Water quality modelling and quantitative microbial risk assessment of Msunduzi river

Bachelor's Thesis

Frida Fischer
Yazan Hamdan
Amanda Hansson
Elin Josefsson
Lisa Sundström

Department of Architecture and Civil Engineering
CHALMERS UNIVERSITY OF TECHNOLOGY
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Department of Architecture and Civil Engineering
Division of Water Environment Technology
Chalmers University of Technology
SE-412 96 Gothenburg
Sweden
Telephone + 46 (0)31-772 1000

Cover:
Photo taken along Msunduzi river by Lisa Sundström

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Abstract

In South Africa, intestinal infection diseases were in the top list of underlying natural causes to death in 2016, the majority of those deaths are caused by poor hygiene and unsafe water. Many surface water sources in the sub-Saharan region of Africa are unsafe for domestic use due to faecal pollution. The bacterium *Escherichia coli* (*E. coli*) is often used as an indicator of the overall microbial quality of drinking and surface water. The aim of this study was to assess the human health risk due to exposure to water from Msunduzi river. The questions that were considered are how *E. coli* concentrations in the river vary over time, which the main sources of faecal pollution are in the study area, and in which ways people are exposed to the water in Msunduzi river. Hydrological modelling was made with Soil and Water Assessment Tool (SWAT) and the risk was assessed with Quantitative Microbial Risk Assessment (QMRA). Results from the SWAT-simulation presented a clear seasonal pattern between simulated water flow and concentration of *E. coli*. However, the measured *E. coli* concentration and water flow did not show the same pattern. To improve the SWAT model in analysing spread of *E. coli*, further investigations regarding pollution sources that have impact on the microbial water quality are required. The calibration of the SWAT model was unsuccessful, mainly due to inadequate data concerning the soil, land use and weather conditions. The soil and land use need further investigations and more weather stations should be established. The risk assessment was made for people exposed to the water through laundry and swimming. After comparing the results from the risk assessment with benchmarks from EU, the microbial water quality in Msunduzi river was evaluated to be poor. One thing that would improve the risk assessment is further investigation on how much water that is ingested during different exposures. Results from the study show the major human health risk of getting infected when exposed to the water in Msunduzi river, which confirms that measures have to be adopted.

Keywords: South Africa, human health risk, water quality, *E. coli*, hydrological modelling, SWAT, risk assessment, QMRA

Vattenkvalitetsmodellering och kvantitativ mikrobiologisk riskanalys av vattendraget Msunduzi

FRIDA FISCHER
YAZAN HAMDAN
AMANDA HANSSON
ELIN JOSEFSSON
LISA SUNDSTRÖM

Institutionen för Arkitektur och Samhällsbyggnadsteknik
Chalmers tekniska högskola

Sammanfattning

I Sydafrika var tarmsjukdomar en av de vanligaste naturliga dödsorsakerna under 2016, de flesta av dessa dödsfall beror på bristfällig hygien och dålig vattenkvalitet. En stor del av ytvattnet i Subsahariska Afrika anses osäkert för hushållsbruk på grund av fekala föroreningar. Bakterien *Escherichia coli* (*E. coli*) brukar användas som indikator för att kontrollera mikrobiell kvalitet på dricks- och ytvatten. Syftet med studien var att bedöma hälsorisker vid exponering av vattendraget Msunduzi. Frågor som har analyserats är hur koncentrationen av *E. coli* varierar över tid, vilka de största källorna till fekala föroreningar är i det studerade området samt på vilka sätt människor exponeras av vattnet i Msunduzi. Hydrologisk modellering har gjorts med hjälp av Soil and Water Assessment Tool (SWAT) och riskbedömning med Quantitative Microbial Risk Assessment (QMRA). Resultat från SWAT-simulering visade ett tydligt mönster mellan flöde och *E. coli* utifrån årstid, medan uppmätta värden på *E. coli* och vattenflöde inte visade samma mönster. För att bättre kunna använda modellen till att analysera spridning av *E. coli* behövs vidare undersökning av de föroreningskällor som påverkar vattnets mikrobiella kvalitet. Kalibreringen av SWAT-modellen misslyckades, främst på grund av bristfälliga indata gällande jordarter, markanvändning och väderförhållanden. SWAT-modellen kan förbättras genom vidare undersökningar av markanvändning och jordarter i området och etablering av fler väderstationer. Riskanalys gjordes för människor som exponeras av vattnet genom tvättning och simning där resultatet visade att vattenkvalitén i Msunduzi är dålig jämfört med EU:s restriktioner. Ett exempel på hur riskbedömningen kan utvecklas är mer undersökning av hur mycket vatten som intas vid olika exponeringar. Resultat från studien visar den stora risken att bli infekterad vid exponering av vattnet i Msunduzi, vilket bekräftar att åtgärder måste vidtas.

Nyckelord: Sydafrika, hälsorisk, vattenkvalitet, *E. coli*, hydrologisk modellering, SWAT, riskbedömning, QMRA

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1. Introduction

One of the seventeen Global Goals for Sustainable Development, set by the United Nations General Assembly, is to ensure availability and sustainable management of water and sanitation for all people, to a fair price (UN, n. d.-b). Available clean water and sanitation is a fundamental requirement for all humankind as well as a human right (WHO, 2018).

Although the basic need of clean water, sanitation and hygiene is a human right, still millions of people are yearly affected with diseases caused by the lack of access to these basic services (UN, n. d.-a). An approximation is that more than 80 % of the world's wastewater is led out in the environment without treatment (Connor et al., 2017). Among the people of the world not having access to basic sanitation facilities, about 892 million people must defecate in the open environment (WHO, 2018). Other sources to faecal pollution of surface water are grazing animals and land use activities using manure or slurry as fertilizer. Pathogenic microorganisms from animal faeces get into the water either directly or indirectly through surface runoff after rainfall or heavy irrigation (Hubbard, Newton & Hill, 2004).

An example of illness that can be transmitted to humans due to inadequate sanitation is diarrhoea (WHO, 2018). Diarrhoea is a common symptom of intestinal diseases. More than 2 million people die annually from diarrhoea, and the United Nations estimates that about 90 % of those deaths are caused by poor hygiene and unsafe water (UN, n. d.-a).

Many surface water sources in the sub-Saharan region of Africa are microbial unsafe for domestic use due to faecal pollution (Van Abel & Taylor, 2018). Although diarrhoeal pathogens remain a serious cause of deaths in developing countries, the majority of microbial data are collected in high income countries. Furthermore, the possibility to understand the extent of the issue is thereof limited, and the human health risks in this aspect remain widely unknown.

South Africa is a country in the sub-Saharan Africa region that in 2016 had intestinal infectious diseases in the top list of underlying natural causes of death (STATSSA, 2018). In 2016, according to Statistics South Africa (2018, p. 37), intestinal infectious diseases were the third and second most common cause of death of South Africans under one year old and in the age group 1 to 14 years old, respectively. Since 1994, the South African government has put a lot of effort in building up the water infrastructure in the country (Luyt, Tandlich, Muller & Wilhelmi, 2012). Many improvements have been made to make clean water and sanitation available, but the progress does not guarantee public health. In 2010, 89.3 % of the population had access to piped and tap water inside, or within 200 m, of their homes, which was almost a five-percentage point increase compared to 2002. Although the access to piped water increased, not all waterborne diseases decreased, e.g. the number of deaths due to intestinal infectious diseases rose between the years of 2000 and 2007, from 14,276 to 37,398 deaths. A lot of factors must be considered to identify the explanation in complex fields like water quality related death, and there are no simple answers. A fragment of the explanation can be what a report by Lehohla (2011) points out. Even though the households have access to the water pipes, there is not always water supply (Lehohla, 2011). For example, 47.6 % of the households in South Africa in 2010 could state that interruptions of the water supply had occurred, and that 36.2 % of those interruptions had lasted more than 15 days at a time (Luyt et al., 2012).

As mentioned earlier, the sources of faecal pollution of surface water arise from a variety of activities. The ability to handle and manage the different levels of sources varies, e.g. managing agricultural sources are more difficult than managing human faecal sources from broken sewage systems (Oliver et al., 2016). Different agricultures require both different amount of manure and irrigation. Manure lands are both irrigated under human control and by rainfalls which are impossible to exactly predict a long time in advance. In other words, there are often external reasons that contributes to the actual microbial pollution from a specific pollution source that eventually enters the study object.

Having to comprehend all the factors affecting microbial water quality is a complex assignment for water managers, but there are tools like hydrological models that can guide in decision-making (Oliver et al., 2016). Several watershed-scale hydrological models are available for water quality modelling, and their strengths vary for different application areas (Cho et al., 2016; Devia, Ganasri & Dwarakish, 2015). Applying models can be cost-effective, and simulations can be made for specific scenarios and over time. The available models still have potential for improvement, including overall knowledge and understanding of faecal pollution. Although the characteristics, like fate and transport, of faecal pathogenic microorganisms are not yet fully described, application of models plays an important role in understanding microbial water quality (Oliver et al., 2016).

Microbial water quality can be analysed in many ways, and one of these is to assess the human health risks due to the use of polluted water. The WHO plays an important role in providing leadership in health issues of the world, including the topic "Water, sanitation and hygiene". Their objectives in the mentioned topic are, among others, to prevent the human burden of water and sanitation related diseases through authoritative statements on water quality management, publication of guidelines and research of methods that can be applied in this field(WHO, n. d.). One of the guiding documents for water, sanitation and health is about approaches and methods for assessing microbial safety of drinking water (WHO, 2003). The approaches mentioned for risk assessment are epidemiological methods, Quantitative Microbial Risk Assessment (QMRA) and qualitative risk assessment, and these methods can also be applied to assess microbial safety of water for recreational use.

This report focuses on 1) to build a hydrological model for a faecally polluted river in order to analyse the microbial water quality and 2) to assess the human health risks caused by exposure to water from the river. The modelling of the river was done using the Soil and Water Assessment Tool (SWAT), and the risk assessment approach used was QMRA.

1.1 Aim and Objectives

The aim of this project was to assess the human health risks due to exposure to water from Msunduzi river. The objectives were to create a hydrological model in ArcSWAT and to use the risk assessment method Quantitative Microbial Risk Assessment on pathogenic *Escherichia coli* (*E. coli*). Msunduzi river flows through Msunduzi Municipality, KwaZulu-Natal, South Africa. The research questions were:

- How do the *E. coli* concentrations vary in the river during the year? Can patterns of concentration peaks and lows be identified?
- Which are the main sources of faecal pollution in the river?
- How do people get exposed to the polluted water and what are the risks of getting infected by pathogenic *E. coli*?

1.2 Limitations

The data used in this project were already available, and no field measurements were performed in this study.

This study is limited to faecal pollution, while other pollutants, such as chemicals, microplastics and pharmaceuticals, are beyond the scope of this project. Furthermore, the study will focus on pathogenic *E. coli*.

This report will analyse the human health risks posed by the pathogenic *E. coli* present in Msunduzi river, but it will not include evaluations or suggestions on solutions of how the water quality should be improved. The results of the report can hopefully serve as input for further analysis of the potential mitigation actions.

2. Theory

This section describes *E. coli* as a faecal indicator and as a pathogen, the Soil and Water Assessment Tool for hydrological modelling, and quantitative microbial risk assessment approach for estimating the health risk due to exposure to polluted water.

2.1 *Escherichia coli*

E. coli is a bacterium which lives naturally in the human and animal intestine. Most of the *E. coli* types do not cause illness, the presence of the bacterium is therefore not necessarily a health risk (Nataro & Kaper, 1998). However, some strains of the *E. coli* have got the ability to cause diarrhoea, which for some people can be life threatening (Hart, Batt & Saunders, 1993). Not all waterborne pathogens can be detected easy and reliably. Since *E. coli* indicates presence of faecal pollution and can be detected with simple methods, it is often used as an indicator of the overall microbial quality of drinking and surface water (Fewtrel & Bartram, 2001).

2.2 General description of SWAT

SWAT is a hydrological river basin or watershed scale model developed by Dr. Jeff Arnold for the U.S. Department of Agriculture (USDA) in the early 1990s (Gassman, Reyes, Green & Arnold, 2007). ArcSWAT is an add on to the Geographic Information System (GIS), and it is an ArcGIS-ArcView extension and interface for SWAT.

The two main types of map files used for spatial data in ArcSWAT are raster files and vector files. SWAT is a tool developed with the aim to simulate water quality and sediment content due to different land uses and wastewater discharges (Gassman et al., 2007). By using SWAT, many processes in a watershed can be simulated in order to study long-term impact of soil and land use management on water flow and water quality (Neitsch, Arnold, Kiniry & Williams, 2011). SWAT models a watershed area with help of specific information, i.e. weather, soil properties, topography and land use. The mentioned information is needed to model the physical processes tied to water movement, sediment movement, pollution transport, nutrient cycling, etc. The model can provide outputs that are interesting for water quality studies, such as spread of bacteria in the watershed (Neitsch et al., 2011).

2.2.1 SWAT model set up

SWAT divides the watershed into different subbasins, and further each subbasin is divided into Hydrologic Response Units (HRSs) based on land use, soil types and slope characteristics (Neitsch et al., 2011). The data needed to run the SWAT model are added in four steps: Watershed Delineation, HRU Analysis, Weather data definition and Edit SWAT input.

The aim of the *Watershed Delineation* step is to determine the hydrological system in the study area and create limits for the main watershed, and further divide the watershed into several subbasins. The watershed is defined by the Digital Elevation Model (DEM) that contains the topographic data in raster format. When the watershed is defined, SWAT can for each subbasin automatically build more parameters, such as the initial stream network and outlet/inlet for each subbasin. The user can refine those parameters if necessary. Further, SWAT calculates the flows, the flow directions and accumulation in the watershed. When this step is done, the model has several layers that describe the stream network and the subbasins as independent entities. SWAT compiles a topographic report including the details about the elevation data for the watershed, topographic details about the water flows and their directions, and inlet/outlet for each subbasin (Winchell, Srinivasan, Di Luzio & Arnold, 2013).

The aim of the *HRU Analysis* step is to describe the terrain of the subbasins and link each subbasin with its unique land use and soil types, and to evaluate slope characteristics. When the required information is added to the model, the subbasins are divided into Hydrologic Response Units (HRSs), to separately define the different land areas, which contain different types of land use and different soil classes. Then, this information is aggregated and put together to determine the classification of land use, soil and slope combinations for the whole watershed and respective subbasin (Arnold et al., 2013). The land use and soil data are added to the project by two steps. First, the land use and soil layers are defined using dataset in raster format in order to link these data to the current watershed, and then the category values of land use and soil are associated to these layers. Before the HRU division is performed, the user needs to determine slope classifications. After the land use, soil and slope are reclassified, the model describes these parameters through layers and a detailed report (Winchell et al., 2013).

The aim of *Weather Definition* step is to associate the divided subbasins with their weather conditions. The required input is added in tables containing data on relative humidity, solar radiation, rainfall, temperature and wind speed (Winchell et al., 2013).

The aim of *Edit SWAT Input* is to add and define microbial organisms, pollutants and management practices of interest in the study. For example, it is possible to add wastewater treatment plants, grazing animals and manure applications. When this step is done, the model is ready for simulation. Simulation of the model can provide outputs through many detailed reports including information such as water flow, pollution concentration and how pollutants are transported with the water. The users have the opportunity to regulate the outputs characteristics such as type of output, time period and time frequency (Winchell et al., 2013).

2.2.2 Calibration and validation

Before the model can be used in real-world applications, calibration and validation are required to optimise the model. This can be done by comparing simulated and observed water flow in specific points. The first step in the calibration process is sensitivity analysis, which is a process to determine how different parameters affect the performance of the model. After analysing the sensitivity of the parameters, the most sensitive are used for calibration.

The calibration is performed by carefully changing values of identified parameters within the acceptable range and comparing the calibrated output with the observed data. The users can perform this step using a calibration software (SWAT-cup) or manually using Microsoft Excel.

The last step is validation which is a process to confirm that the model is successfully calibrated. This is done by comparing observed and simulated data that have not been used in the calibration process to confirm that the model performance is representative for another time period (Arnold et al., 2012).

The most common statistics used for reporting calibration and validation in SWAT modelling are NSE and R^2. The NSE values can range between $-\infty$ and 1, where 1 represents a perfect match between observed and simulated data, and values over 0.5 are considered as satisfactory values for hydrological evaluation performed on a monthly time step (Arnold et al., 2012). The R^2 can range between 0 and 1, where 0 represents no correlation, and 1 represents perfect correlation. R^2 describes how much of the observed data that is explained by the model prediction (Krause, Boyle & Bäse, 2005).

2.3 QMRA

QMRA is a tool that assesses the human health risk from exposure to polluted water (Abia, Ubomba-Jaswa, Genthe & Momba, 2016) and is known as a valuable tool for setting health-based targets (WHO, 2004**).** QMRA results in an estimation of the risk presented either as probability of infection or as Disability Adjusted Life Year (DALY). DALY is a complementary tool to risk assessments which evaluate a global or local burden of diseases (Gao, Wang, Chen, Ngo & Guo, 2015). The results of QMRA can present risks in a simple way and can be used to compare with other values, to give clear understanding. QMRA has been used successfully in studies similar to this study (Timm, Luther, Jurzik, Hamza & Kistemann, 2016; Van Abel & Taylor, 2018) and is known to play an emerging role in guiding water supply and innovation (Bichai & Smeets, 2013). QMRA includes four steps, i.e. hazard identification, exposure assessment, dose-response and risk characterization; these steps are described below.

In the first step in the QMRA process, hazard identification, the problem is formulated. It includes determination of the pathogen(s) of interest together with decision of what conditions to be investigated. The sources and the possible transmission routes for the pathogen must be considered. Understanding of the process, from exposure to infection, and also of the health outcomes are required.

The purpose of the second step, exposure assessment, is to determine the amount of the pathogen associated with an exposure. This amount is determined by the transmission routes and conditions identified in the problem formulation. The concentration of the pathogen and its fate before the exposure, e.g. whether there are any barriers along the transmission route that reduce the concentration, need to be known. The exposure can be seen as a single one or a set of exposures. In addition to the expected dose, an evaluation of statistical distribution of the doses is of interest.

The purpose of the dose-response step, also called the health effects assessment, is to link the exposure dose to the likelihood of occurrence of a negative consequence. The consequence can be infection, illness, severe illness or death. There are different models that can be used for calculating the risk of infection. The two most common are the Exponential Dose-Response Model and the Beta-Poisson Dose-Response Model (Equation 1). The Beta-Poisson model is more complex than the exponential model since, unlike the first mentioned, it takes into account that different people may be affected differently by the same pathogen dose.

The Beta-Poisson Dose-Response Model:

$$P(d) = 1 - [1 + \frac{d}{N_{50}}(2^{\frac{1}{\alpha}} - 1)]^{-\alpha} \qquad \text{(Equation 1)}$$

P(d) - risk of infection
d - concentration of the pathogen ingested in a known volume
N_{50} - median infection dose representing the number of organisms that will infect 50 % of the exposed population
α - dimensionless infectivity constant

To calculate the probability of the risk after multiple exposures, Equation 2 can be used:

$$P(m) = 1 - (1 - P(d))^{n} \qquad \text{(Equation 2)}$$

P(m) - risk of infection after multiple exposure
P(d) - risk of infection from a single exposure to a dose d of the pathogen
n - times of exposure

There are situations when exposures from different sources occurs at the same time. Equation 3 describes the calculation of that combined risk:

$$\eta_t = 1 - (1 - \eta_A)(1 - \eta_B) \qquad \text{(Equation 3)}$$

η_t - combined risk of infection
η_A - infection risk resulting from exposure A
η_B - infection risk resulting from exposure B

The last step in QMRA, the risk characterisation, is performed based on the results from the three first steps - hazard identification, exposure assessment and dose-response assessment. Examples of results that can be of relevance are: expected number of illnesses in a community, or the upper confidence limit for illness to a “highly exposed” individual.

Results from QMRA can be used in risk management, where the intention is to reduce or eliminate the risk. This can be made through different strategies, for example cost-benefit analysis or decision analysis (Romero-Barrios, Hempen, Messens, Stella & Hugas, 2013).

3. Methodology

The overall method for the project was to study microbial water quality by creating a hydrological model using the ArcGIS based software SWAT and to assess the health risk for people exposed to the water using QMRA. The study area was Msunduzi river in the province KwaZulu-Natal, South Africa.

3.1 Study area

The watershed of Msunduzi river is located in uMgungundlovu district, KwaZulu-Natal province in South Africa. KwaZulu-Natal can be divided into three geographical regions depending on terrain, i.e. the low land region by the coast, the KwaZulu-Natal (KZN) Midlands, and the third region, which consists of two high mountainous areas - the Drakensberg in the west and the Lebombo Mountains in the north. The study area is located in the KZN Midlands, which is an inland area characterised by rolling hills, forest and green pastures, situated between the east coast and the mountains in the west. The region is considered one of South Africa's principal agro-ecological regions. The main agricultural production in the area are commercial forestry in the cooler higher elevations, commercial and subsistence crop production as well as livestock farming (Strydom & Savage, 2018). The watershed that was studied in this project (Figure 1) is 898 km^2 and includes two municipalities. The major part of the watershed lies within Msunduzi municipality (uMgeni Water, 2018) which has a population density 976 persons/km^2 (STATSSA, 2011) and in the east it includes a small part of Mkhambathini municipality (uMgeni Water, 2018).

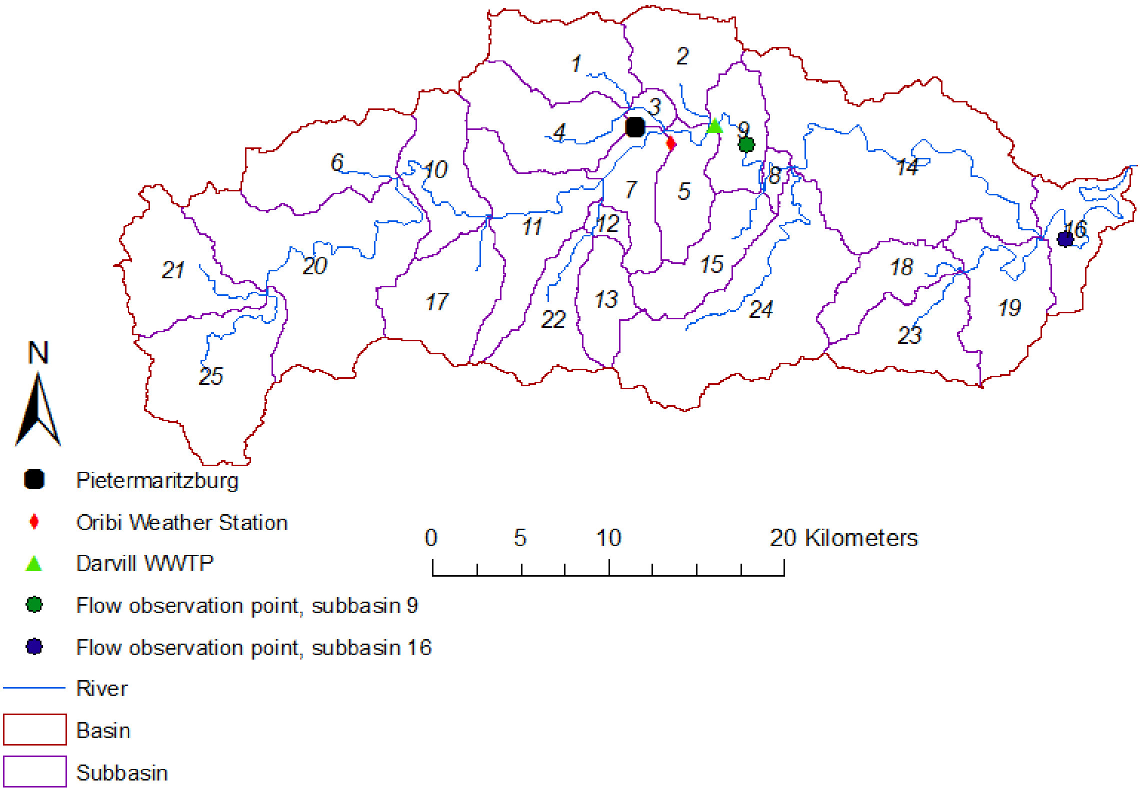

Figure 1. Map of Msunduzi watershed.

Msunduzi river flows from the west and exits the watershed in the east. The landscape in the watershed varies in character, and the river flows through rural areas, agricultural areas, forests, wetlands and urban areas. The river passes through the centre of Pietermaritzburg, which is the capital of the province and has a population of 223,448 people (STATSSA, 2011).

The standard of living along the river is very varied. Some people are on a daily basis dependent on the water from the river which they use for e.g. laundry, swimming, irrigation and industries. Msunduzi river itself does not serve as a drinking water source but the water eventually flows out, via Umgeni river, to the main drinking water source, Inanda Dam, of the KZN Midlands, supplying e.g. the major urban areas Durban and Pietermaritzburg with high quality water (uMgeni Water, 2018).

There is one wastewater treatment plant within the watershed, Darvill WWTP, which serves around 300,000 persons in Msunduzi Municipality (Matongo, Birungi, Moodley & Ndungu, 2015). According to uMgeni Water (2018), the average daily inflow (November 2012 to November 2017) to the treatment plant is approximately 76,000 m^3/day. Until year 2016, the capacity of the WWTP was only 65,000 m^3/day, which means that the WWTP often operated above its capacity and the system was flooding, releasing untreated wastewater directly to Msunduzi river. During 2016, the WWTP was upgraded to a new design capacity of 100,000 m^3/day with the optimal operating capacity of 80,000 m^3/day. An analysis for the new upgraded WWTP showed that it operated above its optimal capacity 18 % of the time and above the new design capacity only 3 % of the time (uMgeni Water, 2018).

The climate in the study area is considered as a subtropical oceanic climate zone with cool dry winters and warm humid summers (Strydom & Savage, 2018). Statistics over the weather in the watershed are collected from the Oribi weather station, which is centrally located in the watershed (Figure 1). The precipitation within the watershed varies between 700 and 1,000 mm per year, and most rainfalls happen during summer (October - March), but there are also some sporadic rainfalls during winter. The maximum temperatures usually occur in the summer months of December to February, and the minimum temperatures occur in the winter months of June to July. The annual maximum, minimum and mean temperatures are around 40, 0 and 15 degrees celsius respectively.

3.2 Study trip

As a part of the study, a trip to South Africa was made. The aim of the trip was to gather knowledge through partners at the Durban University of Technology about SWAT modelling and about the risk assessment approach QMRA. The trip included a field trip along Msunduzi river to understand how the water from the river is both polluted and used, based on observations and interviews of people living in connection to it.

3.3 SWAT modelling

The hydrological SWAT model was used to simulate the variation of *E. coli* concentration in Msunduzi river, in order to identify patterns of concentration peaks and lows. The model was set up for the period 2009-2013, these years were chosen since both observed water flows and *E. coli* concentrations could be obtained for this period. The simulated *E. coli* concentration was studied in two points, one in subbasin 9 and one in subbasin 16 (Figure 1). The observation point in subbasin 9 was chosen because it is located just downstream Darwill WWTP, and the point in subbasin 16 was chosen because it represents the watershed outflow. The simulated water flow and *E. coli* concentrations were compared with observed data in subbasin 9 in order to see if the pattern of *E. coli* concentration is representative of reality. No comparison with observed data were made in subbasin 16 because lack of observed data regarding water flow and *E. coli* concentration.

3.3.1 Model input and setup

The input data were collected from various sources via Z. Ngubane (personal communication, 2019) and manually prepared to be used as SWAT input (Table 1). The coordinate system used was Hartebeesthoek_1994_Albers for all maps that were used as input data in the model.

Table 1. Input data for the hydrological model of Msunduzi river

Data	File type	Resolution	Reference
Digital Elevation Model	Raster	20 x 20 m	National Geo-spatial Information (NGI)
Land use	Raster	1700 x 1700 m	South African National Biodiversity Institute (SANBI)
Soil type	Raster	100 x 100 m	Food and Agriculture Organization (FAO)
Meteorological data	Text	Daily	South African Weather Services

The DEM was used to define watershed delineation, and this defined the river outline, flow directions and subbasins. The modelled watershed was 898 km^2 divided into 25 subbasins. To create the HRU analysis report, the land use map, soil map and slope classification were combined.

The land use raster data were added to the model and then reclassified into 10 different land use classes (Figure 2). The land use area distribution was obtained from the HRU report output (Table 2).

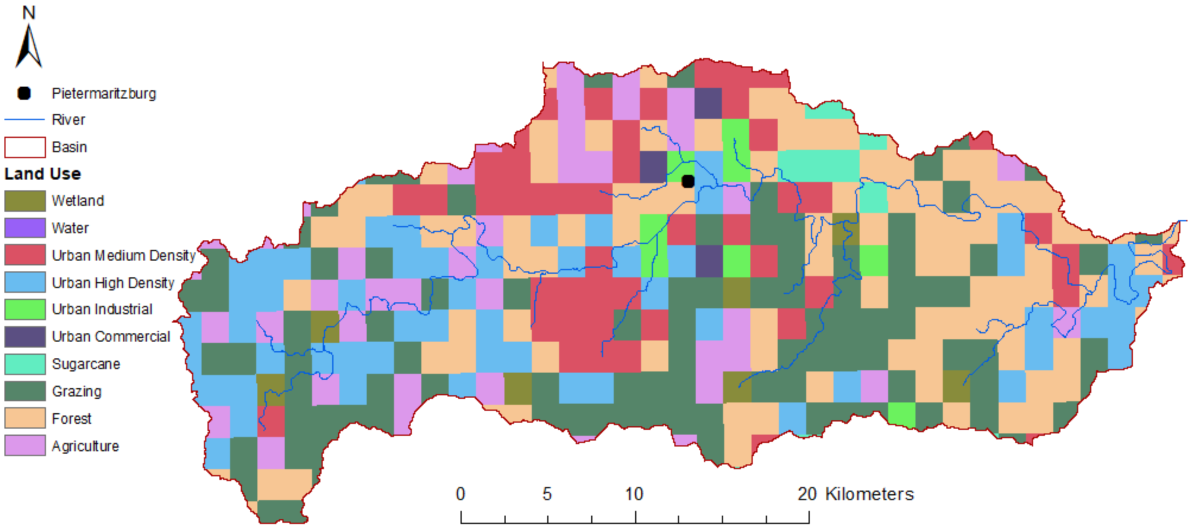

Figure 2. Land use map for the watershed of Msunduzi river.

Table 2. Distribution of the land use types in the watershed of Msunduzi river

Land use[a]	**Area [km^2]**	**% Total Area**
Wetland	18	2
Forest	233	26
Grazing	233	26
Agriculture	90	10
Urban High Density	153	17
Urban Medium Density	122	14
Urban Commercial	9	1
Urban Industrial	18	2
Sugarcane	18	2
Total	**894[b]**	**100**

[a] Water constitutes 0.0017 % of the area, that corresponds to 0.015 km^2.

[b] The total area of the land use map is smaller than the watershed because it does not overlay 100 %.

The soil map layer was added to the model to define the soil types in the area (Figure 3). The map includes four different soil types that have different depth, consist of different amounts of clay, silt, sand and rock, and have different pH (Table 3). These soil types are typical for the area and were added into the SWAT database manually.

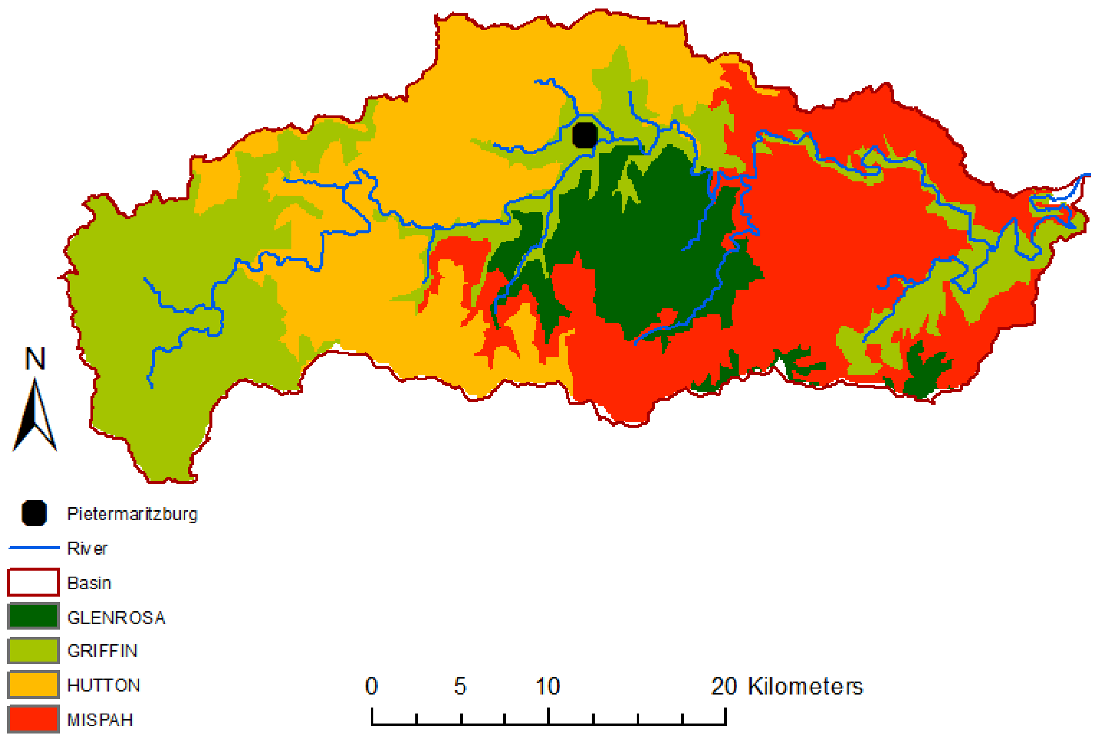

Figure 3. Soil type map for the watershed of Msunduzi river.

Table 3. Distribution of soil types in the watershed of Msunduzi river

Soil types	Total depth [mm]	Clay [%]	Silt [%]	Sand [%]	Rock [%]	pH
Hutton	1500	43	24	32	1	5.6
Glenrosa	1160	33	10	56	1	5.4
Griffin	1000	37	48	13	2	5.4
Mispah	350	17	6	57	20	6.9

Three slope classes were defined: 0-1 %, 1-10 % and >10 % (Figure 4). HRU limits were set to 5 % for land use, soil types and slope class, which means that all areas with less than 5 % rate will be neglected and added to a nearby HRU.

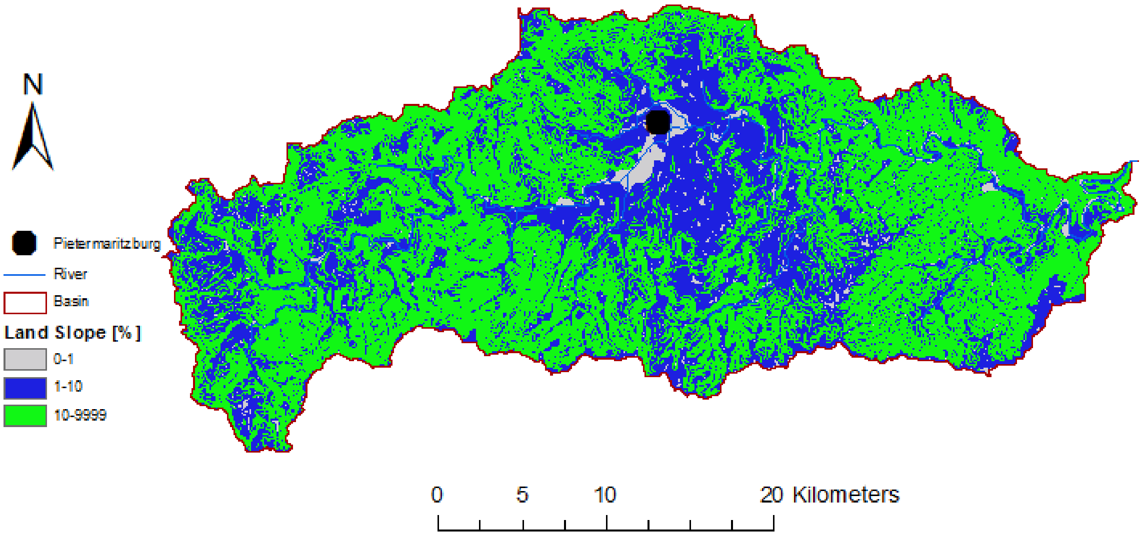

Figure 4. Slope classification map for the watershed of Msunduzi river.

Meteorological data were collected from Oribi weather station, which is located east of Pietermaritzburg (Figure 1). The weather data ranged from 1998-04-01 to 2018-12-31. The data on precipitation, humidity, wind and temperature were available from the previously mentioned weather station, while the solar radiation was simulated data from the Global Weather Database WGEN_CFSR_World. The database contains data that covers the whole world; in ArcSWAT, the data closest to the current area are selected.

3.3.2 Microbial input

The microbial input in the model considered faecal pollution sources. The microbial organism that was studied in this project is *E. coli*.

During the field trip to the watershed area, several faecal pollution sources were identified, e.g. trash dumping spots where diapers could be identified, grazing animals, Darwill WWTP, outhouse dry toilets, and untreated wastewater from informal settlements. Since one of the research questions of this project was to assess how the *E. coli* concentrations in the river vary during the year, a decision was made to only use Darwill WWTP as a pollution source in the SWAT model. It was difficult to find reliable data regarding the other identified pollution sources.

Darwill WWTP was put into the model as a point source, and the function “persistent bacteria” represented the *E. coli* concentration. The discharge from the WWTP was set to a constant value of 76,000 m^3/day based on incoming mean water flow reported by uMgeni water (2018). All water released from the WWTP was considered treated, and discharges such as flooding from combined sewer overflows were not included in the model. The *E. coli* concentration in treated wastewater was set to be 1.0E4 *E. coli*/100 ml, based on an incoming mean

concentration 1.5E6 *E. coli*/100 ml and a removal of 2.4 Log10 units in the wastewater treatment plant (Bergion et al., 2017).
The fate and net transport of *E. coli* in the river depends on different factors, which in SWAT are described using the function "persistent bacteria". Growth of *E. coli* was set to zero (Ohlsson et al., 2011). The decay rate of *E. coli* is calculated by SWAT based on Chick´s law first-order decay equation (Equation 4) (Baffaut & Sadeghi, 2010).

$$C_t = C_0 \cdot e^{-K_{20} \cdot t \cdot \theta \cdot (T-20)} \qquad \text{(Equation 4)}$$

C_t −*E. coli* concentration at time t, [cfu/100 ml]
C_0 −Initial *E. coli* concentration, [cfu/100 ml]
K_{20} −First-order die-off rate at 20 °C, [day^{-1}]
t - Exposure time, [days]
θ −Temperature adjustment factor, [-]
T - Temperature, [°C]

K_{20} and θ need to be defined in SWAT for the organism that is studied, in this case *E. coli.* Used values are presented in Table 4.

Table 4. SWAT parameter values for die-off (K_{20}) and temperature adjustment factor(θ)

Parameter	**SWAT abbreviation**	**Unit**	**Value**
Die-off in soil solution	WDPQ	1/day	0.201[a]
Die-off in streams (moving water)	WDPRCH	1/day	0.35[a]
Die-off adsorbed to soil particles	WDPS	1/day	0.23[a]
Die-off on foliage	WDPE	1/day	0.016[a]
Temperature adjustment factor	THBACT	-	1.08[b]

[a] (Bougeard et al., 2011)

[b] (Iqbal & Hofstra, 2018)

3.3.3 Calibration and validation

The model was calibrated using the data for water flow in the river. The simulated flow was compared with observed flow in two observation points, subbasin 9 and subbasin 16. Observed data were available during 2000-2013 and 2000-2002 for subbasin 9 and 16, respectively. First, the uncalibrated model was run for 2000-2013, with 1999 as a warm-up period, and validation was performed for both observation points, in order to assess the performance of the original model. The simulations were performed on a monthly time step, and the values compared were therefore monthly mean water flows [m^3/s]. For the uncalibrated model, the simulated base flow was too low and the peaks were in general too high, compared to the observed flow (Figure 5). NSE and R^2-values were calculated using Microsoft Excel. NSE was calculated using Equation 5, and R^2 was calculated automatically by Excel when comparing time series in a graph for observed and simulated water flow. The validation resulted in unsatisfactory values for both observation points (Table 7).

$$NSE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - O_{ave})^2} \qquad \text{(Equation 5)}$$

O_i − Observed water flow for time period i.
P_i − Simulated water flow for time period i.
O_{ave} − Observed mean water flow for the whole time period.
n − Number of time periods.

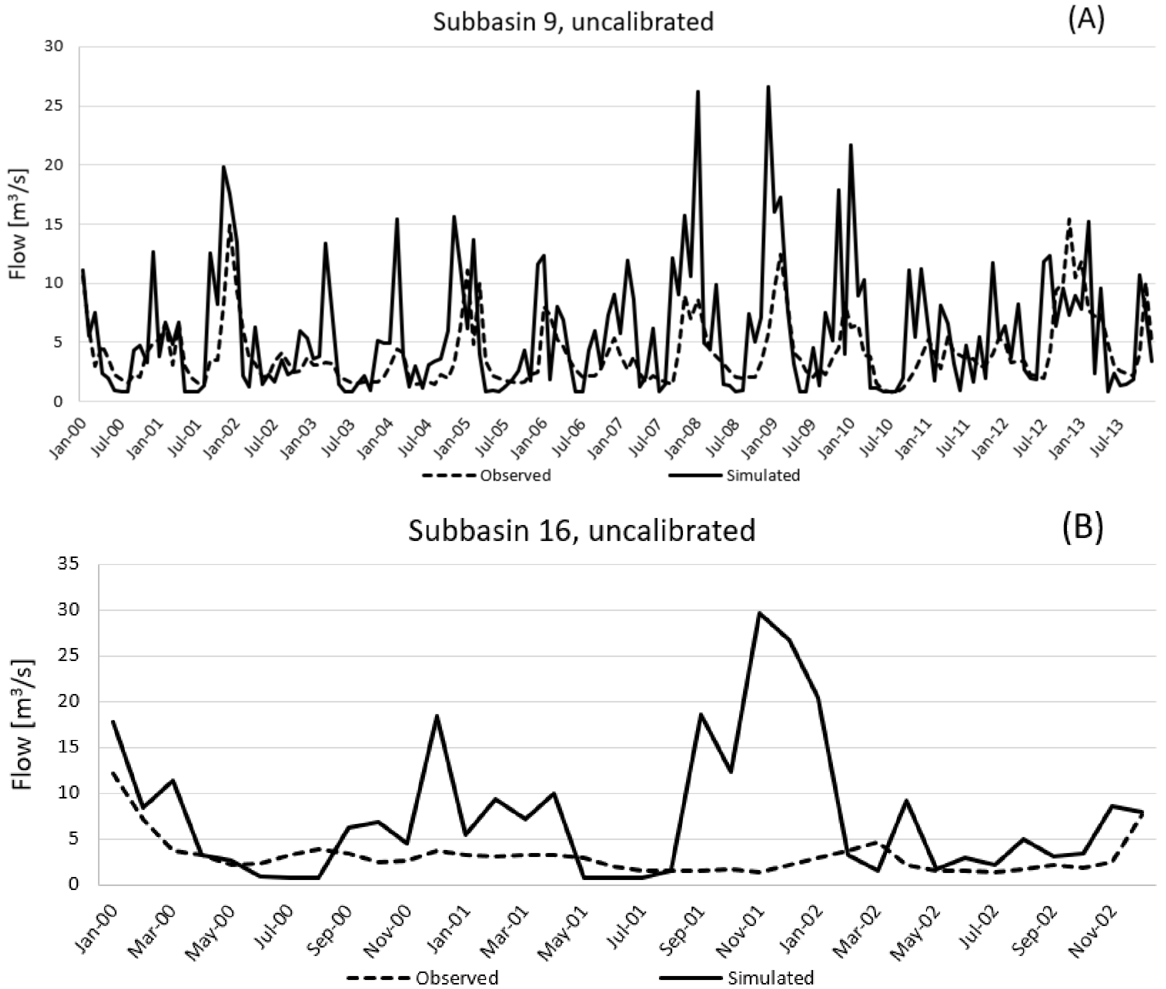

Figure 5. Water flow comparison for uncalibrated model: Simulated and observed water flow in subbasin 9 (A) and subbasin 16 (B).

The method used to improve the performance of the model was manual calibration in Microsoft Excel. For subbasin 9, a decision was made to calibrate for 2000-2008 with 1999 as a warm-up period, and then validate for 2009-2013, with 2008 as a warm-up period. For subbasin 16, the observed data were available only for 2000-2002, therefore no validation was made for another period.

The first step in the calibration process is sensitivity analysis. This step is to identify which parameters have the most influence on the performance of the model, in order to decide which parameters to calibrate. Nine different parameters were included in the sensitivity analysis (Table 5). The choice of parameters was based on literature and earlier studies (Arnold et al., 2012; Brouziyne, Abouabdillah, Bouabid, Benaabidate & Oueslati, 2017; SWAT, n. d.), and the aim was to increase the base flow and decrease the high peak flows.

Table 5. Parameters included in the sensitivity analysis

Parameter	**Description**
Gwgmn	Threshold depth of water in the shallow aquifer required for return flow (mm)
Gw_revap	Coefficient for water movement from shallow aquifer into the unsaturated zone (-)
Gw_delay	Groundwater delay time (days)
Revapmn	Threshold depth of water in the shallow aquifer required for bottom–up water movements (mm)
Sol_awc	Available soil water capacity (mm H_2O/mm soil)
Esco	Soil evaporation compensation factor (-)
Sol_K	Saturated hydraulic conductivity (mm/h)
Cn2	Curve number (-)
Alpha_bf	Base flow recession constant (-)

The sensitivity analysis was made in a copy of the model, and the values for each of the analysed parameters were changed several times to see the response of the model. The values of the parameters were changed to the same for all subbasins, soil types and land uses. The parameters can be changed by three different methods – replace the value, add on to the default value, or multiply the default value by a number. After analysing the sensitivity for each parameter, the four most sensitive parameters were chosen for calibration (Table 6).

Table 6. The most sensitive parameters that were used in the calibration

Parameter name	**Method**	**Min**	**Max**	**Value for calibration**
Cn2	Replace	35	98	60
Sol_K	Replace	0	100	10
Gwgmn	Replace	0	5000	4500
Esco	Replace	0	1	0.9

The calibration and validation in both subbasin 9 and subbasin 16 (Figure 6) resulted in improved but still negative NSE-values (Table 7). Since the NSE-values are below 0.5, the model performance is still unsatisfactory.

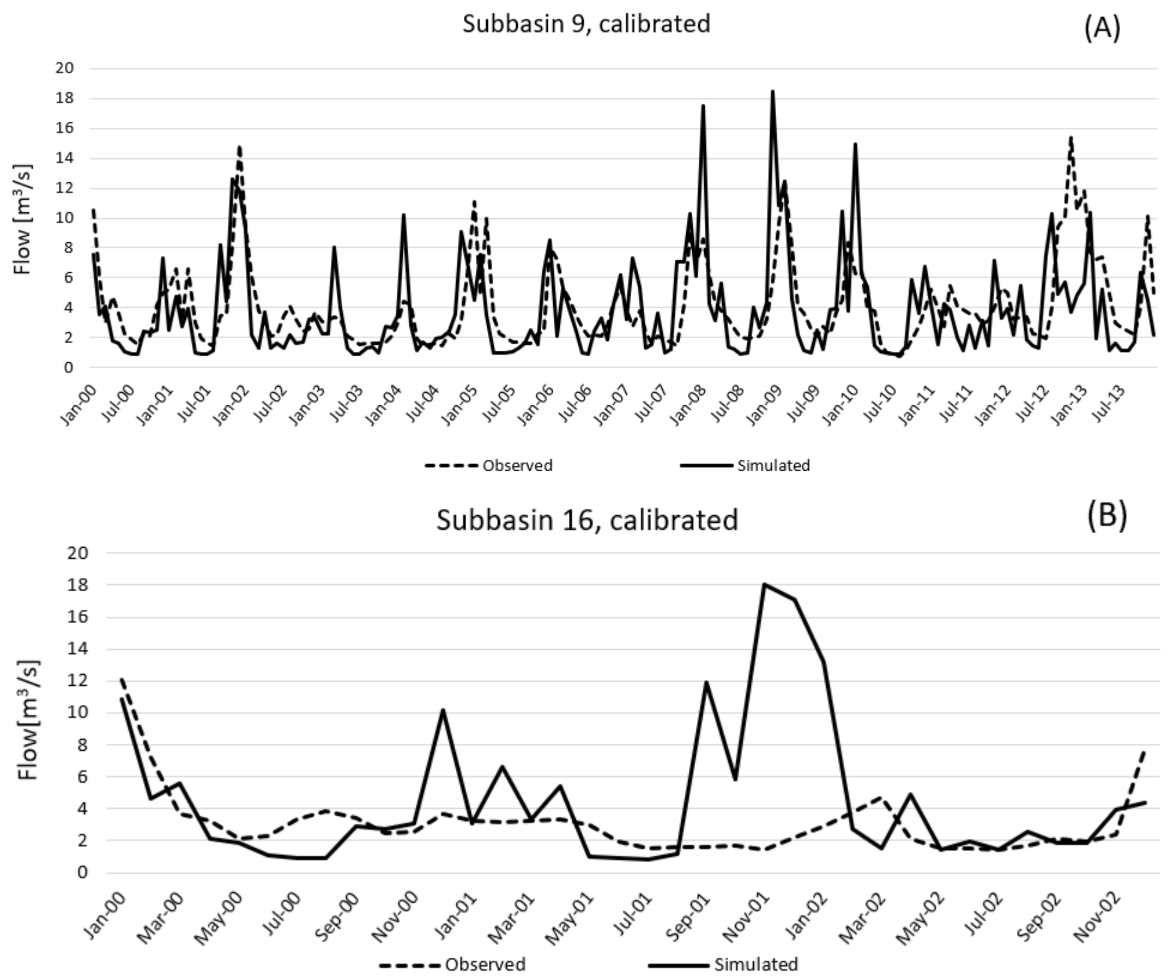

Figure 6. Calibrated water flow comparison: Simulated and observed water flow in subbasin 9 (A) and subbasin 16 (B).

Table 7. Model performance: R^2 and NSE-values for the uncalibrated and calibrated model

Observation Point	**Period**	**R^2**	**R^2**	**NSE**	**NSE**
		Uncalibrated	**Calibrated**	**Uncalibrated**	**Calibrated**
Subbasin 9	2000-2013	0.27		-1.94	
Subbasin 9	2000-2008		0.39		-0.16
Subbasin 9	2009-2013		0.21		-0.16
Subbasin 16	2000-2002	0.02	0.02	-16.48	-4.54

3.4 QMRA

In this project, QMRA was done with help of the tool @RISK, and the results are presented as the risk of infection. @RISK is compatible with Microsoft Excel and uses Monte Carlo simulations to analyse risks. The assessment focused on pathogenic *E. coli*.

For the assessment, measured data for *E. coli* concentration from two locations in the watershed of Msunduzi river were used. One location is close to an informal settlement, Baynespruit, and the other location is in a rural area, Valley of 1000 Hills (Figure 7).

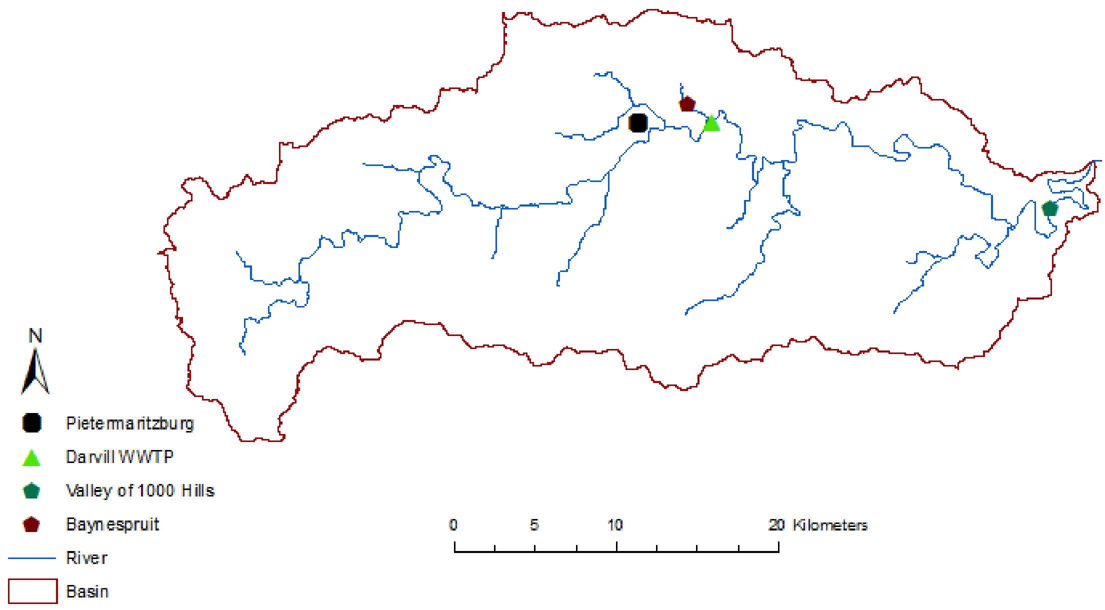

Figure 7. Location of the sampling points for E. coli concentrations.

The field trip mentioned in section 3.2 gave valuable information for the QMRA, especially for the Exposure Assessment. Observations and interviews led to identification of different activities that expose people to the water in the river. The types of exposure that were chosen for this risk assessment are swimming and doing laundry. The transmission routes that were analysed included direct ingestion of the water during swimming and ingestion through aerosols during laundry. The assumption was that swimming in the river means a major risk of ingesting pathogens, while the risk to ingest pathogens through aerosols while doing laundry is much smaller. This gave a wide range of how the risk of being infected can be distributed.

The field trip gave information about that women are the ones often doing the laundry, and that the children like to swim in the river. Based on these insights, the QMRA was performed for the following events:

- children swimming
- women doing laundry
- annual combined exposure when women are doing laundry *and* swimming

3.4.2. Input

Some of the inputs for the calculations in the risk assessment were retrieved from earlier studies, while other inputs were assumptions based on field trip observations.

The values of *E. coli* concentration were measured data received from uMgeni Water via Z. Ngubane (personal communication, 2019). The concentrations were measured between 2009 – 2018 in Baynespruit and Valley of 1000 Hills. In @RISK, the continuous probability distribution was chosen for *E. coli* data, since the values can vary over the whole range and should not be fixed to specific values. Further, @RISK provided and ranked the alternatives of the most suitable distributions for calculations. The Pearson type 6-distribution and exponential-distribution were chosen for calculations for Valley of 1000 Hills and Baynespruit respectively. The distributions fitted to the measured *E. coli* concentrations are presented in Figure 8.

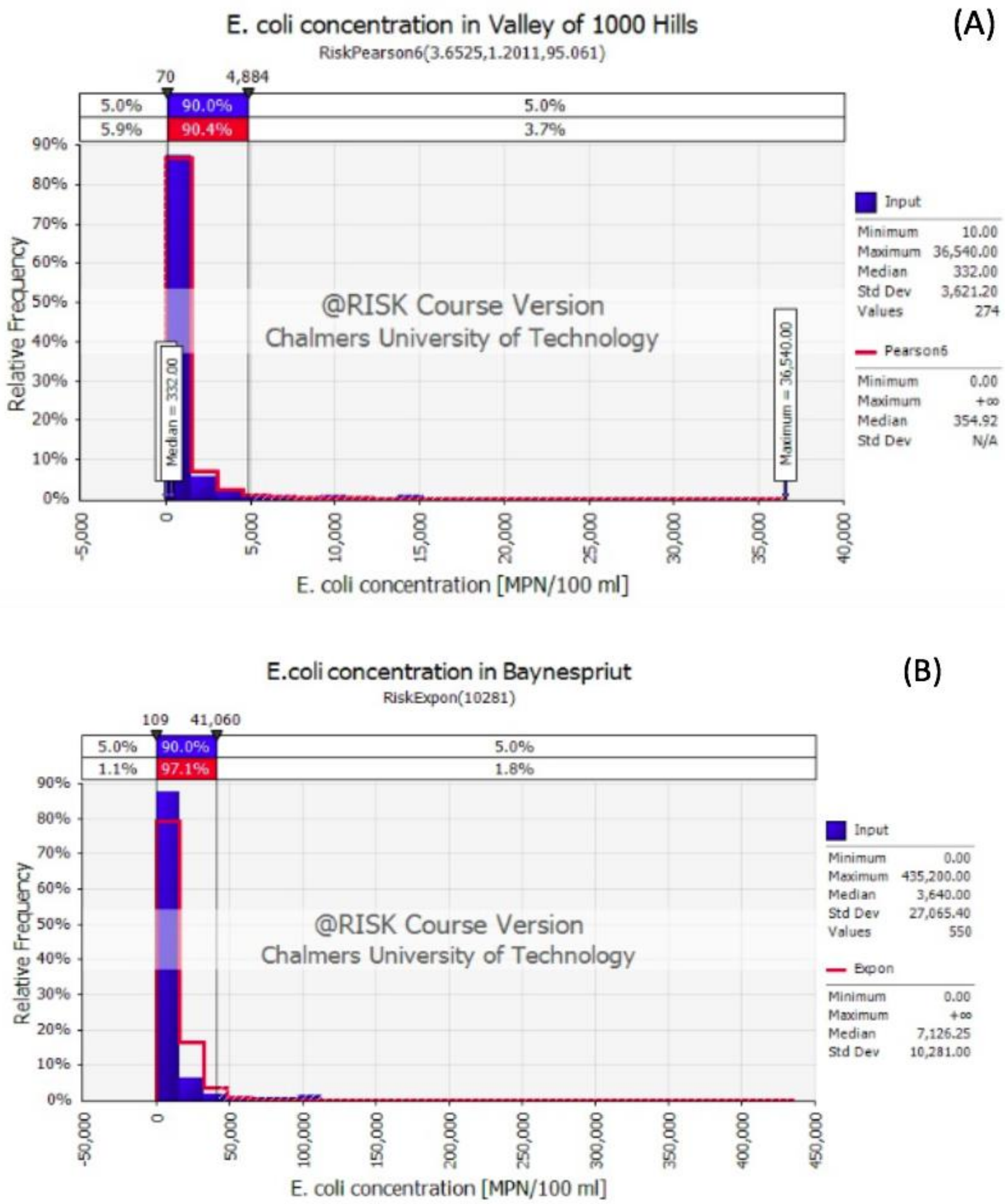

Figure 8. Probability distributions fitted to the E. coli concentrations measured in Valley of 1000 Hills (A) and Baynespruit (B).

Approximately 8 % of the total amount of *E. coli* can be considered pathogenic (Howard, Pedley & Tibatemwa, 2006). In this study, the range of 8-10 % was used to account for the uncertainty in this estimation.

The values that were used for the calculations of the dose of ingested pathogenic *E. coli* were retrieved from earlier studies (Schets, Schijven & de Roda Husman, 2011; Shi, Wang & Jiang, 2018). The amount of ingested water while swimming was assumed to be 18 - 23 ml for woman and 31 - 51 ml for children. For calculation of the dose of ingested water through aerosols during laundry, the following values were used:

- Volume of one aerosol: 1.13097E-13 ml – 8.18123E-12 ml
- Number of aerosols per litre air: 0 - 1.07E+05
- Flow rate for human breathing: 10 – 20 litre/min

The Beta-Poison Dose-Response Model was used in this study, since it takes into account the difference in infection due to the same pathogen dose among different people. The parameters used in Equation 1 for calculating the risk of infection are 2.11E+06 for the N_{50}value and 1.55E-01 for α (Dupont et al., 1971).

After evaluation of what was seen and what people living near the river were talking about during the field trip, the following assumptions were used in calculations of the dose and the risk of infection:

- Children are swimming in the river 40 - 80 times per year.
- Women are using water from the river for laundry 35 - 55 times per year.
- One laundry lasts for 1 hour.
- In both exposure cases, the pathogens do not pass any barrier that reduces the concentration.

3.4.3. Values for evaluation

In the risk characterisation and in discussion about the results from the dose-response model, the results have been compared with two benchmarks. One benchmark has been developed by European Parliament and the European Union council (EU, 2006), and the other value is from South African Department of Water Affairs, DWAF (Gemmell & Schmidt, 2013). The European Union means that if the concentration of the *E. coli* in inland water is higher than 900 cfu/100 ml, the water is assessed to have "bad quality". If the water gets the classification of "bad quality", the recommendation is to not swim in the water. DWAF has considered that if the water has a concentration of *E. coli* higher than 400 cfu/100 ml and it is used for recreational purposes, there is high risk of infection.

The values of the *E. coli* concentration from these benchmarks were used in calculations in @RISK, like the measured concentrations. It resulted in risk values that are easy to compare with the values calculated using the measured data from Baynespruit and Valley of 1000 Hills.

4. Results

This section presents the results from SWAT and QMRA.

4.1 SWAT

Figure 9 presents how the simulated *E. coli* concentration and the simulated water flow vary in subbasins 9 and 16. When the water flow peaks, the *E. coli* concentration goes down and vice versa. The peaks of water flow are higher in subbasin 16 than in subbasin 9, but the *E. coli* concentration is higher in subbasin 9 than in subbasin 16.

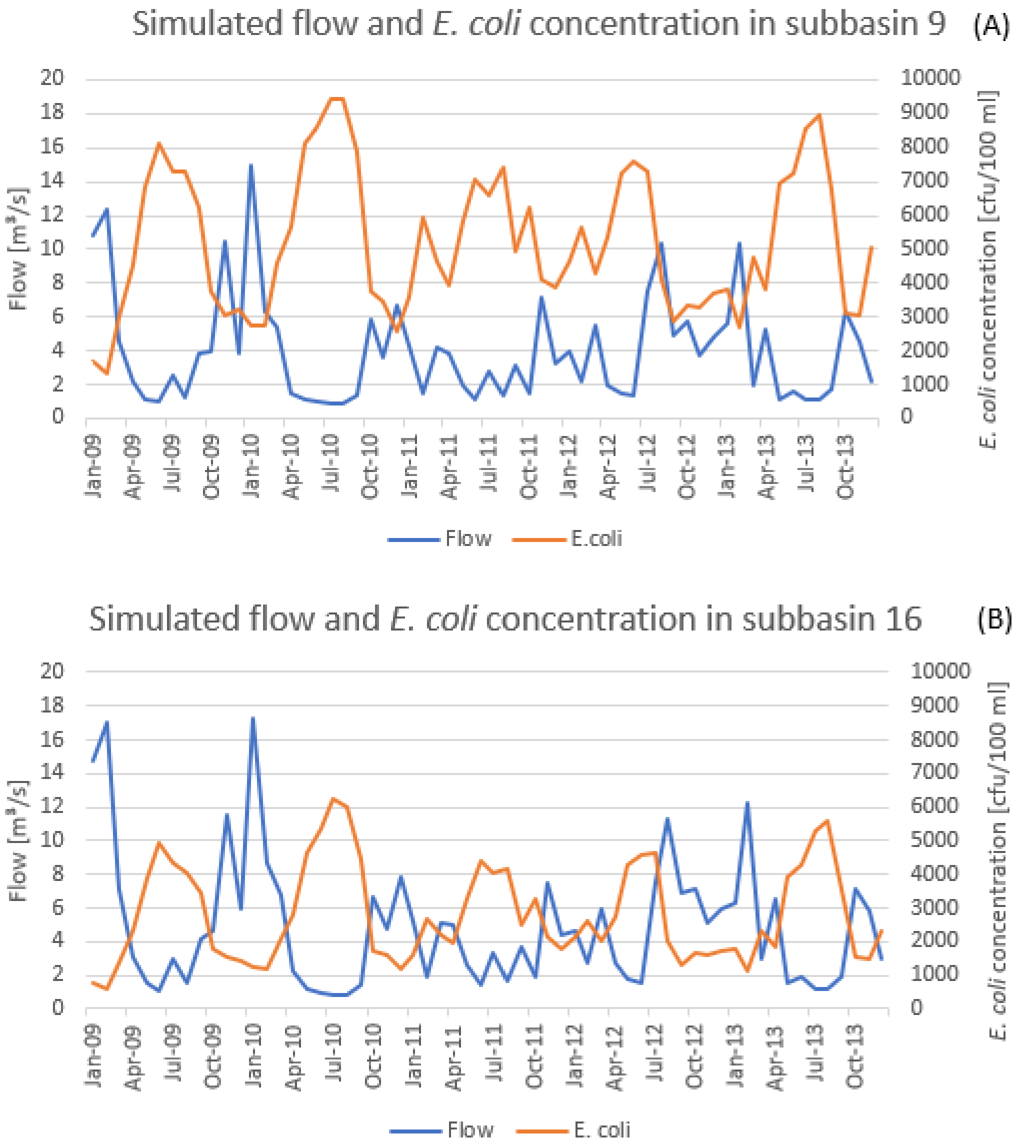

Figure 9. How the simulated E. coli concentration varies with the simulated water flow in subbasins 9 (A) and 16 (B) during a period between January 2009 and December 2013, based on monthly mean values.

Figure 10 presents how the measured *E. coli* concentration and the observed water flow vary in subbasin 9. Here it is harder to see a pattern between the water flow and *E. coli* concentration. The measured *E. coli* concentration is much higher than the simulated values, compare Figure 9A with Figure 10.

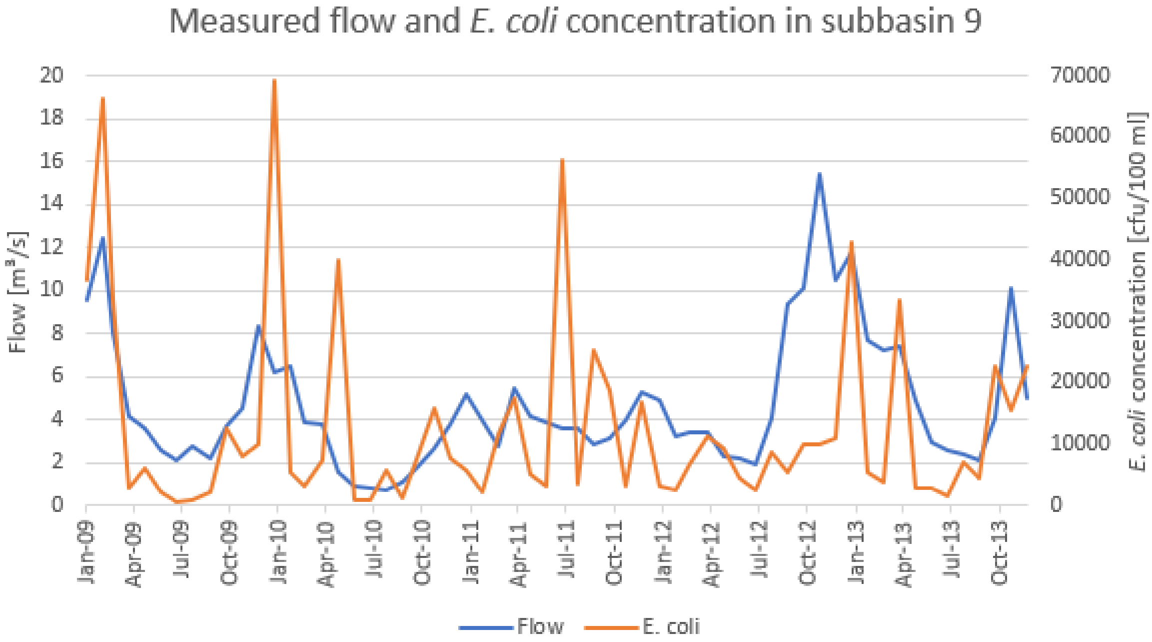

Figure 10. How the measured E. coli concentration varies with the observed water flow in subbasin 9 during a period between January 2009 and December 2013, based on monthly mean values.

4.2 QMRA

Figure 11 shows the risk of infection from pathogenic *E. coli* while children are swimming one time in Valley of 1000 Hills and Baynespruit, compared with benchmarks from DWAF and EU. Figure 11 shows both the median risk and the risk represented by the 95th percentile. For the risk characterisation, the values from the calculations are rounded up to the nearest integer since they concern humans.

The median risk in Valley of 1000 Hills is that 9/100,000 children get infected while swimming, while the 95th percentile is that 9/10,000 children get infected. In Baynespruit the median risk is that 2/1,000 children get infected, while the 95th percentile is that 8/1,000 children get infected. The results of the calculations with the benchmarks mentioned in section 3.4.3. are shown in Figure 11. According to DWAF, it is considered as a high risk if the median risk of infection is higher than if 1/10,000 children get infected, or if the 95th percentile value is higher than 2/10,000. According to EU, it is considered as a high risk of infection if the median risk or the 95th percentile value is higher than if 3/10,000 children get infected.

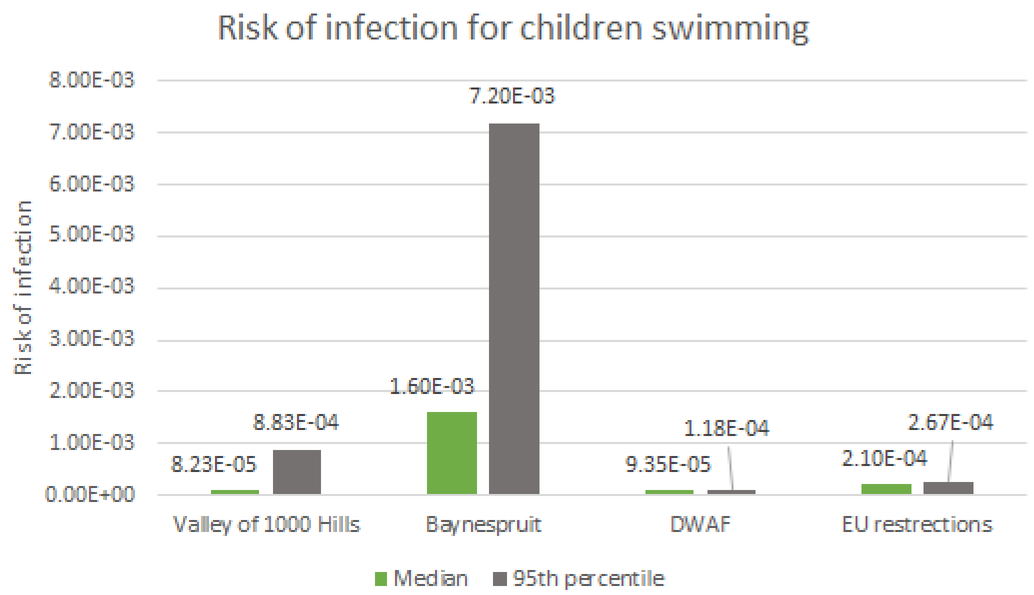

Figure 11. Risk of infection for children swimming in Msunduzi river at two different locations, compared with benchmarks from DWAF and EU.

Figure 12 presents the risk of infection for women who are exposed to the water through aerosols while doing laundry 35-55 times a year, compared with if they, in addition to the laundry, swim in the river one time during the year. The median risk for only laundry is that 3/10,000,000 get infected, and median risk for the combined exposure is that 2/1000 get infected. The higher risk, that is presented as the 95th percentile value, for only laundry is that 3/1,000,000 get infected and the high risk for the combined exposure is that 8/1000 get infected.

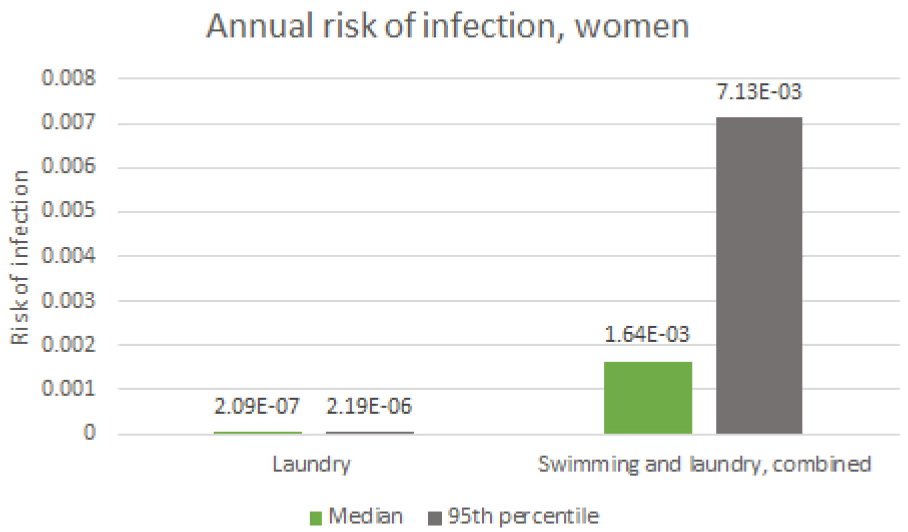

Figure 12. Annual risk of infection for a woman who is exposed to water through aerosols during laundry and the risk if she in addition to that is swimming one time during that year.

5. Discussion

In this section, discussions about the results and the method is presented. Ethical aspects that have been encountered during the project and thoughts about further studies are also included.

The method to use hydrological modelling in this kind of risk assessment is, after evaluation, not so obvious. The results from the SWAT model did not yield the valuable information for QMRA that was expected in the beginning of the study; the first intention was to use the model to evaluate how *E. coli* is transported in the watershed and to use values of *E. coli* concentration direct from the model. The major limitation was the fact that the specified *E. coli* inputs in the built SWAT model constitute just a fraction of the total inputs. Therefore, using *E. coli* concentration from the SWAT model for calculations in QMRA does not give useful values. Measured values on *E. coli* concentration are much more reliable as input data for QMRA. However, the SWAT model can be useful for rough estimates and to see patterns. The model can show relationships between different parameters like rainfall and *E. coli* concentration. In other words, hydrological modelling can be used as a complementary tool to predict occurrence of major risks. Studies regarding using SWAT to predict high concentration of pollutants have been made by others (Baffaut & Sadeghi, 2010).

5.1 Seasonal variations of E. coli concentration

The SWAT model was set up, calibrated and run with the objective to assess a seasonal pattern where peaks and lows of *E. coli* concentration could be identified dependent on seasonal variations in water flow in Msunduzi river. This was made with the aim to predict when the *E. coli* concentration in the river is high, in order to facilitate mitigation measures. The project time was limited to five months and no field measurements were made, which made it necessary to use already available data from literature and earlier studies. This led to many simplifications, assumptions and generalisations regarding weather, land use, soil types and *E. coli* concentration, which impairs the performance of the SWAT model.

The results of simulated water flow and *E. coli* concentration in Msunduzi river show a clear seasonal pattern in both subbasin 9 and subbasin 16 (Figure 9). Apart from the water flow, the temperature is another aspect that has impact on the *E. coli* concentration. The die-off of the bacteria is based on Chick's law (Equation 4) which means that the die-off increases when the temperature increase. According to the model, high *E. coli* concentration generally occur during the winter months (April - September), when both water flow and temperature are low, and the concentration decreases when the water flow and temperature are high during summer (October - March). This is a logical result based on the die-off of *E. coli* and the fact that the only pollution source in the model is Darwill WWTP. Darwill WWTP is a point source releasing a constant volume of wastewater directly into the river, so high water flow means that the concentration is diluted. When comparing the *E. coli* concentration in subbasin 9 and in subbasin 16 it shows that the concentration in subbasin 9 is higher. One reason to this is most likely that the transport time from the pollution source to subbasin 16 is longer than between the pollution source and subbasin 9, and during the transport time the *E. coli* dies off. Another reason is that the water flow is in general higher in subbasin 16 which means that the concentration is diluted.

When comparing the graph of simulated and measured *E. coli* in the same point it shows that the simulated pattern is not representative of reality (Figure 9A and Figure 10). In reality, the *E. coli* pattern is harder to identify, but in general it appears that the *E. coli* concentration increases during summer when the temperature and water flow is higher. The fact that high temperature increases the die-off of *E. coli* (Equation 4), together with results that present that high *E. coli* concentration appears when the temperature is high, indicates that temperature and furthermore die-off has less impact on the *E. coli* concentration than the water flow. Since *E. coli* concentration in reality appears to be higher during summer when there is more rainfall and higher water flow, a conclusion can be that the major part of *E. coli* comes from pollution sources connected to surface run-off, e.g. grazing animals. Seasonal variations have been described in other studies dealing with faecal pollutants (Jayakody, Parajuli & Brooks, 2014). Apart from the difference in seasonal variations between measured and simulated concentration, there is also a difference in the total amount of *E. coli,* with much higher concentration according to the measured data. This result indicates that Darwill WWTP only causes a small part of the total amount of *E. coli* in the river, and that most of *E. coli* comes from other pollution sources.

Apart from the fact that there are many pollution sources that have impact on the *E. coli* concentration in the river, assumptions were made regarding Darwill WWTP that affect the model results. All water released from Darwill WWTP was considered treated, and other discharges, such as combined sewer overflows, were not included in the model. It is also possible that the model overestimates the removal of *E. coli* in the WWTP, due to lack of data an assumption was made that the removal was the same as in the swedish study made by Viktor Bergion (2017). The outcome from these assumptions can be that the *E. coli* concentration from Darwill WWTP overall is to low, especially when the water flow in the river is high.

5.2 SWAT model simplifications and uncertainties

SWAT includes predefined soil types and land uses, which are used together with the slope classification when creating HRU definitions. Since the software is developed in the U.S., these definitions do not always apply to soil types and land use in other parts of the world. Regarding the soil classification in this project, no predefined soil types were considered representative, and the soil types were added manually to the soil database. The available soil data in the study area were insufficient, and assumptions were made regarding soil content, hydrological parameters and pH, based on literature in collaboration with specialists with knowledge of the area. These assumptions may have influenced the simulated river flows and *E. coli* concentrations, both their timing and magnitude. Regarding land use, there are two uncertainties in the model - the reclassification and the low resolution of data (1700 x 1700 m). The land use map layer contained many different land uses, were some only had a slight difference. To simplify the model and to get a representable division of land uses, some areas were grouped together. The low resolution of land use means lower accuracy. The assigned land use class directly affects the run off and furthermore water flow and *E. coli* concentration in the river.

The meteorological data is the main driving force on the hydrological model. The weather definition step in the modelling is to associate the divided subbasins with their weather conditions. If the weather input comes from various stations in the watershed, the model gets more accurate, especially in this project since the watershed is 898 km^2 and cover different altitudes. In this SWAT model just one weather station was used. The weather data were observed at Oribi weather station centrally located in the watershed, and no other local weather data were available. By using weather input only from one station makes the model uncertain, especially in terms of precipitation data, which have critical influence on the hydrological and water quality model (Yen, Jeong, Feng & Deb, 2015).

5.3 Risk of infection

Since assumptions were made in the study, the values on the risk of infection must be interpreted carefully. To calculate the dose of ingested water, in the QMRA, assumptions of the inputs regarding people's lifestyle and habits were made, e.g. how often women and children swim in the river, how often women use the water for laundry, and for how long time laundry usually lasts. If the assumed values of these mentioned inputs are too low, the risk of infection is underestimated. Most of the values were specified by a wide range, reflecting the variation in the reality better than a specific value. The values are chosen after insights from a one-day field trip. More extensive interviews with more people living along the river would have given better basis for the assumptions. For this study that work would have taken too much time.

One apparent conclusion from the result shown in Figure 11 is that the risk of infection is much higher in Baynespruit than in Valley of 1000 Hills. One explanation to the difference can be the volume of the water in the sampling points. The *E. coli* concentration measured close to Baynespruit is made in a smaller influent river to Msunduzi, while the sampling point in Valley of 1000 Hills is located in Msunduzi river. The *E. coli* in Baynespruit is more concentrated since the water flow is lower than in Valley of 1000 Hills. The difference can also be explained by the diverse activities in the two areas. Baynespruit is an informal settlement where untreated wastewater is flowing directly into the river. Also, there is no garbage collection; during the field trip, heaps of garbage were observed close to the river, and during rainfall pollutants from these reach the river. The wastewater and the garbage lead to more faecal pollution in the river. The surrounding area is urban and densely populated, with more settlements like Baynespruit, meaning that the number of sources that lead to increased concentration of faecal pollution are many. The sampling point in Valley of 1000 Hills is in a rural area located in a gorge surrounded by greenery. The standard of living is generally higher than in Baynespruit. Some parts of this area, however, are not "included on the map", which means that these parts are not connected to municipal functions like waste disposal and sewage system. When houses are not connected to the municipal sewage system, faecal pollution is emitted on-site. Another source of faecal pollution in the area is grazing animals. In the surroundings of Valley of 1000 Hills, there are large areas of permeable surfaces which lead to reduction of faecal pollution through infiltration. The difference in land use in Baynespruit and Valley of 1000 Hills, as well as in the adjacent areas, leads to different concentrations of faecal pollution.

In Figure 11, the values from calculations on the benchmarks from the European Union and the Department of Water Affairs in South Africa regarding the *E. coli* concentration are presented. These calculations are made for point values, but because of the range in how much water children ingest while swimming and the assumption that 8-10 % of the *E. coli* concentration is pathogenic, the median risk and the 95th percentile values differ. In Valley of 1000 Hills, the median risk of infection is lower than the DWAF values, but for both Valley of 1000 Hills and Baynespriut, the 95th percentile value of infection risk is higher than the EU restrictions. The DWAF value is a number that the organisation considers as bad water quality for swimming, while the EU restrictions specifies guideline values for different classifications. That means the water quality is considered as “bad quality” according to the EU restrictions in the investigated areas. If it had been in Europe, there would have been a warning sign by the water. That kind of warning systems work fine for populations that have the opportunity to choose somewhere else to swim or take a clean shower instead, but the people in areas similar to Baynespruit are more dependent on the water nearby. The 95th percentile values in the studied areas are much higher than the benchmarks. In Baynespruit, the risk of infection is almost 30 times higher than the EU restrictions. This way of presenting the values clearly shows that the water quality in Msunduzi river is bad for recreational use. The fact that the risk of being infected while swimming in Msunduzi river is 30 times higher than what is considered as bad quality in Europe, is unacceptable. It is unacceptable both since the people along the river are more dependent on the untreated surface water than the most people in Europe and because the bad water quality indicates that the whole surrounding can contain a lot of pollutants. The risk of getting infected when exposed to the water in Msunduzi river have been reported in other studies (Gemmell & Schmidt, 2013).

The result presented in Figure 12 is a comparison between two annual exposures: the risk of infection if a woman uses water from the river for laundry 35 - 55 times during a year and the combined risk for a woman doing laundry like in the first exposure, with addition of the woman taking a swim in the river one time during the year. Even though the only difference between these cases is one swim, this one time of swimming increases the risk of infection approximately 40 times for median values and approximately 60 times for 95th percentile. Comparison of the results illuminates the major risk of swimming in the river. If the transmission route for laundry would have been “hand to mouth” instead of through aerosols, the assessed health risk of doing laundry would show a more critical situation. The difference between the risk of swimming and doing laundry would then decrease. The hand to mouth transmission route is not analysed in this study because of lack of data on the amount of water that gets on the hands during laundry and further on the amount of water ingested.

If the purpose of a study like this is to get an estimation of how big the total risk of infection is while living close by the river, there are many parameters to take into account. Depending on different prerequisites and living in different areas, people are exposed to the water in different ways. The way people are exposed to the water can also depend on their role in the village, e.g. it is typical that women do laundry. Examples of how people living along the river are exposed to the water, except when swimming and doing laundry, that were identified during the field trip are irrigation and fishing. Irrigation means exposure for the farmer through direct contact with the water, but also a risk for the ones that later eat the crops. When fishing in the river, one is exposed to the water just being around the river through direct contact and aerosols, and the ones that eat the fish are exposed to the pathogens as well. It is also necessary to investigate if the polluted water in an exposure scenario passes any barriers that reduces the concentration of the pollution.

Msunduzi river is burden with other pollutants than *E. coli* that also adversely affect human health. Other common waterborne pathogens that can cause infection are *Giardia* and *Salmonella* (Kusiluka et al., 2005). Industries and traffic emit metals, and the hospitals emit pharmaceutical residues (Matongo et al., 2015). Some households in Valley of 1000 Hills have long distance to the place where the waste is collected which is the reason some choose to burn the waste. Burning of waste leads to distribution of pollutants, for instance metals. High concentrations of metals can cause cancer and other diseases. If the intention is to assess the total risk of being affected by the water, all possible pollutants must be included in the assessment.

Expressing the result of QMRA as probability of infection may lead to overestimation of negative consequences, as not all infections lead to a disease, which is important to have in mind while interpreting the results. The advantages of presenting results as DALY are that it takes into account how severe the disease is and that different kinds of risks for human in the society can be compared with each other, for example the risk of infection from a pathogen can be compared with traffic-related risks (Abrahamsson, Ansker & Heinicke, 2009). Calculations with DALY require data like number of death due to the considered disease, incidence of the considered disease and duration of illness. The aim with this project was not to compare the water problem with other problems in the society, therefore probability of infection was preferably used to describe the risks.

5.4 Ethical aspects

To receive input data for the SWAT model, effective collaboration with municipalities is often required. In this study, that collaboration was managed through a contact in South Africa who provided the data. Collecting the data can be challenging, since municipalities may be reluctant to spread it. According to the contact, a reason for that can be that the municipalities may be concerned about the data being used to show problems in the area. During the field trip, one example indicated that the municipalities may not always be able to prioritise water problems was observed. A conduit in the sewage system was leaking and water poured out to Msunduzi river in the area close to a sport center. The municipality did not prioritise to repair the damage, which led to the sport center paying for the repairs.

As mentioned in the introduction, access to clean water is a human right and the topic is one of the Global Goals for Sustainable Development, set by the United Nations General Assembly. In the studied area there is a long way to that status, which indicates that something must be done. The extent of the situation with bad water quality varies in different areas, like in Baynespruit and Valley of 1000 Hills in this study. One possible strategy of how to decide where to start adopting measures is to do it where the quality is worst, but that question is complex. Inanda Dam, located between Msunduzi and the city Durban, is a source for drinking water in Durban. If the water in Inanda Dam is polluted, many people get affected since Durban is a big city. In smaller villages, like informal settlements, there is a risk that problems like these do not get that much attention, which can result in the issue getting ignored. It is important to point out that there, in an area like the one studied, are other issues than water quality problems that also need to be solved. How to manage what problem to prior, and in which areas, is a big question. Who is responsible for adopting measures? However, the problem with the water is a big issue and action plans needs to be set up; where to start and what to do.

5.5 Further studies and recommendations

To obtain a SWAT model that better represents reality, improvement in data both regarding the hydrological model and the microbial input is essential. The hydrological part of the model can be improved by adding more precipitation stations, in-situ testing of the soil parameters, and developing a land use map with higher resolution and better accuracy. Regarding the microbial input, only one point source was taken into account in this study. To be able to predict high *E. coli* concentration in the river, the model needs to be further developed to account for other pollution sources, i.e. on-site wastewater treatment locations and their reduction of *E. coli*, grazing animals and their contribution to *E. coli*, manure application in the area, and rubbish heaps locations and their contribution of *E. coli*. In addition, more field investigations are recommended, since the field trip made in this project did not cover the whole watershed area. A better model would result in better basis for the use of risk assessment connected to different events, e.g. dry and wet seasons.

The QMRA can be improved by addressing the limitations in the input data, e.g. the volume of water ingested through the transmission route hand to mouth while doing laundry and how much water that follows a fish caught in the river. Regarding fishing in the river, probably the concentration of *E. coli* in the fish is reduced by the barriers along the way from the river to the mouth, for example through cleaning and cooking. Since no data about this were found, this exposure route was not included in this study. To enable realistic risk assessments, further research on how many times people are exposed to the water in different ways, like laundry in this study, is needed. These kinds of statistic though can be unique for a specific area, which would require much work.

One step that can be included in QMRA is called risk management. That part is excluded in this study, though it is a step necessary for making changes regarding the water quality. The point is to use the results from the risk characterisation in further action. It is not satisfying to end the project here when the situation with, and consequences of, bad water quality have been obvious during the study. Studies that result in presentation of risk values when exposed to water can work as a basis to show consequences of using the water, but to see a deeper meaning of this kind of studies it is important to know that someone is trying to take it to the next step. An example of actions that have progressed from QMRA is supporting programmes for hygiene practises (Petterson & Ashbolt, 2016).

6. Conclusion

The aim of this project was to assess human health risk due to exposure to water from Msunduzi river. The main questions considered were: how the *E. coli* concentration in the river varies during the year, identification of the main faecal pollution sources, in what way people get exposed to the water, and the risk of getting infected by pathogenic *E. coli*. This was done by building a hydrological model using SWAT and applying the risk assessment approach QMRA on measured *E. coli* concentration in the river.

The hydrological model performance was poor, since it resulted in unsatisfactory NSE and R^2 values, moreover the simulated concentration of *E. coli* and water flow did not represent the pattern of the measured data. The main reason that the simulated pattern of *E. coli* was not representative is most likely that only one pollution source, Darwill WWTP, was considered in the model. To get a more accurate model, more pollution sources must be taken in consideration. The main sources could not be identified, since lack of data made it difficult to evaluate other sources than Darwill WWTP. However, the comparison between measured and simulated *E. coli* showed a big difference in concentration, indicating that Darwill WWTP only causes a small amount of the total *E. coli* concentration. The graph of observed water flow and measured *E. coli* (Figure 10) shows that high *E. coli* concentration in general appears to happen during summer when both temperature and water flow are high. The fact that high temperature increases the die-off of *E. coli,* together with results presenting that high *E. coli* concentration appears when the temperature is high, indicates that temperature and furthermore die-off has less impact on the *E. coli* concentration than the water flow. Since *E. coli* concentration in reality appears to be higher during summer when there is a higher water flow, another conclusion is that the major part of *E. coli* comes from pollution sources connected to surface run-off.

The field trip resulted in valuable information regarding different ways of exposure to the water in the river. The types of exposures evaluated in the risk assessment were swimming and doing laundry. Comparison of the QMRA results based on observed *E. coli* concentrations in Msunduzi river with values that are classified as a high risk based on benchmarks from EU showed the high risk of infection due to the bad water quality in Msunduzi river. Since the calculations were made for pathogenic *E. coli* only, the results obtained in this study do not represent the total risk of using the water.

Results from SWAT modelling can be used to predict occurrence of high concentration of pollutants which can be applicated in QMRA in order to predict high risk of infection. To use that benefit appropriate, the SWAT model needs to reflect the reality. Since the performance of the model in this study was poor, the results from SWAT could not be applied in QMRA. However, the study presents a method that can be used and developed in further similar studies.

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