSS (Assessment of the Performance of Urban Sewer Systems)

URL: http://www.insa-lyon.fr/Laboratoires/URGC-HU/apuss/
5.2. Material and methods

When deriving dispersion coefficients from NaCl experiments, corrections for baseline conductivity were necessary. For 34 of the experiments discharge measurements by the Area-velocity method (Doppler velocity measurements or MID) were available at the downstream measuring point. For the other experiments, the flow was estimated from the tracer data. In these cases the loss of tracer due to exfiltration or erroneous baseline corrections might well cause some degree of uncertainty, but this is assessed to be in the same range as the uncertainty induced by errors in the Area-velocity flow measurements. All datasets are presented in Table 5.2 together with the estimated dispersion coefficients. The fact that for 0-2 data only downstream concentration profiles were recorded complicates the data analysis and raises the question as to whether comparable information on longitudinal mixing can be derived from these.

In the following section we will first discuss different models for the estimation of dispersion coefficients from tracer curves and then present equations for the prediction of dispersion where no such data are available.

5.2.2. Estimating dispersion coefficients from tracer data

Dispersion coefficients are estimated from type 1-2 experiments straightforward by applying a routing procedure. Here, the recently proposed method of Singh and Beck (2003) is used, which characterizes the downstream concentration profile as a function of the upstream concentration profile by a convolution integral

\[ c_2(x,t) = \int_0^t c_1(\tau) \lambda(x, t-\tau) \, d\tau \] (5.2)

where \( c_1 \) = upstream concentration at time \( \tau \) and \( \lambda(x, t-\tau) \) downstream response due to an instantaneous unit concentration upstream. The upstream concentration profile is described as a series of discrete input signals and the convolution represents the transformation during transport. The modelled downstream concentration curve \( (c_2) \) is composed from the superposition of the downstream response pulses which are full analytical solutions to the ADE. Functionally, the dispersion coefficient is contained in the downstream response function and can be estimated by fitting the modelled curve to the data. In this study, we use the notation \( K_S \) for longitudinal dispersion coefficients which were derived with the routing procedure by Singh and Beck (2003).

In contrast, experiments of type 0-2 can only be used for the derivation of dispersion coefficients under the assumption that the impact of the initial period on the transport in the investigated reach is negligible. If the tracer mixes reasonably rapid over the whole cross section, the following analytical solution to (equation 5.1), which is also known as the "Taylor solution", (Rutherford, 1994) can be used as

\[ c_2(x,t) = \frac{M}{A \sqrt{4\pi K_Tt}} \exp\left(-\frac{(x-ut)^2}{4\pi K_Tt}\right) \] (5.3)

where \( M \) = mass of injected tracer, \( K_T \) = longitudinal dispersion coefficient, derived with the Taylor solution.

These models are very useful for quantifying dispersion when field measurements are available. However, in the majority of cases tracer data is lacking and we may want to predict dispersion using information on sewer flow and geometry.
5.2.3. Predicting dispersion coefficients from velocity distributions

Transport in open channels is characterized by the full turbulent 3D velocity profile. Therefore, dispersion in itself is not a fundamental physical process, but arises from averaging the non-uniform velocity over channel depth and width. Consequently, analytical solutions for $K$ can be found for assumptions on the mean velocity distributions in the direction of the flow and cross-sectional mixing. Elder (1959) was the first to transfer Taylor's result of turbulent flow (Taylor, 1954) to open channels; subsequently many other examples have followed.

Table 5.1 contains selected formulae that have since been developed (mostly cited from Seo and Baek (2004) and Seo and Cheong (1998)). Most explanatory comments are also taken from the same sources. In order to properly apply these formulas to urban sewers, important differences between sewers and rivers need to be considered. As rivers are generally much wider than deep, the hydraulic radius $R$ is often replaced by $d$ (e.g., in the computation of the shear velocity $u_*$). In contrast we were using the general notation $u^* = \frac{gR^2S_0}{5.4}$.

In order to apply these formulae we transformed the maximum water depth from flow measurements in a circular pipe to the average water depth of a corresponding rectangular profile by $d = H = A/W$, where $A$ is the wetted area and $W$ the surface width.

5.2.4. Comparing predicted with estimated dispersion coefficients

In order to evaluate the performance of the equations presented in Table 5.1, we compared the measured and predicted dispersion coefficients for each dataset. For those experiments, which were performed in uniform reaches this is straightforward. However, to be able to apply the predictive formulae to non-uniform reaches we transformed them into ”equivalent uniform reaches” with length-weighted mean diameter and discharge.

One must note that it is conceptually problematic to predict dispersion coefficients from average reach characteristics, because transport processes are non-linear and therefore the measured dispersion coefficient from a highly non-uniform reach is functionally neither related to a specific cross-section in this reach, nor to its length-weighted mean characteristics. Despite of this difficulty, we assume the transport properties (e.g., degree of partial filling, mean flow velocity) in sewers not to vary substantially during dry weather conditions. With regard to measured dispersion coefficients from non-uniform reaches, a dilution factor had to be introduced into the parameter estimation procedure that allowed for the scaling of the concentration profiles (measured under maximum flow at the downstream measuring point) to the average flow conditions of the equivalent uniform reach.

As it is desirable to know where non-uniformities cause predicted dispersion coefficients to be meaningless, we computed the Manning-Strickler coefficient as an indicator to identify problematic datasets

$$k_{st} = uR^2S_0I^{-\frac{1}{2}}$$

where $k_{st}$ = friction coefficient after Manning Strickler [m$^{1/3}$s$^{-1}$]. Where $k_{st}$ differs from reasonable values [50 < $k_{st}$ < 100], it indicates either that the reach is highly non-uniform or that the data contain considerable error.

5.3. Results

Can the effect of the initial zone be neglected? Selected data sets which best represent different flow conditions and fill grades were analyzed for both the routing procedure and the
### Results

Table 5.1: Selected formulas for the Longitudinal Dispersion Coefficient

<table>
<thead>
<tr>
<th>Author</th>
<th>Eq.</th>
<th>Model</th>
<th>Comments</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elder (1959)</td>
<td>5.5</td>
<td>$K = 5.93Hu_*$</td>
<td>Based on the assumption of a logarithmic vertical velocity profile. Neglects transversal velocity shear.</td>
</tr>
<tr>
<td>Parker (1961)</td>
<td>5.6</td>
<td>$K = 14.28R^{3/4}2gS_0^{1/2}$</td>
<td>Originally derived for pipelines. Parker also analyzed data from tracer experiments in sewers.</td>
</tr>
<tr>
<td>Sooky (1969)</td>
<td>5.7</td>
<td>$K = C_{Lc}Ru_*$</td>
<td>Based on the assumption of a circular profile and logarithmic velocity profile. Coefficient $C_{Lc}$ is a complex integral that must be solved numerically.</td>
</tr>
<tr>
<td>McQuivey (1974)</td>
<td>5.8</td>
<td>$K = 0.058\frac{Hu_*}{S_0}$</td>
<td>Based on similarity assumptions between the dispersion of solutes and that of hydraulic waves.</td>
</tr>
<tr>
<td>Fischer (1975)</td>
<td>5.9</td>
<td>$K = 0.011\frac{u^2W^2}{u_*H}$</td>
<td>Based on approximations of the transversal velocity profile and transversal turbulent mixing for irregular channels. Neglects vertical velocity shear.</td>
</tr>
<tr>
<td>Liu (1977)</td>
<td>5.10</td>
<td>$K = 0.18\left(\frac{u}{u_<em>}\right)^{1/2}\frac{W}{H}Hu_</em>$</td>
<td>Modification of equation (5.9) which is based on field data.</td>
</tr>
<tr>
<td>Magazine (1988)</td>
<td>5.11</td>
<td>$K = 75.86Ru(0.4\frac{u}{u_*})^{-1.632}$</td>
<td>Based on assumptions on roughness parameters.</td>
</tr>
<tr>
<td>Iwasa (1991)</td>
<td>5.12</td>
<td>$K = 2.0\frac{W}{H}^{3/2}Hu_*$</td>
<td>No influence of friction term. Apparently tends to underestimate dispersion in streams.</td>
</tr>
<tr>
<td>Seo (1998)</td>
<td>5.13</td>
<td>$K = 5.92(\frac{u}{u_*})^{1.43}\frac{W^0}{H}^{0.82}$</td>
<td>Modification of equation (5.9) based on dimensional analysis and field data.</td>
</tr>
<tr>
<td>Koussis (1998)</td>
<td>5.14</td>
<td>$K = 0.6\frac{W^2}{H}Hu_*$</td>
<td>No influence of friction term. Apparently tends to underestimate dispersion in streams.</td>
</tr>
<tr>
<td>Huisman (2000)</td>
<td>5.15</td>
<td>$K = 0.003\frac{u^2W^2}{u_*H}$</td>
<td>Modification of equation (5.9) with assumptions for regular channels to better represent sewer mixing.</td>
</tr>
<tr>
<td>Deng (2001)</td>
<td>5.16</td>
<td>$K = \frac{0.15}{S_{10}}\left(\frac{u}{u_<em>}\right)^{2W^{3/2}}\frac{H}{H}H_</em>$</td>
<td>Modification of equation (5.9) with an extended term for transversal mixing.</td>
</tr>
</tbody>
</table>

$A =$ wetted area and $W =$ surface width, $H = d = A/W$ average water level in a circular pipe, $R =$ hydraulic radius, $S_0 =$ mean slope, $u =$ average velocity, $u_* =$ friction velocity

Note: Eq. 5.11 presented in Singh, S. K. and Beck, M. B. (2003) Dispersion coefficient of streams from tracer experiment data. J. Environ. Eng-ASCE, 129(6), 539-546 is incorrect, because the exponent -1.632 was omitted. This is the reason why the authors predict values of $K$ which are two orders of magnitude bigger than those predicted with the other formulae.
Taylor solution. As sewer geometry and flow conditions are mostly constant, any significant difference in estimated dispersion coefficients should be related to the initial zone. We found the average relative deviation between $K_T$ and $K_S$ to be only -12% with no apparent bias, which justifies the application of the Taylor solution to the 0-2 data (Table 5.2). Consequently, the estimated dispersion coefficients of both methods are considered equivalent and the impact of the initial zone can be neglected (Figure 5.2).

**What are typical values for the dispersion coefficient in sewers?** Dispersion coefficients in urban sewer systems have been found to be very small and they are in the same order of magnitude for all datasets. The average value of the skewed distribution of $K$ is $0.16 \text{ m}^2\text{s}^{-1}$ [$K_{10} = 0.05 \text{ m}^2\text{s}^{-1}, K_{50} = 0.10 \text{ m}^2\text{s}^{-1}, K_{90} = 0.36 \text{ m}^2\text{s}^{-1}$] (Figure 5.3). Impacts of biofilm, rain events and sediments on the dispersion coefficient could not be evaluated from this database. However, it is observed that some tracer curves show pronounced tailing, which might correlate with the structural state. In rivers and canals, which are generally more irregular, observed dispersion coefficients are one or two orders of magnitude larger (Seo and Cheong, 1998).

**Can $K$ be predicted from geometry and flow data?** Where a sewer reach has uniform characteristics, equations (5.12), (5.15) and (5.13) predict dispersion coefficients ($K_p$) that agree very well with the measurements ($K_m$) (Figure 5.4, black symbols). Where diameters, flow conditions or slopes are considerably different within a reach (grey symbols), predictions may differ by one or two orders of magnitude. However, the predictions are mostly accurate to $\pm 0.3 \text{ m}^2\text{s}^{-1}$ if a reasonable formula is chosen (Figure 5.4, right graphs). Whether this degree of variability is acceptable or not strongly depends on the individual application and the desired accuracy. The sensitivity of the downstream tracer concentrations of dataset 03 to the dispersion coefficient (Figure 5.3) indicates that peak concentration change moderately for the 10% and 90% quantiles of $K$. A reasonable alternative to the use of a predictive equation might be to simply choose a dispersion coefficient according to our database, because they include the irregularities (sediments, etc.) of real-life sewers. However, where the response of a reach has to be characterized precisely, the authors strongly advocate the performance of tracer measurements.

### 5.4. Discussion

First, our results were obtained under dry weather conditions and must not be used to describe transport during rain events. Boxall et al. (2003) reported dispersion coefficients under storm conditions that are an order of magnitude higher than in dry weather. As transport processes under such extreme flow conditions might be completely different from the dry weather situation, it must even be questioned the whether the ADE is a useful model for these situations (Guymer and Obrien, 1995; Guymer et al., 1996).

Second, it must be taken into account that concentrated solutions of NaCl show a greater density than wastewater, which complicates mixing and makes NaCl a non-conservative tracer in a hydraulic sense. Although we observed that the dispersion coefficients estimated from experiments with NaCl do not differ systematically from those obtained with dyes, the use of NaCl as a tracer clearly increases the mixing length which limits the investigation of short reaches.

Third, dispersion in a heterogeneous sewer line cannot be predicted from mean reach characteristics. The correct solution to this problem would be to subdivide the reach into locally uniform units, for which the suggested formulae should give reasonable results.
5.4. Discussion

Figure 5.2.: Observed (circles) and modelled (lines) concentrations that were obtained with the routing procedure after Singh and Beck (2003) and the Taylor solution for dataset 03.

Figure 5.3.: Left: Empirical distribution of $K$ ($n=60$) from experimental data. Average dispersion coefficient: 0.16 m$^2$s$^{-1}$ [$K_{10}=0.05$ m$^2$s$^{-1}$; $K_{50}=0.10$ m$^2$s$^{-1}$; $K_{90}=0.36$ m$^2$s$^{-1}$]; Right: The predicted concentration profiles for different quantiles of $K$ show the sensitivity of the concentrations to the dispersion coefficient for data set 03.

However, on the one hand this would require a GIS based approach, which is quite the opposite of a simple formula to rapidly estimate dispersion. On the other hand this would still not take into account effects of eventual sediment deposits, bends, and other disturbances. Such disturbances might be the reason why the equations of (Huisman et al., 2000), which was based on the assumption of a well-maintained straight sewer, and Sooky (1969) perform well for uniform reaches but tend to underestimate measured values of $K$ for the majority of datasets. One could argue that therefore the estimated $K$ from sewer data must be taken as an "operational" dispersion parameter which "contains" more information than only the effects of velocity shear and transversal mixing. Following this reasoning, large dispersion coefficients from tracer experiments might also indicate poor sewer performance.

**Why was no predictive formula developed?** First of all, we suggest that the above mentioned formulae already perform satisfactorily in their range of application. In addition, searching the database for explanatory variables for $K$, only very weak relationships were found with the ratio $W/H$ and the mean velocity in the reach. Besides collecting more datasets, future work towards the development of a predictive equation could concentrate on the analysis of sewer velocity profiles to obtain dispersion from vertical and lateral mixing processes in a similar way as Fischer did for rivers.
Chapter 5. Dispersion in sewers

5.5. Conclusions

- 60 datasets from tracer experiments in different urban sewer systems have been analyzed with regard to longitudinal dispersion. In the case that upstream and downstream concentration profiles were measured for a sewer reach, we suggest the routing procedure of Singh and Beck (2003) for data analysis. Where only downstream tracer measurements are available, the classical Taylor solution for the ADE can be a useful model.

- Dispersion in sewers was generally found to be very small and to show little variation in an absolute sense, although different sewer systems were investigated. We observe a skewed distribution of the longitudinal dispersion coefficient $K$ with an average value of 0.16 m$^2$s$^{-1}$ [$K_{10} = 0.05$ m$^2$s$^{-1}$, $K_{50} = 0.10$ m$^2$s$^{-1}$, $K_{90} = 0.36$ m$^2$s$^{-1}$].

- In situations of uniform geometry and stable flow, equations (5.12), (5.15) or (5.14) are suitable to predict the longitudinal dispersion from structural and hydraulic data. For non-uniform reaches, predictions may differ from measured values by a factor of 100, because the measured dispersion coefficient is not necessarily related to length-weighted average characteristics.

- Where the transport properties of a specific reach has to be described precisely, the authors advocate the performance of field experiments. As the dispersion coefficient contains integrated information on a reach, it is hypothesized that remarkable large dispersion coefficients could indicate poor sewer performance.

- For the development of a specific equation for the prediction of dispersion coefficients more datasets and detailed information on sewer velocity profiles are needed.

Figure 5.4.: Discrepancy between predicted dispersion coefficients and values derived from field data. Left: relative differences; Right: absolute differences for three selected models. Circles label datasets which were analysed by the routing procedure and crosses datasets to which the Taylor solution was applied. Black symbols mark data-sets with $k_{st}$ values between 50 and 100 m$^{1/3}$s$^{-1}$, whereas grey colour is used for datasets with unreasonable $k_{st}$ values. This points to considerable non-uniformities in a reach or bad data quality.
Table 5.2.: Summary of hydraulic and dispersion data measured at 37 different sewers in Europe and the USA

| ID | IDS | Loc | L₁₋₂ | L₀₋₂ | Q   | S₀   | Dₛ   | d   | W   | R   | u   | u*   | Kₛ   | Kₜ   | kₛₘ |   |   |
|----|-----|-----|------|------|-----|------|------|-----|-----|-----|-----|-----|------|------|-----|-----|---|---|
| A  | ZH  | 1671| 1788 | 0.028| 0.9 | 0.9  | 0.11 | 0.68 | 0.1 | 0.37| 0.03 | 0.12 | 0.11 | 60  |   |   |
| B  | ZH  | 469 | 574  | 0.028| 0.9 | 0.9  | 0.11 | 0.69 | 0.1 | 0.38| 0.03 | 0.07 | 0.08 | 60  |   |   |
| C  | ZH  | 974 | 1079 | 0.028| 0.9 | 0.9  | 0.11 | 0.69 | 0.1 | 0.37| 0.03 | 0.06 | 0.07 | 58  |   |   |
| D  | ZH  | 156 | 1669 | 0.028| 0.9 | 0.9  | 0.11 | 0.68 | 0.1 | 0.38| 0.03 | 0.07 | 0.07 | 61  |   |   |
| E  | ZH  | 201 | 2120 | 0.028| 0.9 | 0.9  | 0.11 | 0.68 | 0.09| 0.39| 0.03 | 0.09 | 0.09 | 63  |   |   |
| F  | ZH  | 505 | 0.028| 0.9  | 0.9  | 0.11 | 0.69 | 0.1  | 0.36| 0.03 | 0.06 | 0.07 | 56  |   |   |
| G  | ZH  | 1095| 0.028| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.38| 0.03 | 0.08 | 0.08 | 61  |   |   |
| H  | ZH  | 1546| 0.028| 0.9  | 0.9  | 0.11 | 0.68 | 0.09 | 0.4 | 0.03 | 0.09 | 0.09 | 64  |   |   |
| I  | ZH  | 1041| 0.028| 0.9  | 0.9  | 0.1  | 0.67 | 0.09 | 0.42| 0.03 | 0.13 | 0.13 | 69  |   |   |
| J  | ZH  | 505 | 0.028| 0.9  | 0.9  | 0.1  | 0.66 | 0.09 | 0.44| 0.03 | 0.21 | 0.21 | 73  |   |   |
| K  | ZH  | 1095| 0.031| 0.9  | 0.9  | 0.12 | 0.7  | 0.1  | 0.38| 0.03 | 0.07 | 0.07 | 58  |   |   |
| L  | ZH  | 1564| 1669 | 0.031| 0.9  | 0.9  | 0.11 | 0.7  | 0.1  | 0.38| 0.03 | 0.12 | 0.07 | 57  |   |   |
| M  | ZH  | 505 | 0.031| 0.9  | 0.9  | 0.12 | 0.71 | 0.1  | 0.37| 0.03 | 0.12 | 0.12 | 57  |   |   |
| N  | ZH  | 1095| 0.031| 0.9  | 0.9  | 0.11 | 0.69 | 0.1  | 0.4 | 0.03 | 0.07 | 0.07 | 62  |   |   |
| O  | ZH  | 590 | 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.43| 0.03 | 0.03 | 0.03 | 68  |   |   |
| P  | ZH  | 1041| 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.42| 0.03 | 0.53 | 0.53 | 66  |   |   |
| Q  | ZH  | 505 | 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.43| 0.03 | 0.21 | 0.21 | 73  |   |   |
| R  | ZH  | 1095| 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.42| 0.03 | 0.26 | 0.26 | 97  |   |   |
| S  | ZH  | 505 | 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.4  | 0.03 | 0.32 | 0.32 | 120 |   |   |
| T  | ZH  | 1095| 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.35| 0.03 | 0.03 | 0.03 | 120 |   |   |
| U  | ZH  | 505 | 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.35| 0.03 | 0.03 | 0.03 | 120 |   |   |
| V  | ZH  | 1095| 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.35| 0.03 | 0.03 | 0.03 | 120 |   |   |
| W  | ZH  | 505 | 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.35| 0.03 | 0.03 | 0.03 | 120 |   |   |
| X  | ZH  | 1095| 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.35| 0.03 | 0.03 | 0.03 | 120 |   |   |
| Y  | ZH  | 505 | 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.35| 0.03 | 0.03 | 0.03 | 120 |   |   |
| Z  | ZH  | 1095| 0.031| 0.9  | 0.9  | 0.11 | 0.68 | 0.1  | 0.35| 0.03 | 0.03 | 0.03 | 120 |   |   |
| AA | ZH  | 105 | 2130 | 0.029| 2.88 | 0.9  | 0.11 | 0.69 | 0.1 | 0.38| 0.05 | 0.32 | 0.35 | 34  |   |   |
Table 5.2.: (continued) Summary of hydraulic and dispersion data measured at 37 different sewers in Europe and the USA

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ID= ID of dataset, ID_S= ID of sewer, Loc= Location of sewer, L= Length, D_S= Diameter of sewer, S_0= slope, Q= Discharge, R= Hydraulic radius, W= width, d= average water level (in a circular pipe), u= average velocity, u_*= shear velocity, K_S= Dispersion coefficient (Singh and Beck, 2003) K_T= Dispersion coefficient (Taylor, 1954), k_{st}= Manning-Strickler friction coefficient
ZH= Zurich (CH), DI= Dillhaus (CH), SA= Saaland (CH), BA= Bauma (CH), DU= Dübendorf (CH), DR= Dresden (D), BE= Berlin (D), OP= Opfikon (CH), EF= Effretikon (CH), RO= Rome (I), LO= London (GB), LV= Louisville (USA), LY= Lyon (F)
Chapter 6.
Inferring exfiltration rates from tracer experiments

6.1. Introduction

Rutsch et al. (2005) evaluate different methods for the quantification of sewer leakage. They conclude that the tracer methods developed in the scope of this thesis present a valuable tool to quantify wastewater losses under realistic conditions (i.e., dry weather flow, undisturbed sewer environment). For a single pipe without lateral inflows, the assessment of exfiltration is straightforward because the result of a tracer test (i.e., exfiltration ratio as a fraction of the labelled flow) is readily converted into an exfiltration rate. However, in a network situation with a series of inflows and leaks, the relationship between tracer loss and water loss is not unique. Furthermore, only integrated information is gained from tracer tests and the exact locations where losses occur remain unknown.

While the location is relevant for sewer operators who would like to improve their rehabilitation planning by explicit consideration of exfiltration, urban water managers (e.g., water supply or regulation authorities) need absolute leakage values for quantitative risk analysis of sewer exfiltration. In this chapter, the question of interest is: How can we learn the most from tracer experiments with regard to the magnitude and the location of exfiltration?

In the following it will be explored how this question can be answered with a Bayesian approach to data analysis. The investigation will rather be conceptual than exhaustive and the goal is to examine the nature and quality of expected results for typical situations.

6.2. Methods and Material

6.2.1. Application of the tracer methods in networks

The integrated leakage from a sewer reach can be measured by tracer experiments (chapter 2 and 3). Precisely-known amounts of tracer are injected at the beginning and at the end of the investigated sewer and a mass balance is computed over the investigation reach. Exfiltration can then be estimated from the ratio of tracers in wastewater samples taken at a measurement point downstream in comparison to the added tracer masses. Given that the tracer is conservative and fully mixed in the wastewater, any tracer loss is directly correlated to the leakage in the reach. From such experiments exfiltration is computed as a ratio or fraction of the labelled labelled flow (e.g., 5%).

If tracer methods are applied in a network situation, practical difficulties arise because the results do not readily allow to draw conclusions on total exfiltrating volumes or the location of leaks. For example, considering an investigation reach with lateral inflows where the indicator tracer is added at the beginning to a flow of 20 ls⁻¹ and the reference tracer is dosed at the end to a flow of 200 ls⁻¹: What does it mean if a 5% tracer loss is detected to an accuracy of ± 2% of tracer mass? And what is the actual value of this information for rehabilitation planning?
Chapter 6. Inferring exfiltration rates from tracer experiments

Apparently, the relation between tracer and water loss depends on the location and magnitude of inflows as well as leaks in a reach. To illustrate this problem, one could imagine the above example as a simple network of two reaches with the inflow to the first segment being 20 ls\(^{-1}\) and to the second 180 ls\(^{-1}\). One possibility is that all 5% leakage occurs in the upstream part, which would mean that 1 ls\(^{-1}\) is lost. In case that the leaks are located further downstream, 5% of 200 ls\(^{-1}\) would represent a loss of 10 ls\(^{-1}\), which would be much more critical for the environment.

This basic model has already four parameters (2 inflows and 2 leaks), two of which are of particular interest. Even in this simple case, the estimation of absolute leakage rates from the experimental data is not feasible with a frequentist approach due to non-identifiability of the model parameters (e.g., leakage in the first reach can be compensated by less leakage in the second reach and vice versa). If additional experiments are impractical (e.g., due to a limited budget), the most one can hope to do is to make the best inference based on the experimental data and any prior knowledge that is available. This is the goal of Bayesian data analysis.

6.2.2. Bayesian data analysis

Bayesian data analysis uses the concept of probability in a broader sense than frequentist theory, which considers probability as the long-run frequency with which an event occurs (given infinite experimental trials). Bayesian inference is statistical inference in which probabilities are interpreted as the degree-of-belief in the occurrence of an event given the evidence at hand (Gelman et al., 1995).

The name comes from the frequent use of the Bayes’ theorem in this discipline, which provides a method for adjusting degrees of belief in the light of new information. It is based on conditional probabilities, which express how the probability \(\text{prob}(X)\) of event \(X\) is modified to a conditional probability \(\text{prob}(X|Y)\), if \(Y\) already occurred:

\[
\text{prob}(X|Y) = \frac{\text{prob}(X,Y)}{\text{prob}(Y)}
\]

Using the product rule

\[
\text{prob}(X,Y) = \text{prob}(X|Y) \cdot \text{prob}(Y)
\]

Bayes’ Theorem can be derived as

\[
\text{prob}(X|Y) = \frac{\text{prob}(Y|X) \cdot \text{prob}(X)}{\text{prob}(Y)}
\]

For the assessment of sewer leakage, the usefulness of this approach becomes more clear when \(X\) and \(Y\) are replaced with hypothesis (e.g., a certain magnitude of tracer loss at a specified location) and data (e.g., tracer measurements)

\[
\text{prob(hypothesis|data)} \propto \text{prob(data|hypothesis)} \cdot \text{prob(hypothesis)}
\]
is true. This modification procedure yields the posterior probability, representing the state of knowledge on the magnitude of leakage in the light of the new information. While this process is often expressed as “updating current” knowledge or “learning from data” (Sivia, 1996; Gelman et al., 1995), it is important to be aware that in parameter estimation this is inextricably linked to the applied model through the likelihood function. Note that in parameter estimation the expression \( \text{prob}(Y) \) needs not necessarily to be considered, because it is a normalization term, which does not affect the results (Sivia, 1996).

The strength of this approach lies in the fact that it relates the quantity of interest (hypothesis: the probability that the assumed loss of wastewater occurs at a specific location) to the term that is easier to assess: the probability that one would have observed the measured data if the hypothesis were to be true. As mentioned above, it also allows for the incorporation of other knowledge, besides the data, through the prior.

For problems where it is reasonable to specify the type of the posterior distribution, analytical solutions of the posterior can be obtained. Where this is not the case, computational algorithms can be applied to calculate a sample of the posterior pdf without explicit assumptions on its shape (Gamerman, 1997).

### 6.2.3. Computational realisation

As a simple model is used for this problem (see further below), it is possible to perform a large number of simulations in reasonable time. This makes it possible to apply a Markov chain Monte Carlo method (MCMC), which explores the parameter space with an efficient trial-and-error algorithm (Hastings, 1970) to get a sample representing the posterior distribution.

Basically, the chain is constructed such that new points on the posterior pdf are constructed with an iterative scheme involving a random draw from a jump distribution. From a given starting point in parameter space, the proposed new point is always accepted if it yields a higher posterior probability density. In case that the new point yields a lower value it is accepted with a probability equal to the ratio of the probability density of the new point to that of the previous point. With an adequate acceptance rate (0.44-0.23, (Gelman et al., 1995, 334f)) this efficiently samples the parameter space, asymptotically approximating the posterior, and might even provide a mechanism for escaping entrapment in local minima if the posterior is multimodal.

While there have been smart algorithms developed in recent years (e.g., Simulated Annealing, Gibbs sampling, Propp and Wilson algorithm), that even allow for an assessment of convergence in some cases, a conventional Metropolis algorithm was applied in this study (Gelman et al., 1995).

### 6.2.4. Simulation Model

The suggested conceptual model (Figure 6.1) constitutes of generic elements from which networks can be formed. Each element represents a sewer reach of arbitrary length. All inflows (i.e., house connections, connected sewers, infiltrating groundwater) are lumped together into a single inflow at the upstream end, and all leakage is equally lumped together into one outflow which is occurring in the reach. The remaining discharge after each element is calculated as the water balance of inflow and outflow. The tracer balance is computed under the assumption that i) the tracer is conservative and ii) the tracer is fully mixed with the wastewater. The mass balance is computed correctly, in such that negative inflow is treated as exfiltration and negative exfiltration as inflow, which means that tracer does not enter the system irregularly. Furthermore, a natural background concentration of tracer is taken into account by explicitly considering a random error on the experimental data.
Although the amount of leakage is functionally related to the water level in the pipe, which varies during the day, it is assumed that a steady state approach to the problem is adequate for this conceptual analysis.

In the following, a simulation study of a virtual case is presented. The main results and drawbacks of the Bayesian approach will be discussed based on a brief sensitivity analysis. Finally, a preposterior analysis will be performed in order to investigate the expected value of information from tracer experiments similar to the analysis of chapter 4.

6.3. Bayesian analysis of exfiltration rates in a network situation

The investigated network consists of only two elements, each of which has a length of 5 km (Figure 6.2). With the suggested analysis two questions should be explored:

A) What is the gain of information with regard to absolute leakage?

B) What can be learned about the need for rehabilitation of the investigated pipe?

While the evaluation of A in the context of Bayesian data analysis is possible by definition of an appropriate statistic, question B is more relevant for practitioners. As it concerns the consequences of sewer leakage, it goes beyond pure uncertainty analysis, because the issue of rehabilitation or no rehabilitation is more related to a decision analysis context. A concise answer therefore requires additional information (e.g., vulnerability of soil and groundwater, hazard potential of wastewater, preferences of decision maker), which is discussed briefly in chapter 4. In this chapter, the problem of assigning monetary values to environmental values is not be picked up, because the main point here is that it is more sensible to use absolute leakage values for risk assessment (e.g., to assess groundwater contamination) than exfiltration ratios.

In general, Bayesian data analysis of the leakage problem consists of three types of analysis:

a) The prior analysis determines the optimal action (e.g., rehabilitation strategy) on the basis of known information (e.g., exfiltration, structural defects, drainage capacity).

b) The preposterior analysis assesses the expected gain in information before tracer measurements are actually performed. This is also known as analysis of expected value of sample information (EVSI) or expected value of imperfect information (Clemen, 1996).

c) The posterior analysis is carried out, when experimental data have actually been acquired. It then revises the prior optimal rehabilitation scheme, given the new information.
For reasons of clarity we will first give the results of the prior analysis (a) and then continue with the posterior analysis (c), using fictitious tracer experiment data. The understanding of these steps is necessary before presenting the preposterior analysis (b), which conceptually relies on the methods of the two other analyses.

6.3.1. Prior analysis

Prior analysis means that one uses the current knowledge on a certain problem as the basis for decision making. Here, this means to define the appropriate rehabilitation strategy given the prior information on inflow and exfiltration rates.

Sewer rehabilitation is a complex topic that equally considers hydraulic performance, environmental impact and structural integrity of sewer pipes (Davies et al., 2001; Jacobi and Sympher, 2002). For reasons of simplicity, it is assumed here that i) rehabilitation is only dependent the assessment of exfiltration and ii) a reach has to be rehabilitated if leakage rates significantly exceed 0.001 l/(sm)\(^{-1}\) (i.e., 5 l/s\(^{-1}\) per 5-km-reach). To assess the probability of excessive leakage, it is necessary to formulate prior knowledge on exfiltration, gathering all relevant information for the simulation model.

For the inflows, the available knowledge may be estimated from modelling of connected households or population equivalents or simply obtained by discharge measurements. For leakage rates, however, it is more difficult to come up with prior information, as no general measurement method has been available in the past.

One possibility to assess leakage rates is to use literature values (Rauch and Stegner, 1994; Ullmann, 1994; Decker, 1998; Vollertsen et al., 2002; Vollertsen and Hvitved-Jacobsen, 2003; Ellis et al., 2003; Fenz et al., 2005; Blackwood et al., 2005; Wakida and Lerner, 2005). Alternatively, one could assess exfiltration in a specific catchment from expert interviews, considering the various sources of information to which a sewer operator has access:

- measurements or maps of groundwater table
- measurements of groundwater quality parameters
- maps of sewer network, damages and defects
- information on detailed investigation of sewers (e.g., structural state, leakage values from pressure testing, CCTV)
- information on soil type and transmissivity
- literature on soil type and transmissivity (Davies et al., 2001)
- own operational experience or third-party information (e.g., water supply company, sewer inspection companies)

In the Bayesian context, the formulation of prior knowledge is usually done as probability distributions, which express the degree of belief on the value of a certain variable (Sivia, 1996).

For the prior information a reasonable set of model inflows and exfiltration (Figure 6.2) was chosen. Inflows were set to 50 l/s\(^{-1}\) for both reaches and exfiltration rates of 5 l/s\(^{-1}\) and 10 l/s\(^{-1}\) were chosen for the two reaches. As the knowledge on the inflows is supposed to be more precise than that on the individual losses, the relative uncertainties (sd) were defined accordingly (Table 6.1). All model parameters were assumed to be normally distributed.

In the following, Inf \(n\) describes the inflow to the \(n^{th}\) reach and Erf \(n\) the Exfiltration from the \(n^{th}\) reach. The choice of appropriate prior distributions, which is often criticized as being a weakness in the Bayesian approach because it would lead to subjectivity in the results, is discussed further below.
Chapter 6. Inferring exfiltration rates from tracer experiments

Figure 6.2.: System sketch of conceptual network analyzed in this study.

Table 6.1.: Prior information of the conceptual network.

<table>
<thead>
<tr>
<th>distr.</th>
<th>Inf1</th>
<th>Exf1</th>
<th>Inf2</th>
<th>Exf2</th>
</tr>
</thead>
<tbody>
<tr>
<td>mean [ls⁻¹]</td>
<td>50</td>
<td>5</td>
<td>50</td>
<td>10</td>
</tr>
<tr>
<td>sd [ls⁻¹]</td>
<td>2.5</td>
<td>2</td>
<td>2.5</td>
<td>4</td>
</tr>
</tbody>
</table>

Results

The prior analysis is used to assess whether it is rational to rehabilitate a reach or not (question B). As described above, rehabilitation is the best option when leakage was significantly greater than a critical exfiltration of 5 ls⁻¹ (i.e., \( P(\text{Exf} \ n < 5 \text{ ls}^{-1}) = 0.05; n = 1, 2 \)). In order to assess the probability of leakage in a reach, the marginal prior pdfs of the Exf1 and Exf2 are integrated up to the critical exfiltration rate. In addition, information on the probability of simultaneous pollution from both reaches can be obtained by integration over the joint distribution of Exf1 and Exf2. For better comparability, the results of the prior analysis are presented in Table 6.3 together with the results of the posterior analysis, which is explained later.

The prior analysis suggest that the first reach has a 0.5 probability of being below the 5 ls⁻¹ threshold (Table 6.3, \( P(\text{Exf} < 5 \; \text{ls}^{-1})_{\text{pri}} = 0.50 \)) and consequently renovation is recommended. Accordingly, the second reach also has a low probability of being environmentally safe (Table 6.3, \( P(\text{Exf} < 5 \; \text{ls}^{-1})_{\text{pri}} = 0.11 \)). The joint probability that exfiltration in both reaches does not exceed the threshold is practically 0, which suggests that the simultaneous renovation of both reaches is almost certain (\( P(\text{Exf} < 5 \; \wedge \; \text{Exf} < 5 \; \text{ls}^{-1})_{\text{pri}} = 0.00 \)).

As this assessment crucially depends on our a priori belief on the magnitude of exfiltration (e.g., expert knowledge, literature values), the evaluation might be different if additional information from measurements is considered.

6.3.2. Posterior analysis

For the posterior analysis, the prior information (Table 6.1) is analyzed together with experimental data from tracer tests. It was assumed that a fictitious tracer experiment over the two reaches was performed which yielded a result \( (y_m) \) of 5% of tracer mass loss for both reaches combined (Figure 6.2). It was further assumed that the measurement result has an uncertainty \( (\sigma_{y_m}) \) of 5% of tracer mass loss, expressed as single standard deviation of a normal distribution.

With regard to the computational implementation, the mode of the posterior was approximated before the Markov chain simulation using a robust simplex optimization algorithm (Nelder
and Mead, 1965). By taking the parameter values at the mode of the posterior as the starting point for the MCMC, efficiency is improved and errors from a large "burn in" phase are avoided (Gelman et al., 1995). The algorithms for mode-finding and inference are simplified R (R Development Core Team, 2004) implementations of the routines available in the UNCSIM package (Reichert, 2002). An acceptance rate of 0.27-0.35 was obtained for all simulations by implementing a loop for the Markov chain, checking the acceptance rate after the first few hundred steps of the chain and iteratively adjusting the spread of the jump distribution. To obtain a representative sample from the posterior, 10 000 runs were performed per simulation.

Results

The results of the posterior analysis (Table 6.2 Simulation 1) are presented in Figure 6.3 (Simulation 1). In light of the experimental data, which indicate less leakage in comparison to the prior knowledge, it can be seen that the prior information is updated to better match the measurement results. Furthermore, it is observed that the posterior marginals of Exfl and Exf2 are negatively correlated, which was also expected. This is due to the fact that the model puts a constraint on the two parameters as the sum of both equals total tracer loss. In other words it means that, if the first reach is leaky, exfiltration does not occur in the second and vice versa.

As one is originally interested in the gain of information with regard to absolute leakage (question A), the differences between posterior and prior distribution were analyzed, using the average (mean) and standard deviation (sd) as statistics. From Table 6.2 (Simulation 1) it can be seen, that the mean value of Exfl is reduced from 5.00 ls⁻¹ to 2.93 ls⁻¹ which is a decrease of 41.4%. Similarly, the uncertainty is reduced from 2.00 ls⁻¹ to 1.63 ls⁻¹, which is 18% less.

How does this gain in information influence the rehabilitation strategy (question B)? In the prior analysis, the first reach was assessed to have a 0.5 probability of being environmentally problematic. In the light of the new information, the probability of excessive leakage is decreased to 0.11 (P(Exfl >= 5)post = 1-P(Exfl < 5)post = 1-0.89 = 0.11). However, this does not meet the 0.05 threshold of significance and consequently renovation still seems the most rational decision. Accordingly, the second reach would still be rehabilitated (P(Exf2 >= 5)post = 1-0.41 = 0.59), although the probability of being environmentally safe (i.e., below the threshold) increased from 0.11 to 0.41 (Table 6.3).

Sensitivity analysis

A rough sensitivity analysis was performed to evaluate the sensitivity of the posterior to i) the uncertainty in tracer measurements (Simulations 1-3) and ii) correlations in the prior knowledge (Simulations 4-6), because these are the factors which can be most influenced by the investigator. Considering a typical range of values, the uncertainty of the measurement (σm) was subsequently decreased from 5 to 2 and 1% of tracer mass loss and correlation coefficients for the prior knowledge on exfiltration (r) were either assumed to be 0 or 0.9 (Table 6.2).

In addition, two supplementary simulations were performed. In Simulation 7, the uncertainty in the prior knowledge on exfiltration was cut in half and in Simulation 8 the uncertainty in the inflows was drastically reduced from 2.50 to 0.025 ls⁻¹ (Table 6.2).

The results of Simulation 1 to 6 lead to the conclusion that in this setting, the correct elicitation of the prior knowledge is very important to compute reasonable exfiltration rates. In particular, it is observed that the consideration of correlation in the prior (Simulation 4) leads to the same gain of information as an extreme measurement accuracy (Simulation 3) and it is observed that the marginals of Exfl and Exf2 are very similar for both scenarios (Figure 6.3, Simulation 3 and 4). This is of practical relevance, because it generally takes a considerable effort to perform
### Table 6.2: Results from posterior analysis for different simulation studies.

- $y_m$ = Experiment data.
- $\sigma_{y_m}$ = Uncertainty of tracer measurement.
- $\psi = $ prior knowledge.
- $\psi_{post} = $ posterior knowledge.
- $r$ = correlation coefficient between $Exf_{1,\psi}$ and $Exf_{2,\psi}$.

<table>
<thead>
<tr>
<th>Simulation no. unit</th>
<th>Simulation no. data</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8b</th>
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<tr>
<td></td>
<td>$y_m$ [% mass]</td>
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<td></td>
<td>$\sigma_{y_m}$ [% mass]</td>
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<td>0.05</td>
<td>0.05</td>
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<tr>
<td>reach 1 mean</td>
<td>$Exf_{1,\psi}$ [ls$^{-1}$]</td>
<td>50.0</td>
<td>50.0</td>
<td>50.0</td>
<td>50.0</td>
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<td></td>
<td>$Exf_{1,\psi}$ [ls$^{-1}$]</td>
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<td></td>
<td>$Exf_{1,\psi}$ [ls$^{-1}$]</td>
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<td>reach 2 mean</td>
<td>$Exf_{2,\psi}$ [ls$^{-1}$]</td>
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<td>$Exf_{2,\psi}$ [ls$^{-1}$]</td>
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<td></td>
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<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
</tbody>
</table>

### Table 6.3: Decision Analysis: Probability $P(Exf < 5)$ of no environmental hazard given that the critical value equals 0.001 l(ms)$^{-1}$ (i.e., 5 ls$^{-1}$ per reach).

<table>
<thead>
<tr>
<th>Simulation no. 1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P(Exf_{1,\psi} &lt; 5)$</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
<td>0.50</td>
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<tr>
<td>$P(Exf_{1,Post} &lt; 5)$</td>
<td>0.89</td>
<td>1.00</td>
<td>1.00</td>
<td>0.99</td>
<td>1.00</td>
<td>1.00</td>
<td>0.81</td>
</tr>
<tr>
<td>$P(Exf_{2,\psi} &lt; 5)$</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
<td>0.11</td>
<td>0.01</td>
</tr>
<tr>
<td>$P(Exf_{2,Post} &lt; 5)$</td>
<td>0.41</td>
<td>0.72</td>
<td>0.86</td>
<td>0.54</td>
<td>0.94</td>
<td>0.99</td>
<td>0.03</td>
</tr>
<tr>
<td>$P(Exf_{1,\psi} &lt; 5 \cap Exf_{2,\psi} &lt; 5)$</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.01</td>
<td>0.01</td>
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<tr>
<td>$P(Exf_{1,Post} &lt; 5 \cap Exf_{2,Post} &lt; 5)$</td>
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<td>0.54</td>
<td>0.94</td>
<td>0.99</td>
<td>0.03</td>
</tr>
</tbody>
</table>
measurements with a very high accuracy. By wrongly estimating the priors, this effort could be without avail.

Assuming more precise prior knowledge on $Erf_1$ and $Erf_2$ (Figure 6.3, Simulation 7), it can be seen that the gain in information from the prior to the posterior is only about 5% (relative difference of sd) (Table 6.2, Simulation 7). This is considered logical, because normally much less is learned, when the available information is already "good".

For Simulation 8, a much more precise knowledge on the inflows was assumed (Table 6.2, column 8) which leads to interesting results. The first observation is that the MCMC algorithm performed badly, because clusters are visible in the scatterplot (Figure 6.3, 8a). Although this is often an indicator of a too low acceptance rate, in this case an acceptance frequency of 0.34 was obtained by the automatic adjustment of the jump distribution.

Further analysis suggests that the bad behavior stems from the fact that the other dimensions of the prior are so narrow (the plot only shows the two of the four dimensions), that a much larger sample size (or a different algorithm) would be needed to adequately sample the posterior. It was found that, in this setting, it was inadequate to scale the jump distribution equally for all four dimensions as was done before. Instead, the jump distribution should be scaled individually in each dimension to better take into account the individual uncertainty of each parameter and eventual correlations (Gelman et al., 1995). Re-running the MCMC with the proper adjustments leads to a more representative sample of the posterior (Figure 6.3, 8a) which contains, as expected, similar information than Simulation 1.

Summarizing the above results, it was found that the Bayesian approach, which allows for the combination of existing information on sewer leakage with measurement data, may lead to significant gain in information. It is expected that this is especially the case, when the prior knowledge on exfiltration is rather uncertain and precise measurements are possible. Besides the prior knowledge, difficulties arise when the MCMC algorithm delivers an unrepresentative sample of the posterior (e.g., too small or biased).

These findings are all concerning data analysis given that tracer experiment data is available. However, in practice, one is often confronted with the fundamental decision whether it is worth measuring or not.

6.3.3. Preposterior analysis

The preposterior analysis is a framework to formally assess the expected value of sample information (EVSI). Often this analysis is performed in monetary units and the decision for an experimental campaign is taken if the expected gain is higher than the expected cost for investigations (Clemen, 1996).

As explained above, a detailed risk analysis of sewer exfiltration was set aside. Instead, the procedure is demonstrated using the same nonmonetary values to describe a gain of information as above (absolute differences in mean and sd).

The EVSI is conveniently assessed by means of Monte Carlo Simulation (MCS) (Figure 6.4). First, a single realization from the prior distribution is drawn and propagated through the model to create one potential value of tracer loss. Then, this is used as potential measurement to update the prior information by MCMC. Repeatedly creating potential measurement values and performing the inference several hundred or thousand times approximates the distribution of mean and sd. This procedure must be reasonable, because each possible measurement value must represent a realistic measurement value if the prior reflects all available information.

As an example, in the following it will be described how one could assess the necessary measurement accuracy of a planned tracer experiment to obtain a significant gain of information.
Figure 6.3.: Results of the different posterior analysis showing MCMC samples from the posterior probability density distribution (points and histograms) and the prior distribution (dashed lines and density curves). The lines in the scatterplot indicate contour levels of 0.95 (0.5, 0.05) prior probability density.
6.3. Bayesian analysis of exfiltration rates in a network situation

Expected tracer loss

Bayesian inference

Figure 6.4.: Schematic illustration of preposterior analysis. First, potential measurement data are simulated from the prior knowledge (black bar in middle graph indicates that procedure is repeated many times). Then, the posterior analysis is performed on the potential exfiltration data. Repeating this process a large number of times the expected value of sample information (EVSI) can be assessed.

Due to large computation times, the investigation was restricted to two alternatives: less accurate \( (\sigma_{\text{m}} = 0.05) \) and more accurate measurements \( (\sigma_{\text{m}} = 0.01) \). Practically, 800 MCS of the Markov chain were performed for each alternative, which resulted in 8 million runs of the network model for each alternative.

**Results**

In general, the less accurate and the accurate alternatives both provide valuable information (Figure 6.5 and Figure 6.6). The less accurate measurements do not affect the development of the mean knowledge on exfiltration, whereas the uncertainty \( (sd) \) on the exfiltration values is reduced slightly (Figure 6.5, \( \Delta sd \)). This is what one would normally expect from repeated measurements on the same system. For the more accurate measurements, similar results are obtained (Figure 6.6). The only difference is that the 5-times more accurate experimental data substantially reduce the uncertainty \( (sd) \) from prior to posterior knowledge (i.e., by a factor of 5).

Comparing the two alternatives with regard to probability of environmental damage, one observes that the measurement accuracy seems to affect the distribution of expected exfiltration in the network.

The less accurate measurements (Figure 6.5), one sees that the uncertainty in the measurements does not allow for significant updating between prior and posterior information in the first reach (white boxes). Although information is shifted, the differences are rather small (e.g., \( \Delta \text{Probability of env. pollution} \) in reach 1 is \([-0.2;0.2]\)). For the second reach (grey boxes), a significant gain in probability is observed. In general the increase of probability can occur from i) a gained precision of the distribution (which shifts the mass more and more over the threshold of 5 ls\(^{-1}\)) or ii) a shifting of the mean. These effects cannot be separated here, because although on average the mean is not shifted, some of the MCS show considerable shifts, more extreme than \( \pm 2 \) ls\(^{-1}\) (Figure 6.5, \( \Delta \text{mean} \)).

With the more accurate measurements, the results are similar to the case before. However, the outliers observed for reach 2 indicate that for some of the 800 simulations the posterior is not much different from the prior distribution (outliers in Figure 6.6, right boxplot). Also the median of the differences in probability is slightly higher than in the first case, which means that more precise measurements would more reliably diagnose the significant leakage in reach 2.
Chapter 6. Inferring exfiltration rates from tracer experiments

Less accurate tracer experiments ($\sigma_{ym} = 0.05$)

Figure 6.5.: Expected gain of information for less accurate tracer measurements ($\sigma_{ym} = 0.05$). The graphs show differences from prior to expected posterior information with regard to mean, sd and $P(Exf > n; n = 1, 2)$. White boxes are used for reach 1 and grey boxes for reach 2.

More accurate tracer experiments ($\sigma_{ym} = 0.01$)

Figure 6.6.: Expected gain of information for less accurate tracer measurements ($\sigma_{ym} = 0.01$). The graphs show differences from prior to expected posterior information with regard to mean, sd and $P(Exf > n)$. White boxes are used for reach 1 and grey boxes for reach 2.
It can be concluded that the tracer measurements could contribute significantly to the assessment of leakage. They are particularly useful if i) the knowledge on exfiltration is incomplete, ii) precise measurements are obtained and iii) many iterative measurements can be performed. In general, this is a promising result for the usefulness of the tracer methods, because tracer methods are considered to be less expensive than CCTV analysis or remediation measures and comparatively more repetitive measurements could be performed on a restricted budget. However, one must keep in mind, that CCTV might be the major source of information for the prior knowledge on exfiltration (e.g., when this is assessed based on the class or the extent of sewer damages). Furthermore, when the tracer methods are used in a decision analysis context, one would have to have in advance a clear conception how groundwater pollution could reasonably be compared to measurement cost.

6.4. Discussion

The above analysis shows that much can be learned from tracer data by Bayesian data analysis. However, certain important aspects regarding the Bayesian data analysis and exfiltration-based sewer rehabilitation must be critically discussed.

As explained above, the results from the posterior analysis show negatively correlated results for the posterior exfiltration of the two reaches. Although conceptually this is a somewhat trivial result, it might be beneficial from a practical point of view. Given this information, it might be sufficient to investigate only one of the two reaches more thoroughly for exfiltration (e.g., pressure testing) instead of both reaches.

Reconsidering the investigations concerning the EVSI, the question arises: What do we learn from this analysis about the importance of the prior information? The sensitivity analysis suggests that the updating is rather dominated by the prior than by the accuracy of the measurements. This is not surprising given that the inference is based on one measurement. For this reason, it seems most important to avoid systematic errors in the elicitation of the exfiltration rates.

With regard to the correct prior information, the proper consideration of correlations is considered crucial. This is, because it is rather likely that exfiltration rates are systematically over- or underestimated if they are deferred from external data or based on expert opinion, which might be biased. Furthermore, they are rather difficult to elicit in interviews, because most practitioners are rather ignorant about quantitative data and have a more qualitative view on exfiltration. One feasible approach to overcome these problems might be to infer exfiltration rates from influential factors, which might be more accessible for sewer operators (e.g., potential leakage area of damages, water level in the reach, local groundwater table, etc.). Probability networks could prove useful for this task as they would allow for i) a combination of different types of information ii) an assessment of the uncertainty of prior information on exfiltration.

In this context, one should be aware that data on influential factors is also relatively sparse in practice. Leakage areas are not routinely recorded, the exact location of the local groundwater table in the vicinity of a pipe is often unknown and the evaluation of CCTV investigations are believed to vary largely from one operator to the other (Ullmann, 1994). Furthermore, it is reported from earlier investigations using pressure-testing that severe structural defects do not necessarily correlate with large losses (Ullmann, 1994; Decker, 1998).

Therefore, it should be considered whether absolute exfiltration rates might be elicited correctly or whether the analysis could better be performed with relative information on exfiltration (e.g., “reach 1 is 5 times more leaky than reach 2”).

In addition to the above comments, which are rather specific for this Bayesian analysis, some conceptual problems might arise which concern the overall risk assessment of sewer leakage.
First, sewer exfiltration is a dynamic process. It is known that leakage is influenced by sewer cleaning, rain events (combined systems) and sediment transport (Decker, 1998; Ellis et al., 2003; Vollertsen and Hvitved-Jacobsen, 2003). Second, leaks clog due to self-sealing (biofilm growth reduces the hydraulic conductivity of the soil) as well as colmation and sediment deposition (Ellis et al., 2003; Vollertsen and Hvitved-Jacobsen, 2003; Fuchs et al., 2004; Mohrlok et al., 2004; Iliuta and Larachi, 2005). As these processes are rather distributed and dynamic, this has only partly been investigated in-situ and results from laboratory studies do often not represent real-life conditions.

6.5. Conclusions and outlook

The tracer methods are considered a useful tool to assess sewer leakage. However, the interpretation of the experimental results is not unique if they are applied in a network situation. The above analysis suggests that the use of Bayesian data analysis could help to overcome this problem.

As only one data point is obtained per tracer experiment, frequentist methods do not allow to estimate neither the magnitude nor the location of leakage. Assuming that a priori knowledge on water losses can be obtained from generally available information (e.g., defect maps, pressure testing) it is possible to convert the results of tracer experiments (loss ratio) into absolute exfiltration rates.

With regard to the Bayesian data analysis procedure, it is foreseen that difficulties will arise from the elicitation of the prior knowledge, which is expected to contain a high degree of correlations. This is particularly important as the analysis seems to be dominated by the prior information. It was formally shown that results of the tracer tests are particularly useful if the uncertainty in the prior knowledge on leakage is large and repetitive measurements can be performed. The Bayesian method is also useful to better analyze decision problems (e.g., to determine which accuracy the tracer measurements must have to decide on rational rehabilitation strategies). However, to correctly perform such an analysis one would need further information on how to compare the risk of environmental pollution to measurement cost.

Conceptually, it is appealing that rehabilitation strategies based on exfiltration rates would allow for a more rational rehabilitation practice. However, sewer exfiltration is influenced by both soil and sewer properties and consequently is a spatially distributed process that is believed to show considerable dynamics. The repetitive use of tracer methods (e.g., over different seasons, before and after rain events) could generate valuable knowledge to close this gap in knowledge.

In order to further develop Bayesian data analysis techniques for the computation of absolute exfiltration figures from tracer experiments, the following investigations are suggested:

- With regard to the prior analysis the potential of probability networks to elaborate meaningful prior knowledge of exfiltration rates should be investigated. The investigation of suitable models must take into account the availability of exfiltration-related data. Most probably one must accept a compromise between model complexity and data availability.

- With regard to the expected value of sample information (EVSI) one should further investigate what measures can be used to quantify a “gain of information”. Instead of merely looking at the development of means and standard deviations of parameters, one could eventually also analyze the integral under the posterior function regarding a certain confidence level. Eventually, the analysis can be performed for relevant groups of pipes (e.g., all pipes in one street or catchment).
6.5. Conclusions and outlook

Figure 6.7.: Illustration of experimental design problem in a network. Black arrows indicate direction of flow. The question of interest is: Which would be the optimal way to explore the entire network with a limited number of tracer experiments?

- Furthermore it would be interesting to explore possibilities for clever experimental design of the tracer studies and how the prior knowledge influences the performance of measurement campaigns. For example, given that the number of experiments in a network situation is limited due to budget constraints: What would be the optimal performance of a series of measurements to make the best inference for exfiltration volumes from a sewer system (e.g., that in Figure 6.7)? Is the layout B-C, C-E, E-F, F-H, A-E, D-C more favorable than D-H, A-H, B-E? Is the optimal experimental setup different when short term (per day) or long-term exfiltration rates (per month or year) are investigated?

- Finally, it would be interesting what the potential of this Bayesian methodology is to detect systematic errors in the tracer measurements. From practical experience in the APUSS project, it is known that the results from tracer tests are subject to severe errors, when the experiments are not performed with the necessary great care. It would be very useful to have a formal method which could be used to check the experimental results against certain plausibility criteria.
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Chapter 7.

Conclusions

At the beginning of this project, many questions were open regarding the quantification of exfiltration from sewers with tracers. Some of those could be answered.

- It was shown that tracers can be used to quantify exfiltration from sewers. The QUEST method (Quantification of Exfiltration from Sewers with Tracers) uses pulse injections of one single tracer, while the QUEST-C (Continuous dosing) method applies a continuous dosing strategy. The methods were validated experimentally in a watertight sewer and the results were found to have no significant bias. The expected accuracy of the methods (expressed as single standard deviation) was found to be in the order of a few percent when the experiments were performed with the necessary care. However, a general statement about the uncertainty of the methodology is not realistic and an individual error assessment for each experiment is suggested instead.

- For the QUEST method the tracer system that was most applied was NaCl as tracer, measured with spade-shaped conductivity probes for the pulse dosing method. As the tracer peaks are highly dynamic the use of inline measurement devices is required. NaCl has the advantage that it behaves conservatively in the wastewater and the available measurement technique is robust enough for sewer applications. Optical measurement devices (e.g., fluorescent dye probes) were found to be difficult to operate reliably without a cleaning mechanism and ion-selective electrodes performed unsatisfactory due to cross-sensitivity and fouling of the membrane. The QUEST-C method was mostly applied with Li⁺ (as Lithiumchloride) and Br⁻ (as Sodiumbromide), which were measured using ion chromatography.

- The experimental design of a tracer experiment has different levels. On a methodological level, the dosing of an indicator input in combination with a reference input leads to a reduction of uncertainty because relative systematic errors in tracer measurements are eliminated by the experimental setup. On a practical level, it is relevant to know the best dosing strategy for a specified investigation reach. A framework was developed based on decision analysis that selects the best alternative from a set of experimental layouts, weighing tracer cost against potential cost of unnecessary pollution. As this differs from application to application it is the task of the analyst to specify the set of different experimental layouts and environmental cost.

- It was found that for the continuous dosing method the hydrodynamics of the reach influence the result. Sewer discharge is never completely steady and even waves with $\partial h / \partial x \ll \text{slope of the sewer}$ travel faster than the mean flow. For a two-point dosing of different substances, this means that reference and indicator tracers are diluted differently at the measuring point, which can cause errors of a few percent. This indicates that the choosing of a suited experimental time is more important than the use of a very elaborate tracer substance.

- Knowledge on mixing properties of the sewer under investigation are crucial to perform and to plan an experiment. It can be concluded that great care has to be taken to avoid
incomplete mixing at the measuring point (e.g., due to density currents or inflows), because this might cause large errors. The accurate prediction of longitudinal mixing in the reach is critical for a sound experimental design. Suitable formulae are suggested to assess dispersion in sewers, which were tested on a large dataset of sewer tracer measurements. It must be noted that these models might fail under storm conditions and in heavily damaged sewers, because the underlying assumptions of dispersion theory are violated.

- As tracer tests measure exfiltration relative to the labelled flow, absolute exfiltration rates are only directly obtained from measurements in reaches without inflows. When tracer experiments are performed in a network, Bayesian data analysis can be used to compute exfiltration rates conditional on the prior knowledge on exfiltration. Practically, problems may arise from the relation of exfiltration to influential factors (e.g., elevation of groundwater table, water level in the pipe, etc.), because the underlying processes and especially their dynamics are still not fully understood.

The results from a conceptual study show that most information is gained from tracer experiments if the knowledge on exfiltration is incomplete and many iterative measurements can be performed. As the tracer methods are far less expensive than CCTV analysis or remediation measures, this is a promising result for the usefulness of the tracer methods, because comparatively more measurements could be performed on a restricted budget.

In this thesis several studies have been presented which are aimed at giving a more solid foundation to the quantification on wastewater exfiltration. However, the tracer methods have a potential for further development and the following improvements could make tracer methods a better tool for quantitative assessment:

- It would be useful to further investigate or develop suitable tracer systems for wastewater systems: as measurement technology advances, more elaborate sensor technique will improve the reliability and accuracy of tracer experiment data. On the one hand inline measurements of more elaborate substances could avoid problems with tracer background concentration. On the other hand the simultaneous use of multiple tracer substances as indicator and/or reference tracer should make the method more robust against systematic errors.

- With regard to the assessment of uncertainty, it would be beneficial to have a sound framework how to estimate uncertainty in the light of high-resolution measurement data, which often reveal insufficiencies in current deterministic models. This is the case for the peak and baseline models of the QUEST method, but is also relevant in other fields of environmental engineering, where an assessment of uncertainty is important. As identically distributed residuals are a requirement in standard parameter estimation, a systematic deviation of model and data could lead to overconfident standard errors of the model parameters, because the random error process is no longer dominant. Although this most probably would not affect best estimates of parameters, too confident parameter errors result in overconfident results from error propagation.

- Bayesian data analysis was found to be promising to infer absolute exfiltration rates from relative exfiltration ratios. However, as only a conceptual investigation was performed open questions remain:

  - It would be interesting to explore possibilities for clever experimental design of the tracer studies and how the prior knowledge influences the performance of measurement campaigns.
- It should be investigated what potential probability networks have to elaborate meaningful prior knowledge of exfiltration rates.
- One could investigate what optimal statistics can be used to quantify a "gain of information" with respect to exfiltration volumes.

• With regard to further development of the tracer method, two fundamental modifications could be envisioned:

The first alternative could copy a technique from pipeline monitoring. In oil pipeline investigations, leak detection is often performed by first pumping radioactive fluids through the pipe and later passing a detector through the line when oil is being transported again. At locations where fluid has left the pipe, radioactivity is detected by the sensor, which allows for a location of the leaks (eventually even on an automated basis with full GIS support). If an environmentally friendly tracer was available (e.g., magnetically coated nano-particles), a similar procedure could be imagined for leakage detection in sewers. First, the quantitative information is gained from the QUEST tracer methods described here. After the completion of the experiments, a detector is passed down the reach to identify the exact locations of leakage.

Second, the assessment of exfiltration from house connections could be improved with tracers following the approach of Bechteler and Günthert (2001). The current state of the art is to check watertightness with pressure tests, which is often criticized for biased results. Leakage might be overestimated because i) pressurized conditions, which do normally not occur in house connections, activate defects in the upper part of the pipe, ii) the applied pressure as well as the injection of the testing devices can originally cause damage to weak pipes and iii) eventual self-sealing layers might be destroyed. A more reliable estimate of leakage can be obtained, if the house connection is blocked and a pump is installed at the downstream end, which is used to circulate a exact volume of water in the house connection. Adding tracers to the circulating water, which passes the connection in free surface flow before it is pumped back, exfiltration could even be identified when infiltration and exfiltration occur in the same reach.


Bibliography


Appendix A.

The APUSS project

Assessing Infiltration and Exfiltration on the Performance of Urban Sewer Systems (APUSS)
European Commission 5th R&D Framework Programme
Contract number: EVK1-CT-2000-00072 APUSS

This text is an excerpt from the executive summary of the project. All final reports, software and other documents are publicly available on the APUSS website at http://www.insa-lyon.fr/Laboratoires/URGC-HU/apuss/

A.1. Objectives

Urban sewer systems constitute a very significant patrimony in European cities. Their structural quality and functional efficiency are key parameters to guarantee the transfer of wastewater to treatment plants without infiltration or exfiltration. Infiltration is detrimental to treatment plant efficiency while exfiltration of wastewater can lead to groundwater pollution. The APUSS research project, associating universities, SMEs and municipalities in 7 European countries, had four main objectives:

- to develop new methods and techniques based on tracers (chemicals and/or natural radioisotopes) in order to assess and quantify infiltration and exfiltration in sewer systems, at different spatial scales (from the sewer reach or from the elementary sub-catchment to the whole catchment) and under different conditions (steady and dynamic groundwater levels, seasonal effects)

- to develop volumetric methods for the measurement of infiltration and exfiltration in house connections

- to establish models and accompanying tools for large scale application and end-user decision support

- to propose approaches to help end users assess the performance of their sewer systems and to choose investment strategies according to a multi-criteria methodology.

A.2. Scientific achievements

For exfiltration measurements, two novel tracer methods have been developed, tested and validated under field conditions: the QUEST pulse injection method and the QUEST-C continuous dosing method. Analytical procedures and data processing programs have been developed and tested by the APUSS partners. Concerning infiltration measurements, two methods have been developed. The first method is based on oxygen and/or hydrogen isotopic ratios, whereas the second method is based on continuous flow and pollutant concentration time series. In particular COD time series measured by means of UV-visible spectrophotometers have been tested. Laboratory tests have been carried out to evaluate i) the adsorption and interaction of tracers with wastewater solids, and ii) the effect of sewer solids and sediments on exfiltration. Volumetric
methods have been tested and applied on experimental sites to measure I/E in house connections (HC). As there are many thousands of HC in a city, A matrix procedure for a catchment-wide extrapolation has been proposed.

Conceptual models for infiltration at sub-catchment scale and for exfiltration at sewer reach scale have been selected and implemented in the *AquaBase* software. Models and tools have been established and tested in the frame of a large scale example of application, with an end-user application perspective. As I/E experiments and measurements are unlikely to cover all pipes within a city, a statistical method based on the similarity approach has been developed in order to identify sub-catchments and groups of sewers which have similar characteristics and which should potentially have similar orders of magnitude in I/E rates.

Performance indicators (PIs) for both infiltration and exfiltration have been established and a software named *PIs Tool* has been adapted for the calculation of these PIs and their associated information. A generic methodology including modelling of the sewer system and of the WWTP has been established to compare different investment strategies (rehabilitation of the sewer system, adaptation of the downstream wastewater treatment plant (WWTP), storage tanks, or any combination of the above solutions). The multi-criteria method Electre III is used to compare and rank the various strategies regarding the impacts of I/E. Different criteria are considered for this purpose (environmental, operational, financial, etc.).

**A.3. Conclusions**

Appropriate methods to measure infiltration and exfiltration in sewer systems have been developed, evaluated and validated at various experimental sites. Experimental protocols are available, which includes detailed assessment of measurement and data processing errors and uncertainties. Infiltration and exfiltration models have also been selected and implemented in an integrated software based on the *AquaBase* platform. Performance indicators, investment strategies and economic valuation have been made, with examples of application. All results are publicly available on the project website.

**A.4. Acknowledgements**

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Appendix B.

Documentation, applicability and practical experience

B.1. Documentation and availability

Both the QUEST and QUEST-C methods have been documented thoroughly. Standard operation procedures for the performance of field experiments and data analysis have been provided. The underlying theoretical concepts and statistical methods for data analysis and experimental design have been described in scientific publications which have been submitted for review to peer-reviewed journals. The algorithms for data analysis and experimental design, which have been programmed in the R language (R Development Core Team, 2004), are packed in libraries. R is available under the GNU public license; all libraries and code examples are freely available for public use.

The complete software, documentation and exemplary datasets will be made available for download from the APUSS homepage (see Appendix A, the ETH e-collection http://e-collection.ethbib.ethz.ch/ or the personal homepage of the author http://www.internal.eawag.ch/~rieckejo/. At present, however, only the latter alternative is feasible due to ongoing negotiations.

B.2. Practical experience

Within the last year of the APUSS project, the exfiltration methods have been finalized with regard to experimental protocol and data analysis. Several test runs have been performed under a variety of conditions in different European cities and it was found that both QUEST and QUEST-C are generally applicable in practice. Our practical experience with the tracer methods is limited to open channel flows and most experiments have been performed under dry weather conditions.

We can further conclude that the success of the tracer methods crucially depends on a thorough preparation of the experimental campaign and the local boundary conditions at the investigation site (flow, tracer background, accessibility, etc.). As a result, a final conclusion on the overall precision of the tracer methods does not seem conclusive. However, we expect that the uncertainty in the obtained tracer loss should be in the order of a few percent of total flow, if the measurement campaign is prepared and performed with the required care and according to the provided documentation. In order to formally assess the confidence in the obtained results, procedures for error analysis have been developed.
Appendix B. Documentation, applicability and practical experience
Appendix C.

Curriculum Vitae

2001 - 2005  Dissertation at EAWAG, Dübendorf
1994 - 2000  M.S. in Civil Engineering (Urban Water Management), University of Hanover, Germany
Oct 99 - Nov 00  Institute for Technical-Scientific Hydrology (ITWH), Hanover, Germany, Assistant Engineer
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Mar 96 - Jul 98  Institute for Urban Water Management (ISAH), University of Hanover, Germany, Student assistant
1990 - 1993  University-entrance diploma, Petrus-Legge Gymnasium, Brakel, Germany

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Languages  German mothertongue, fluent in written and spoken English and Spanish. Advanced French language skills.