A QUANTITATIVE APPROACH TO ASSESSING THE EFFECTIVENESS OF CATCHMENT MANAGEMENT FOR THE IMPROVEMENT OF DRINKING WATER QUALITY

KATHY CINQUE

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A quantitative approach to assessing the effectiveness of catchment management for the improvement of drinking water quality

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Kathy Cinque
B.Eng.

School of Civil Environmental and Chemical Engineering
College of Science, Engineering and Health
RMIT University
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DECLARATION

I certify that except where due acknowledgement has been made, the work is that of the author alone; the work has not been submitted previously, in whole or in part, to qualify for any other academic award; the content of the thesis is the result of work which has been carried out since the official commencement date of the approved research program; any editorial work, paid or unpaid, carried out by a third party is acknowledged; and, ethics procedures and guidelines have been followed.

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Kathy Cinque

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TABLE OF CONTENTS

INDEX OF FIGURES

INDEX OF TABLES

ABBREVIATIONS

$\propto$	Level of statistical significance
#	Number
ADWG	Australian Drinking Water Guidelines
AEP	Annual Exceedence Probability
AIDS	Acquired Immune Deficiency Syndrome
ARI	Average Recurrence Interval
B	Bunyip rainfall
BASINS	Better Assessment Science Integrating Point and Non-point Sources
BOM	Bureau of Meteorology
C. perfringens	*Clostridium perfringens*
CSIRO	Commonwealth Scientific Industrial Research Organisation
D	Drouin rainfall
DAPI	4',6-diamidino-2-phenylindole stain
DCFL	Department of Conservation, Forests and Land
DIC	Differential Interference Contrast
DNRE	Department of Natural Resources and Environment
Dr	Doctor
DSE	Department of Sustainability and Environment
E	Nash-Sutcliffe coefficient of efficiency
EC	Electrical Conductivity
E. coli	*Escherichia coli*
EG	Pathogen transport model
EMC	Event Mean Concentration
EPA	Environmental Protection Authority, Victoria, Australia
ESS	Event Sampling System
FA	Factor Analysis
FITC	Fluorescein Isothiocyanate
GL	Gigalitre
GWLF	Generalised Watershed Loading Function
ha	Hectare
hrs	Hours
IFD	Intensity Frequency Duration

IMS	Immunomagnetic Separation
km	Kilometre
L	Litre
log	Logarithmic
LT2 Rule	Long-term 2 Enhanced Surface Water Treatment Rule
m	Metre
m^3/sec	Cubic metres per second
mg/L	Milligrams per litre
ML	Megalitres
mm	Millimetre
MPN	Most Probable Number
N	Nayook rainfall
NATA	National Association of Testing Laboratories
NTU	Nephelometric Turbidity Units
NYDEP	New York Department of Environmental Protection
orgs/100mL	Organisms per 100 millilitre
orgs/day/km^2	Organisms per day per square kilometre
orgs/hour	Organisms per hour
orgs/sec	Organisms per second
PCA	Principal Component Analysis
pers. comm.	Personnel communication
PEST	Parameter Estimation model
PET	Potential Evapotranspiration
Pt-Co	Platinum Cobalt scale
QMRA	Quantitative Microbial Risk Assessment
R	Tarago Reservoir rainfall
R^2	Coefficient of determination
SCA	Sydney Catchment Authority
SDWA	Safe Drinking Water Act, Victoria, Australia
TKN	Total Kjeldahl Nitrogen
TMR	Tarago Main Race
TOC	Total Organic Carbon
TVOL	Total streamflow volume
µS/cm	Micro-siemens per centimetre
US(A)	United States of America
US EPA	United States Environmental Protection Authority

VDEQ	Virginia Department of Environmental Quality
WHAT	Web-based Hydrograph Analysis Tool
WHO	World Health Organisation
WMO	World Meteorological Association
WSAA	Water Services Association of Australia
WSP	Water Safety Plans

LIST OF PAPERS PUBLISHED/SUBMITTED

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EXECUTIVE SUMMARY

Access to safe drinking water is essential to maintain life. Ensuring that water is safe for consumption requires an understanding of all the potential risks to the supply and an ability to manage those risks. Pathogenic organisms are the greatest risk to consumers of drinking water and the main source of these organisms is from non-point sources such as catchment runoff. The high risk is clearly demonstrated by the numerous cases of waterborne disease outbreaks in the developed world in the last 40 years, some of which have resulted in the death of consumers.

The multiple barrier approach to drinking water protection is a well supported management technique which requires multiple scientifically validated mechanisms that prevent contamination of or remove contamination from the water supply prior to consumption. Catchment management is a barrier that aims to control contamination at the source which provides a greater surety of the absence of contaminants, and therefore safety, than does the subsequent removal or reduction of contaminants by treatment. The implementation of buffer strips is one catchment management technique that is thought to improve water quality. They reduce the momentum and magnitude of surface and sub-surface runoff thereby aiding infiltration into the soil column and promoting entrapment of pollutants. This process has been well researched in terms of constituents such as sediments and nutrients. In a drinking water catchment, however, the ability of these buffer strips to trap or remove human infectious pathogens is of most interest. Having the capability to quantify the effectiveness of buffer strips specifically for pathogen removal, could give drinking water quality managers a validated barrier to contamination and a reduction in risk to consumers.

The hypothesis is that the implementation of buffer strips, in a rural drinking water catchment, will have a positive and quantifiable impact on drinking water quality. Specifically this research aims to determine a way of predicting the decrease in risk to public health due to the implementation of buffer strips in an agricultural catchment. The Tarago Reservoir catchment, about 100km east of Melbourne, was chosen as the study catchment as it currently supplies drinking water to the Greater Melbourne area. Over the past 10 years buffer strip implementation has been taking place in this catchment in an effort to improve water quality. The catchment has an extensive water quality data set spanning over 30 years that includes both physical-chemical and

pathogenic parameters as well as storm event data. These factors make it an ideal catchment to study the effects of catchment management.

The Tarago catchment has three sub-catchments which were determined to be from different populations using discriminant analysis. This analysis also showed that land-use and soil types were the major contributing factors to poor water quality. Trend analysis showed that some parameters associated with erosion were trending down; possibly indicating the positive effects of catchment management initiatives. Additional statistical analysis using Factor Analysis (FA) showed that surface runoff and erosion are the most significant catchment processes affecting water quality. Furthermore it showed that since the implementation of catchment management, colour and phosphorus were less dominant in the agricultural runoff.

Regression analysis, FA and analysis of the Event Mean Concentration (EMC) on the pathogen, pathogenic indicator and event data sets showed that *Clostridium perfrigens* and enterococci were mobilised by surface runoff. EMC analysis also showed that rainfall has a significant impact on water quality highlighting the importance of sampling during storm events. Catchment management efforts need to focus on lessening the effect of erosion, surface runoff and rainfall. This can be achieved through the implementation of buffer strips.

A model that simulates pathogen fate and transport through a catchment was necessary to predict the decrease in pathogens due to the buffer. The model needed to be continuous to allow assessment of the impact of events and non-point sources. A simple lumped conceptual model, EG, was chosen. This model uses the partitioned flows from a hydrological model as inputs, which is vital as buffer strips will only affect pathogen concentrations in the surface flow.

EG was not specifically developed to determine the effectiveness of buffer strips and therefore modifications to the pathogen transport processes were required. An understanding of pathogen movement at a catchment scale was necessary, as was an understanding of the likely impact of buffer strips in terms of their ability to remove pathogens. The buffer is only effective during storm flow conditions as pathogens transported during baseflow conditions are too deep and therefore too far away from the filtering effect of plants or their root systems. The modified EG model allows different buffer ratios to be input into a calibrated model and the model outcomes

indicate the effects the buffer will have on pathogen transport to the stream. Uncertainty analysis was also carried out on the modified EG model.

A number of different analyses were undertaken with the calibrated model and different buffer ratios to determine the overall effect of having a buffer and relating any of these effects to storm characteristics. The peak flow of an event was found to be a good predictor of pathogen transport during an event. It was also able to predict the difference in pathogen numbers between a catchment with and without a buffer. The average flow and event volume did not correlate as well to the pathogen data sets as peak flow indicating that the effectiveness of the buffer was less related to the duration or overall magnitude of an event and that it was the peak intensity which dominated the number of pathogens that were mobilised.

Relationships were formed between the buffered and non-buffered catchments which are useful in determining the amount of pathogen reduction likely in certain circumstances given a particular increase in buffer. The ability to quantify the benefits that buffer strips will give to water quality may allow the comparison of investing in catchment management to treatment costs and an assessment of the risk reduction benefits of both.

Quantification of the benefits of buffer strips can assist catchment managers and water quality managers in planning and securing funding for works in the catchment. The ability to show that the on-ground works can have a positive and measurable effect on drinking water quality is important for various stakeholders including regulators and the community. Having confidence in catchment management initiatives to provide reduction and having the ability to quantify that reduction may lead to more on-ground works and less conventional treatment. This has benefits for the community on a number of different levels including, but not limited to, the following: a reduced cost of treating their drinking water, a more aesthetic landscape and healthier streams.

1. INTRODUCTION

1.1 Background

> "*Access to safe and plentiful drinking water is a fundamental human need and a basic human right. Contaminated water jeopardizes both the physical and social health of all people*" United Nations Secretary-General Kofi Annan, World Water Day, March 22, 2001.

Water is essential for life and each person requires between 20 and 50 litres of clean fresh water per day for drinking, cooking and cleaning (National Academy of Sciences, 2008). The number of people without access to safe drinking water was estimated in 2002 to be 1.1 billion people world-wide. It is estimated that 1.6 million deaths per year worldwide are from diarrheal, or gastrointestinal, diseases and can be attributed to unsafe water, inadequate sanitation or poor hygiene (WHO, 2004).

Although the majority of deaths occur in developing nations, the developed world is by no means immune to the effects of contaminated or unsafe drinking water. As an example Hrudey and Hrudey (2004) explore over 70 cases of waterborne disease outbreaks that have occurred in developed nations in the past 30 years, which resulted in almost 600,000 cases of, mostly, gastrointestinal illness. It is more than probable that this figure is underestimated - by as much as 99% (Kramer et al. 2001) - as communicable disease surveillance and reporting systems are likely not to detect all cases of gastroenteritis. This is due to the symptoms, which include diarrhea, vomiting, fever and dehydration, are often mild and generally short lived and therefore not necessitating a visit to the doctor (Medema et al. 2003). There is the possibility of death from these illnesses, the numbers for which are also reported in Hrudey and Hrudey (2004) and are also most likely underreported. The majority of deaths from water related diseases, in the developed world, occur among the elderly, infants and the immunocomprimised.

The most common cause of gastrointestinal illnesses is the consumption of water contaminated with microorganisms whose original source is faecal matter from infected humans or animals. This type of transmission of infectious microorganisms, more

commonly known as pathogens, is known as the faecal-oral route. Although other transmission pathways exist, such as recreational contact or inhalation, the faecal-oral route is the most dominant form of transmission of waterborne pathogens (Haydon, 2006). Some of the more well known pathogens that are transmitted this way include the following: protozoa such as *Cryptosporidium* and *Giardia*, bacteria such as *Campylobacter* and *Escherichia coli* (*E. coli*) O157:H7 and viruses such as the Norwalk virus. The severity, longevity and consequences of infection can vary depending on the health of the individual and on the pathogen characteristics.

As stated, the main source of pathogens in water is faecal material containing pathogens. Faecal material can either be deposited directly into the water body, whether that is a stream or a reservoir, or deposited on the catchment of the water body and then transported to the water in overland or sub-surface flow. The risk of human infection from faecal material depends on the source of that material; generally human faecal material carry the most risk followed by livestock and domestic animals with the least risk coming from wildlife (Ferguson, 2005). Taking this into consideration, the overall pathogen risk to drinking water safety depends largely on the type of land-use and the level of human, livestock and wildlife interaction within the catchment. Water supply catchments can range from fully protected, which have minimal or no human or livestock interaction, and therefore pose minimal risk, to developed, which can be completely urbanised and carry a much higher level of risk. The worlds increasing population means that there will continue to be pressure on available productive land, including water supply catchments, to be developed for housing and agriculture. The challenge in water supply and catchment management lies in how best to align residential living and farming practices with the supply of safe drinking water.

Past studies have shown the public health benefits of having a fully protected catchment as compared to a peri-urban catchment (Roser & Ashbolt, 2005) but whether or not an impacted catchment, with the appropriate catchment management, could produce similar quality water to a protected one has not been studied. The significance of providing outcomes related to this question could mean that diverse, and seemingly conflicting, land-uses, such as water supply and farming, could be carried out on one parcel of land and be reliable and productive for both uses. This would possibly make for a resourceful and sustainable way to manage land.

The supply of safe drinking water relies on the principle of multiple barriers to contamination. This is a holistic approach and means that sole reliance is not placed on one barrier, such as a treatment plant or catchment management, to remove contamination. Instead a number of barriers are put in place to prevent and remove contamination. It is widely accepted that reduction of pollution at the source is much more reliable than removal of contaminants by treatment and therefore the catchment can be the most important and effective barrier (ADWG, 2004). The importance of source water protection is also explicitly stated in the World Health Organisation's (WHO) Guidelines for Drinking-water Quality (WHO, 2008), which states that catchment management is the first barrier to contamination and should be a priority. Additionally this document highlights some of the other benefits to reducing contamination at the source, such as reducing the amount of treatment required and possibly reducing treatment by-products and operational costs.

As a way of incorporating the concept of multiple barriers, and catchment management in particular, into regulatory frameworks, the application of a risk management approach is increasingly being expected. Preventative risk management encompasses all steps in the water supply process and aims to identify all potential hazards, their health significance and how they are managed. As the first and therefore most important barrier to contamination, the role of the catchment, or more specifically catchment management, is integral to a preventative risk management plan. Gaining a better understanding of the effectiveness of the catchment as a barrier will improve the thoroughness of a risk management plan. Additionally providing evidence that the specific catchment barriers put in place are working to reduce pathogenic transport will allow for greater confidence among water suppliers and therefore greater willingness to invest in such works.

One of the risk management tools being used to assess drinking water safety is Quantitative Microbial Risk Assessment (QMRA). This tool systematically combines quantitative information on exposure and dose-response to determine the health impacts of supplying water from different systems (WHO, 2008). Defining the quality of the source water is an important part of QMRA (Signor et al. 2007) and therefore having the ability to estimate quantitatively the impact of barrier implementation on pathogen numbers in the source water is also important. With this information QMRA could be used to simulate the potential reduction in the disease burden due to particular barriers.

The term catchment management is used to describe many different initiatives from regulations regarding farming practices to septic tank rehabilitation. In terms of pathogens the risk of animal waste entering the water and the practical on-ground works that can reduce this risk are of most interest; specifically fenced vegetative buffer strips. The ability to be able to quantify the benefits, in terms of pathogenic reduction, of implementing buffer strips would mean that a QMRA could be carried out and the potential health benefits of this catchment management tool could be estimated. Currently within the drinking water industry, catchment management, and more specifically buffer strip implementation, is seen as a 'nice-to-do' without much understanding of the quantitative benefits it is providing for pathogen reduction and therefore for human health.

1.2 Hypothesis and research questions

An understanding of how effective catchment management, and more specifically buffer strips, can be on water quality and in particular on drinking water quality is required. To be able to quantify any improvement would be of additional benefit. The ability to be able to give the drinking water industry confidence in the catchment as a barrier to contamination and as an important part of the supply of safe drinking water is the goal.

The main hypothesis is that ***the implementation of buffer strips, in a rural drinking water supply catchment, has a positive and quantifiable impact on drinking water quality.***

Specifically the research questions being asked are:

- Is there a measurable impact on water quality following catchment management?
- How effective is catchment management at improving water quality and reducing pathogen transport?
- Can a reduction in pathogens following buffer implementation be predicted?
- Does the quantification of buffer effectiveness give drinking water quality managers a validated barrier to contamination?
- Are the resources necessary to implement catchment management justifiable based on the risk reduction to water quality?

1.3 Aims and objectives

The overall aim is to determine if it is possible to see a change in water quality following the implementation of catchment management and to quantify that change with respect to drinking water quality.

The following objectives should that this aim is fulfilled and the research questions are answered:

1. Document the biggest risks to drinking water from catchment sources, how those risks are managed and how catchment management can reduce those risks. Additionally document the current thinking around catchment management and buffer strips and where the gaps in knowledge are.
2. Identify the relevant and dominant catchment processes by undertaking a screening analysis of available water quality data in a study catchment where catchment management has taken place. Undertake preliminary statistical analysis to identify any trends or changes in water quality that could be attributed to catchment management. Use these results to predict the risks to drinking water quality.
3. Design a model capable of quantifying the effectiveness of buffer strip implementation in terms of the biggest risks to drinking water. This will involve reviewing available contaminant transport models that can simulate catchment processes at an appropriate scale. An understanding of contaminant reduction due to catchment management will also be needed.
4. Test and refine the model including calibration and validation using targeted water quality monitoring data. An uncertainty analysis on the model will also be required.
5. Make recommendations regarding the usefulness of results to catchment managers and suppliers of drinking water, including recommendations for water quality monitoring. Based on the results a discussion on how best to align farming practices with the supply of safe drinking water and determining whether buffer strips can be considered a validated and quantifiable barrier to pathogenic contamination will be had.

1.4 Scope of study

In order to test the hypothesis, fulfil the aims and answer the research questions it is important to first define the scope of the investigation.

The major focus on the research is on drinking water quality. Although water quality parameters not directly related to the safety of water for human consumption will be investigated, the overall aim is not to assess nutrient or sediment inputs or the effect of catchment management initiatives on stream health. There is a significant amount of research and understanding already existing in this area (Gharabaghi et al. 2000; Gilley et al. 2002). Additionally it will be demonstrated that the biggest risk to the safety of drinking water is the presence of protozoan pathogens. Certain viruses and bacteria can also pose a risk to human health by transmission through drinking water, although in most cases they are destroyed by adequate disinfection. They are therefore not the focus of this study. Other constituents in the water such as fertilisers and pesticides can also affect human health. The effect of catchment management on the fate and transport of these contaminants is, however, not researched in this study and is a possible area for further investigation. Algal toxins are also not included as they are aquatic and do not have a catchment phase and therefore would not be affected by catchment management. The effect of catchment management on nutrient inputs, which may influence algal growth, is already an extensively studied area, as discussed above, and is also excluded from the study.

Only one drinking water catchment is being investigated. It is predominately an agricultural catchment with some forestry and rural living. It has no urban land-uses and no known point source pollution. The catchment management initiatives that have been carried out in this catchment make it an ideal test catchment, as explained in Chapter 3. It does however mean that any results or conclusions obtained throughout the study may be catchment specific. This will be further explored in Chapter 10.

1.5 Thesis structure

This thesis comprises 10 chapters each with its own objectives while still being relevant to the overall aims, hypothesis and research questions. Chapters 1, 2 and 3 explain the context in which the thesis was undertaken. Chapters 4 and 5 cover the screening analysis and Chapters 6 to 9 cover the model design and testing. Chapter 10 gives the major conclusions and areas for further work. The thesis finishes with References and Appendices which are referred to within the text. Each chapter is summarised in more detail below.

Chapter 1 gives a background to the thesis topic as well as sets out the research questions, the aims and objectives and the structure of the thesis.

A review of the significant and relevant literature is given in Chapter 2. It is not a comprehensive review of all the literature cited during this thesis as relevant literature is examined throughout the document and included as part of the appropriate individual chapters. Chapter 2 does however identify the gaps in knowledge and states the significance of the work. It also describes why buffer strips are chosen as the catchment management initiative that the research will focus on.

The catchment chosen as the case study to carry out this work is described in Chapter 3. The importance of the catchment as a drinking water source is detailed along with a background of the catchment management initiatives and the water quality monitoring in the catchment. Additionally the processes by which the historical data was collated and the more recent data was collected are described.

Chapters 4 and 5 cover the screening analysis section of the thesis. For reasons explained within the thesis, physical-chemical data is separated from the pathogen/pathogenic indicator data, Chapters 4 and 5 respectively. In these chapters, the statistical methods are used to determine the processes within the catchment that are most dominant in terms of affecting water quality. Trends or changes in water quality are also assessed in an attempt to show the impacts of catchment management in the study catchment.

The modelling section of the thesis is described in Chapters 6 through to 9. Chapter 6 explains the pathogen transport model chosen for modelling the effects of buffer strips, the reasons why that particular model was chosen and the modifications that were necessary to that model to ensure its relevance to the objectives of the thesis. Additionally, in Chapter 6, the importance of accurate rainfall runoff modelling and flow partitioning is detailed.

Chapter 7 looks at model calibration and validation of both the rainfall runoff model and the pathogen transport model.

Analysis of the outcomes of the modelling, and therefore on pathogen numbers in the runoff, given different buffer scenarios is covered in Chapter 8. This chapter looks at

when the buffer is effective, the relationships between flow and buffer effectiveness and compares different buffer ratios. The work presented in this chapter quantifies the effectiveness of having a buffer and describes why they can be considered a validated barrier to contamination of a drinking water source.

Chapter 9 covers the modified model's uncertainty analysis. It looks at the sources of uncertainty with reference to relevant literature, the methods for uncertainty analysis and the confidence that model results should be viewed with.

The thesis finishes with Chapter 10 where conclusions that relate back to the research questions covered in Chapter 1 are presented. It also looks at where further work in this area outside of the scope of this thesis could be undertaken.

2. LITERATURE REVIEW

2.1 Introduction

Access to safe drinking water is essential to maintain life. In the United States the provision of safe drinking water and sanitation has increased the general health and lifespan of its citizens more than any other advancement in the field of medicine (Last, 1998 cited in Meinhardt, 2006). 'Safe' in this context refers to water that has contaminant levels below that which is known to cause illness in a healthy human. To ensure water is safe for public consumption requires an understanding of the potential risks to water quality and implementation of management techniques to manage those risks.

This chapter will outline literature related to the risks to drinking water quality and the likelihood and consequences of these risks occurring. The characteristics of pathogenic organisms and the risks they pose to public health are discussed, along with an outline of water quality monitoring. Drinking water regulation, in an Australian and international context, is reviewed which emphasises the multiple barrier and risk management approach to the provision of safe drinking water. Catchment management as a tool for the protection of drinking water from pathogenic contamination is then highlighted and the focus on quantification and buffer strips is explained. A summary of the knowledge gaps in the field and how they relate to the thesis will conclude the chapter.

2.2 Risks to drinking water

In terms of drinking water quality there are two broad categories of risks: aesthetic and health. Aesthetic water quality issues include things such as elevated levels of sediment, which makes the water look dirty or geosmin, which is produced by blue-green algae and can affect the taste of the water (WSSA, undated). Ideally water should be aesthetically pleasing to the consumer but when supplying water for human consumption it is those contaminants which pose a threat to human health that are the most significant (ADWG, 2004). In terms of health related risks there are contaminants which have the potential to cause chronic illness, such as cancer, and contaminants

which have the potential to cause acute illnesses, such as gastroenteritis. Linking the prevalence of chronic diseases to drinking water quality is extremely difficult (Grabow, 1996). This is due a number of factors including: other environmental factors influencing chronic diseases, the long exposure time that is required before a chronic disease becomes evident and the limited knowledge regarding what waterborne contaminants may cause chronic diseases. Although there are some chemicals in drinking water that have been directly linked to chronic diseases, such as arsenic causing cancer (Rahman et al. 2009) and lead which can affect the nervous system and kidneys (Gowd & Govil, 2008), in most cases the risk of illness and death from chemicals is low, speculative and unproven (Sobsey, 2006). It is therefore those contaminants which can be directly linked to causing acute illness that are of greatest concern to the suppliers of drinking water.

The Australian Drinking Water Guidelines (ADWG) (2004) state that, 'the greatest risks to consumers of drinking water are pathogenic microorganisms'. The WHO estimate that over 1.6 million people world-wide die annually from diseases attributed to unsafe water (WHO, 2004). Pathogenic organisms including, viruses, bacteria and protozoa, are the most prevalent cause of acute illness and have been directly linked to many disease outbreaks within communities (Smith & Perdek, 2004). Most pathogens infect humans via the faecal oral route meaning that water contaminated with human and/or animal waste is ingested by a susceptible person. Although there are other routes of infection, such as inhalation of droplets or contact through bathing, ingestion is the most dominant form of transmission of waterborne pathogens (Haydon, 2006). Infection can cause illnesses such as, severe diarrhoea, blood poisoning and vomiting, and in extreme cases can result in death. A poor understanding of the risks, failures in treatment, inadequate treatment and unprecedented events, such as large rainfall, can all lead to pathogenic waterborne outbreaks.

In terms of assessing the risk of infection from a drinking water source, the likelihood of contamination and the severity of the consequences, both to the community and to the water authority, have to be considered. The likelihood of pathogenic contamination is related to the drinking water source, the available treatment and the integrity of the distribution system. Pathogenic characteristics influence the likelihood of contamination and these are discussed along with the sources, transport and survival or these microorganisms in the following sections.

The consequences of contamination of a water supply can be assessed by reviewing waterborne disease outbreaks worldwide. It is a common misconception that waterborne disease outbreaks only occur in developing countries where treatment technologies may be less advanced than in the developed world and hygiene levels are generally lower. However, as Hrudey and Hrudey (2004) demonstrate, many outbreaks occur in affluent nations. One of the most referenced waterborne disease events occurred in Walkerton, Ontario, Canada in 2000. A groundwater well used for the town's water supply was contaminated following a heavy rainfall event by cattle manure from a nearby farm. A number of factors attributed to the outbreak of disease in the community; the chlorinator set point was below that which was required to give an adequate residual and there was inadequate compliance sampling following chlorine dosing. However, the initial event that caused the outbreak was the 1 in 60 ARI rainfall event and subsequent contaminated catchment runoff entering the raw water. *Escherichia coli* (*E. coli*) O157:H7 and *Campylobacter* were identified as the primary pathogens responsible for the severe consequences; over 2,300 individuals were estimated to have suffered gastroenteritis, 65 of those were hospitalised and 7 died (Hrudey & Hrudey, 2004). It was estimated that the financial cost of the outbreak was in excess of $CAN64 million (Hrudey & Hrudey, 2004).

As another example, the worst waterborne disease outbreak of recent times in terms of people affected, occurred in 1993 in Milwaukee, Wisconsin, USA. The water supply was infected with *Cryptosporidium* oocysts, the main source of which is thought to have been raw human sewage. The water was fully treated before being distributed. Evidence suggests that the filter performance was sub-optimal during the outbreak and this along with an event in the catchment that produced highly elevated turbidity peaks resulted in the disease outbreak. The outbreak resulted in 87 deaths and over 400,000 reported cases of illness (Smith & Perdek, 2004). These particular events, along with the many others discussed in detail in Hrudey and Hrudey (2004), show that affluent nations are not immune to pathogenic waterbourne disease outbreaks. They also highlight the disastrous consequences possible following an outbreak and the need for a multi-barrier approach to the protection of drinking water.

To ensure a valuable risk assessment the potential impacts of anticipated events, both likelihood and consequence must be identified and measured. This will enable the selection of the most appropriate management techniques to minimize the potential damages (Sullivan et al. 2005). These outbreaks demonstrate that understanding the

water supply system, including the catchment, as well as implementation of source protection is imperative. They also highlight that effective source protection requires knowledge about the biggest threat to water quality, pathogens.

2.3 Characteristics of pathogens

There are three types of pathogenic organisms, viruses, bacteria and protozoa and each have their own characteristics which will be discussed.

Viruses, such as hepatitis A, rotavirus and Norwalk-like virus, are the smallest waterborne microorganism that is able to infect humans and replicate in the intestine. The majority of viruses are host specific meaning that human infectious viruses are usually spread through sewerage impacted water, although contaminated food and person to person contact can also spread infection. Non-specific symptoms and long incubation times often mean that implicating a waterborne virus for a disease outbreak is difficult (WSAA, undated). Additionally their small size makes them difficult and costly to identify in water samples (Ferguson, 2005). Their susceptibility to disinfectants, such as chlorine, ensures that most viruses are removed from water prior to distribution.

Bacteria are generally larger than viruses and more susceptible to disinfection which, providing the treatment process is adequate, means they should not be present in finished water. Bacterial pathogens can be zoonotic, meaning that they are not host specific and can be transmitted from animals to humans. Therefore to prevent the faecal-oral route of infection it is both human and animal excreta that should be prevented from entering the water supply. They have a poor survival rate in the environment and therefore a short life outside their host reducing the risk of contamination and subsequent infection. *E. coli* O157:H7 and *Campylobacter* are examples of bacteria that are pathogenic to humans.

Protozoa are larger than viruses and bacteria and are much more resistant to chemical disinfection due to their ability to form a protective outer coat (Hrudey & Hrudey, 2004). This outer coat also protects them from environmental stresses such as temperature changes and sunlight. Protozoa can be zoonotically transmitted, meaning that they can be transmitted from animals to humans. The most common examples of human infectious protozoa are *Cryptosporidium* and *Giardia*. It is these enteric protozoa that

are the most significant in terms of waterborne illness in Australia (ADWG, 2004) and are responsible for numerous waterborne outbreaks throughout the world (Hrudey & Hrudey, 2004). Both *Cryptosporidium* oocysts and *Giardia* cysts are excreted in large numbers from infected hosts, up to 10 billion ooysts per gram of faeces (Olson et al. 1999; Trask et al. 2004), and the infectious dose for a human can be as little as 10 organisms (Ferguson, 2005). Healthy people infected with pathogenic protozoa can be asymptomatic and show no signs of illness. Others can have symptoms ranging from diarrhoea to vomiting and abdominal pain, and will fully recover (WSAA, undated). For immunodeficient individuals, however, such as the young, the elderly or those with AIDS, infection can be deadly (Teunis et al. 1997). It is therefore these protozoan organisms that are usually the focus of risk management within a water supply.

2.3.1 Risk factors

Pathogens are found in the intestinal tract of infected hosts and are deposited in the catchment by humans, via septic tanks, and by animals, via direct faecal deposition. The risk to water safety arising from different hosts depends on factors such as: population density, faecal deposition rates, prevalence of pathogens in the population, age and behaviour of the host species and the potential for zoontic transfer (Ferguson, 2005). Factors, such as season, can also have a significant effect on the risk of pathogen contamination of water. For example, during periods of calving, when the number of juvenile cattle is high, significantly more pathogens can be shed in the catchment. Calves are a significant source of pathogens due to the large number of oocysts they shed in their faeces. Additionally animals infected with particular pathogens can increase the frequency of defecation further increasing the risk of contamination (Ferguson, 2005).

2.3.2 Pollution sources

Pathogens within a catchment can come from two different pollution sources, point or diffuse (Ferguson, 2005). Point sources refer to pollution being discharged at a known location usually either through a pipe or a drain. Point sources are typically stormwater discharges or wastewater treatment plant outlets. The frequency and concentration of contamination can be recorded or measured relatively easily for these sources as the location and timing of contamination events is usually known. Similarly it is relatively easy to treat point source pollution to an acceptable standard and they are therefore well regulated (Randhir, 2007). Quantifying and controlling diffuse pollution, such as

surface runoff contaminated with livestock waste, is a lot more difficult due to it being dispersed, often randomly, across a catchment and it being transported sporadically (Ahearn et al. 2005; Ferguson et al. 2003). Pollution events in terms of diffuse sources usually follow the temporal and spatial characteristics of rainfall as it mobilises contaminants and transports them to the stream (Davies et al. 2004). It is this pollution source which is of most concern to the suppliers of drinking water due to the largely unknown risks it could pose and the haphazardness of the risk.

Sampling during diffuse pollution events is important to adequately assess the highest risk periods to drinking water quality. To enable diffuse pollution events to be captured knowledge of the best sampling location within the catchment and a monitoring program that specifically samples during rainfall is required. The logistical difficulties of this type of sampling mean that some studies looking at the movement of pathogens through catchments often overlook diffuse pollution within a catchment (Medema & Schijven, 2001; Teunis et al. 1997). Diffuse pollution sources such as livestock waste in a rural catchment are the primary source of pathogenic contamination (Ferguson, 2005) and therefore neglecting to sampling during events is unacceptable and gives a false indication of the risk.

2.3.3 Transport and survival

An understanding of the transport and survival characteristics of pathogens within a catchment is important as it will help ensure that the risk of them contaminating the water supply is managed appropriately. Protozoan pathogens are negatively charged (Davies et al. 2004) and generally travel as a single organism, that is, not attached to particles (Davies et al. 2005b). This means that the characteristics of pathogens, such as size and hydrophobicity, greatly affect their interaction with the environment. This is of great importance when considering their movement through catchments in that they should not be considered as acting the same as other contaminants, such as nutrients or sediment.

In order for a pathogen to be a hazard to public health the following three events must occur: first, the pathogen must be released from the faecal material, second, the pathogen must be entrained in overland flow and not filtered out by catchment processes and lastly the pathogen needs to remain viable throughout these events (Tate et al. 2004). A number of studies have investigated these events, specifically in relation to *Cryptosporidium*, and their findings are summarised below.

The importance of the viability of a pathogen relates to its ability to be infectious to humans. Pathogens may be found in the environment but if they are no longer viable then they pose no risk. The survival of pathogens in the environment is influenced by temperature, sunlight, salinity and available nutrients (Smith & Perdek, 2004). Inactivation in the environment is dependent on the specific microorganism and can be as long as several years in the case of adenovirus (Haydon, 2006). Generally protozoa have been shown to be environmentally robust; *Cryptosporidium* oocysts can last for more than 12 weeks in both soil and water depending on the temperature (Olson et al. 1999). In terms of replicating, most pathogens require a host; although it has been shown that *E. coli* can grow in a tropical environment (Byappanahalli & Fujioka, 1998).

Davies et al. (2004) looked at *Cryptosporidium* oocyst transport in a laboratory setting using artificial faecal pats spiked with *Cryptosporidium* to determine the release and subsequent transport from the faecal pats. They used intact soil blocks, which aimed to maintain the soil structure and vegetation of the natural catchment. The study found that in terms of dispersion, between 3% and 64% of oocysts found in fresh faeces were mobilised and transported in catchment runoff. The runoff volume, intensity and duration of the event, vegetation status and slope all significantly affected pathogen load in the runoff.

Atwill et al. (2002) and Trask et al. (2004) undertook experiments in the laboratory using naturally occurring *Cryptosporidium* oocysts, soil boxes and simulated rainfall to determine pathogenic transport characteristics over different vegetative surfaces. Both of these studies applied the pathogens to the soil boxes by creating a concentrated faecal slurry which may not be representative of what occurs at a catchment scale in terms of dispersion of pathogens directly from faecal matter as in Davies et al. 2004. Additionally the soil boxes in these studies and in another carried out by Tate et al. (2004), were packed with loose soil and vegetated from seed which may not provide a realistic simulation of pathogen transport due to the soil structure in an intact soil block providing a fast vertical flow path for pathogens (Smith et al. 1985). Extrapolation of results from laboratory experiments, such as these, to a catchment scale should be done with great care and should be verified by ground-truthing (Ferguson, 2005).

All of the four studies referenced (Atwill et al. 2002; Davies et al. 2004; Tate et al. 2004; Trask et al. 2004) found that the transport of *Cryptosporidium* oocysts were greatly

affected by the presence of vegetation. Vegetation acts by impeding the horizontal flow and promoting vertical movement of flow and pathogens are then more likely to be affected by processes such as filtration and adsorption to plant material.

2.4 Pathogen and indicator monitoring

As stated previously, the greatest risks to consumers of drinking water are pathogenic microorganisms (ADWG, 2004). Pathogen monitoring is however of little value for determining the risk to public health (Allen et al. 2000) and it is not generally recommended practice to monitor for pathogens directly (ADWG, 2004; WHO, 1996). This is due to the many issues related to pathogen monitoring including the complexity of the sampling and testing methods, the cost involved and the time required (Signor et al. 2005).

In terms of sampling and testing, obtaining a representative sample is difficult as pathogens are usually only present in water in low numbers. This means that a large volume of water has to be collected, sometimes up to 1000 litres (Deere et al. 1999), and transported to the laboratory. This can cause logistical issues especially when more than one site or points in time are being sampled. Once at the laboratory there are issues with concentration of the sample, extraction, purification, identification and counting which all affect the recovery efficiency (Walker, 2001). Recovery efficiency indicates the number of pathogens detected compared to the total number present. One paper reports that recovery efficiencies for *Cryptosporidium* and *Giardia* in stream and reservoir waters can vary from 2% to 110.2% (Weintraub, 2006). This wide variation can be due to issues with the testing method or to the inexperience of laboratory staff and can result in misleading data being reported. In terms of having an operational benefit the collection of pathogen samples is questionable as it can take up to one week from delivery of the sample before the results are known. By this time it is likely that the water being tested will already have been supplied to consumers making the results useless. Until the development of more reliable pathogen testing methods, the assessment of safety of water is reliant on pathogenic indicator organisms.

Standard drinking water quality practice is to monitor for pathogenic indicator organisms, such as *E. coli* and enterococci (Astrom et al. 2007). They are excreted with faeces and their detection can indicate the presence of faecal contamination and

therefore the probable presence of pathogens (Hein et al. 2007). Indicator organisms generally have the following characteristics:

- present in large numbers in faeces
- detectable by simple methods
- do not grow in the environment

Additionally it is preferable that the indicator behaves similarly to pathogenic organisms in terms of its persistence in water and its resilience, or otherwise, to treatment technologies such as chlorine and filtration. Some other examples of widely used faecal indicator organisms include the following: faecal coliforms and *Clostridium perfringens* (*C. perfringens*). Indicator organisms are cheap to monitor for, have a relatively fast turn around time and the methods used to detect them are relatively accurate.

As discussed above, pathogen and indicator monitoring must include event sampling if knowledge of the highest pathogen loads and therefore the highest risk to drinking water quality is required. The risk of contamination of a stream significantly increases during storm events; 51% of waterborne disease outbreaks in the USA between 1948 and 1994 were attributed to rainfall events (Epstein, 1998, cited in Shehane et al. 2005). Additionally, it was also shown by Roser and Ashbolt (2005) that as much as 300 years worth of dry weather pathogens could be exported during 1 day in a small rainfall event. Kistemann et al. (2002) state that in the context of multiple-barrier protection and risk assessment, sampling during extreme runoff events should be undertaken as regular samples are inadequate for representing microbial contamination. It is therefore imperative that any sampling program incorporates some form of rainfall event runoff sampling, or storm sampling. This is an area of work, however, that has received limited attention due to any number of factors, including: uncertainty about when to monitor and what to monitor for and the time and cost involved in catchment scale monitoring. Event monitoring can also be difficult in a catchment with many sources of diffuse pollution and therefore careful consideration of the monitoring program specifics is required. The small number of studies examining pathogen loading during storm events is surprising, especially given the significance of the human health risks that can be posed by such events.

2.5 Regulation of drinking water quality

The many issues with pathogen sampling mean that regulation of drinking water is often not based on monitoring data but instead on a risk management based approach. Risk management is a well accepted concept and management tool within the drinking water industry and within Australia its importance is highlighted in the Australian Drinking Water Guidelines (ADWG). More locally, in the state of Victoria the risk management approach is legislated through the Safe Drinking Water Act (SDWA).

The ADWG (2004) is a national guideline document that is used throughout Australia as a basis for managing and supplying safe drinking water. It is a guideline document in that it does not set out standards or limits that must be adhered to instead it sets out a preferred management framework and provides a reference document for water suppliers. Specific guideline values are given for many physical and chemical contaminants, although for some pesticides the guideline is simply that they should not be detected. In the case of pathogens, however, no specific guideline values are specified. It states that the protection of drinking water supplies requires a precautionary approach. This suggests that even in the absence of scientific evidence of pathogenic contamination, protection of water supplies from contamination should not be compromised. The ADWG encourages a multiple barrier approach to protect water supplies from pathogenic contamination, which reduces the reliance on a sole barrier, such as a treatment plant and promotes the implementation of a series of barriers. This approach allows for periods of failure or reduction in efficiency of one barrier as it will be compensated for by other barriers.

In the state of Victoria the Government recently passed into legislation the SDWA (2003). It requires all water authorities to prepare, implement and review a risk management plan and have that plan regularly audited. It is a requirement that the risk management plan describes the water supply system, identifies and assess all possible risks and sets out prevention strategies to manage those risks. Implicit within the SDWA is the need for the use of multiple barriers. The SDWA provides a regulatory framework for the management of drinking water quality without having mandatory water quality limits.

The World Health Organisation (WHO) has a similar regulatory approach to ensuring the supply of safe drinking water. In their document Guidelines for Drinking-water Quality (WHO, 2008) it states that:

> "*A holistic approach to drinking-water supply risk assessment and risk management increases confidence in the safety of drinking-water. This approach entails systematic assessment of risks throughout a drinking-water supply – from the catchment and its source water through to the consumer – and identification of the ways in which these risks can be managed.*"

It does not recommend setting specific standards for pathogens due to the difficulties in monitoring for them in finished water, as discussed in Section 2.4. It instead encourages the implementation of Water Safety Plans (WSP) which are essentially a comprehensive risk assessment and risk management document. The main elements of a WSP include hazard assessment and risk characterisation, identification of control measures and development of monitoring strategies to verify the plan's effectiveness.

It is clear from the guidelines and regulations both in Australia and as recommended by WHO that risk management and multiple barriers are important tools in managing drinking water quality and specifically for managing pathogens.

2.6 Catchment management as a barrier

The multiple barrier approach to drinking water protection is a well supported management technique which requires multiple scientifically validated mechanisms that prevent contamination of or remove contamination from the water supply prior to consumption. Multiple barriers can refer to both engineered barriers such as filtration or a closed distribution system as well as to natural processes, such as detention in large storage reservoirs. One of the most critical barriers is catchment management, which is defined as a coordinated approach to various plans that will ultimately improve water quality (ADWG, 2004). It is a preventative measure in that it aims to control contamination at the source. Preventing contamination from entering the water provides a greater surety of the absence of contaminants and therefore safety than relying on removal of contamination by treatment (ADWG, 2004). Furthermore,

preventative measures such as catchment management have potential additional health benefits in that the reduction of contamination in the water may lead to a reduction in the use of chemicals in treatment (ADWG, 2004).

The importance of catchment management is highlighted in Hrudey and Hrudey (2004) who identify over 35 cases of waterborne disease outbreaks in affluent nations that are directly related to events or practices within the catchment. Heavy rainfall, septic tank or sewerage failure and cattle grazing near an offtake are all events/practices which have been implicated in waterborne disease outbreaks. These catchment events resulted in faecal material, either human or animal, entering the water supply, the treatment barrier being insufficient to handle the load or the treatment barrier being inadequate for the particular contaminants and contaminated water being supplied to consumers. Preventing contamination at the source will go some way to ensuring these outbreaks occur less frequently.

Protection of the source water through catchment management can include any number of techniques, whether they are structural, such as providing alternate stock watering sources, vegetative, such as reforestation, or managerial, such as ensuring planning regulations limit inappropriate development (Benham et al. 2005). In addition there are the community elements such as promoting awareness of water quality issues within the catchment and encouraging sustainable farming practices. All of these techniques have the ability to reduce non-point source pollution to streams either by eliminating the pathogen source or by restricting pathogen transport. Assessing the effectiveness of these works in terms of pathogenic reduction is challenging and the research done to date is largely inconclusive (Smith & Perdek, 2004). As a result of inadequate monitoring strategies and the difficulties in data analysis along with the long time periods required to assess their impact, the effectiveness of catchment management initiatives has often been assessed on visual observations rather than on water quality monitoring (Benham et al. 2005). Elements such as design, site selection, implementation and maintenance can be assessed using a survey-like tool. Although relevant for a quality assessment of catchment management, in terms of a quantitative water quality tool, this approach is unacceptable. As acknowledged by Ferguson (2005) one of the biggest knowledge gaps in the conceptual understanding of catchment management processes is in the efficiency of those processes to trap contaminants.

Despite the lack of knowledge of the effectiveness of particular catchment management works, it is widely accepted that different land-use and land-use activities influence water quality (Ahearn et al. 2005; Ferguson et al. 2003; Jiang et al. 2005). Roser and Ashbolt (2005) looked at storm events in several catchments with differing land-uses and the concentrations of pathogens and indicators being transported to streams during these events. They found that in terms of the concentration of *Cryptosporidium* there was 1,000 fold less, or a 3-log reduction, in a protected catchment versus a septic impacted catchment. It is worth considering whether an impacted catchment with appropriate catchment management would be able to provide this level of reduction in pathogens.

An additional acknowledgement that catchment management has some benefit as a tool for reducing contamination can be found in the ADWG (2004) which suggests that the estimated removal rates for enteric pathogens given a watershed protection, or catchment management, barrier is 0.5-1-log. The United States Environmental Protection Agency's (US EPA) Long-term 2 Enhanced Surface Water Treatment Rule (LT2 Rule), which is the legislation relevant to all public drinking water systems in the USA that are influenced by surface water, is similar. The LT2 Rule (US EPA, 2006) specifies a source water monitoring program that ultimately determines the level of treatment that is required for that system and gives a list of options available to meet that level of treatment. Watershed control is offered as one of those options for which it gives a 0.5-log presumptive credit. The words "estimated" and presumptive" within these documents suggests a lack of scientific data to validate the removal rates possible through catchment management.

The absence of legislative confidence and definitive evidence in terms of the drinking water quality benefits of catchment management has not hindered its uptake as a risk management tool in drinking water supplies around the world, as demonstrated below.

2.6.1 Examples of catchment management in major cities

There are many examples around the world of where catchment management forms an integral part of the supply of safe drinking water. Two examples have been chosen to show the importance of catchment management and the strategies and projects that are being undertaken within the respective catchments to improve water quality: New York City and Sydney.

New York City, USA

New York City is supplied with drinking water that is sourced from inhabited and farmed catchments. Despite the United States Environmental Protection Agency (US EPA) mandating under their Safe Drinking Water Act that all water supplied from surface water requires filtration before distribution, the water supplied to New York City is unfiltered. The New York Department of Environmental Protection (NYDEP) were able to obtain a filtration avoidance determination by showing that the implementation of a source water protection program was enough to protect against microbial contamination of the water supply thereby ensuring the supply of safe drinking water for the 9 million residents of New York City. The source water protection program consists of the following three main initiatives: land acquisition, water supply rules and regulations and catchment protection and partnerships (Brown, 2000). These initiatives aim to give the water authority more control over the catchment by purchasing land, specifying enforceable standards for wastewater treatment and educating local residents about catchment management. In 2004 the funds committed to these programs totalled over $US400 million, which is a relatively inexpensive investment when compared to the cost of filtration; $US6 billion for design and construction plus $US300 million/year for operating expenses (Pires, 2004). Monitoring, modelling and research on both water quality and disease prevalence in the community are important components of the program and provide verification that the programs are protecting public health. There is a continued desire to avoid filtration for New York City and a general belief that protecting public health through complex watershed management is possible (Pires, 2004). The large investment in not only money but also in time, in terms of stakeholder engagement and implementation of programs, indicates that the NYDEP are fully committed to catchment protection.

Sydney, Australia

In 1998 high levels of the protozoan pathogens *Cryptosporidium* and *Giardia* were detected in the treated drinking water being supplied to Sydney residents. It resulted in a boil water notice being issued Sydney-wide which affected over 3 million people and cost the water authority considerable amounts of money; over $AUS35 million was spent on rebates, lost revenue, water testing and damages claims (Stein, 2000). Despite no illnesses in the population being directly related to the water quality, the confidence in the water supply and the supplier's reputation were severely damaged. Additionally many people in high level jobs within the water authority, including the Chairman and Managing Director, lost their jobs. Although it remains unclear what the

exact cause of the high levels of pathogen detection were, the consequences from the crisis were significant in terms of the way the drinking water and its protection is managed in Sydney. An independent inquiry was ordered by the state Government which produced many reports and over 90 recommendations, 32 of which were aimed specifically at protecting water supply catchments and minimising contamination (Stein, 2000). The inquiry resulted in Sydney Water Corporation, who at the time were responsible for managing and supplying drinking water to Sydney, being split into a distribution manager, Sydney Water, and a catchment manager, the Sydney Catchment Authority (SCA). The role of the SCA is to "capture, store and supply quality raw water from well managed catchments" (SCA, 2009b). The development of the SCA demonstrated an understanding as to the importance of catchment management in the supply of safe drinking water as well as a commitment to source water protection. Since their inception the SCA have developed a Healthy Catchments Program, which through a greater understanding of catchment processes and focused research aims to improve catchment health and reduce the risks to water quality (SCA, 2009a). Some of the key strategies that are being implemented include a sewage strategy, riparian management and stormwater infrastructure improvements. Each strategy aims to develop remedial and preventative strategies to improve water quality and catchment health. SCAs vision of "Healthy catchments, quality water – always" reinforces their role and the importance of catchment management to the supply of safe drinking water in Sydney.

2.7 Catchment management initiatives

As highlighted in the above examples, the term catchment management covers a wide range of management techniques that can be used to control diffuse pollution sources within a catchment. The best techniques to apply depend on the particular objectives of implementing catchment management and on the characteristics of the land. Additionally the attitudes of land-owners and their willingness to be involved in the particular catchment management initiatives are important considerations.

In the case of drinking water quality the main objective of any catchment management initiative is to prevent faecal matter contaminated with human infectious pathogens entering the water supply. In an agricultural catchment it is the livestock waste that is of most concern. Preventing contamination can be done in two ways, through removal of the contamination source or obstructing the contamination transport mechanism.

Source management includes things such as reducing the incidence of infection among livestock, reducing faecal deposition intensity and/or removal of faeces from the catchment. These source management options are difficult to manage over large areas and with different herd populations within the catchment. Additionally management of herd-health is hampered by a poor understanding of the medical ecology of pathogens within livestock (Atwill et al. 2002). The best methods, therefore, of preventing animal waste from entering the water supply is through obstructing the transport mechanism. One such method is the implementation of fenced vegetated riparian buffer strips.

Livestock are generally attracted to streams for drinking water, shade and palatable vegetation (McKergow et al. 2003). This can result in direct deposition and therefore a direct pathway for pathogens to contaminate the water. Exclusion of cattle from these areas by constructing fences and providing food, water and shade elsewhere in the catchment can result in a 90% reduction in faecal contamination (Line et al. 2002). Apart from the physical exclusion of livestock from these vulnerable areas, vegetative buffer strips also provide a barrier between faecal deposition in the catchment and the stream.

Literature suggests that the implementation of buffer strips as a catchment management tool has been steadily increasing since the 1970's (Correll, 1996) and this is most likely due to their many benefits. In terms of water quality one of their most important benefits is their proven ability to reduce nutrient and sediment transportation to streams (Lovell & Sullivan 2005; McKergow et al. 2003) but in addition to this they are simple and inexpensive to implement, they improve stream health by providing shade and woody debris, they can help to reduce stock loss and they increase the visual amenity and biodiversity of the catchment (Barling & Moore, 1994). These benefits make them appealing to land-owners and catchment managers alike.

2.7.1 Buffer strips

Buffer strips, in the context of this work, are defined as a strip of vegetated land along the riparian zone of a river or stream, where the riparian zone is the transitional zone between terrestrial and aquatic ecosystems (Randhir, 2007). They can act as a filter for sediment, nutrients and pathogens in non-point source pollution (Barling & Moore, 1994), thereby improving water quality.

Buffer strips work by reducing the momentum and magnitude of surface and sub-surface runoff and in doing so aid infiltration into the soil column and promote the entrapment of pollutants (Parkyn 2004). Their effectiveness in terms of sediment and nutrient reduction is an area of significant research. Gharabaghi et al. (2000) report that between 50-98% of sediment is removed through buffer strips, while similar results were found by Lee et al. (2003) who report a removal rate of over 97%. For nutrients results vary based on the length of buffer, the plant cover and the hydrologic conditions (Lovell & Sullivan, 2005). Gilley et al. (2002) states, however that buffer strips can significantly reduce both concentration and load of nitrogen and phosphorus. As well as the physical barrier nutrients, such as nitrogen, can be removed through mechanisms within the buffer such as denitrification and assimilation (Correll, 1996). Lovell and Sullivan (2005) also report that buffer strips can protect water supplies by removing pesticides and fertilisers. This is of interest to drinking water quality managers, due to the potentially toxic nature of these contaminants. Pesticides and fertilisers in drinking water will, however, most likely result in chronic illnesses (WHO, 2001) and of more immediate importance is acute illness caused by pathogens, as discussed previously. Although these aforementioned benefits are valuable for the environment or for chronic chemical exposure, in terms of drinking water it is the ability of the buffer strip to remove pathogens and the risks due to acute exposure that is of most interest.

The study of pathogen reduction through buffer strips at a catchment scale is limited. Ferguson (2005) identifies the entrapment of pathogens through a buffer strip as a "large knowledge gap" in the conceptual understanding of a drinking water catchment and the management strategies used to reduce risk. Davies et al. (2005b) also state that the contamination of surface water by pathogens and the modelling of risk is an area that has been slow to advance. There are however a number of laboratory-based studies that have looked at the movement of pathogens and buffer strip efficacy (Atwill et al. 2002; Davies et al. 2004; Tate et al. 2004; Trask et al. 2004). Each of these studies were able to show a certain reduction in pathogen concentration given movement over a vegetated surface; results varied from 90 to 99.9% reduction.

There are many benefits of having buffer strips within a catchment, including: for the community, for the environment, for stream health and for drinking water safety. For many of these benefits assessing the impact of the buffer can be based purely on a visual inspection or community survey but for drinking water safety this is not sufficient.

Not only is a greater level of surety required, due to the health of the public being at risk, but there are also regulatory standards and guidelines that have to be met. Quantification and validation of buffer effectiveness at the catchment scale is required.

2.7.2 Quantifying buffer strip benefits

As demonstrated, catchment management within the water industry is an important facet of supplying safe drinking water and reducing risk. A crucial question, therefore, is what public health benefits are actually being gained by implementing catchment improvement works, or more specifically buffer strips. If the implementation of catchment management is going to be seen as a legitimate risk reduction tool in drinking water supply then visual inspection, as undertaken by Benham et al. (2005), is not adequate and some form of quantitative analysis of pathogen reduction is necessary. Although both the ADWG (2004) and the LT2 Rule (US EPA, 2006) give some credit to catchment management for reducing pathogen load, it is clear that more definitive scientific evidence is required. It is widely acknowledged that the study of pathogens, in particular, in relation to catchment management is limited (Davies et al. 2005b; Ferguson, 2005; Pachepsky et al. 2006). An understanding of the magnitude of any change is therefore also limited.

Scientific validation of the implemented barriers is preferred to ensure that drinking water is safe and that the identified risk has been reduced (WHO, 2001). In the case of engineered barriers such as treatment plants, validating their effectiveness is mostly a standard and accepted process (Ferguson, 2005). For a natural barrier such as buffer strips, however, such knowledge or confidence does not exist.

Validation is carried out to ensure the barriers put in place are effective and although some methods of validation include system audits or maintenance records (ADWG, 2004), the most comprehensive way of proving effectiveness is through quantifying the barriers' ability to reduce risk. Quantified risk assessment can assist in understanding and managing risks (WHO, 2008) and it can also feed into the Quantitative Microbial Risk Assessment (QMRA) process. QMRA is a tool that is beginning to be more widely used in the field of drinking water and public health as it determines the risk of infection of water-related diseases (Signor et al. 2005). QMRA is a systematic evaluation of water quality that produces a disease burden associated with exposure to pathogens from a certain water supply (WHO, 2008). It incorporates hazard identification and exposure pathways with dose-response. In order to enable an accurate prediction of

exposure, quantitative data is necessary (Davies et al. 2005b). Similarly then in order to predict any decrease in the disease burden due to the implementation of barriers, the decrease in pathogens numbers due to those barriers also needs to be quantified.

QMRA in the supply of drinking water should consider all of the barriers to contamination to ensure an accurate assessment. Due to the difficulties in quantifying the effects of catchment barriers they are often left out of a QMRA, meaning that their true benefits to public health are not realised.

To enable an understanding of whether buffer strips have a measurable benefit to drinking water quality, a quantitative approach to assessing their effectiveness in terms of pathogens at a catchment scale is required. This review suggests that such an approach has not been undertaken despite this type of assessment being essential for validating buffers as a barrier to drinking water contamination.

2.8 Summary

It is clear from the above review that risk management is an important component of supplying safe drinking water. In terms of public health the biggest risks to drinking water come from pathogenic organisms therefore reducing or avoiding their presence in water is imperative. A preventative approach to risk management, as encouraged by ADWG and WHO, gives a greater surety of contaminant absence than does removal by treatment by advocating management of contaminants at the source. In order to do this a comprehensive knowledge of the catchment and the processes that affect contaminant movement is necessary. Ultimately this will lead to appropriate management tools being implemented at the source and result in safer water. Having the ability to quantify the benefits that the management tools will give to drinking water safety would aid in setting priorities in catchment management and in treatment plant design.

A number of gaps, or areas where information or research is limited, have been identified throughout this review. Diffuse pollution and therefore storm events are the major source of pathogenic pollution in an agricultural catchment. It is therefore essential that sampling programs are set up to capture these storm events. Similarly any assessment of risks to drinking water can not be undertaken without this data. Risks should also be assessed in a quantitative manner as visual analysis, or similar,

of protection measures is completely inadequate when the health of the public is at risk.

Vegetated buffer strips have been identified as a suitable tool for the management of stream pollution. Many studies exist that determine the effects of buffers on nutrients and sediments but in terms of pathogens the research is limited and in terms of scale they are mostly laboratory-based. To enable the public health benefits of buffers to be understood, specific consideration of pathogens is required due to their unique transport and survival characteristics. Additionally using data collected at a catchment scale to validate the results obtained in the laboratory will ensure that processes such as re-entrainment and development of preferential pathways are included. A novel approach to reporting and quantifying catchment processes is required.

The aim of this work is to determine if there is a measurable difference in the risk to drinking water quality following the implementation of buffer strips and if that difference justifies the resources needed to implement these strategies. This will be achieved by gaining an understanding of the dominant catchment processes, statistical analysis of changes in water quality, assessing the impact of storm events on contaminant transport and modelling as a form of prediction for different scenarios. These approaches and their significance in the context of drinking water quality management are discussed in detail in the following chapters.

3. CATCHMENT AND DATA DESCRIPTION

3.1 Introduction

The investigation of catchment management initiatives and their effect on drinking water quality requires a suitable study catchment to be chosen. The chosen catchment had to fulfil a number of criteria, which included:

- being an open catchment with past catchment management works
- having a good quality and extensive data set both in terms of sampling length and number of parameters
- having a current water quality monitoring program that included sampling during storms and pathogen sampling.

The Tarago Reservoir catchment in south-east Victoria, Australia, fulfilled all of these criteria.

This chapter gives a description of the study catchment, including its history as a drinking water supply, its land-uses and its past water quality issues. It then goes on to describe the catchment management initiatives, both past and present, as well as the water quality monitoring programs during these times. Water quality data availability and limitations are discussed along with the hydrological data availability, which is required for catchment modelling. Presented at the end is a description of the faecal deposition likely in the catchment, the relevance of which will also be explained.

3.2 Study catchment description

The Tarago Reservoir, with a 37.5 GL capacity, is a dam located in Victoria, Australia, about 100km east of Melbourne. It is a drinking water reservoir that currently supplies water to surrounding townships, including Neerim South and Bunyip, and has recently been reconnected to the Melbourne system; Melbourne has a population of almost 4 million people. The Tarago Reservoir collects water from an 11,400 hectare (ha) catchment. Of this area approximately 2,300 ha contributes to direct runoff into the reservoir and the remaining areas drain into three perennial streams, the West branch of the Tarago River (with a catchment area of 7,200 ha), East branch of the Tarago River (1,300 ha) and Crystal Creek (800 ha), see Figure 3.1.

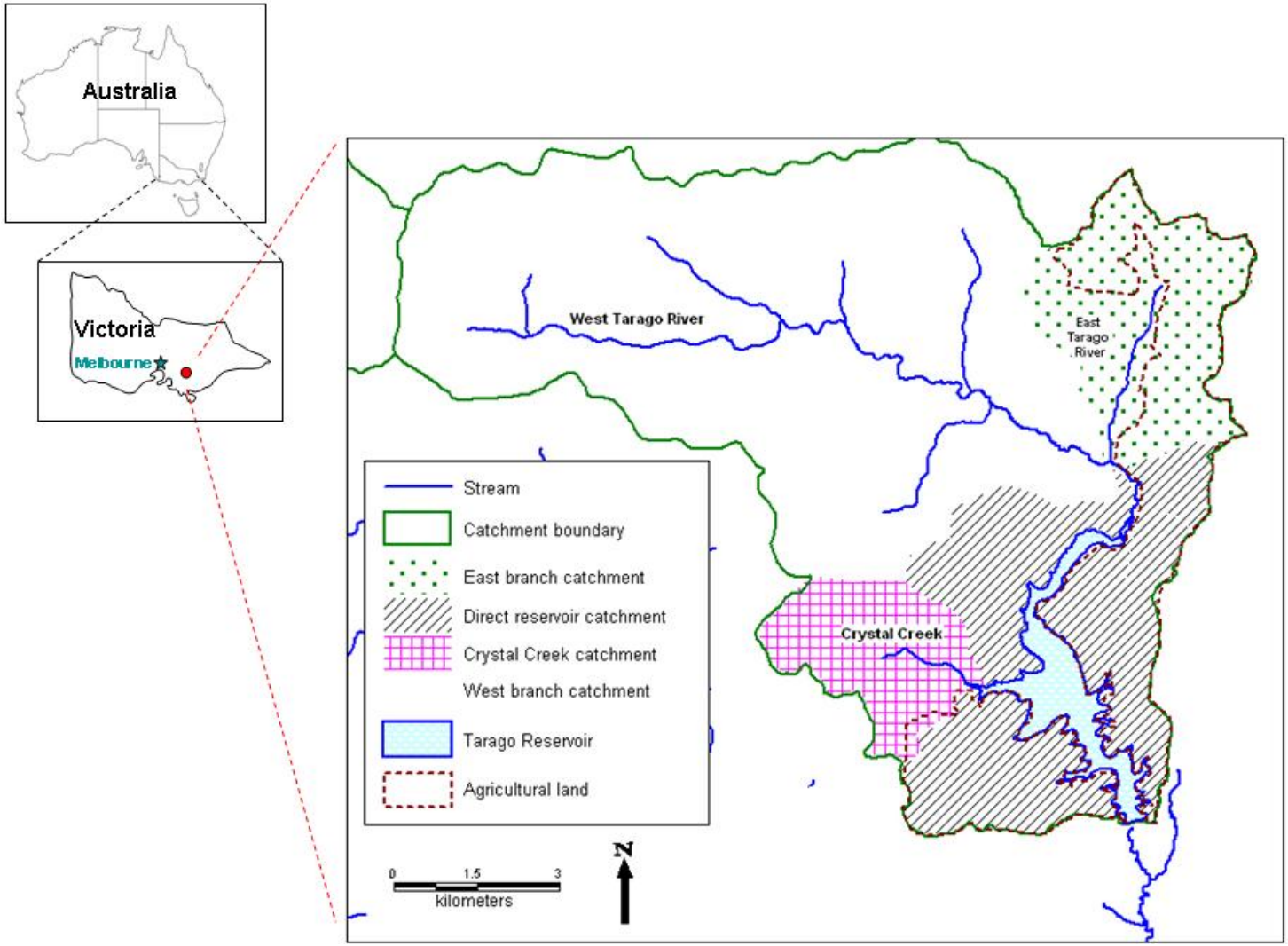

Figure 3.1 – Tarago Reservoir catchment

Drinking water supply history

The Tarago Reservoir was constructed in 1969 and supplied drinking water to outer Melbourne suburbs and townships to the south east of Melbourne. Responsibility for the reservoir was assumed by Melbourne Water in 1991 and in 1994 due to poor water quality, specifically an algal bloom, the reservoir was taken offline. It was still, however, used to supply water to surrounding townships, including Neerim South and Bunyip. Water is filtered and disinfected before distribution and these townships continue to be fed from the Tarago Reservoir.

Poor water quality, a lack of adequate treatment and the availability of more reliable water sources elsewhere meant that supply to Melbourne from the Tarago ceased in 1994. At the time of commencing this thesis the Tarago Reservoir was being mooted as a future drinking water source for Melbourne. The Victorian Government had just completed a review of the water resources in the state, which stated that to provide Melbourne's projected increase in water use by 2050, a small increase in supply was required (DSE, 2004). Reconnecting the Tarago Reservoir to the Melbourne system would achieve this and the review called for an investigation into the projects timing, costs and environmental impact. The reconnection date of 2050 would have allowed for catchment management initiatives to be implemented and would also have allowed a consideration of the benefits of such works in the design of the necessary treatment plant. In June 2005, however, the then Environment Minister John Twaites announced that due to the findings of a collaborative report between CSIRO and Melbourne Water on climate change, which stated a 35% drop in flows to reservoirs by 2050 (Howe et al. 2005), the reconnection of the Tarago Reservoir would be brought forward to 2011.

In 2009 the Tarago Water Treatment Plant was completed ahead of schedule and drinking water from the Tarago is currently being supplied to the Greater Melbourne area.

Land-uses

The quality of water in each of the three streams in the Tarago catchment varies due to the different land-uses of each sub-catchment. The catchment of the West branch catchment is entirely made up of State forest – which is publically owned land reserved for a number of values including timber harvesting, conservation and recreation (DSE, 2008). The East branch catchment has land-uses including agricultural and rural

residential and Crystal Creek catchment is a mixture of State and private forest with some agricultural land-uses.

The West branch of the Tarago River contributes approximately 60% of the flow into the reservoir. Generally the water coming from the West Tarago River is of relatively good quality. The main water quality concerns from this inflow are physical parameters, such as colour, suspended solids and turbidity. Land-uses within the West Tarago catchment that contribute most to water quality degradation are logging and recreational activities such as four wheel driving and horse riding. These uses require the construction, either formally or informally, of road networks and it's these unsealed roads that have been shown to contribute the majority of the sediment to streams (Cornish, 2000). While sediment and other physical parameters degrade the aesthetic quality of the water and can affect water treatment efficiency and contribute to sedimentation of the reservoir, their direct threat to public health is minimal. Current catchment management efforts in the West Tarago are focused on reducing sediment by managing the road networks, on ensuring sustainable forestry practices and by reducing inappropriate recreation in the catchment, such as trail bikers and horse riding.

The risk arising from the West catchment in terms of human infectious pathogens is minimal. This is due mainly to the lack of both human activity and domestic animals. While there is some human activity, in the form of recreators, in the West Tarago catchment, their density is low and the duration of their presence is such that their impact on both the environment and on water quality is minimal. The West Tarago catchment supports mainly native animals which, compared to domestic/livestock or feral animals, have a lower population density, produce less faecal material and are less likely to excrete human infectious pathogens (Ferguson, 2005). A further benefit of the West catchment is that the forest has a filtering effect and can reduce the pathogen load entering a stream by up to 1,000 times, or 3-log, as compared to an impacted catchment (Roser & Ashbolt, 2005).

Crystal Creek catchment consists of both forested and agricultural land-uses and contributes only a very small percentage of runoff to the reservoir.

The East branch of the Tarago River only contributes approximately 25% of the total inflow to the reservoir but from a drinking water perspective it represents the majority of

the risk. This risk is human infectious pathogens which are mainly sourced from domestic animals and humans. The East catchment supports residential and rural land-uses including horticulture, dairies and grazing. There are around 36 houses in the East catchment and as there is no reticulated sewerage system all houses treat their waste-water on-site. The East catchment supports 1 dairy harbouring over 150 cattle in total, both fully grown heifers and calves. There are also beef and deer farms located in the catchment. Grazing cattle are kept at a lower density to dairy cows but cover a much larger total area in this catchment. There are about 150 grazing cattle, which does not include very many calves, as most farms buy in steers to fatten and then sell off as beef. There is only one deer farm, and it is thought to harbour up to 300 deer at a time[1]. Figure 3.2 shows the location of these land-uses within the East catchment.

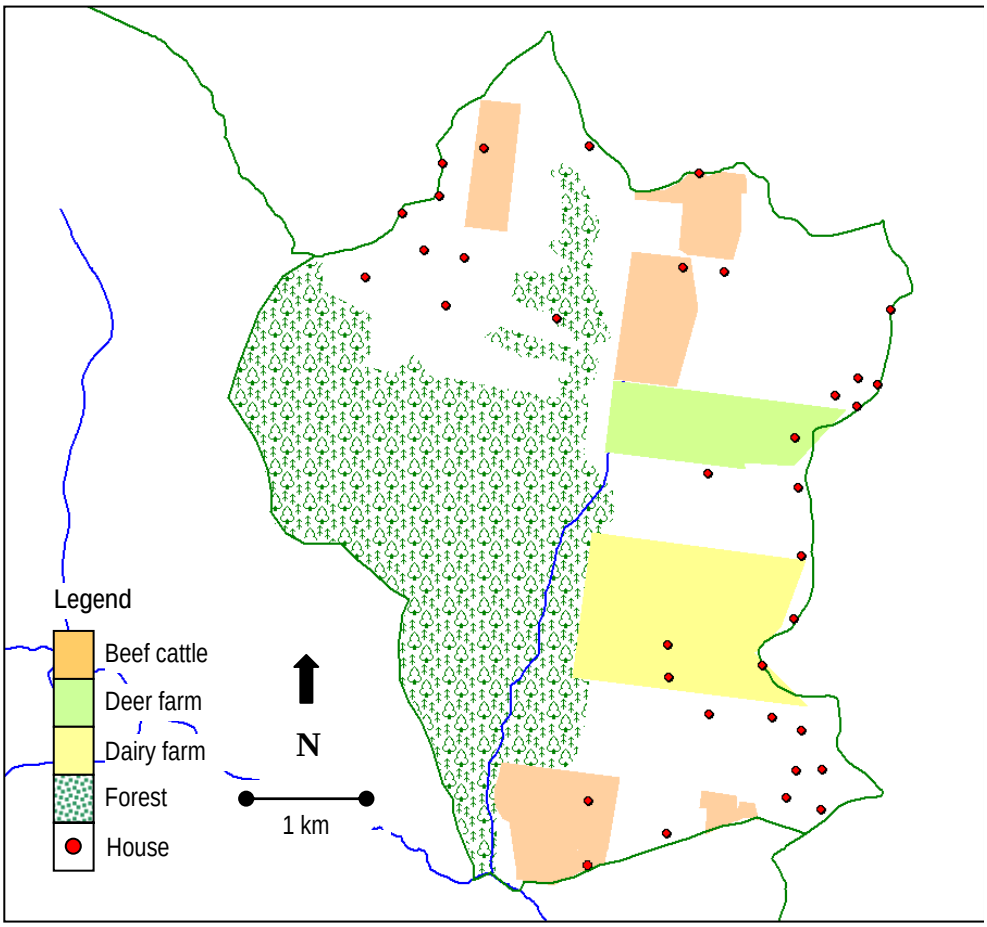

Figure 3.2 – Land-uses in the East Tarago catchment

[1] Numbers quoted are only for the East catchment and not the total number of these land-uses within the catchment

The majority of the land-uses in the East catchment harbour either humans or domestic animals which are both known sources of pathogens and the greatest risks to consumers of drinking water are pathogenic microorganisms (ADWG, 2004). In an effort to reduce the risks to drinking water quality and aesthetic water quality a number of catchment management initiatives have been undertaken in this catchment over the past ten years. The details of these programs will be detailed in the following Section.

Soil types

The soil types found within the catchment and their characteristics dictate the land-uses and can also have an impact on water quality. The East catchment is predominately a basalt rock with a clay soil overlay. This soil type has good permeability and is moderately high in nitrogen and phosphorus which makes it productive farming soil (Melbourne Water, 2003). The West catchment is predominately granite base overlay by a sandy soil. This has a high permeability and is low in nitrogen and phosphorus. It is a relatively stable soil structure if vegetated but is subject to erosion if exposed (Melbourne Water, 2003). The third soil type in the catchment, sedimentary rock, is found closer to the reservoir. Both the basalt/clay and the sedimentary rock have a tendency to slump in steep terrain, which is evident in the East catchment and around the reservoir.

Past investigations

The Tarago catchment is an extensively investigated catchment and there are many published research studies and papers referring to it (Bowles, 1979; Dyer & Olley, 1999; Siriwardhena, 1999). In the early 1990's the reservoir experienced a toxic blue green algal bloom of *Microcystis sp.* which caused the reservoir to be taken offline (Swingler, 2003). A number of studies have therefore looked at the nutrient inputs from non-point sources (Dyer et al. 1999; Jayasuriya et al. 1994). A major study by Hairsine (1997) investigated the sediment movement within the catchment and its effect on water quality and stream health and Motha et al. (2004) used the Tarago catchment to investigate the impact of unsealed roads as a source of sediment.

Despite the Tarago Reservoir being a drinking water reservoir none of the published studies have focused on the risks to drinking water quality from human infectious pathogens. This could be due to one of two of the following factors: the seemingly imminent threat of continued algal blooms in the early 1990's or the relatively limited

knowledge in the past regrading pathogens, including their sources, their transport and survival mechanisms and their potential impact on human health.

In order to determine if there is a measurable benefit to drinking water quality from the implementation of catchment management, analysis of both the works that have been undertaken along with pathogenic data is crucial.

The following section will discuss the catchment management works that have been undertaken in the past and that are occurring in the present. Details about the monitoring programs that will be used to assess their ability to reduce risk will also be presented.

3.2.1 Catchment management history in the East Tarago catchment

The Tarago catchment has seen two distinct periods where catchment management has taken place. The first commenced in 1991 when responsibility for the Tarago Reservoir was assumed by Melbourne Water, the bulk water supplier for metropolitan Melbourne. It was recognised at this time that the land based practices in the East Tarago catchment were contributing to the poor water quality being delivered to the reservoir and ultimately to consumers. Therefore the majority of both past and present catchment management works have been focused in the East Tarago catchment. However, due to budgetary constraints and a realigning of priorities within Melbourne Water, the continued financial assistance for the management and implementation of these catchment works ended in the mid nineties. In 2003 due to the reservoir being mooted as a future water resource for metropolitan Melbourne the concept of multiple barriers, and especially catchment management, was seen as the management option that would ensure the highest water quality. A history of each of these programs including details about their objectives and their time frames are outlined below.

In the early 1990's the threat of algal blooms were the main concern to the water authority. In an attempt to reduce the nutrient input to the reservoir and improve aesthetic water quality three different management options were looked at:

- acquisition and revegetation of agricultural land
- construction of diversion drains to intercept contaminated runoff
- land based improvement works.

The first option, revegetation, would have involved forcing residents off their land and out of their homes and was seen as too costly and not politically or socially favourable. The second option, constructing diversion drains, was also quite costly and would have resulted in a loss of yield. Implementation of land based improvement works was thought to have benefits not only for water quality but also for the farming community within the catchment and the community at large.

The Tarago Catchment Management Strategy (Melbourne Water, undated) was developed in the early 1990's which involved both the water authority, Melbourne Water, and the local community. It outlined a strategy aimed at improving water quality and included the details of the water quality sampling collection, the research projects to be undertaken and the publicity around the strategy. In terms of improving water quality, there were a number of works that were implemented, which included:

- fencing and revegetating streams
- constructing stream crossings for livestock and farm equipment
- providing off stream water for stock in dams or troughs
- installing appropriate drainage on farm tracks and cow lanes
- ensuring dairy farms were complying with EPA regulations for the disposal of their effluent.

The works were promoted as improving access, shelter and productivity on farms as well as increasing the lands capital value through improved amenity (Melbourne Water, undated). From a water quality perspective the works were focused on limiting nutrient and sediment transport to the reservoir as these were the water quality parameters of most concern at the time.

As discussed above this program ceased in the mid-nineties due to budgetary constraints but in 2003 catchment management was again seen as playing an important role in the management of water quality.

As a result of government agencies, landowners and community groups sharing a vision for the catchment's management the Tarago Catchment Management Plan (Melbourne Water, 2003) was developed. The aims of the plan include protecting water quality for current and future human consumption, soil conservation and encouraging sustainable farming practices. The plan outlines a number of

management actions that are practical and achievable and are ultimately aimed at making a real difference to the long-term condition of the catchment (Melbourne Water, 2003). These actions and their main purpose are listed in Table 3.1.

Table 3.1 – Catchment management actions in the Tarago catchment post 2003

Management action	Purpose
Whole farm planning	To improve farmland productivity and reduce environmental and water quality impacts
Roadside management	To improve road maintenance and management to minimise erosion
Stormwater management	To improve the quality of stormwater
Septic tank management	To determine the number, condition and effect on water quality of on-site wastewater management systems in the catchment and look at practicable improvements
Stream frontage protection	To improve the structural stability and ecological health of streams by providing financial and technical support to landowners to assist them fence off and revegetate stream frontages. Additionally providing alternate watering points for stock
Forestry management	To ensure sustainable forest management
Planning scheme improvement	To ensure that the planning scheme is clear in regards to what development is appropriate within the catchment
Recreation management	To improve the management of recreational access and activities within the catchment

An additional management action in the Tarago Catchment Management Plan was Monitoring. The purpose of this action was twofold: the first was to ensure that all the management actions were progressing satisfactorily and the second was to undertake water quality monitoring so that the effect of the works could be measured and evaluated. The following section explains the water quality monitoring program both before and following the implementation of the Tarago Catchment Management Plan. It outlines the data that is necessary to enable a quantitative approach to assessing catchment management effectiveness.

3.2.2 Monitoring programs

The Tarago Reservoir and catchment has a number of different water quality data sets. Each had, or has, their own objectives and therefore their own characteristics in terms of parameters, locations and time-frames.

The objectives for collecting in-stream water quality data can vary depending on the type of catchment and the objectives of the organisation undertaking the sampling. The ultimate objective of any water quality monitoring and assessment is to ensure that

the source water is suitable for its intended purpose (WHO, 1996). Beyond that the objective is usually to either determine if there are any long-term trends or to pick up any sudden changes in water quality. Identifying, describing and explaining the major factors which affect the outputs of water quality monitoring assessment is usually the long-term objective of monitoring (Yu et al. 1993). Relating trends or observations to an event or change in the catchment requires an extensive amount of high quality data and an understanding of the processes that affect water quality. To ensure a high quality data set ideally a water quality monitoring program would have the following qualities:

- consistency – same parameters, same sampling locations and same sampling and detection techniques before, during and after any changes within the catchment
- long time-frame - usually in the order of tens of years
- comprising both baseflow and storm samples.

An extensive search of databases within Melbourne Water identified seven separate sampling programs that have been undertaken in the catchment of the Tarago Reservoir since the early 1970's. The programs range from routine grab sampling and continuous in-stream monitoring to event based monitoring and community programs. The seven programs span six different locations, predominately just prior to the confluence of the East and West branches of the Tarago River, see Table 3.2. In total the programs monitor for almost 40 different parameters, see Table 3.3. The lack of consistency across programs, in terms of locations and parameters is due to a number of factors including changing objectives and priorities in the catchment and the water industry as well as economic constraints.

Table 3.2 – Sampling Programs in the Tarago catchment (1974 - now)

Sampling Program Name	Location	Details	Objectives	Period of data collection	Undertaken by
Routine	East and West branch of the Tarago River and Crystal Creek	Grab samples taken approximately once a month	Maintain a long-term water quality data-base	1974 – now[2]	Relevant water authority
Waterwatch	Various points along the West and East branches of the Tarago River	Interested community members doing water quality testing monthly	Encourage the community to become active in the protection of their waterways	2004 – now	Community members
Event based	East and West branch of the Tarago River	Automatic samplers that take samples when streamflow rises	Determine the water quality during high risk times	1993 – 1999 2005 – now	Melbourne Water
Continuous in-stream	East and West branch of the Tarago River	Readings taken every minute and stored on an internal logger	Continuous water quality record	2004 – now	Melbourne Water
Victorian Water Quality Network	East and West branch of the Tarago River	A database of water quality data maintained by DSE	Collect data for the community to use	1974 – 1994	Various
Special program	Tributaries directly entering the reservoir and East branch	Targeted monitoring on East branch of the Tarago River	Monitor turbidity and colour entering the reservoir	1993	Melbourne Water
POA Aquatica	Wetland system near the north end of the reservoir	Samples taken prior to, within and after a wetland system	Determine the effectiveness of wetlands in reducing sediments and nutrients	1994	Melbourne Water

[2] The Routine grab samples are missing data from 1994 to 2004

Table 3.3 – Measured parameters for each water quality monitoring program and the approximate number of data points

	Routine	Water-watch	Event based[3]	Continuous in-stream	Victorian Water Quality Network	Special program	POA Aquatica	Total data points
Alkalinity	✓							923
Aluminium	✓							240
Ammonia	✓	✓	☑					>500
Bromide	✓							36
Calcium	✓							485
Chloride	✓							655
Chlorophyll	✓							2
Clostridium perfringens (C. perfringens)	✓							96
Total coliforms	✓							81
Colour	✓		☑		✓	✓	✓	>10,000
Cryptosporidium	✓		☐					89
Dissolved oxygen	✓	✓						>200
Escherichia coli (E. coli)	✓		☐					>200
Electrical Conductivity (EC)	✓	✓	☑	✓	✓		✓	>30,000
Enterococci	✓		☐					>150
Fluoride	✓							113
F-RNA phage	✓		☐					>150
Giardia	✓		☐					>100
Hardness	✓							669

cont…

[3] Ticks in a box (☑) indicate pre 1994 samples only, just a box (☐) indicate post 1994 samples only and two ticks (✓✓) indicate parameter included in both pre 1994 and post 1994 samples

cont…

	Routine	Water-watch	Event based[4]	Continuous in-stream	Victorian Water Quality Network	Special program	POA Aquatica	Total data points
Iron	✓		☑				✓	>1,000
Magnesium	✓							484
Manganese	✓							817
Nitrate	✓	✓	✓✓				✓	>5,000
Nitrite	✓		✓✓				✓	>1,000
Ortho phosphorus	✓		☐					>500
pH	✓	✓	☑				✓	>5,000
Phosphorus	✓	✓	✓✓		✓		✓	>5,000
Potassium	✓							357
Silica	✓							114
Sodium	✓							428
Sulphate	✓							370
Suspended solids	✓		✓✓				✓	>1,000
Temperature		✓		✓				>30,000
Total Kjeldahl Nitrogen (TKN)	✓		✓✓				✓	>1,000
Total Organic Carbon (TOC)	✓						✓	>400
Turbidity	✓	✓	✓✓	✓	✓	✓	✓	>30,000
Total data points	>15,000	270	>25,000	>100,000	3,270	260	430	**>145,000**

[4] Ticks in a box (☑) indicate pre 1994 samples only, just a box (☐) indicate post 1994 samples only and two ticks (✓✓) indicate parameter included in both pre 1994 and post 1994 samples

Although the collection of data from the Routine sampling in the catchment has been largely ongoing since 1974, there is a period of missing data, which extends from 1994 to 2004 inclusive. This was due to water quality being deemed unnecessary following the reservoir being taken offline in 1993 as a result of poor water quality. In 2004 as part of its contribution to the Tarago Catchment Management Plan and the increasing likelihood of Tarago Reservoir being again required to supply drinking water to greater Melbourne, Melbourne Water developed and implemented a comprehensive water quality monitoring program. The main objectives of the program were to:

- aid in the design of a new treatment plant by determining the risk to public health
- determine the risk of algal blooms in the reservoir
- provide information to the Tarago Catchment Management Plan as to what effect the on-ground works were having on water quality.

The programs major focus is drinking water quality, meaning that recent and emerging knowledge about human infectious pathogens and their indicators along with an understanding of the way they are transported through catchments was important. This led to a more representative monitoring program for the Tarago catchment. The Australian Drinking Water Guidelines, released in 2004, highlight the need for risk identification through appropriate monitoring and the program was designed with this in mind. Details of the program can be seen in Table 3.4.

One of the most important programs in the Tarago catchment is the Event based sampling. Most water quality monitoring programs incorporate a routine sampling component as this is simple to arrange in terms of frequency and reporting and is therefore relatively inexpensive and not very time-consuming to undertake. Although routine sampling is thought to be a good indicator of long-terms trends in water quality, it will usually not span a range of hydrological conditions, and most importantly will most likely exclude high runoff periods making them inadequate for representing microbial contamination of a stream (Kistemann, 2002). Rainfall induced runoff periods, or storms, are when the majority of contaminants are transported and have been shown to significantly increase concentrations of pathogenic organisms (Atherholt et al. 1998). To ensure the risks to water quality are not underestimated monitoring over a long time period and through differing hydrological conditions is very important.

Table 3.4 – Current water quality sampling program in the Tarago catchment

Program	Site	Frequency	Parameters	
Event based[5]	East branch West branch	Storm events	Pathogens Microbial indicators Nutrients Phys/Chem	*Cryptosporidium*, *Giardia* *E. coli*, enterococci phosphorus, nitrate, TKN turbidity, suspended solids
Grab sampling	East branch West branch Crystal Creek	Monthly[6]	Pathogens Microbial indicators Nutrients Phys/Chem	*Cryptosporidium*, *Giardia* *E. coli, C. perfringens*, enterococci, total coliforms phosphorus, nitrate, ammonia, TKN, iron, manganese, TOC turbidity, suspended solids, colour, pH
Continuous monitoring	East branch West branch	Continuous	Phys/Chem	temperature, turbidity, conductivity

Event based sampling

To allow storm events in the Tarago to be sampled a program incorporating automated sampling equipment was employed. The system was based on the Event Sampling System (ESS), developed by Roser et al. (2002). The samplers are set up to automatically sample at a set stream height above baseflow which will occur following a significant rainfall event. Once triggered the samplers collect volumes of water at regular pre-determined time intervals to ensure that both the rising and falling limbs of the event hydrograph are sampled. High volume samples of 10 litres are collected for the detection of pathogens and 1 litre samples are also collected to enable physical-chemical properties as well as nutrients and indicators to be measured. The 1 litre samples are refrigerated due to the liable nature of the indicator organisms. An ESS was set up on both the East and West branches of the Tarago River and each comprises:

- vandal proof and secure housing in the form of a shipping container
- a pressure sensor to monitor stream height

[5] Event based sampling not carried out in Crystal Creek due to lack of streamflow data

[6] Pathogens sampled every 3 months due to the cost and time involved

- two modified ISCO 3700 automatic samplers, one connected to 24 sample bottles capable of holding 20 litres each and the other attached to a refrigerator containing 24 x 1 litre bottles (further detail available in Roser et al. 2002), see Figure 3.3
- 5 x 12 volt deep cycle batteries topped up by solar panels to supply the power needed.

Figure 3.3 shows the EES at the East branch.

To determine the best rate of rise trigger level for the stream and the sampling interval, hydrological and rainfall data over a number of years was collected. This was then assessed and the large storms were extracted and analysed. The peak flows, the duration of the storm, the time taken for conditions to return to baseflow levels and the corresponding rainfall were all looked at. For the East branch site it was determined a rainfall event of 20mm was a significant event and warranted sampling and this equated to a rise of 0.025m in 2 hours or 0.035m in 4 hours. Initially an interval between samples of 45 minutes was thought to be sufficient. This was increased to hourly following two events that failed to sample during the falling limb. The West branch trigger level was more difficult to determine as there was no direct streamflow monitoring at this site therefore a figure was chosen based on local knowledge and a detailed site assessment. A rise of 0.04m in 2 hours or 0.05m in 4 hours was initially used as the trigger points. Following about 6 months of deployment, the trigger level in the West was decreased to try and capture more events.

Over the four year period in which the samplers were deployed they triggered a total of 6 times, once in the West and 5 times in the East. Table 3.5 gives details of each of the six storms that were captured.

Table 3.5 – Details of the captured storm events

	West	East				
	Even W1	**Event 1**	**Event 2**	**Event 3**	**Event 4**	**Event 5**
Date	31/08/05	11/09/05	15/11/06	27/07/07	11/09/07	21/11/07
24 hr rainfall [mm][7]	37.9	58.3	1.6[8]	14.3[9]	18.3	25.1
Peak flow [m^3/s]	0.56	0.38	0.14	0.47	0.17	0.14
Antecedent dry period [days]	9	12	2	8	7	17
Sampling duration [hrs]	8	16.5	22	23	12	12
Event duration [hrs]	34	37	20	20	22	17
ARI [years]	<1	<1	<1	<1	<1	<1
Number of samples	11	22	24	24	24	24

The ARI (Average Recurrence Interval) refers to the average, or expected, number of years between exceedences of a given rainfall total accumulated over a given duration (BOM, 2009). It is calculated by determining the intensity of the rainfall event, which is simply the total sum of rainfall for the storm event divided by the duration. This figure is then plotted on a rainfall Intensity Frequency Duration (IFD) graph, which is specific to a particular location and downloadable from the Bureau of Meteorology (BOM) website. The IFD graph gives rainfall duration and rainfall intensity for different ARIs; the IFD for Tarago can be seen in Appendix A, Figure A.1. According to the BOM it is preferable to represent ARIs as Annual Exceedence Probabilities (AEPs) as they are easier for the general public to understand. They are calculated using Equation 3.1.

$$AEP = 1 - \exp\left(\frac{-1}{ARI}\right) \qquad \text{(}\textit{Equation 3.1}\text{)}$$

where:

AEP = Annual Exceedence Probability

ARI = Average Recurrence Interval

[7] 24 hour rainfall is the rain that fell in the 24 hours prior to the last sample being taken

[8] In the 3 days prior to this sampling period there was 57.13mm of rainfall. The sample took place on the falling limb of the third peak of the storm.

[9] There was an additional 17.7mm of rainfall in the 12 hours prior to this period

Each of the captured storms had an ARI of less than 1 year which equates to an AEP of 0.63, meaning that in any 1 year there is more than a 63% chance of that rainfall total in that duration being equalled or exceeded. The storms captured are therefore not large events.

The “Number of samples” refers to the number of 1 litre samples taken and analysed. Only 4 of the large volume samples were analysed for each storm due to the cost involved in transporting and analysing the pathogen samples. It was believed that a good indication of pathogen concentration across an event could be gained from four samples.

The seemingly low number of events, given the long time-period, and the low ARIs is due mainly to the study being run during the worst drought in Victoria’s history. This obviously impacted on the number of significant rainfall events, but also contributed to the drying out of the catchment, which meant that when it did rain most of the water was absorbed into the ground and no or very little runoff was produced. Additional issues impacting the number of events captured included, having an inadequate trigger level, equipment failure and the strict sampling regime which meant that some samples were unable to be delivered to the laboratory within the required 24 hour time-frame.

Figure 3.3 - The event sampler on the East branch

(a) and (b) shipping container that housed the sampling equipment, (c) 1 litre sample bottles in fridge and (d) 20 litre sample bottles

3.3 Water quality data availability

In total the above sampling programs have analysed water quality samples using almost 40 different parameters, resulting in over 145,000 data points, see Table 3.3. As the majority of these programs were either designed with short-term objectives in mind or undertaken as part of the routine or compliance water quality testing at a particular time, the consistency of parameters across the programs is not good. An additional difficulty, when it comes to consistency is that emerging contaminants and new sampling and detection techniques mean that the water quality parameters that are used to determine whether water is safe to drink can change over time.

This section discuses the available water quality data and the programs and parameters that will be used going forward in this study. Physical-chemical parameters and pathogens/pathogenic indicators will be considered separately.

3.3.1 Physical-chemical parameters

To enable reasonable and meaningful conclusions to be reached when looking at this magnitude of data it is necessary to determine the best parameters to analyse. The value of each of the parameters depends on a number of factors, which include but are not limited to:

- the amount of data,
- the frequency of sampling,
- the stability of the sample location and
- any changes in method over time.

Additionally, in this study one of the most important factors is the ability of the parameters to show improvements in water quality that can be directly related to catchment works.

Choosing the appropriate parameters for analysis involved assessing previous studies as well as gaining an understanding of constituent movement through catchments. Siriwardhena (1999) undertook Factor Analysis (FA) using Tarago catchment water quality data sampled prior to 1993, the aim was to determine the significant pollutant transport processes and the water quality parameters associated with them. The study found that the most significant processes were erosion and surface runoff. The water

quality constituents released by these processes were found to include Total Kjeldahl Nitrogen (TKN), phosphorus, turbidity and colour. Additionally the East catchment released iron and manganese due to a high mineral content of the soil, as compared to the West catchment, and greater surface runoff and erosion. Therefore, these parameters were important to include. Detection of increased levels of suspended solids also relates directly to erosion so this was also included.

The remaining parameters chosen for analysis were included based on their ability to show the impact of different land-uses on water quality. Nitrate is related to fertiliser application, which occurs in the Tarago catchment due to horticultural land-uses. Agriculture activities are also the main source of ammonia production (Dragosits et al. 1998). Total Organic Carbon (TOC) indicates the organic content of the water and an increase in levels can be due to agricultural chemicals and domestic waste and result in the growth of microorganisms. Electrical Conductivity (EC) estimates the number of dissolved ions in the water while pH affects the solubility of ions.

The amount of available data for each parameter was also considered. Based on knowledge of the catchment, its significant transport processes and general water quality issues, the following parameters were chosen for detailed analysis, see Table 3.6.

Table 3.6 – Water quality constituents chosen for analysis and the available data points for each sub-catchment

Constituent	***units***	**Available data points**		
		East	**Crystal**	**West**
Ammonia	*mg/L*	203	199	193
Colour	*Pt-Co*	454	310	444
EC	*µs/cm*	414	278	412
Iron	*mg/L*	398	269	379
Manganese	*mg/L*	363	237	343
Nitrate	*mg/L*	297	178	279
pH	-	450	311	440
Phosphorus	*mg/L*	364	253	368
Suspended solids	*mg/L*	169	147	153
Total Kejandal Nitrogen (TKN)	*mg/L*	231	204	189
Total Organic Carbon (TOC)	*mg/L*	122	136	128
Turbidity	*NTU*	474	312	453

The data summarised in Table 3.6 only considers the “Routine” program (see Table 3.3) this is to reduce the likelihood of inconsistencies in location and detection technique, as discussed in Section 3.4.1.

3.3.2 Pathogens and indicators

Prior to 2005, human infectious pathogens and their indicators were not monitored in the Tarago catchment, due to the limited knowledge regarding pathogens and their impact on public health. The amount of data available for analysis of these parameters is therefore also limited. The current water quality sampling program for the Tarago catchment includes a number of pathogens and pathogenic indicators. The protozoan pathogens, *Cryptosporidium* and *Giardia*, are monitored as are the indicators, *Escherichia coli* (*E. coli*), enterococci, total coliforms, and *Clostridium perfringens* (*C. perfringens*).

It is necessary to monitor for pathogenic indicators as well as protozoan pathogens as there are many inherent problems with monitoring specifically for human infectious pathogens. Methods for detecting and quantifying protozoa are difficult, time-consuming and expensive (Atherholt et al. 1998). Protozoa are usually present in quite low numbers therefore to increase the likelihood of getting a representative sample the volume of water collected is quite large. In addition to the sampling issues, the detection methods used by laboratories are inaccurate; the main limitation being in the widely varied recovery efficiencies (Weintraub, 2006). These limitations often result in protozoan pathogen numbers being recorded as above or below detection limit which is likely to be an inaccurate representation of the actual environmental conditions.

Due to these issues it is recommended practice to monitor for pathogenic indicator organisms such as *E. coli* and enterococci (ADWG, 2004). These organisms are generally found in the gut and are excreted with faecal material. They are found in higher numbers than pathogens in environmental samples and the testing is relatively inexpensive. Additionally they are of similar sensitivity to disinfection as pathogens and survive in the environment as long as pathogens. Although not directly a measure of health risk they indicate the presence of faecal contamination and therefore the possibility of human infectious pathogens and therefore risk (Astrom et al. 2007).

All analysis for pathogens and pathogenic indicators were undertaken by National Association of Testing Laboratories (NATA) accredited laboratories. The method used to detect *Cryptosporidium* and *Giardia* is based on the US EPA (1999) Method 1623. Specifically samples are concentrated by calcium carbonate flocculation and settled overnight. The supernatant is collected, further concentrated by centrifugation and then processed by immunomagnetic separation (IMS) using the Dynal IMS kit. The

final concentrate is stained using DNA-staining fluorochrome DAPI and FITC-conjugated monoclonal antibodies. Blue-light exclusion is used to scan the slides for cells with the characteristics of *Cryptosporidium* or *Giardia*. Structural integrity is confirmed using UV excitation and differential interference contrast (DIC) is used to determine the internal structures. The method detects numbers of oocysts/cysts but does not identify species or genotypes.

The pathogenic indicators, *E. coli* and total coliforms are analysed using Australian Standard 4276.21 (2005) which uses enzyme hydrolysable substrates to determine the most probable number (MPN) of organisms in the sample. The quantification of enterococci in a water sample is determined using Enterolert™ and the method as specified by the manufacturer (IDEXX Laboratories, Inc., Westbrook, ME, USA) and as explained in Hs and Huang (2008). Enumeration of *C. perfringens* is undertaken using the method developed by Gibbs and Freame (1965).

Table 3.7 shows the number of data points available for the pathogen and indicator parameters up to the end of 2007, they include both baseflow and storm event samples.

Table 3.7 – Pathogen and pathogen indicator available data points for each sub-catchment

(2005 – 2007, inclusive)

Pathogen/Indicator	*units*	Available data points		
		East	Crystal	West
Cryptosporidium	*oocysts/L*	40	24	28
Giardia	*cysts/L*	40	24	28
E. coli	*orgs/100mL*	116	44	55
Enterococci	*orgs/100mL*	124	36	47
Total coliforms	*orgs/100mL*	27	27	27
C. perfringens	*orgs/100mL*	43	32	32

The above table shows there is less pathogenic and pathogenic indicator data for the West branch of the Tarago and Crystal Creek as compared to the East. This is due mainly to the number of events that were captured in the East catchment, as explained above.

3.4 Water quality data limitations

Water quality data can be analysed in many different ways. The objectives of the analysis and the components of the data sets will most likely determine what tools should be used. However, before analysis can be undertaken on an environmental data set, some manipulation is often required to reduce the impact of the data set's limitations. Data sets taken over a long period of time and for different programs are likely to exhibit some of the following issues/limitations:

- changes to measurement or recording technique
- missing data
- errors
- multiple observations
- censored data
- outliers .

In most cases there are a number of ways to deal with these issues (Gilbert, 1987), these options as well as the way the Tarago data was handled and its likely impact as well as the outcomes of the analysis is discussed below. Sections 3.4.1 to 3.4.6 are discussing only the physical-chemical data while the pathogen and indicator data are discussed separately in Section 3.4.7.

3.4.1 Changes to measurement or recording technique

The specific tests or techniques used to measure, sample or record data over a long period of time is likely to have changed. In order to ensure that these changes do not unduly influence the statistical analysis it is important to note when the changes occur and not mistake a change in techniques for a change in water quality. Unfortunately it is almost impossible to determine when changes in technique may have taken place as this information is not stored with the Tarago water quality data sets. The only indication a change in technique has occurred is when the detection limit changes.

In order to ensure consistency across the parameters, only one sampling program, the Routine program, was chosen to be analysed in depth. There is more assurance that the sampling, measurement and recording techniques will remain the same then would be the case if various programs were used.

3.4.2 Missing data

Water quality data sets can have missing data for a number of reasons including the inability to obtain samples due to weather or other physical constraints, equipment failure and human error. In large water quality data sets, especially those that involve grab samples, ie with a changing sampling frequency, it is difficult to locate any missing data. Tabachnick and Fidell (2001) report that for large data sets with a low number of missing data points, that missing data can be ignored. Therefore, assumed missing values in the Tarago water quality data set were left blank.

3.4.3 Errors

To detect any obvious errors it can be sufficient to simply visually inspect the data and create basic scatter plots of data points (Gilbert, 1987). Values that were negative or outside of the probable range in the water quality data were deleted. As missing values are not an issue, as discussed above, this method is acceptable.

3.4.4 Multiple observations

Multiple observations usually occur as a result of human error, that is, the same data point is accidentally entered into the database more than once. As there is a significant amount of water quality data being analysed, over 10,000 data points, any multiple observations are not likely to interfere with the statistical analysis. It was estimated that less than 1% of observations could be considered multiple. Therefore, they were not identified or dealt with.

3.4.5 Censored data

Data are defined as censored if one of more values fall below a level associated with some minimum acceptable level of reliability (Gilliom et al. 1984). Censored values, or values recorded as being below detection limit, can have a significant impact on statistical analysis. It is not possible to determine the exact concentration levels based on censored data and therefore they must be managed. There are a number of methods for dealing with censored data and some of the simpler methods include:

- removing the censored data
- assigning zero values
- assigning half the detection limit or
- using statistical techniques that are insensitive to data values.

No one method is thought to be the best approach as it depends on the data set and the objectives of the data analysis (Demayo & Steel, 1996).

Only 2.23% of the Tarago physical-chemical water quality data was recorded as being below the detection limit. A comparison of results from replacing censored values with zero and replacing them with half their detection limit found no significant difference. Therefore censored data was replaced with half their detection limit which is an effective and efficient method for dealing with these values (Zhang et al. 2004).

3.4.6 Outliers

A value that does not conform to the perceived measurement group as a whole is defined as an outlier (Demayo & Steel, 1996). Dealing with values that are outside the measurement group requires a judgement to be made on the reasonableness of the value and about the effect of the outlier on the statistics. In the case of the Tarago water quality data, outliers were identified as any value that was more than 3 times the standard deviation away from the mean. These values were highlighted and assessed individually. If the identified outlier corresponded with outliers or high values in other parameters then the value was considered to be reasonable and true and the value was retained, however if it was the only outlier it was simply deleted from the data set.

Less than 1% of the Tarago water quality data was identified as being a true outlier and deleted. A further 0.8% were detected as outliers but retained in the data set. Inclusion of all outliers in the analysis proved to have very little to no effect on the final results.

3.4.7 Pathogens and indicators

Due to the limited amount of data and the quality of the data set pathogens and pathogenic indicators were dealt with separately to the physical-chemical data sets. The most common limitation with microbial data is censored data, that is data either being recorded as non-detects, as being at above the detection limit or as being less than the minimum detection limit.

In terms of the human infectious pathogens sampled for, *Cryptosporidium* and *Giardia*, over 88% of the 184 samples across all three sub-catchments were recorded as non-detects. This included both baseflow and event samples. As discussed previously the

non-detects are not necessarily zeros, they simply mean that the laboratory was unable to recover any pathogens in the sample. This could be a result of one of the many limitations involved in pathogen sampling, including sampling or laboratory error or poor recovery efficiencies. Due to the number of non-detects the pathogen data is not able to adequately define the risk to public health. It was therefore not used for regression analysis or modelling and pathogenic indicator data was used instead.

The indicator data to the end of 2007, not only has more data points than the pathogen data set but the quality of the data is much better. Table 3.8 shows the number of data points, and the percentage of the total number of data point for that indicator that were recorded as above the detection limit, as non-detects and as less thans.

Table 3.8 – Limitations of the pathogenic indicator data set[10]

	Total data points	Above detection limit	Non-detects	Less thans
E. coli	215	15 (7%)	0	1 (<1%)
Enterococci	207	0	1 (<1%)	3 (1%)
Total coliforms	81	13 (16%)	0	0
C. perfringens	107	0	21 (20%)	1 (1%)

Values recorded as at the maximum detection limit were changed to the detection limit, as there is no way of knowing how high the reading could have been. All non-detects were changed to zeros and readings recorded as less thans were changed to half the minimum detection limit. As shown in Table 3.8, the *E. coli* and enterococci data are both of good quality and have over 200 data points each, the relevance of this will be discussed in Section 3.6.

The pathogen monitoring program had only been running for a total of 4 years at the time of analysis which means that it is very unlikely that there has been a change in recording or measurement technique. Missing data, as with the physical-chemical data was simply ignored and any errors were identified by visually inspecting the data and then they were deleted. Any multiple observations were able to be located and were deleted as they could interfere with the statistical analysis due to the relatively small number of data points.

[10] Percentages are of the total data points for that indicator

3.5 Hydrologic data availability

As hydrology dictates the movement of contaminants within catchments, simulating catchment runoff is one way of determining the impact on water quality of catchment management. Hydrological modelling, linked with a contaminant model, will also enable the benefits to be quantified.

In order to simulate catchment runoff, water quantity data such as rainfall, evapotranspiration and streamflow, is needed. Rainfall and evapotranspiration enable the prediction of streamflow and observed streamflow data is important for calibration and validation. Equally as important is the reliability and applicability of all of this data.

In the Tarago catchment there are two sites at which streamflow gauges are located, one on the East branch of the Tarago River and one on the Tarago River after the confluence of East and West. Additionally there are two abstraction points on the West branch for which some data is collected. In terms of rainfall there are a number of gauges in and around the Reservoir catchment. Figure 3.4 shows the sampling and gauging points in relation to the catchment boundary.

3.5.1 Streamflow

Streamflow data has been collected after the confluence of the East and West branches since September 1980 and in the East branch since March 1993. The data is collected every 6 minutes at both sites and stored on data loggers. These loggers are downloaded on a 2 monthly basis. The data is quality checked before being entered into the database, which is maintained by Melbourne Water (IS Watson, 2008, pers. comm.). In terms of the quality of the streamflow data there is relatively good confidence in the data collected by the gauge located after the confluence, while the gauge on the East branch has some inherent issues as discussed below.

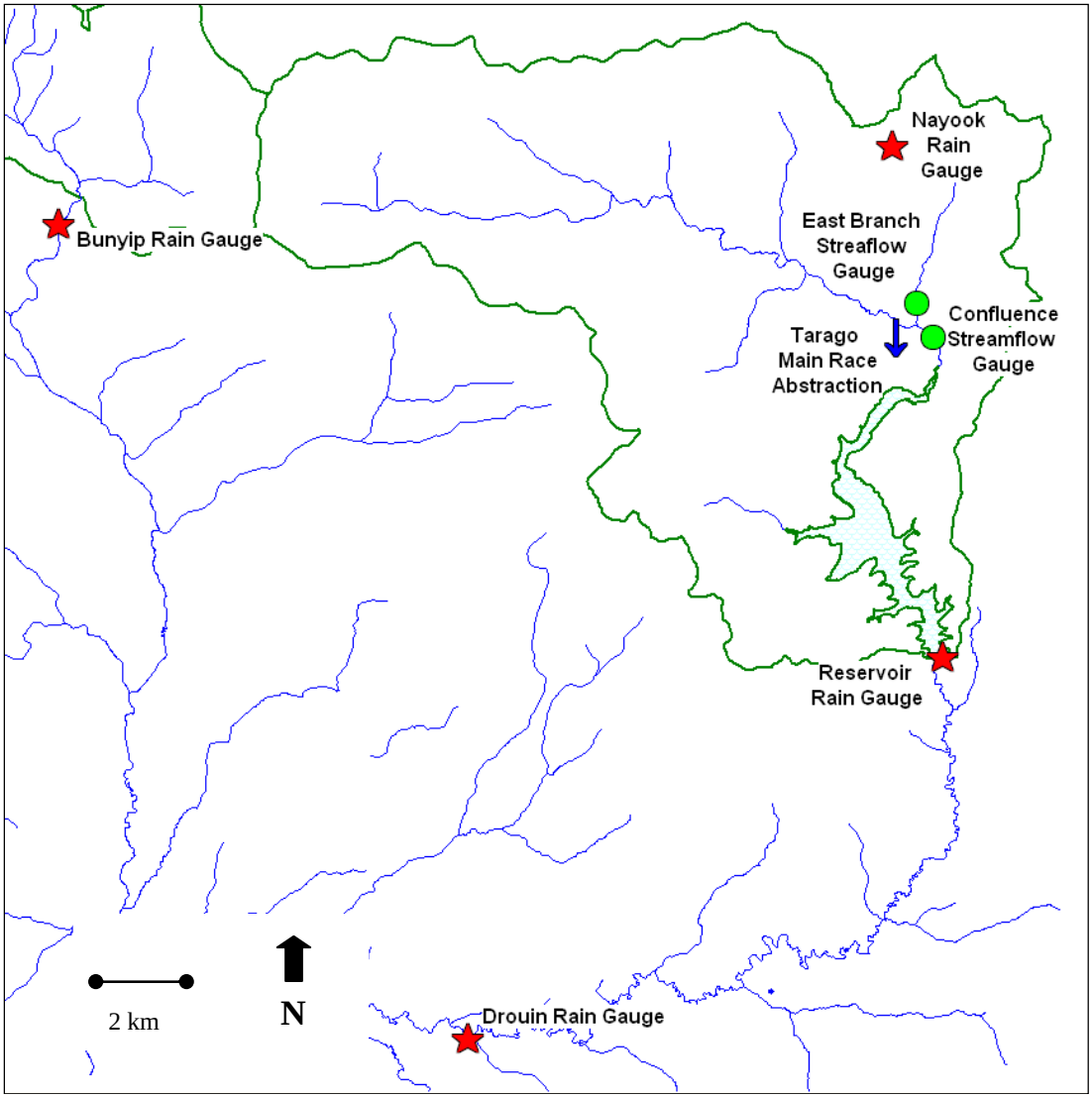

Figure 3.4 – Rain gauge, streamflow gauge and flow abstraction point locations in and around the Tarago catchment

The stream gauge on the East branch is compromised due to the weir at that location having regularly filling with silt. This silting is a result of erosion in the agricultural catchment and is related to the soil type which has a tendency to slump in steep terrain (Melbourne Water, 2003). This erosion causes the rating table, which is used to determine the flow rate from a stage height, at that site to become inaccurate. There is a general opinion that some of the flows may be underestimated as a result of the silting up (I.S. Watson, 2008, pers. comm.).

There are also issues with the gauge after the confluence as it is not an accurate representation of the total flow for the catchment. This is due to an abstraction taken prior to the confluence gauge; the Tarago Main Race (TMR) which transfers water to

irrigators, see Figure 3.4. Daily figures relating to the TMR abstractions are available. This abstraction can be added to the observed streamflow to determine a predicted catchment total streamflow. In order to do this the total daily figures were simply divided by the number of hours in a day to come up with an hourly figure. The relatively low frequency of data collected makes the total predicted streamflow data somewhat inaccurate. In terms of the West streamflow, Equation 3.2 will be used to calculate this.

$$Q_W = Q_C - Q_E + Q_{TMR} \qquad \text{(Equation 3.2)}$$

where:

Q_W = West branch streamflow

Q_C = Confluence streamflow

Q_E = East branch streamflow

Q_{TMR} = Abstraction for the TMR

Flow data for the TMR was only available as a daily total. This was converted into hourly data by simply dividing the total daily figure by 24. On average the flow abstracted at the TMR was less than 20% of the total flow in the West branch. The inaccuracies in the "observed" flow are important to keep in mind when viewing calibrated statistics and results.

A rough streamflow for Crystal Creek could have been predicted using the change in storage volume in the reservoir and the inflow rate from the Tarago River and an assumed ratio between the direct reservoir catchment and Crystal Creek. It was determined, however, that there would be too much uncertainty in this calculation. Therefore, analysis of water quality load or flux values and rainfall runoff modelling for Crystal Creek were unable to be undertaken.

3.5.2 Rainfall

Four rainfall gauges were located in and around the Tarago catchment and included in this study. Three out of the four gauges identified were positioned outside of the catchment boundary. It was, however, necessary to include them to account for the

spatial variability likely in rainfall across the catchment, as explained later. It was also necessary that the chosen gauges had particular characteristics including:

- hourly measurements
- a confirmed location
- a sufficient amount of data
- data which continues to be collected.

The gauges are shown in Figure 3.3 and further details about them are supplied in Table 3.9.

Table 3.9 – Rain gauge information

	Bunyip	Drouin	Nayook	Reservoir
Location	15 km west of Tarago Reservoir dam wall	12 km south-west of Tarago Reservoir dam wall	3 km north of East streamflow gauging site	At Tarago Reservoir dam wall
Elevation [*m*]	124	71	800	189
Average annual rainfall [*mm*]	1084	730[11]	1145	946
Gauge type	203mm tipping bucket	203mm tipping bucket	203mm tipping bucket	203mm tipping bucket
Data collection method	Telemetry	Telemetry	Data logger	Telemetry
Start data collection	October 1995	December 2001	July 1987	June 1971

Errors in rainfall measurement and prediction

When modelling catchment behaviour, an accurate portrayal of spatial variation in rainfall is necessary to enable an accurate simulation of streamflow (Beven & Hornberger, 1982). It is usually the sampling errors and variability in the rainfall data that is the biggest problem when modelling catchment scale water balances (Boughton, 2004). Specifically for the model used in Chapter 7, uncertainty analysis has shown that rainfall uncertainty has a significant influence on model outcomes, see Chapter 9. It is therefore necessary to ensure that the rainfall data used for modelling is the best representation of actual rainfall in the catchment possible. Inherently there are issues with the device used for measuring rainfall as well as there being issues with having an accurate representation of spatial variability.

[11] The lower average annual rainfall at Drouin is a result of all the rainfall data being collected during the drought

Rainfall measurement, using a standard tipping-bucket device, can be influenced by a number of factors which can be categorised as either counting or catching errors. Counting errors are caused by mechanical issues of the device which can affect the measurement of rainfall intensity. At high intensities rainfall is usually underestimated and at lower intensities overestimated (Molini et al. 2005). Catching errors relate to environmental issues that can influence the amount of water captured by the device and include factors such as: wind, splashing and evaporation.

An additional area which leads to errors in rainfall data is the spatial distribution of gauges as they relate to the actual spatial distribution of rainfall in the catchment of interest. Rainfall gauges represent the rainfall at a particular point but are not necessarily representative of the rainfall over a larger area. Spatial variation in the rainfall is likely in the Tarago catchment due to the differing land-uses, land-cover and topography across the catchment. All rainfall records within the catchment and its immediate surroundings must be analysed to take proper account of the spatial and temporal variation of rainfall over the basin (WMO, 1994). Four separate rainfall gauges were chosen for these reasons.

Dealing with uncertainty

It was necessary to attempt to mitigate the effect of the errors identified above to ensure that the best fit for the hydrological model was achieved.

Counting and catching issues with the tipping-bucket rain gauges can result in under and over estimation of the actual rainfall. It was therefore necessary to apply scaling factors to the rainfall data. Factors of 1.2 and 0.8 ($\pm$20% error) were chosen based on a study by Molini et al. (2001) who investigated the sampling error of tipping-bucket rain gauges and found it to be in the order of 10-30%. Additionally in a study looking at calibrating rainfall runoff models with poor quality data, Boughton (2006) found that over 50% of catchments with previously poor calibration statistics were improved by scaling the rainfall between 1.2 and 0.8.

The scaling of the rainfall data is further justified given the results of a previous study which looked at extending the streamflow records for catchments throughout Australia using a simple rainfall runoff model (Peel et al. 2000). Over 300 catchments were involved, including the Tarago catchment, and the study reports on the calibration results for each catchment. According to the model performance criteria set out in the

paper, the Tarago catchment performed “poorly”. As discussed previously, it is usually errors in rainfall data that are the cause of a poor hydrologic fit and therefore some scaling of the rainfall data may assist in model calibration and performance.

The scaling factors will also account for additional influences that may affect the amount of rainfall reaching the stream gauge. Catchment specific losses in water volume could be as a result of, for example, farm dams capturing runoff, illegal, or legal, pumping from the stream or exceptionally dry soil conditions promoting infiltration rather than runoff. Conversely, gains in water could be due to farm dams spilling excess water during high rainfall. Scaling can also account for issues with a faulty weir or silt build up in the weir, as reported for the East branch gauge.

In terms of modelling spatial variability across a catchment from point measurements, it is an area of much research. There are many different models that can be used to predict the rainfall in a certain location based on the rainfall gauges that surround that location and there is some debate about which method gives the best results. As an example Renard et al. (2007) suggested that Kriging, when compared against 3 other methods (Inverse Distance Weighting, Spline and Global Polynomial Interpolation) provided the best results, whereas a study by Ball and Luk (1998), which also tested Kriging, along with Thiessen Polygons, Inverse Distant Weighting and Spline, said it was one of the worst performers. Chang et al. (2005) stated that there is no single method suitable that can be applied in every circumstance. A common and simple method for spatially distributing rainfall when there is more than one gauge, providing those gauges are evenly distributed, is a straightforward arithmetic average (Ward & Trimble, 2004). An alternate and widely used method to determine the average rainfall over a catchment is the Thiessen polygon method (Ward & Trimble, 2004), explained below.

In an attempt to find the scaling factor and the rainfall combination that provided the best hydrologic fit for each catchment, all combinations were trialled. This is further explained in Chapter 7.

Application of the Thiessen method

The Thiessen method works on the theory that for any point in an area, or polygon, the best estimate of rainfall is the measurement made closest to that point. The polygons are created by drawing connecting lines to each rain gauge and then drawing

perpendicular bisectors. Applying the Thiessen polygon method for the West catchment meant weighting the Nayook (green), Bunyip (yellow) and Dam (red) rainfalls by 0.722, 0.272 and 0.006 respectively, see Figure 3.5.

The Thiessen method was not able to be applied in the East catchment as it results in only one rain gauge, Nayook, being relevant.

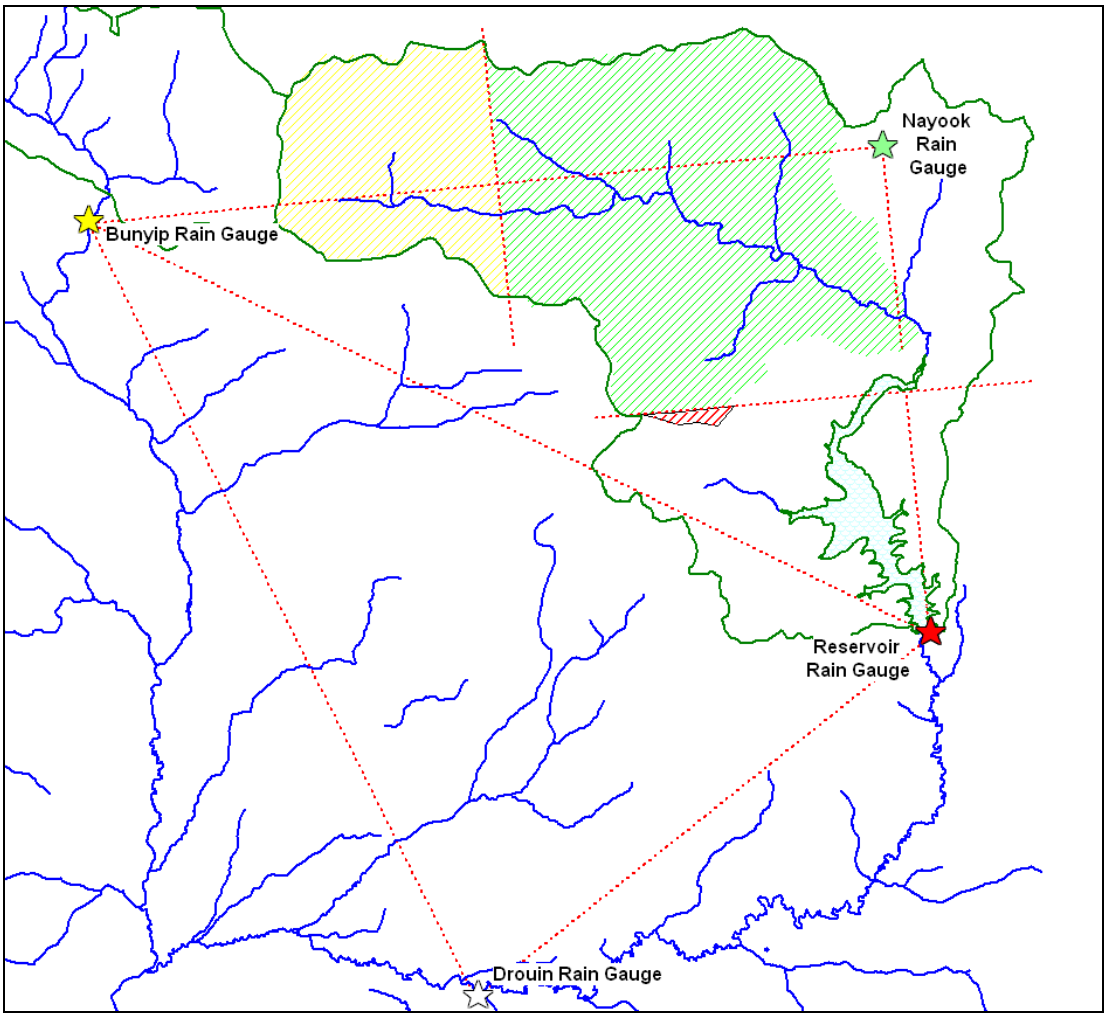

Figure 3.5 - Thiessen polygons for the West catchment

3.5.3 Evapotranspiration

Evapotranspiration is the sum of evaporation and plant transpiration and is another important factor when considering water movement. Potential evapotranspiration (PET) is the ability of the atmosphere to remove water from the surface and is a function of temperature, vapour pressure and solar global exposure (Wang et al. 2001). Values of PET were obtained from the Climatic Atlas of Australia (BOM, 1988), which

uses Morton's complementary relationship areal evapotranspiration model (Morton, 1983) to derive estimates of areal PET, point PET and areal actual evapotranspiration. Data in the Atlas is displayed in monthly areal PET maps for the whole of Australia. These average monthly PET values were converted to hourly values by dividing by the number of hours in that month. Jones et al. (2006) reports that the inter-annual variability of PET is relatively low and that the day-to-day variation in PET has little influence on water balance, it is therefore acceptable to use the converted mean monthly value of PET as an input to the hydrological model (Chiew et al. 2002).

3.5.4 Data errors

Streamflow and rainfall data sets commonly have missing data, errors, multiple observations and outliers. These anomalies can usually be detected visually either graphically or by inspecting the data set. It is important that rainfall and streamflow data sets be continuous to allow for accurate modelling and calibration. Therefore data that is missing or incorrect needs to be managed. The data can be filled in using either a seasonal or surrounding gauge mean or by using a regression equation.

For rainfall data, surrounding gauges were taken into consideration. If for the period of missing data the surrounding gauges showed readings of zero then data was replaced/filled in with zeros, when there was rain at other gauges, an average was taken. For the rainfall data sets used less than 3% of the data was filled in as a result of being missing or incorrect. In the instances where there was an extended period of time of missing data, this was simply left blank and therefore not able to be used in some of the calibration runs.

Missing streamflow data was replaced by calculating a regression equation from the data around the missing data points or by interpreting between points. This was necessary for less than 1% of the streamflow data used.

3.6 Faecal deposition

Having discussed the data requirements for the hydrologic model it is now important to consider the inputs necessary to predict contaminant behaviour. In this study, as the main focus is drinking water quality and quantifying the effectiveness of catchment management for its improvement, the contaminant of interest is pathogenic organisms.

To enable the modelling of pathogens in the runoff, it is necessary to know how much faecal deposition occurs in the catchment. The deposit rate is obtained by collecting the following data, from which a daily deposition rate can be predicted:

- the type and number of animals within the catchment
- the number of pathogens per gram of faeces for each animal type
- the number of grams of faeces excreted per animal per day.

The number and types of animals was based on the five different land-use types within the Tarago catchment (see Figure 3.2) and a combination of local knowledge and published data. Although the animals included for each land-use only covers the larger animals and not all the species that are likely to be within the catchment, it is the larger animals where the majority of the pathogen risk comes from. This is due to their high densities and the quantity of faecal material that they produce. It is therefore reasonable to exclude smaller animals such as rodents and birds.

In order to ensure an accurate model and calibration of that model both theoretical and field pathogen data is necessary. Although there has been significant research and verification on loads of *Cryptosporidium* and *Giardia* in faecal matter of various animals (Atwill et al. 2003; Olson et al. 1996; Sturdee et al. 2003) this data was unable to be used due to the quality of field data collected during the study, as discussed in Section 3.4.7. Instead indicator data had to be used to predict pathogen movement. The quantity and the quality of the field data was taken into consideration when determining which indicator would be best suited for modelling purposes as was the amount of literature regarding indicator loads in various faecal material.

In terms of the field data *E. coli* and enterococci had the most data points across both the East and West catchments and the least percentage of non-detects, less thans and above the detection limit, as shown in Tables 3.7 and 3.8 above. These data sets also cover both event and baseflows.

The literature regarding enterococci loads in faecal matter from different animals is limited. Kay et al (2008a) look at the loads of enterococci running off different land uses in the UK in both base and high flow periods but the study does not indicate the types of animals related to each land-use. In a separate study by Kay et al. (2008b) the number of enterococci during different levels of sewerage treatment is reported but

again the exact species contributing to the raw sewerage are not specified making the data inadequate for this particular study. Conversely, *E. coli* levels in faecal matter has been extensively researched (Davies et al. 2005b; Jones & White, 1984) and loads are available for most animals.

The Tarago catchment harbours a significant population of deer, both feral and farmed, but there was no literature that quoted *E. coli* levels in deer faecal material. Faecal coliform data was, however, available (US EPA, 2000) and this was converted to *E. coli* numbers using an equation developed by the Virginia Department of Environmental Quality (VDEQ) (2003), see Equation 3.3.

$$C_E = 2^{-0.0172} \times C_C^{\ 0.91905} \qquad \text{(Equation 3.3)}$$

where:

C_E = *E. coli* concentration

C_C = faecal coliform concentration

The relationship was developed using 493 paired date sets from the state of Virginia and resulted in reasonable results across a range of values (VDEQ, 2003). Given that only total coliform data is collected in the Tarago and not faecal coliforms, the validity of the equation in this catchment is unable to be tested. As the equation is only being used to predict *E. coli* numbers in animal faeces and not actual indicator levels in the water or catchment, it is acceptable to use.

The relatively good field data set for *E. coli* and the adequate research data on *E. coli* loads in faecal material means that this is the indicator that will be used for modelling purposes.

The rates of faecal deposition were obtained from Ferguson (2005). Tables 3.10 and 3.11 show the faecal loads for both the East and West Tarago catchments.

The land-uses clearly influence the number of organisms deposited daily for each catchment. The West catchment is all forest its faecal load per day is over 3-logs less than in the East catchment, which has intensive cattle and deer farming. When

assessed on a per area basis the difference is almost 4-logs. Specifically, the rates are as follows:

- West = 9.2×10^{9} orgs/day/km^2
- East = 5.5×10^{13} orgs/day/km^2.

This confirms that the risk to public health from the East catchment is far greater than that from the West.

Table 3.10 – Determining the faecal loads in the East Tarago catchment

Land-use	Area	Animals	Densities	Faecal deposition rates	*E. coli*	
	km²		*animals/km²*	*kg/animal/day*	*mpn/g*	*mpn/day*
Forest	5.3	Kangaroo	200	0.2	5.8×10^{5}	1.2×10^{11}
		Deer	0.5	1	9.8×10^{7}	2.6×10^{8}
Beef cattle	1.4	Cattle (grazing)	70	25	2.1×10^{6}	5.2×10^{12}
		Cattle (grazing < 1yr)	0.7	5.3	4.2×10^{9}	2.2×10^{13}
Dairy farm	1.2	Cattle (intensive)	120	45	2.1×10^{6}	1.4×10^{13}
		Cattle (intensive < 1yr)	25	5.3	4.2×10^{9}	6.7×10^{14}
Deer farm	0.6	Deer (farmed)	490	1	9.8×10^{7}	5.7×10^{10}
Horticulture	4.5	-	-	-	-	-
Total area	***13.0***			***Total [organisms/day]***		***7.1×10^{14}***

Table 3.11 – Determining the faecal loads in the West Tarago catchment

Land-use	Area	Animals	Densities	Faecal deposition rates	*E. coli*	
	km²		*animals/km²*	*kg/animal/day*	*mpn/g*	*mpn/day*
Forest	72.0	Kangaroo	200	0.2	5.8×10^{5}	6.6×10^{11}
		Deer	0.5	1	9.8×10^{7}	3.5×10^{8}
Total area	***72.0***			***Total [organisms/day]***		***6.6×10^{11}***

3.7 Summary and conclusions

The Tarago Reservoir catchment was chosen as the study catchment based on a number of factors including its mix of land-uses, its past catchment management works and its importance as a drinking water reservoir, both presently and into the future. Additionally the catchment has been the focus of a number of different studies meaning that an extensive amount of high quality data was available. The catchment of the East Brach of the Tarago River has been the focus of the majority of the catchment management works that have been implemented since the early 1990's. This is due to the agricultural land-uses it supports which include horticulture, grazing, residential and one dairy. Although the East branch only contributes about 25% of the flow to the Reservoir it presents the majority of the risk based on these land-uses. Human infectious pathogens pose the biggest risk to drinking water quality and these land-uses are known sources of microbiological pathogens.

In the past, catchment management works in the East have mainly focused on reducing nutrients to the reservoir as this was thought to present the greatest threat to water quality in the reservoir. Constructing fences along streams, installing appropriate drainage on roads and providing stream crossings for cattle are some examples of the work carried out. Knowledge in the drinking water industry regarding pathogens and the risk they pose to public health has increased rapidly over the last 20 years, as has the concept of multiple barriers and preventative risk management. This has meant that the more recent catchment management works have been aimed at reducing pathogen transport. Fortunately many of the works already implemented in the Tarago can affect pathogen movement which makes it an ideal test catchment.

The quality of the monitoring data can affect the analysis that is able to be carried out and therefore a thorough investigation of the available data and its limitations was necessary. Many different monitoring programs have been carried out in the Tarago catchment resulting in a large amount of data. To ensure consistency in sampling location, testing techniques and recording methods one program was chosen to be analysed in depth: the Routine program. In terms of physical-chemical parameters, 12 different parameters were chosen to be included in the detailed analysis which, between the three sites, totalled over 10,000 data points. Recently the Routine program was extended to include pathogen and pathogenic indicator data as well as

storm based sampling. The storm sampling was an important part of this study as the majority of pollutants, including pathogens, are transported during high runoff events. In order to gain an understanding of the risk to drinking water quality, monitoring during these periods is vital. A total of 6 small events were captured during the sampling period.

Contaminant movement through catchments is usually as a result of rainfall runoff. Therefore in order to quantify the amount of contaminant movement and the effectiveness of catchment management to reduce this movement, hydrological modelling of rainfall runoff is required. Data including rainfall, streamflow and evapotranspiration is important for hydrological modelling of the catchment. In particular, accurate measurements of catchment rainfall and streamflow are important. Streamflow is directly measured for the East branch but the West requires some estimation therefore decreasing its accuracy. In terms of rainfall, there are four different gauges surrounding the catchment which will all be used, along with a scaling factor, in order to find the best fit for the hydrologic model.

Faecal deposition within the catchment was predicted based on the likely number of animals for each land-use and the area that land-use occupied. Only large animals were considered based on the volume of faecal material they produce. The *E. coli* levels in animals faeces were determined based on numerous published laboratory studies. Using this data the number of *E. coli* deposited per day per hectare for each catchment was determined. The East catchment, due to its more intense land-uses and domestic animal population, produced almost 4-logs more *E. coli* per day per unit area than the West.

The data described in this chapter will be used to determine if there is a measurable difference in water quality following catchment management. Additionally the hydrologic and faecal deposition data will be used to predict contaminant movement through the catchment and hopefully quantify the benefits to drinking water quality. By undertaking data analysis and modelling catchment management may be confirmed as a validated buffer to drinking water contamination.

The following chapter looks at the physical-chemical data in detail to determine, whether the East and West catchments are producing different water quality and to look for any trends that may be related to catchment management.

4. WATER QUALITY DATA ANALYSIS

4.1 Introduction

Having collated all of the available water quality data, and assessed it in terms of its limitations and applicability, the chosen parameters can now be analysed. This chapter reports on the analysis of the physical-chemical parameters and discusses if there is any measurable impact on water quality following catchment management. Revegetation of buffer strips and cattle exclusion, both of which form a major component of catchment management in the Tarago, have been shown to be the main contributors to improved water quality in terms of pathogen reduction (Trask et al. 2004). It is therefore hypothesised that general improvements or trends in other water quality parameters, although not a direct indicator of pathogens, can indicate that processes such as filtration, adsorption and sedimentation which are enhanced by buffer strips, are effective. The pathogen and pathogenic indicator data is not included in this chapter and is dealt with separately in Chapter 5.

Water quality analysis, including statistics, is performed on data sets so as valid conclusions and reasonable decisions can be made based on the data collected. There is a range of statistical analysis tools that can be used in order to reach the desirable end point. The decision about which tools to use should be based either upon the objectives of collecting the data or upon on a particular question or hypothesis. In this study the question relates to the following two things: firstly do the different land-uses in the different sub-catchments contribute to water quality and secondly are there any trends over time that could be related to changes in land management practices. Additionally the dominant catchment processes in each sub-catchment will be assessed.

Two statistical methods are available to analyse data sets: parametric, which assume the data is drawn from a known distribution (for example normal or log-normal) and nonparametric, which can be used when the distribution of the data set is unknown. Hirsch et al. (1982) report that most water quality data is non-normally distributed as there are nearly always exceedences and outliers in data sets. Berryman et al. (1988) also report that there is no way to know if the population of a given water quality data set is normal enough to allow the parametric tests to be used and that the use of

nonparametric tests is advisable whenever the normality of the population distribution is in doubt. Nonparametric tests also have the advantage of being robust against missing values and values below the detection limit. It is therefore nonparametric tests that will be used to assess the data in this chapter.

Discriminant analysis will be used to show that the three sub-catchments have different pollution levels and that they can be assessed separately. This analysis will also be used to indicate that it is the differences in each sub-catchment, specifically land-use and soil type, which is contributing to water quality. Trend analysis will be used to show if there has been a measurable impact on parameter levels, either increasing or decreasing, and the significance of these trends. The effectiveness of the catchment management practices on reducing pollution to the streams will be indicated by the trend analysis results.

Factor analysis (FA) will be used primarily to identify the major pollution sources within each sub-catchment. As an additional means of showing trend, FA will be carried out before and after catchment works to determine if the variables in the dominant processes has changed.

4.2 Preliminary statistical analysis

Basic descriptive statistics, such as means and medians, give a clear and simple overview of the data and can indicate that two data sets are largely different from each other or, conversely, quite similar to each other. In terms of water quality data from different sub-catchments these statistics can potentially lead to conclusions about the effect of land-use on the water quality parameters. Tools such as time series plots, rolling averages and distribution plots can also quickly and easily indicate seasonality and trends, which can later be investigated with more sophisticated statistical tools.

Basic statistical information for the parameters chosen in Chapter 3 are presented in Table 4.1.

Table 4.1 – Basic statistics for the parameters chosen for analysis for each sub-catchment in the Tarago

Catchment	Parameter	*units*	Min	Max	Median	Mean	Std Dev	Count
West	pH	-	5.4	7.9	6.5	6.6	0.3	425
	EC	*uS/cm*	39	160	72	72	10	412
	Colour	*Pt-Co*	10	350	70	73	28	429
	Turbidity	*NTU*	1.4	38.0	4.0	5.3	4.3	427
	Iron	*mg/L*	0.08	3.90	0.36	0.44	0.32	364
	Manganese	*mg/L*	0.002	0.150	0.017	0.020	0.010	328
	Nitrate	*mg/L*	0.003	0.890	0.310	0.320	0.110	253
	Phosphorus	*mg/L*	0.002	0.550	0.016	0.020	0.030	342
	Ammonia	*mg/L*	0.001	0.144	0.011	0.020	0.020	178
	TOC	*mg/L*	1.8	18.6	5.4	5.9	2.5	128
	Suspended solids	*mg/L*	0.5	75.0	6.4	9.5	11.0	127
	TKN	*mg/L*	0.06	1.45	0.32	0.37	0.19	163
Crystal	pH	-	6.0	7.4	6.7	6.7	0.3	296
	EC	*uS/cm*	65	270	108	108	15	278
	Colour	*Pt-Co*	20	300	100	101	38	295
	Turbidity	*NTU*	1.0	46.5	8.0	10.0	6.4	297
	Iron	*mg/L*	0.16	3.90	0.65	0.72	0.39	254
	Manganese	*mg/L*	0.002	0.162	0.020	0.020	0.020	222
	Nitrate	*mg/L*	0.005	1.630	0.280	0.310	0.170	163
	Phosphorus	*mg/L*	0.003	0.167	0.025	0.030	0.020	238
	Ammonia	*mg/L*	0.002	0.095	0.010	0.020	0.020	184
	TOC	*mg/L*	2.1	26.6	6.3	7.1	3.3	136
	Suspended solids	*mg/L*	0.5	151.0	14.0	19.4	18.6	132
	TKN	*mg/L*	0.04	1.20	0.41	0.43	0.18	189

cont…

cont…

Catchment	Parameter	*units*	Min	Max	Median	Mean	Std Dev	Count
East	pH	-	6.0	7.9	6.9	6.9	0.3	434
	EC	*uS/cm*	62	170	103	102	15	417
	Colour	*Pt-Co*	10	600	70	80	45	439
	Turbidity	*NTU*	1.3	163.0	16.0	18.1	13.4	437
	Iron	*mg/L*	0.01	9.40	1.30	1.60	1.21	383
	Manganese	*mg/L*	0.004	0.270	0.040	0.050	0.040	348
	Nitrate	*mg/L*	0.005	2.400	0.950	0.980	0.400	259
	Phosphorus	*mg/L*	0.003	0.500	0.061	0.070	0.050	349
	Ammonia	*mg/L*	0.001	0.074	0.010	0.020	0.010	188
	TOC	*mg/L*	0.5	39.0	3.7	4.6	3.7	130
	Suspended solids	*mg/L*	0.5	268.0	28.9	36.3	34.2	132
	TKN	*mg/L*	0.06	2.14	0.47	0.51	0.25	194

The summary statistics show that the levels of turbidity, iron, manganese, nitrate, phosphorus and suspended solids are all a lot higher in the East branch as compared to the West and Crystal Creek. Figure 4.1 shows the 3-year rolling averages of manganese in the three sub-catchments and further reiterates this observation. For time-series water quality data, a rolling average is a simple way to smooth out any outliers and give an indication of trend.

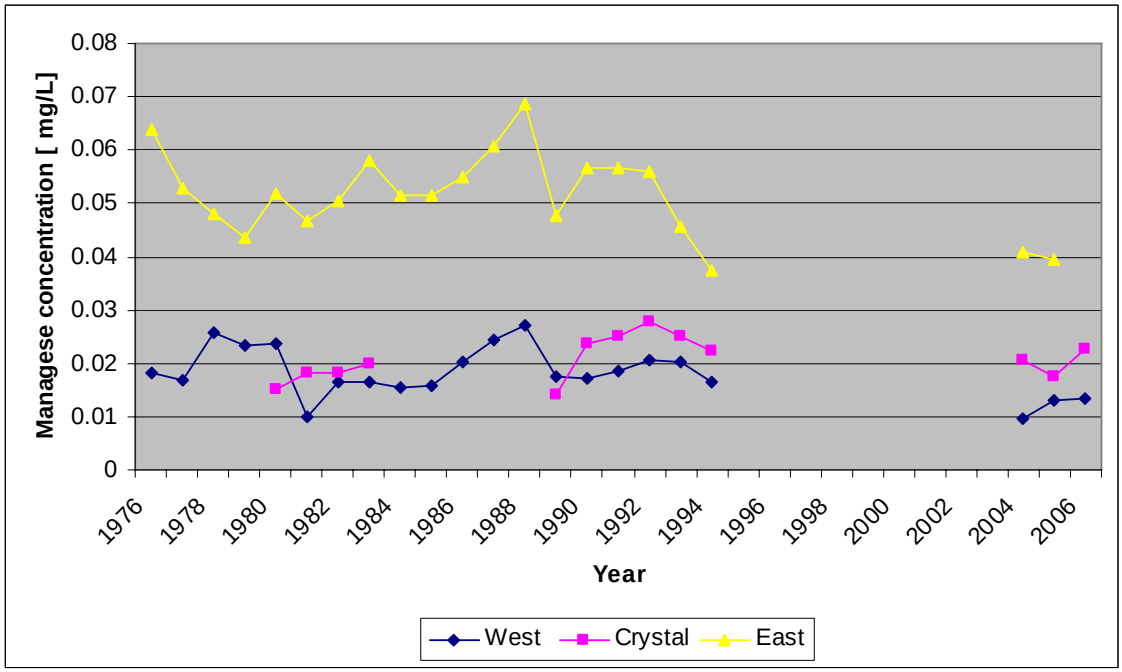

Figure 4.1 – 3 year rolling averages for manganese showing the East branch with higher levels than the West and Crystal

The period of missing data, which is evident from the above graph, is as a result of Tarago Reservoir being taken off-line from supplying drinking water to Melbourne, as explained in Chapter 3. The data can still, however, be used to show differences between sub-catchments as well as trends as discussed later.

The higher values in the East branch catchment are most likely due to it being a predominately cleared catchment. This means that naturally occurring iron and manganese in the soil can more easily wash off into streams and it is also farmed, which means that land applied fertilisers, containing nitrogen and phosphorus, can wash into streams. In the West branch and Crystal Creek catchments, however, the land is mostly forested and overland flow is contaminated by colour and organic carbon from rotting leaf matter on the forest floor. The levels of TOC and colour are therefore generally higher in Crystal Creek and the West branch than in the East. These

differences between the sub-catchments will be further confirmed by the use of discriminant analysis.

Time series plots can show the variation due to the effect of season, which is known as seasonality. This can be seen in Figure 4.2, with EC in the West catchment rising in the summer months to around 80 µS/cm and dropping to around 60 µS/cm in winter. Although these values are quite low (an EC below about 160 µs/cm classifies the water as excellent according to the ADWG (2004)) the difference between summer and winter values is still obvious.

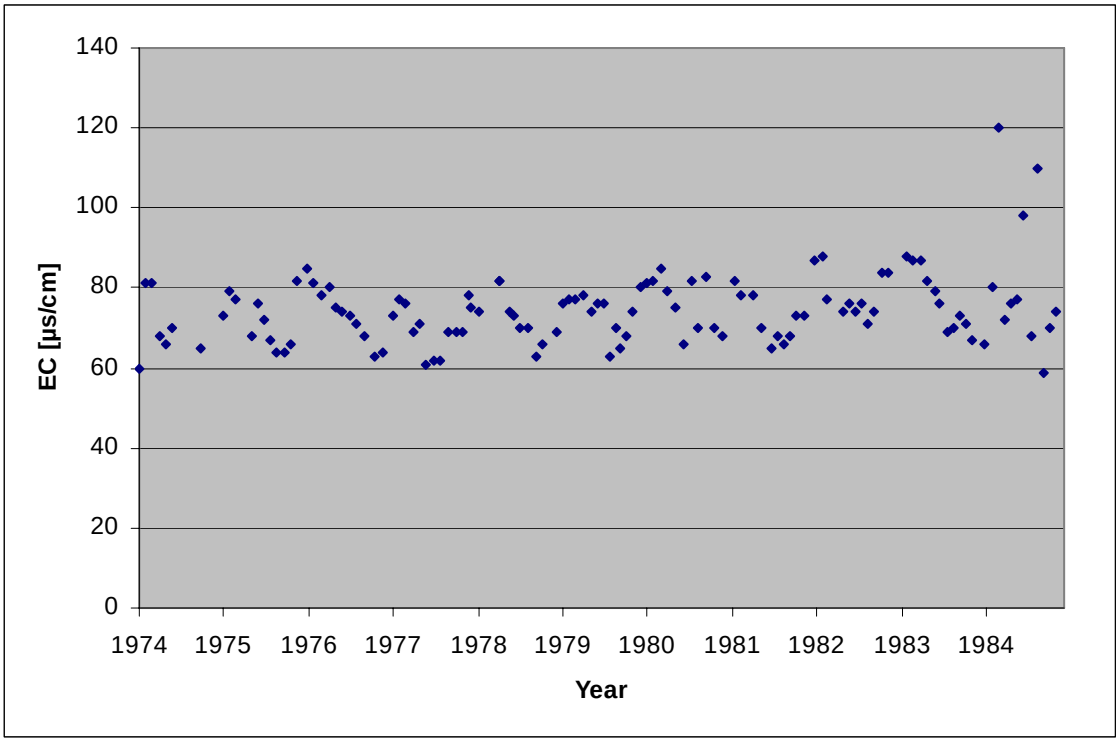

Figure 4.2 – West branch EC showing possible seasonality

Turbidity, which is associated with particles in the water, also showed seasonality. Rainfall, which creates overland flow and mobilises particles, is highly influenced by season hence this parameter shows seasonality. Both EC and turbidity data sets have a lot of data points, over 400 points each, and they are therefore more likely to clearly show seasonality than those data sets with less points. It is possible that some of the other parameters are also influenced by season. It is desirable to limit the influence of season to give a more realistic picture of any trends in the catchment (Hirsch et al. 1991). The concept of seasonality and how to remove its effect to allow for trend analysis will be further explained in Section 4.4.1.

Visual analysis of the graphs of the 3-year rolling averages shows that there are general trends down in all sub-catchments in iron, manganese, ammonia, TOC and suspended solids. Figures 4.2 and 4.3 show manganese and iron respectively while the others are shown in Appendix B, Figures B.1 to B.3. This downward trend may be an initial indication that the catchment management initiatives undertaken in the Tarago catchment in the early 90's or more recently are having a positive impact on water quality and that the impact may be measurable.

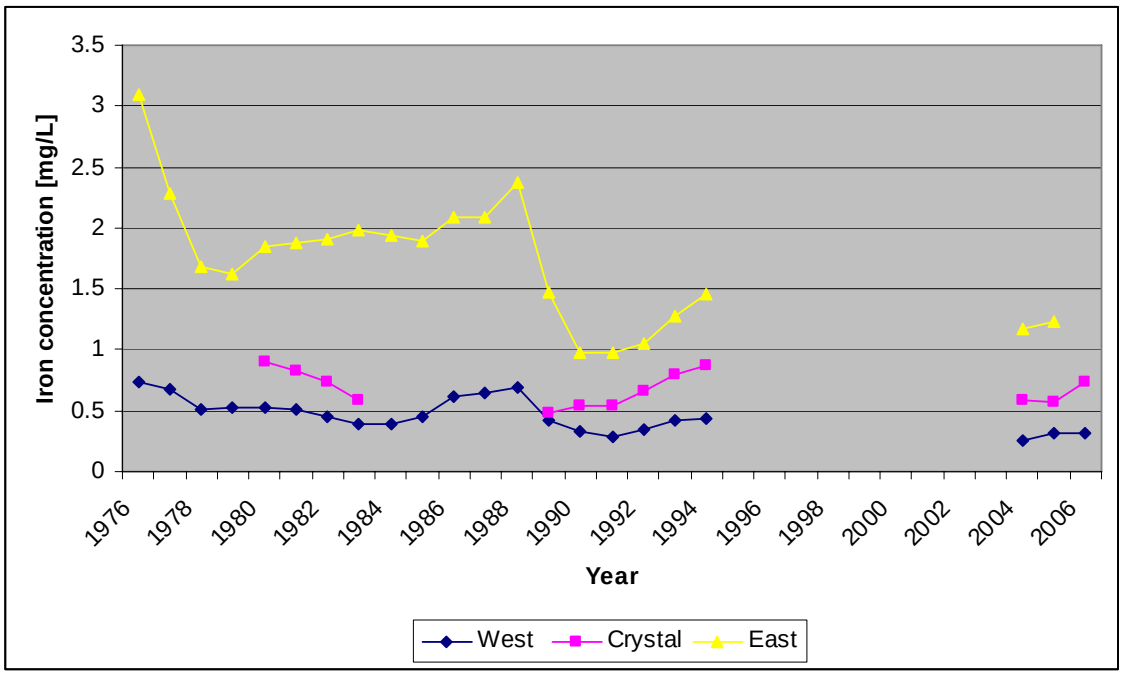

Figure 4.3 – 3-year rolling averages of iron concentrations showing a possible downward trend

The hypothesis of trend will be more thoroughly tested using nonparametric monotonic and step trend analysis in Section 4.4. More specifically, the Seasonal Kendall test for trend in seasonal data and Mann-Kendall and Mann-Whitney tests for monotonic and step trends respectively will be used. These tests will be explained in the following sections.

4.3 Discriminant analysis

In order to determine if the data sets from each sub-catchment are from the same population, a technique called discriminant analysis is used. This is important as it will confirm that the different soil types and land-uses in the three sub-catchments are contributing to water quality in the streams and that each sub-catchment should be

analysed separately. Discriminant analysis is a multivariate statistical technique that can be used to classify data into a set of predefined classes. In terms of water quality these classes can range from the sources of faecal bacteria, human or non-human, in a water sample (Carroll et al. 2009) to the grouping of different sample locations (Kowalkowski et al. 2006). In this analysis, the technique will be used to confirm that each sub-catchment is unique in terms of the dominant contributing factors to water quality in the streams. A similar analysis which was undertaken by Siriwardhema (1999) concluded that the three sub-catchments were not from the same population. This finding will hopefully be confirmed here with the benefit of 5 years of additional data.

4.3.1 Mann-Whitney test

The Mann-Whitney test (Mann & Whitney, 1947) is used for nonparametric independent data sets to compare water quality from the three different sub-catchments. This test is used in preference to the pooled two-sample t-test as it does not require the samples to be normally distributed nor do they have to have the same variance. The Mann-Whitney test looks for a shift in location between two independent populations, that is, the measurements from one population tend to be consistently larger (or smaller) than those from the other population. The null hypothesis (H_0) is that the populations from which the two data sets have been drawn have the same median (Gilbert, 1987). The test requires that all values are replaced with a relative rank, which makes the data sets easier to work with and ensures that distributions are not important.

The Mann-Whitney test is undertaken by first ranking the data from each data set. Data with the same value is assigned the average of the rank that would otherwise be assigned to those data points. The ranks from each data set are then summed; this value is known as the ‘rank sum’. It is assumed that if the rank sums of the two data sets are similar that the data sets come from the same population but if they are different than the medians of the data sets are different and therefore they come from separate populations. This conclusion is reached by calculating the test statistic using Equation 4.1.

$$Z_{rs} = \frac{W_{rs} - n_1(m+1)/2}{\sqrt{n_1 n_2 (m+1)/12}} \qquad \text{(Equation 4.1)}$$

where:

Z_{rs} = test statistic

W_{rs} = sum of ranks from population 1

n_1 = number of samples in population 1

n_2 = number of samples in population 2

$m = n_1 + n_2$

The hypothesis that the two data sets are from the same population is designated by the null hypothesis, H_0. This hypothesis is rejected and the alternate hypothesis, H_A, that the first data set is larger than the second accepted if $Z_{rs} \geq Z_{1-\alpha}$.

The significance level of the test is signified by $\propto$. In most water quality work a significance of 5-10% in terms of rejecting the null hypothesis when it is actually true an acceptable level of risk (Chapman, 1996). A significance level of 0.05 was chosen as this is the most commonly used level in scientific research (Varkevisser et al. 2003). The value, $1-\propto$, is equivalent to the acceptance level of the test (Demayo & Steel, 1996).

The Cumulative Normal Distribution table, available in most statistical texts, is where the value of $Z_{1-\alpha}$ is obtained and in this case is equal to 1.645.

As the data sets being analysed in this case are reasonably large, doing the Mann-Whitney test manually was considered too time consuming. Therefore the statistical program Minitab® was used.

In the case of the Tarago catchment the alternate hypothesis (H_A) was that the East would have poorer water quality than Crystal and that the West would have the best water quality. This hypothesis was based on the following land-uses within each sub-catchment: farming in the East, forestry in the West and a mixture in Crystal. Discriminant analysis was used to test this hypothesis and the results are shown in

Table 4.2. The highlighted rows indicate where H_A was accepted and a different conclusion was reached where there is no highlight.

Table 4.2 – The significance of the difference between sub-catchments using the Mann-Whitney test

Catchments	Parameter	Z	Conclusion
East -v- West *H_A: East has a larger median than West*	pH	15.803	Accept H_A
	EC	22.191	Accept H_A
	Colour	1.599	Accept H_0
	Turbidity	21.363	Accept H_A
	Iron	19.731	Accept H_A
	Manganese	16.048	Accept H_A
	Nitrate	17.563	Accept H_A
	Phosphorus	18.153	Accept H_A
	Ammonia	0.031	Accept H_0
	TOC	-7.415	West has larger median than East
	Suspended solids	11.458	Accept H_A
	TKN	7.386	Accept H_A
East -v- Crystal *H_A: East has a larger median than Crystal*	pH	10.428	Accept H_A
	EC	-5.249	Crystal has a larger median than East
	Colour	-9.330	Crystal has a larger median than East
	Turbidity	13.203	Accept H_A
	Iron	12.856	Accept H_A
	Manganese	11.964	Accept H_A
	Nitrate	15.385	Accept H_A
	Phosphorus	14.153	Accept H_A
	Ammonia	-0.293	Accept H_0
	TOC	-8.136	Crystal has a larger median than East
	Suspended solids	7.522	Accept H_A
	TKN	3.712	Accept H_A
Crystal -v- West *H_A: Crystal has a larger median than West*	pH	6.696	Accept H_A
	EC	21.275	Accept H_A
	Colour	12.381	Accept H_A
	Turbidity	15.632	Accept H_A
	Iron	12.394	Accept H_A
	Manganese	3.824	Accept H_A
	Nitrate	-2.919	West has a larger median than Crystal
	Phosphorus	6.960	Accept H_A
	Ammonia	-0.201	Accept H_0
	TOC	3.285	Accept H_A
	Suspended solids	8.452	Accept H_A
	TKN	9.541	Accept H_A

4.3.2 Discussion of discriminant analysis results

The results from Minitab® statistical package showed that most data sets differed from their corresponding data set from a different sub-catchment. The only exception was the ammonia levels which were shown to be the same in all three sub-catchments.

It was assumed that in most cases due to their different land-uses and soil types, the water quality parameters will have higher values in the East branch followed by Crystal with the lowest values being seen in the West branch. Although this was true with most of the data sets, there were some exceptions. As shown in Table 4.2, the EC was higher in Crystal than in the East branch and Crystal had the highest colour results with East and West branches being equal. The TOC values showed the East branch having lower levels than both Crystal and West branch. Nitrate was found to be highest in the East branch, with the next highest in the West and the lowest values in Crystal Creek.

These results mostly confirm the majority of results obtained from the basic statistical analysis in that the East branch has the highest concentrations followed by Crystal and then West branch. The exceptions, EC, colour and TOC can all be related to the fact that West branch is forested and rotting leaf matter contributes these parameters to runoff and therefore to in-stream water quality. The result that Crystal Creek has the lowest values of nitrate is hard to explain but could be due to fewer samples having larger variation rather than anything catchment specific.

The overall result of the discriminant analysis is that the three sub-catchments are not statistically similar and are from different populations. The water quality processes occurring in each sub-catchment are different and they should therefore be analysed separately.

4.4 Trend analysis

Visual inspection, usually graphically, of data can sometimes show an obvious trend in a data set. In these cases the use of regression analysis is probably reasonable. In most environmental data sets, however, regression analysis is flawed due to it being unable to deal with data that is non-normally distributed or if serial correlation, flow relatedness or seasonality is present (Hirsch et al. 1982). Additionally characteristics such as missing values and values below the detection limit can make trend analysis difficult. There are several techniques available that are not affected by these complications but it is first important to understand the type of trend hypothesis, the right statistical method and the kind of data that is being analysed (Hirsch et al. 1991).

There are two common types of tests that can examine the hypothesis of trend: step and monotonic. Step trend analysis can be used in two instances: one being when something dramatic, usually influenced by human activity, has occurred that would change the water quality almost instantaneously and the second being when the data is split into two distinct periods with a relatively long period of no data collection between them (Hirsch, 1988). Monotonic trend analysis simply detects an increase or decrease in the mean level over time and is used where no step is identified. Assessing data using monotonic trend analysis does not require that a prior knowledge about the form of the trend exists, whereas step trend analysis does (Thas et al. 1998). As the data from the Tarago catchment is in two distinct periods, see Figure 4.3, it was analysed using both the step trend and the monotonic trend tests.

An important consideration when assessing water quality data is the variation added by season or other cycles. Water quality concentrations can show strong seasonal patterns due to, for example, variations in precipitation or the regular application of land based fertilisers. These issues may affect the ability to detect a true trend but can be alleviated by removing the cycle before analysis or by using a test unaffected by the cycle (Gilbert, 1987).

When water quality data is collected it is usually collected as a concentration. This data, in some cases, has concurrent measurements of streamflow, which allows the analysis of load and flux as well as concentration. Load is defined as the total mass of a constituent passing through a stream during a given time period. Load is expressed as a mass and is simply the product of the average concentration of a water quality parameter and average flow over the same time period. Flux is the instantaneous load at a certain time and is expressed in units of mass per unit of time. A trend in concentration will not always mean that there is a trend in flux, therefore, in some cases depending on the overall objectives, it may be relevant to look at both data sets. For example, values of concentration are used when assessing landscape influence on water quality as it is linked to the health of the system and values of flux and load are used when mass balances and the relative importance of catchment inputs is of interest (Ahearn et al. 2005). Values of load are also important as treatment plant design is a function of dilution (Roser & Ashbolt, 2005). Both concentration and flux data sets will be analysed for trend. As there is no flow data recorded for the Crystal Creek, flux and load data for this site were unable to be calculated.

4.4.1 Seasonality

When seasonality is present in a data set, the test used to look for a trend should either remove these cycles or be unaffected by them. In order to determine whether or not a data set has seasonality a test known as the Kruskal-Wallis test can be used (Conover, 1980, cited in Yu et al. 1993). The test is an extension of the Mann-Whitney test (explained in Section 4.3.1) and determines whether the means of *k* independent data sets are the same. In this case *k* = 12, that is there are 12 'seasons' or months in a year. A significance level of 0.05 is chosen. The null hypothesis, "H_0: all populations have the same mean and therefore no seasonality exists", is rejected if the test statistic H is more than the test statistic, X_{α}^{2}. The test statistic is obtained from the Chi-Squared Distribution Table, available in most statistical texts; for $k-1$ degrees of freedom (df), $X_{0.05}^{2} = 19.68$.

Both concentration and flux data sets are analysed for seasonality and the results are shown in Tables 4.3 and 4.4 respectively, where the seasonal data sets are highlighted.

Table 4.3 – Determining the seasonality of water quality concentrations using the Kruskal-Wallis test

Catchment	Parameter	H	Conclusion
West	pH	12.31	No seasonality
	EC	111.78	Seasonality exists
	Colour	11.17	No seasonality
	Turbidity	13.52	No seasonality
	Iron	7.29	No seasonality
	Manganese	29.34	Seasonality exists
	Nitrate	102.33	Seasonality exists
	Phosphorus	15.77	No seasonality
	Ammonia	10.95	No seasonality
	TOC	5.82	No seasonality
	Suspended solids	15.47	No seasonality
	TKN	20.36	Seasonality exists
Crystal	pH	10.22	No seasonality
	EC	65.71	Seasonality exists
	Colour	21.46	Seasonality exists
	Turbidity	7.95	No seasonality
	Iron	12.14	No seasonality
	Manganese	22.06	Seasonality exists
	Nitrate	59.24	Seasonality exists
	Phosphorus	15.26	No seasonality
	Ammonia	8.27	No seasonality
	TOC	6.74	No seasonality
	Suspended solids	18.52	No seasonality
	TKN	18.04	No seasonality
East	pH	16.55	No seasonality
	EC	99.82	Seasonality exists
	Colour	9.03	No seasonality
	Turbidity	19.47	No seasonality
	Iron	17.30	No seasonality
	Manganese	11.90	No seasonality
	Nitrate	70.53	Seasonality exists
	Phosphorus	13.55	No seasonality
	Ammonia	11.92	No seasonality
	TOC	6.09	No seasonality
	Suspended solids	23.04	Seasonality exists
	TKN	13.36	No seasonality

In terms of concentration, 11 of the 36 data sets tested showed some seasonality, at a 0.05 significance level. Interestingly it was not always the same parameters in each sub-catchment. EC and nitrate had seasonal patterns in all three sub-catchments but manganese was only seasonal in the West branch and in Crystal Creek. TKN, colour and suspended solids were each only seasonal in one sub-catchment: the West, Crystal and East respectively. A number of factors can influence seasonality including the seasonal application of fertilisers, the different sources of water on the catchment (persistent winter rain as opposed to intense summer rain) and the influence of

groundwater in different months. Obviously land use, land cover and soil types can all influence the severity of impact of these factors.

Table 4.4 – Determining the seasonality of water quality fluxes using the Kruskal-Wallis test

Catchment	Parameter	H	Conclusion
West	pH	111.88	Seasonality exists
	EC	101.62	Seasonality exists
	Colour	85.13	Seasonality exists
	Turbidity	74.67	Seasonality exists
	Iron	56.86	Seasonality exists
	Manganese	34.67	Seasonality exists
	Nitrate	86.64	Seasonality exists
	Phosphorus	66.85	Seasonality exists
	Ammonia	35.27	Seasonality exists
	TOC	38.88	Seasonality exists
	Suspended solids	28.76	Seasonality exists
	TKN	50.57	Seasonality exists
East	pH	105.86	Seasonality exists
	EC	97.71	Seasonality exists
	Colour	49.16	Seasonality exists
	Turbidity	57.69	Seasonality exists
	Iron	51.55	Seasonality exists
	Manganese	50.97	Seasonality exists
	Nitrate	84.00	Seasonality exists
	Phosphorus	62.64	Seasonality exists
	Ammonia	43.90	Seasonality exists
	TOC	26.65	Seasonality exists
	Suspended solids	36.09	Seasonality exists
	TKN	53.10	Seasonality exists

Analysis of the flux data showed that all 24 data sets had seasonality, at both a 0.05 significance level and a 0.005 significance level. This is, however, expected as flow, which is a component of flux, is generally highly influenced by the season.

Seasonal Kendall test for trend

For the data sets that show seasonality, a test that is not affected by the cycles must be used to determine whether there is a trend present. Such a test is the Seasonal Kendall test developed by Hirsch et al. (1982). It is an extension of the Mann-Kendall (Mann, 1945; Kendall, 1975, cited in Yu et al. 1993) test where for each season (or month) a test statistic and its variance is computed. The test statistics and the variances are then summed and are used to determine the Z statistic. This is further explained by the following equations.

The Mann-Kendall statistic is computed for each season using Equation 4.2.

$$S_i = \sum_{k=1}^{n_i-1} \sum_{l=k+1}^{n_i} \mathrm{sgn}(x_{il} - x_{ik}) \qquad \textit{(Equation 4.2)}$$

where:

S_i = Mann-Kendall statistic for season *i*

l and k = year where $l > k$

n_i = number of data points for season *i*

The value of $\mathrm{sgn}(x_{il} - x_{ik})$ is defined below:

$$\mathrm{sgn}(x_{il} - x_{ik}) = \begin{cases} 1 & \text{if } x_{il} - x_{ik} > 0 \\ 0 & \text{if } x_{il} - x_{ik} = 0 \\ -1 & \text{If } x_{il} - x_{ik} < 0 \end{cases}$$

For the whole data set the Mann-Kendall statistic is calculated using Equation 4.3.

$$S' = \sum_{i=1}^{K} S_i \qquad \textit{(Equation 4.3)}$$

where:

K = total number of seasons

Equation 4.4 is used to compute the variance for each season.

$$VAR(S_i) = \frac{1}{18}\left[n_i(n_i-1)(2n_i+5) - \sum_{p=1}^{g_i} t_{ip}(t_{ip}-1)(2t_{ip}+5) \ \ldots \right.$$

$$\left. - \sum_{q=1}^{h_i} u_{iq}(u_{iq}-1)(2u_{iq}+5) \right] \ \ldots$$

$$+ \frac{\sum_{p=1}^{g_i} t_{ip}(t_{ip}-1)(t_{ip}-2) \sum_{q=1}^{h_i} u_{iq}(u_{iq}-1)(u_{iq}-2)}{9n_i(n_i-1)(n_i-2)} \ \ldots$$

$$+ \frac{\sum_{p=1}^{g_i} t_{ip}(t_{ip}-1) \sum_{q=1}^{h_{ii}} u_{iq}(u_{iq}-1)}{2n_i(n_i-1)} \qquad \text{(Equation 4.4)}$$

where:

g_i = number of groups of tied data in season *i*

t_{ip} = number of tied data in the p^{th} group for season *i*

h_i = Number of sampling times in season *i* that contain multiple data

u_{iq} = number of multiple data in the q^{th} time period in season *i*

To determine the variance for the whole data set Equation 4.5 is used.

$$VAR[S'] = \sum_{i=1}^{K} VAR(S_i) \qquad \text{(Equation 4.5)}$$

The Z statistic is then calculated using the two summed values:

$$Z = \begin{cases} \dfrac{(S'-1)}{\sqrt{VAR(S')}} & \text{if } S' > 0 \\ 0 & \text{if } S' = 0 \\ \dfrac{(S'+1)}{\sqrt{VAR(S')}} & \text{if } S' < 0 \end{cases}$$

As for the standard Mann-Kendall test the null hypothesis (H_o) is that the data (x_1,..., x_n) are a sample of *n* independent and identically distributed random variables and therefore there is no significant trend in either direction. A significance level of $\propto = 0.05$ is chosen and H_o is rejected if $-Z_{1-\alpha} > Z > Z_{1-\propto}$, which is equivalent to

$-1.645 > Z > 1.645$. A positive value of Z indicates an upward trend and a negative, a downward trend.

Tables 4.5 and 4.6 show the results of the Seasonal Kendall test for trend on those 11 concentration data sets that were shown to be influenced by seasons and all of flux data sets, respectively. The highlighted values indicate where a downward trend was detected.

Table 4.5 – Results using the Seasonal Kendall test for trend on seasonal concentration data sets

Catchment	Parameter	Z	Conclusion
West	EC	6.652	Upward trend
	Manganese	0.851	No trend
	Nitrate	-4.283	Downward trend
	TKN	0.151	No trend
Crystal	EC	7.925	Upward trend
	Colour	1.858	Upward trend
	Manganese	0.124	No trend
	Nitrate	1.961	Upward trend
East	EC	10.192	Upward trend
	Nitrate	-1.866	Downward trend
	Suspended solids	0.781	Upward trend

Table 4.6 – Results using the Seasonal Kendall test for trend on seasonal flux data sets

Catchment	Parameter	Z	Conclusion
West	pH	-4.312	Downward trend
	EC	-4.118	Downward trend
	Colour	-3.046	Downward trend
	Turbidity	-6.064	Downward trend
	Iron	-2.522	Downward trend
	Manganese	-2.361	Downward trend
	Nitrate	-3.232	Downward trend
	Phosphorus	-0.372	Downward trend
	Ammonia	4.208	Upward trend
	TOC	1.761	Upward trend
	Suspended solids	1.551	No trend
	TKN	-0.345	No trend
East	pH	-6.272	Downward trend
	EC	-6.643	Downward trend
	Colour	-6.911	Downward trend
	Turbidity	-9.267	Downward trend
	Iron	-3.454	Downward trend
	Manganese	-2.395	Downward trend
	Nitrate	-2.751	Downward trend
	Phosphorus	-7.176	Downward trend
	Ammonia	4.281	Upward trend
	TOC	1.182	No trend
	Suspended solids	1.624	Upward trend
	TKN	-1.303	No trend

4.4.2 Monotonic trend analysis

Monotonic trend analysis is looking for a general direction in the population. The monotonic test for trend used is the Mann-Kendall trend test, which is a widely used method in hydrological time series analysis to detect important changes (Ma et al. 2009). The null hypothesis, H_o, is that there is no significant trend in either direction.

Mann-Kendall test for trend

Firstly, the Mann-Kendall statistic, *S*, must be computed for the whole data set, as seen in Equation 4.2.

The statistic is calculating the number of positive differences minus the number of negative differences. If *S* is large then measurements taken later in time are larger than those taken earlier, conversely if *S* is small (ie negative) then measurements taken later in time tend to be smaller. For a data set larger than 40 data points - Tarago has over 100 data points per parameter - the variance of *S* must be obtained using an alternate equation, see below.

$$VAR(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p (t_p - 1)(2t_p + 5) \right] \qquad \textit{(Equation 4.6)}$$

where:

n = number of data points

t_p = number of data points in the p^{th} group

Other variables as defined previously

Using Equations 4.3 and 4.6 the Z statistic is calculated as in Section 4.4.1.

A positive value of *Z* indicates an upward trend and a negative, a downward trend. The absolute value of *Z* is compared against the test statistic $Z_{1-\alpha}$ to determine if the trend is significant or not. The significance level, $\propto$, was set at 0.05. The null hypothesis H_0 is rejected if absolute $Z > Z_{1-\alpha}$, where $Z_{0.95} = 1.645$.

Table 4.7 shows the results of this analysis and they will be discussed in Section 4.4.5.

Table 4.7 – Mann-Kendall results for trend in water quality data

Catchment	Parameter	Z	Conclusion
West	pH	-3.695	Downward trend
	Colour	-1.289	No trend
	Turbidity	6.263	Upward trend
	Iron	-3.260	Downward trend
	Phosphorus	-0.322	No trend
	Ammonia	0.000	No trend
	TOC	1.303	No trend
	Suspended solids	-0.027	No trend
Crystal	pH	1.466	No trend
	Colour	6.104	Upward trend
	Turbidity	2.828	Upward trend
	Iron	-0.581	No trend
	Phosphorus	-0.046	No trend
	Ammonia	-0.164	No trend
	TOC	0.207	No trend
	Suspended solids	-0.354	No trend
East	pH	-6.062	Downward trend
	Colour	7.145	Upward trend
	Turbidity	3.986	Upward trend
	Iron	-5.718	Downward trend
	Phosphorus	-0.668	No trend
	Ammonia	-0.944	No trend
	TOC	0.012	No trend
	Suspended solids	0.204	No trend
	pH	0.026	No trend

4.4.3 Step trend analysis

The use of step trend analysis is acceptable in two cases: one, when there has been a dramatic occurrence in the catchment which would alter water quality or two, when there are two distinct periods of data collection. This latter case is relevant for the Tarago catchment. Step trend analysis is used to determine if there is any significant change in water quality before and after the gap in data collection. The Mann-Whitney test, as described above in Section 4.3.1, is used to determine whether data collected after catchment works are from a distinctly different population than the data collected before that time. There are alternatives to using this test, but in a paper by Yu and Zou (1993) it is reported that all the tests have practically the same power at a statistical significance level of 0.05 for a record length of 9 years or greater; the Tarago data set has a record length of over 20 years. Step trend analysis was not carried out on those data sets which showed seasonality.

Table 4.8 shows the results of this analysis.

Table 4.8 – Mann-Whitney test to indicate trend in water quality data

Catchment	Parameter	Z	Conclusion
West	pH	3.375	Upwards trend
	Colour	-1.848	Downward trend
	Turbidity	-0.773	No trend
	Iron	-2.105	Downward trend
	Phosphorus	-0.441	No trend
	Ammonia	-1.919	Downward trend
	TOC	-2.811	Downward trend
	Suspended solids	-2.854	Downward trend
Crystal	pH	4.774	Upwards trend
	Turbidity	1.680	Upwards trend
	Iron	-0.624	No trend
	Phosphorus	0.513	No trend
	Ammonia	-3.574	Downward trend
	TOC	-3.708	Downward trend
	Suspended solids	-1.035	No trend
	TKN	-0.609	No trend
East	pH	3.243	Upwards trend
	Colour	1.044	No trend
	Turbidity	3.755	Upwards trend
	Iron	-0.455	No trend
	Manganese	-1.032	No trend
	Phosphorus	1.737	Upwards trend
	Ammonia	-1.299	No trend
	TOC	-3.611	Downward trend
	TKN	-2.660	Downward trend

4.4.4 Summary of trend analysis results

Table 4.9 gives a summary of both of the trend tests done on the concentration data sets and indicates whether a significant trend was detected and if so in which direction the trend was shown to be going.

Of the 61 trend tests done on the concentration data a downwards trend was seen in 25% of the data sets, an upwards trend in 28% and the remainder showed no significant trend. Where both the monotonic and step trend tests were performed, that is not the seasonal data sets, they showed the same trend direction in 36% of cases. The pH in the East and the West showed a downward trend with the monotonic analysis and an upward trend with the step analysis, see Table 4.9. These were the only cases where there were opposite results between tests. Given that pH is recorded as a log scale, the absolute change observed is very small so these apparent 'trends' are likely to be just noise.

Table 4.9 – Summary of trend results for each parameter in each catchment

Legend O = Upward trend; ◆ = Downward trend; - = No trend in either direction					
Catchment	**Parameter**[12]	**Concentration**			**Flux**
		Seasonal	**Monotonic**	**Step**	**Seasonal**
West	pH		◆	O	◆
	EC	O			◆
	Colour		-	◆	◆
	Turbidity		O	-	◆
	Iron		◆	◆	◆
	Manganese	-			◆
	Nitrate	◆			◆
	Phosphorus		-	-	◆
	Ammonia		-	◆	O
	TOC		-	◆	O
	Suspended solids		-	◆	-
	TKN	-			-
Crystal	pH		-	O	*No streamflow data available*
	EC	O			
	Colour	O			
	Turbidity		O	O	
	Iron		O	-	
	Manganese	-			
	Nitrate	O			
	Phosphorus		-	-	
	Ammonia		-	◆	
	TOC		-	◆	
	Suspended solids		-	-	
	TKN		-	-	
East	pH		◆	O	◆
	EC	O			◆
	Colour		O	-	◆
	Turbidity		O	O	◆
	Iron		◆	-	◆
	Manganese		-	-	◆
	Nitrate	◆			◆
	Phosphorus		-	O	◆
	Ammonia		-	-	O
	TOC		-	◆	-
	Suspended solids	O			-
	TKN		-	◆	-

Common across all three sub-catchments in terms of parameter trends were EC and turbidity trending up and TOC trending down. Nitrate and iron trended up in Crystal but down in the other two sub-catchments and colour trended down in the West branch but up in the other two. In the East branch where catchment works are expected to have had some influence on water quality, TKN also trended down and phosphorus and

[12] Highlighted values are seasonal data sets

suspended solids trended up. There was no trend detected in any of the manganese data.

For the flux data only, the Seasonal Kendall test for trend was preformed and the results showed a significant downward trend in most of the data sets, see Table 4.9. TOC in the West and ammonia at both sites were the only parameters to show a significant increase while TOC in the East and suspended solids and TKN at both sites showed no significant trend in either direction. All other parameters at both sites trended down.

4.4.5 Discussion of trend analysis results

The results obtained from the statistical analysis can be used to give an indication as to any long-term trends and to determine if catchment management is having a measurable impact on water quality.

The concentration data sets showed that EC and turbidity were trending up in all three sub-catchments and TOC down in all three sub-catchments. Given these trends are consistent across the whole catchment, and catchment management differed for each sub-catchment, it is not likely that the trends are the result of catchment management initiatives. Instead the trends indicate a catchment wide change such as lower rainfall or climate variability.

The East branch had downward trends in iron and TKN which in this sub-catchment are parameters associated with erosion as identified by the FA in Section 4.5.1. This could be an indication that the impact of erosion has lessened over the past 10 years, possibly as a result of catchment management. Conversely Crystal Creek has seen upward trends in nitrate and iron perhaps indicating that erosion is an issue in this sub-catchment that may need some targeted management.

Parameters in the West that have previously been related to groundwater in that sub-catchment, colour and iron (Siriwardhena, 1999), both trended down. This could be a consequence of less rainfall which could result in a decrease in the transport mechanisms needed for those parameters to reach the groundwater and subsequently the stream. It could also be a simple case of less groundwater movement due to less water being available in the catchment.

The flux data yielded different results in that 16 of the 24 data sets trended downwards. Only TOC, suspended solids, TKN and ammonia in both the East and West sub-catchments showed no trend or a significant upward trend. The analysis of flux can represent runoff quality more accurately than concentration. It can help set priorities in relation to contaminant sources and can indicate the level of risk arising from that source. The downward trends observed indicate that there has been some reduction in contaminant fluxes, which could be related back to the impact of catchment management. Parameters such as turbidity, phosphorus and nitrate trending down, especially in the East, are good indications that changed agricultural practices could be responsible for improving water quality. As flux is inherently affected by streamflow, a downward trend could also be a result of a reduction in streamflow over time. In the East branch there has been a noticeable decrease in flow since the early 1990's, most likely due to the drought. The West branch flows, however, appear relatively consistent.

The trend analysis has shown limited consistency across the three sub-catchments or across parameters. It is therefore difficult to conclude that catchment management has had a measurable impact on water quality. It is important to remember, however, that the analysed water quality was taken, for the most part, during baseflow conditions. The relevance of this will become clear in the following Chapters.

4.5 FA

Multivariate statistics, including FA, have been used in various studies assessing different aspects of water quality. In most cases FA is used to evaluate the spatial and temporal changes in water quality and to determine trends. Groundwater analysis has been the focus of a number of studies, for example, delineating the boundaries where groundwater is affected by seawater intrusion (Liu et al. 2003) and gaining a better understanding of the processes affecting shallow groundwater in an irrigation district (Ahmed et al. 2005). Paul et al. (2006) used FA to group different watersheds with similar characteristics to allow the study of the catchments as a group, effectively reducing the quantity of sampling and the number of individual studies required. As was undertaken by Siriwardhena (1999), FA will be used here for exploratory water quality analysis. It will be used to interpret water quality data and relate it back to processes, hydrologic or anthropogenic, within the catchment. It will also be used as

an additional test of trend or more specifically to determine any changes in the variables included in the dominant catchment processes over time.

FA is a multivariate statistical method that can be used to reduce the amount of data being used to predict a response. The usual first step in FA is Principal Component Analysis (PCA) which summarises the data by means of a linear combination of observed variables with the goal being to determine the smallest number of variables that will explain most of the variance. FA simplifies even further the data structure coming from PCA by attempting to explain the common variance shared by the observed variables. It tries to find any underlying factors that are responsible for the interrelationships between observed variables.

PCA converts the original data into new, uncorrelated variables, or axis, which are linear combinations of the original variables. The axes are aligned along the direction of maximum variance. Equation 4.7 from Shrestha and Kazama (2007) shows how PCA can be expressed.

$$z_{ij} = a_{i1}x_{1j} + a_{i2}x_{2j} + a_{i3}x_{3j} + ... + a_{im}x_{mj} \qquad \text{(Equation 4.7)}$$

where:

z = component score

a = component loading

x = measured value of variable *i*

i = component number

j = sample number

m = total number of variables

FA reduces the contribution of the less significant data even further to simplify the structure coming from PCA. This is done by rotating the axes and results in a small number of factors accounting for approximately the same amount of information as the larger original set of variables. FA can be expressed as seen in Equation 4.8 (Shrestha & Kazama, 2007).

$$z_{fi} = a_{f1} f_{1i} + a_{f2} f_{2i} + a_{f3} f_{3i} + ... + a_{fm} f_{mi} + e_{fi}$$ (*Equation 4.8*)

where:

z = measured variable

a = factor loading

f = factor score

e = residual terms accounting for errors or other sources of variation

i = sample number

m = total number of factors

Undertaking PCA and FA requires a correlation matrix to be calculated to determine the factorability of the data or the amount of intercorrelation between variables. Tabachinick and Fidell (2001) state that for a correlation matrix without any correlations over 0.3, FA should be reconsidered. A sufficient number of significant correlations indicate that there may be some underlying processes affecting several variables and that undertaking PCA/FA could successfully reduce the dimensionality of the original data set.

The next step involves determining the appropriate number of factors that need to be extracted in order to explain most, or a sufficient amount, of the variance in the data set. This can be done in a number of ways based on the amount of available data and the number of variables. The Scree test is a visual test where the eigenvalues, which measure the significance of the factor, are plotted against the factors. The number of factors selected corresponds to the point at which the eigenvalues go below 1.

Interpreting the loadings obtained from FA is an important part of the process. The loadings represent the degree to which that variable is influenced by that factor. According to a large scale study by Liu et al. (2003) factor loadings can be classified as strong, medium and weak corresponding to values of >0.75, 0.75>0.5 and 0.5>0.3 respectively. Other researchers, such as Comrey and Lee (1992), indicated a similar interpretation of results, as follows: >0.71 = excellent, 0.7>0.63 = very good, 0.62>0.55 = good, 0.54>0.45 = fair and 0.44>0.32 = poor. Based on these studies, in this work a factor loading of over 0.75 was chosen as indicating that the variable was significant for that factor.

In order to find the best solution when undertaking FA, rotation techniques may be implemented. This improves the interpretability and scientific utility of the solution but it does not improve the quality of the results (Tabachnick & Fidell 1996). There are many rotational techniques but by far the most popular is the varimax method devised by Kaiser (1958). Varimax rotation maximises the variance of the squared loadings for each factor and polarises the loadings so they are either high or low therefore making it easier to identify factors with specific observed variables (Marcoulides & Hershberger, 1997).

PCA and FA were undertaken using the software package Minitab®. Factors were extracted using principal component and then rotated using the varimax rotation. Two different analyses were done using FA; the first used the whole data set to allow comparisons between sub-catchments and the main processes affecting water quality, and the second was to compare the main water quality processes before and after catchment works to determine if there was any difference in the variables.

4.5.1 Results of FA

The factorability of the data was assessed by determining the correlations between parameters, see Appendix C, Tables C.1 to C.3. Over a third of the correlations related to physical-chemical parameters were greater than 0.3 which was deemed to be a sufficient number to indicate the possibility of an underlying process and therefore FA could be carried out.

A Scree plot was created for each of the sub-catchments, see Figure 4.4.

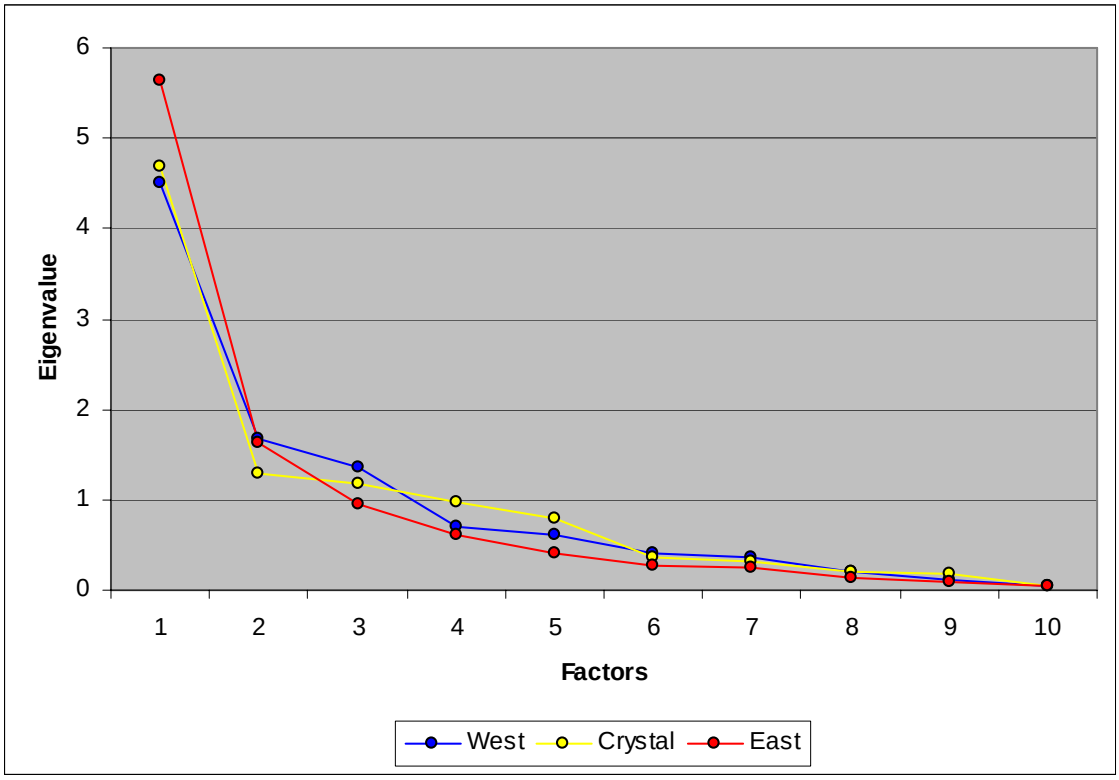

Figure 4.4 – Scree plot for the Tarago sub-catchment

From analysis of this graph it is reasonable to extract 3 factors for each sub-catchment as after this point the eigenvalues are below 1. Three factors should explain the majority of the variance and determine the processes in the catchment affecting water quality. Table 4.10 below shows the percentage of variance explained by each of the first three factors as well as the total cumulative variance.

Table 4.10 – Total percentage of variance explained by each factor for each sub-catchment

Catchment	Factor	Variance [%]	Cumulative Total Variance [%]
West	1	40.5	75.5
	2	19.7	
	3	15.3	
Crystal	1	46.8	71.4
	2	12.9	
	3	11.7	
East	1	55.6	82.2
	2	16.1	
	3	10.5	

In all three sub-catchments over 70% of the variance in the data is explained with the first three factors. Additionally, in each sub-catchment the first factor in each case

explains over 40% of the data variance and so this will represent the dominant water quality parameters within that catchment.

Tables 4.11 to 4.13 show the varimax rotated factor loadings for each of the sub-catchments, West, Crystal and East respectively with the highlighted values indicating that the variable is significant for that factor.

Table 4.11 – Varimax rotated factor loadings for the West catchment

Variable	Factor 1	Factor 2	Factor 3
pH	-0.037	-0.193	0.808
Colour	0.848	0.152	-0.116
Turbidity	0.808	0.363	-0.048
Iron	0.897	-0.081	0.276
Manganese	0.841	-0.181	0.202
Nitrate	-0.141	-0.273	-0.809
Phosphorus	0.173	0.745	-0.096
Ammonia	0.011	0.820	0.122
Suspended solids	0.777	0.452	-0.233
TKN	0.713	0.480	0.073

Table 4.12 – Varimax rotated factor loadings for the Crystal catchment

Variable	Factor 1	Factor 2	Factor 3
pH	0.012	0.009	-0.974
Colour	0.805	-0.174	0.244
Turbidity	0.925	-0.148	-0.048
Iron	0.882	-0.215	-0.170
Manganese	0.775	0.233	-0.181
Nitrate	0.019	0.585	-0.150
Phosphorus	0.533	0.189	-0.126
Ammonia	-0.002	0.861	0.189
Suspended solids	0.920	0.044	0.092
TKN	0.817	0.128	0.133

Table 4.13 – Varimax rotated factor loadings for the East catchment

Variable	Factor 1	Factor 2	Factor 3
pH	-0.015	-0.833	0.173
Colour	0.876	0.087	-0.001
Turbidity	0.942	-0.199	0.014
Iron	0.854	-0.372	0.117
Manganese	0.875	-0.097	0.145
Nitrate	-0.074	0.091	-0.976
Phosphorus	0.853	0.003	-0.053
Ammonia	-0.06	0.834	0.060
Suspended solids	0.949	0.106	-0.050
TKN	0.879	0.060	0.162

A variance of more than 0.75 was deemed to indicate that the parameter was significant for that factor. The figures that are highlighted represent these variables.

4.5.2 Discussion of FA results

It is evident that Factor 1 in all three sub-catchments represents erosion and particle movement. Parameters such as turbidity, suspended solids, colour, iron and manganese are strongly associated with sediment movement from land surfaces. There are, however, differences between the sub-catchments in terms of additional parameters related to Factor 1, in particular phosphorus and TKN, and these can give some indication as to the differences in land-uses and soil type. The significance of TKN in the East and in Crystal is most likely the result of manure application or simply the higher density of domestic animals compared to the West. Phosphorus was significant only in the East which could be due to a number of reasons. It could indicate that fertiliser use in this sub-catchment is higher than in Crystal or it could be that the land is cleared and therefore more prone to erosion of topsoil. Swan and Volum (1984, cited in Siriwardhena, 1999) classified the majority of the soils in the East as being clay with high phosphorus levels; therefore supporting the erosion theory.

Factor 2 shows a high loading for ammonia across all three sub-catchments. Ammonia is soluble and as it is not associated with the erosion component it is either transported in solution as surface runoff or as groundwater. In the East catchment, ammonia and pH both have high loadings and are negatively correlated. This negative correlation is due to the fact that as pH decreases the solubility of ammonia increases.

The third Factor relates to nitrate in the East and nitrate and pH in the West catchment. In Crystal it relates to just pH. Nitrate, like ammonia, is soluble and this factor could therefore be indicating the influence of groundwater on water quality or the influence of surface runoff. As with Factor 2, Factor 3 is not related to erosion or to particle movement and suggests that both ammonia and nitrate have unique transport mechanisms.

In a study by Siriwardhena (1999) FA was carried out on data obtained from the Tarago catchment from 1974 to 1993. The analysis in the current study includes an additional 5 years of data. Comparison of the results from both studies may give an indication as to what, if any, impact land-use change and/or climatic change has had on water quality. The results for the East catchment were similar in that erosion was the dominant factor. In the West, however, the current study showed that erosion was the dominant factor, whereas Siriwardhena (1999) found that it was groundwater. This difference could be due to the additional data used in the current study meaning a

more extensive and complete analysis. An increase in activity in the catchment, which could disturb more topsoil, or a change in rainfall patterns, which could reduce groundwater flow, could both also affect the outcomes of FA.

The overall ability of FA to reduce the number of parameters needed to explain the majority of the data in these cases was weak. In the East catchment all 10 parameters across the 3 factors were needed to explain 82% of the variance. In the West and Crystal, 8 of the 10 parameters were needed in each case. FA was however successful in identifying the most significant processes within each sub-catchment.

4.5.3 Using FA to determine trend

The use of FA can find information about the similarities or dissimilarities of various physical and chemical properties in runoff from the different sub-catchments. FA can also be used to verify temporal and spatial variations caused by natural and anthropogenic factors linked to seasonality (Boyacioglu, 2006; Shrestha & Kazama, 2007; Yu et al. 2003). Here, the same techniques used in these referenced studies are being used to asses the changes in catchment runoff processes and pollution sources before and after catchment improvement works. To do this FA was carried out with data up to and including 1994 and then repeated with data from after 1994. The differences in significant variables for Factor 1 were then assessed. Only Factor 1 was deemed important as over 40% of the variance is explained by this factor in all sub-catchments. Additionally Factor 1 represents erosion and is therefore the factor that is most likely to be impacted by catchment works. In the West catchment, TKN data was omitted from the analysis as its inclusion halved the amount of data analysed in the “After” case. The results of the analysis are presented in the Tables 4.14, 4.15 and 4.16, for the West, Crystal and East catchments respectively with the highlighted values being significant for that Factor.

Table 4.14 – West catchment loadings for Factor 1 before and after catchment works

	Before	After
Variable	**Factor 1**	**Factor 1**
pH	-0.088	-0.428
Colour	0.854	0.831
Turbidity	0.776	0.864
Iron	0.928	0.893
Manganese	0.839	0.618
Nitrate	-0.123	-0.237
Phosphorus	0.167	-0.033
Ammonia	-0.153	0.288
Suspended solids	0.772	0.130
TKN (omitted)	-	-
Variance [%]	39.6	32.9

Table 4.15 – Crystal Creek catchment loadings for Factor 1 before and after catchment works

	Before	After
Variable	**Factor 1**	**Factor 1**
pH	-0.071	-0.208
Colour	0.715	0.818
Turbidity	0.924	0.915
Iron	0.788	0.961
Manganese	0.764	0.882
Nitrate	0.057	0.005
Phosphorus	0.579	0.648
Ammonia	0.162	-0.095
Suspended solids	0.880	0.971
TKN	0.761	0.938
Variance [%]	42.9	55.1

Table 4.16 – East catchment loadings for Factor 1 before and after catchment works

	Before	After
Variable	**Factor 1**	**Factor 1**
pH	-0.094	-0.052
Colour	0.954	0.696
Turbidity	0.959	0.970
Iron	0.943	0.960
Manganese	0.848	0.961
Nitrate	-0.117	-0.121
Phosphorus	0.920	0.694
Ammonia	-0.002	-0.151
Suspended solids	0.961	0.947
TKN	0.843	0.978
Variance [%]	59.4	56.4

In the West catchment in the After case, the significance of manganese and suspended solids was reduced. This could relate to logging and roading practices being improved within the catchment and decreasing the amount of sediment movement. The Code of

Forest Practices for Timber Production (DNRE, 1996) was released during the sampling period. It specifies that the minimum distance between a stream and logging activities be between 20 and 40 m, whereas the previous plan - Code of Forest Practices for Timber Production (DCFL, 1989) - stated that only a 20 m buffer be implemented. This additional buffer distance could be contributing to improved water quality, especially in terms of suspended solids.

The Crystal catchment results indicate that there has been very little change in the parameters associated with erosion in the catchment.

The East catchment shows that both colour and phosphorus are less dominant after catchment works. As phosphorus in this catchment is linked to topsoil erosion, the reduction in its dominance in the “After” case could indicate that plantings in riparian strips and erosion prone areas is reducing the movement of soil. The reduction could also be attributed to appropriate application of fertiliser in the catchment according to nutrient levels in the soil, which is one of the initiatives of the Tarago Catchment Management Plan (Melbourne Water, 2003).

Using FA to determine trend is an innovative way of applying this statistical tool and it can show the parameters that are significant during different periods.

4.6 Summary and conclusions

The main objectives of the water quality analysis was to determine whether the three sub-catchments were different and to relate that back to land-use or soil type and to determine the trend of the raw water quality parameters and relate that back to changes within the catchment. Additionally the catchment processes that most influenced water quality were determined. A series of statistical approaches were utilised including: discrimnant analysis, which was used to confirm the sub-catchments were unique; monotonic and step trend analysis. FA was used to assess the dominant processes in each sub-catchment and as an additional test of trend.

The three sub-catchments were shown to be significantly different from each other with regards to all the parameters analysed, with the exception of ammonia which was equal across all three. As expected the East branch catchment showed the worst water quality for all but three of the twelve parameters, namely EC, colour, and TOC.

These parameters are mainly related to decomposing leaf matter which is more prevalent in the West and Crystal catchments as there is more forested area in these catchments. The poorer water quality in the East branch is most likely due to the intensive land-uses within the catchment including farming of domestic stock and application of fertilisers. The summed area of cleared land would also be a contributing factor in increasing the concentrations of parameters such as turbidity and suspended solids. These results confirm that both land-use and soil type can influence water quality and that the three sub-catchments need to be considered separately for water quality analysis.

FA confirmed that erosion was the most dominant catchment process impacting on water quality in all three sub-catchments. Parameters such as colour, turbidity, suspended solids, iron and manganese are generally associated with sediment movement from the surface and these were found to be the most dominant parameters in terms of water quality in the Tarago catchment. This knowledge helps in determining the type of catchment management initiatives that will have the most impact on water quality. Initiatives that encourage filtration, dilution and elimination of sediments are likely to have the greatest impact on water quality.

As discussed previously there was limited consistency across the three sub-catchments or across parameters in terms of trend. The results, however, do provide a basis for some conclusions about the effect of the catchment management works. Generally erosion is trending down in the West branch with parameters such as colour, iron, manganese and suspended solids all showing evidence of reducing over time. This result may be due to an increased focus and awareness about the role that buffer strips play in logged areas in reducing sediment movement. In the Crystal catchment, however it is the opposite with colour, turbidity, and iron all trending up. Catchment management in this sub-catchment has been limited and these results indicate that more needs to be done in terms of erosion control. The East catchment was varied in relation to trends in its dominant erosion parameters; colour, turbidity and suspended solids all trended up while iron, phosphorus and TKN trended down. A more considered application of fertilisers may account for the downward trends, while the increasing sediment movement may indicate that more needs to be done in erosion prone areas.

Despite the large amount of data available for analysis, it was difficult to find a clear and measurable impact on water quality related to catchment management. This is not

to say that catchment management is not working, just that it is difficult to quantify the impact on water quality using standard water quality samples.

In most cases the main objective of collecting water quality data is to enable long-term trends to be detected and for these trends to be related back to changes within the catchment. One of the main elements for a good monitoring program is consistency over time and ensuring that the initial objectives are recognised throughout the sampling period, which could be in the range of tens of years. Another important element is the collection of samples during storm events. Event sampling represents the highest risk period and is the period where the greatest reduction in risk will be seen. This will be further discussed in the following Chapter.

5. PATHOGEN AND EVENT DATA ANALYSIS

5.1 Introduction

While Chapter 3 outlined the available data within the catchment and Chapter 4 analysed and discussed the physical-chemical parameters in an attempt to determine trends related to water quality, this chapter deals with the pathogens, pathogenic indicators and event data. These data sets have been looked at separately to the physical-chemical data for a number of reasons:

- pathogenic and event data have only been collected in the Tarago catchment for a short period of time
- different statistical techniques are required to analyse this type of data
- the objectives of this analysis compared to the physical-chemical parameters is not the same.

In this chapter the objectives of the analysis are focused on determining the processes within the catchment that most affect pathogen and pathogenic indicator movement and therefore where catchment management efforts should be focused for the benefit of drinking water quality. Additionally, determining a method for predicting pathogen movement will be assessed. As with Chapter 4, the overall objective is to determine whether there is a measurable impact on water quality that can be attributed to catchment management.

To determine the catchment processes which are most likely to influence pathogens and their indicators, Factor Analysis (FA) is used. Regression analysis will be used to find any significant relationships between pathogens or pathogenic indicators and other parameters which are more frequently and easily measured. The analysis of data sampled during different storm events within the catchment will show which parameters are most affected by rainfall and surface runoff.

5.2 Data analysis methods

The methods employed to analyse the pathogen, pathogenic indicator and event data are described below. The data used for the analyses was detailed in Chapter 3.

5.2.1 Regression

The lack of pathogen data prior to 2003 and therefore prior to any catchment works, means that in order to determine if there is a measurable impact on pathogens, or pathogenic indicators, before and after catchment management a way of predicting them prior to 2003 is required. Regression analysis is a simple form of modelling and is widely used for prediction purposes by finding significant relationships between parameters. The analysis looks for a relationship between two or more variables by means of a single number or equation and reports on the amount of variance explained by the relationship (Sanders et al. 1980). Relationships between variables can also help in identifying the impact of different catchment processes. Linear, non-linear and multiple regression techniques were employed to attempt to find a meaningful and useful relationship between parameters.

5.2.2 FA

The method of FA was explained in Chapter 4 and will be employed here inclusive of the indicator data to determine the processes most likely to be influencing their movement through the catchment. This was done as a separate piece of work to the previous FA due to limited number to data points that could be included. There were 19 days when data was collected and with 14 variables this resulted in 266 data points. Although this is a low number of data points it was deemed to be acceptable given the work by Boyacioglu (2006) who successfully performed FA on two groups with limited data: one with 180 data points and one with 350.

5.2.3 Storm events analysis

In order to determine what effect storms have on contaminant movement within the catchment and what processes are most affected by rainfall events, two different methods are employed: analysis of Event Mean Concentrations (EMCs) (Huber, 1993) and visual inspection of the data.

To enable the analysis of the magnitude of the effect that rainfall has on the catchment, it is necessary to compare baseflow parameter concentrations to event parameter concentrations. When assessing events it is not just the maximum or average contaminant concentration that is significant but rather the total storm flow weighted average. This is calculated using the EMC which is defined as the total storm load (mass) divided by the total runoff volume, see Equation 5.1.

$$EMC_j = \frac{\sum_{i=1}^{n} Q_{ij} C_{ij}}{\sum_{i=1}^{n} Q_{ij}} \qquad \text{(Equation 5.1)}$$

where:

EMC_j = EMC of the j^{th} event

Q_{ij} = i^{th} flowrate during the j^{th} event

C_{ij} = i^{th} concentration during the j^{th} event

This equation is more correctly displayed iteratively but the difference in values obtained from each method is negligible when compared with other measurement uncertainties (Signor et al. 2005).

A t-test was then used to determine if the EMCs were statistically significantly different from the mean concentrations during baseflow conditions. It tests the null hypothesis that the means are from the same population compared to the alternate hypothesis that they are not. This statistic is calculated using Equation 5.2.

$$t = \frac{\overline{X}_E - \overline{X}_B}{\sqrt{\frac{SD_E^2}{n_E} + \frac{SD_B^2}{n_B}}} \qquad \text{(Equation 5.2)}$$

where:

$\overline{X}_E$ = event mean concentration

$\overline{X}_B$ = mean baseflow concentration

SD_E = standard deviation of event concentration

SD_B = standard deviation of baseflow concentration

n_E = number of samples during the event

n_B = number of samples during baseflow

The value of *t* is compared to the value determined by the Student t-test table, available in most statistical texts. Given a significance level of 0.05, if t is greater than 1.645 then the null hypothesis is rejected, meaning that the alternate is true and the

values are from different populations. A significance level of 0.05 indicates that the findings from the t-test have a 95% chance of being true.

Visual inspection of the storm event data by plotting simple graphs of concentration versus flow can be used to determine the behaviour of contaminants during an event and show at what stage during the storm most pollutants are mobilised. This information can lead to a better understanding about the source of the contaminant, and therefore how best to reduce its impact. The graphs can also be used to show whether or not there is a first flush phenomenon, as reported in urban stormwater sampling (Lee et al. 2002; Taebi & Droste, 2004), or whether once mobilised there is a seemingly endless supply of pollutants (Davies et al. 2005b; Roser et al. 2002).

Since the storm sampling equipment was set up in 2005 to the end of 2007, 6 rainfall events have been captured, as detailed in Chapter 3. These events will be used to test the significance of storm events on water quality and consequently the significance of surface runoff.

5.3 Results and discussion

5.3.1 Linear regression

A correlation matrix of all the available data including the pathogen and pathogenic indicators was developed for each of the sub-catchments. See Appendix C, Tables C.1 to C.3. Correlation refers to the interdependence or co-relationship of variables and in the context of linear regression it reflects the closeness of the relationship to linearity (Bland & Altman, 1996). When assessing a large number of correlation coefficients (in the case of the Tarago it was over 550 correlations) it is important to have a set of rules to follow to determine whether or not a relationship should be deemed significant. There is no recognised or agreed way of doing this as it depends on the type and amount of data being assessed. In this case it was determined that for a relationship to be considered strong the correlation needed to involve more than 10 data points, which will increase the likelihood that a range of seasonal conditions are included, and have an R^2 over 0.6, which indicates that the values used for prediction are explaining over 60% of the variability in the outcome values. Table 5.1 shows the correlations that were deemed significant based on these rules.

Table 5.1 – Significant linear regressions for the Tarago catchments

(significant = R^2>0.6 and >10 data point)

Catchment	Correlating		R^2	Data points
West	Suspended solids	Turbidity	0.86	153
	TKN	Turbidity	0.80	188
	TKN	Suspended solids	0.83	103
Crystal	Iron	Turbidity	0.71	267
	Enterococci	*E. coli*	0.66	20
	C. perfringens	Turbidity	0.69	36
East	TOC	Colour	0.68	122
	TOC	Turbidity	0.61	121
	TOC	Manganese	0.62	114
	Suspended solids	Colour	0.69	147
	Suspended solids	Turbidity	0.76	167
	Suspended solids	Manganese	0.77	144
	TKN	Turbidity	0.76	229
	TKN	Manganese	0.66	206
	TKN	Suspended solids	0.81	141
	Enterococci	Manganese	0.61	28
	Enterococci	*E. coli*	0.67	42

There were no relationships that were significant across all three sub-catchments. East and West shared a number of significant relationships, namely between turbidity, suspended solids and TKN. Although none of these relationships are useful for predicting likely pathogen concentration, they do reinforce the finding from the FA in Section 4.5.1 that TKN is related to erosion. The lack of relationship between TKN and any pathogens or pathogenic indicators raises questions about the theory that TKN is related to manure application, in this catchment at least. The East and Crystal shared significant linear regressions between enterococci and *E. coli*, which is not unexpected given that both are indicators of faecal contamination. The similar land-uses, namely farming which contributes to faecal contamination, in the East and Crystal catchment combined with the greater percentage area of cleared land compared to the West could explain why this relationship is not catchment wide.

The relationship between *C. perfringens* and turbidity in the Crystal catchment indicates that this indicator is related to erosion and is potentially attached to soil particles. The lack of a similar relationship in the East catchment, however, suggests that it may not be a significant or true result.

One of the parameters used in the correlation matrix for East and West catchments was instantaneous flow; parameters assigned with only a date were assumed to be

sampled at midday. The analysis showed that none of the water quality parameters had a statistically significant relationship with flow.

5.3.2 Non-linear regression

Using the statistical package Minitab® non-linear relationships between variables were looked for, including polynomial and exponential,

Based on the rules for significance as stated for the linear regressions, Table 5.2 shows the significant non-linear regressions which resulted in a higher R^2 than the linear regression.

Table 5.2 – Significant non-linear regression outcomes for the Tarago catchments

Catchment	Correlating		Type	R^2	Data points
West	TKN	Enterococci	Exponential	0.62	25
Crystal	Turbidity	*C. perfrigens*	Polynomial	0.71	36
	Iron	*C. perfrigens*	Polynomial	0.71	36
	Manganese	Enterococci	Polynomial	0.84	27
	E. coli	Enterococci	Polynomial	0.67	20
East	Colour	TOC	Polynomial	0.76	122
	Turbidity	TOC	Polynomial	0.71	121
	Turbidity	TKN	Polynomial	0.77	229
	Iron	TOC	Polynomial	0.74	117
	E. coli	Enterococci	Polynomial	0.71	42

The only common relationship across more than one catchment was a polynomial one between *E. coli* and enterococci in the East and Crystal catchments. This relationship achieved a slightly higher R^2 than it did when a linear relationship was assumed (+0.04). Overall there were only 10 noteworthy non-linear regressions that showed an improved R^2 when compared to the linear regression. Only 4 of those 10 increased the R^2 by more than 0.10, see the highlighted values in Table 5.2. The mostly minor improvements in R^2's, along with the lack of consistency across sub-catchments, indicates that there are no significant non-linear relationships between parameters.

5.3.3 Multiple regression

Multiple regression analysis was undertaken to assess the ability of two or more variables to predict an outcome or dependent variable. In this case, the dependent variable was chosen as being pathogenic indicators and the remaining parameters used as the predictors. Given the number of possible variables that could be used to predict the dependant variable a method known as stepwise regression (Efroymson,

1960) was used. This method methodically screens a large number of independent variables in order to select a useful set of predictors. There are two frequently used methods: backwards and forwards. Backwards involves including all the variables under consideration and systematically deleting those which are not statistically significant. The forwards method starts with only 1 variable and proceeds by adding additional statistically significant variables until a step is reached at which the addition of more variables does not increase the predictability of the model.

Forwards stepwise regression was undertaken in this case to determine if a suite of parameters could be used to predict the pathogenic indicator data. It is important not to have too few data points or conclusions could be drawn from results that are not significant or true. Stepwise regression can only consider those data points where all parameters have a data point for that particular time, therefore TOC was omitted from the regression analysis due to the lack of data during the periods when pathogenic indicator data was collected. Indicator and pathogen data were not used as predictors for themselves so as to determine if more frequently and easily monitored parameters could be used to predict them. Table 5.3 shows the outcomes of the stepwise regression analysis.

Table 5.3 – Stepwise regression outcomes for pathogenic indicators in the Tarago catchments

Response	Catchment	Predictors	R^2	Data points
Enterococci	West	manganese, phosphorus	0.28	28
	Crystal	manganese, turbidity, suspended solids	0.85	24
	East	manganese, turbidity, phosphorus	0.82	27
Total coliforms	West	manganese, pH, nitrate	0.63	20
	Crystal	manganese, pH, nitrate, ammonia	0.80	20
	East	iron	0.17	20
E. coli	West	manganese, colour, iron	0.47	21
	Crystal	manganese	0.38	20
	East	manganese	0.22	21
C. perfrigens	West	-	-	29
	Crystal	turbidity, phosphorus	0.95	25
	East	manganese, colour	0.59	28

The stepwise analysis didn't reveal any consistency across catchments or across responses, although it did yield some positive individual and general results from which some conclusions can be drawn.

In general enterococci can be predicted using combinations of turbidity, manganese, phosphorus and suspended solids. As these predictor parameters are mainly associated with erosion it can be assumed that enterococci is also transported via this pathway. Overall the best R^2 was 0.95 achieved for predicting *C. perfrigens* in Crystal Creek with turbidity and phosphorus. This reiterates the previous finding based on the linear regression that *C .perfrigens* concentration is related to erosion and sediment movement.

Generally the pathogenic indicators were not well correlated to physical-chemical parameters, although some useful observations were made regarding which pathogenic indicators are related to erosion.

5.3.4 Factor Analysis

FA was undertaken using the software package Minitab®. The results of the FA with varimax rotation, 3 factors extracted and with the inclusion of indicators in the data set are shown in Tables 5.4, 5.5 and 5.6 for the West, Crystal and East catchments respectively.

Table 5.4 – West catchment FA including indicators

Variable	Factor 1	Factor 2	Factor 3
pH	-0.046	0.498	0.612
Colour	0.864	0.119	0.202
Turbidity	0.956	-0.083	-0.137
Iron	0.848	-0.393	0.007
Manganese	0.690	-0.502	0.124
Nitrate	-0.266	0.237	-0.850
Phosphorus	0.824	0.052	0.518
Ammonia	0.641	-0.029	0.607
Suspended solids	0.930	-0.054	-0.190
Total coliforms	0.325	-0.819	0.206
E. coli	0.040	-0.949	-0.080
Enterococci	-0.079	-0.905	0.198
C. perfrigens	0.066	0.065	-0.251
% Variance	38.5	24.1	15.3

Table 5.5 – Crystal catchment FA including indicators

Variable	Factor 1	Factor 2	Factor 3
pH	-0.475	-0.399	0.579
Colour	0.953	0.190	0.160
Turbidity	0.977	0.124	0.137
Iron	0.955	0.270	0.064
Manganese	0.618	0.709	-0.040
Nitrate	0.187	-0.074	0.942
Phosphorus	0.29	0.621	0.511
Ammonia	-0.129	-0.100	-0.519
Suspended solids	0.864	0.424	0.222
TKN	0.787	0.544	0.054
Total coliforms	0.406	0.582	-0.298
E. coli	0.069	0.910	-0.069
Enterococci	0.174	0.884	0.143
C. perfrigens	0.970	0.075	0.075
% Variance	43.0	25.8	14.1

Table 5.6 – East catchment FA including indicators

Variable	Factor 1	Factor 2	Factor 3
pH	-0.140	0.010	0.772
Colour	0.301	0.604	-0.582
Turbidity	0.798	0.377	-0.399
Iron	0.817	0.433	-0.306
Manganese	0.860	0.379	-0.266
Nitrate	-0.127	-0.384	-0.784
Phosphorus	0.881	0.107	-0.137
Ammonia	-0.048	-0.658	-0.097
Suspended solids	0.768	0.392	-0.464
TKN	0.812	0.403	-0.393
Total coliforms	0.303	0.784	0.145
E. coli	0.622	0.241	0.279
Enterococci	0.897	0.119	0.087
C. perfrigens	0.888	-0.129	0.125
% Variance	44.8	17.5	17.1

As stated in Chapter 4 for the FA without the inclusion of indicators or pathogens, a variance of more than 0.75 was deemed to indicate that the parameter was significant for that factor; these are the highlighted values in the above tables.

In the previous FA (see Chapter 4), most of the variables were needed to explain the variance within the data sets and similar outcomes were seen here. Between 9 and 10 variables out of a possible 14 were required to explain up to 83% of the variance in the data. This indicates that the majority of parameters are required to define water quality in this catchment.

In the West catchment, none of the pathogenic indicators were related to either the erosion factor, Factor 1, or the baseflow factor, Factor 3, and instead they formed their own factor, Factor 2. This may imply that indicator organisms, and therefore pathogenic material, is deposited directly into streams and not transported through the catchment or that they are transported via a mechanism independent of the erosion process. In the Crystal Creek catchment, *C. perfrigens* was the only indicator included in the erosion factor. This could be due to their persistence in the environment or it could suggest that there is some human septic influence in the surface water as *C. perfringens* have been linked to human wastes (Sorenson et al. 1989). This may also be relevant in the East catchment as *C. perfringens* are included in the erosion factor here too.

The East catchment FA shows that the indicators *C. perfrigens* and enterococci are related to Factor 1 which has been shown to be the erosion factor as it was in the FA work in Chapter 4. This suggests that these indicators are either attached to soil particles or behave in a similar way. In the East catchment, Factor 2 was dominated by total coliforms, which are commonly but incorrectly used as an indicator of faecal pollution. Coliforms can occur naturally with most having an environmental origin either as plant pathogens or as normal inhabitants of soil and water (Stevens et al. 2003). In this catchment total coliforms are not associated with Factor 1 and therefore neither erosion nor *E. coli* (a type of coliform found almost exclusively in the gut of humans and warm blooded animals[13]). This indicates that total coliforms are environmental rather than faecal in origin.

It is interesting that *E. coli* is not significantly associated with any of the factors in the East, even those that include the other two faecal indicators. *E. coli* has been shown to have a faster die-off rate in the environment than *C. perfringens* (Medema et al. 1997) and this may be why it is less dominant in Factor 1. For Factor 1 *E. coli* has a loading of 0.622, which is high but not significant when judged on the criteria set out at the beginning of the analysis.

The outcomes of the FA with the inclusion of indicators matched well with the previous FA in that Factor 1 for all sub-catchments was the erosion factor. Additionally nitrate was again found to form its own factor, indicating that its movement through the catchment is irrespective of sediment movement. In the most impacted catchment, the

[13] *E. coli* has been shown to grow in the environment (Byappanahalli & Fujioka, 1998), although this is rare

East branch, the pathogenic indicators were generally associated with Factor 1, the erosion factor. The significance of this will be further highlighted in the following section.

5.3.5 Storm event analysis

As a preliminary assessment of the impact of storm events Table 4.1 is referenced. When comparing the individual parameters sampled, primarily during baseflow conditions, it is evident that there are not large differences in values of means and medians. This indicates a lack of skew in the distributions and suggests that routine water quality sampling is not adequate to detect high risk periods. It is therefore necessary to specifically analyse data collected during storm events.

EMCs

Over the course of the sampling period, 2003-2007 inclusive, six events in total were captured: one in the West and 5 in the East. There was only one event in the West due to difficulties in estimating the necessary rate of rise, as explained in Chapter 3. EMCs were calculated for each of the parameters sampled during each event and these are shown in Table 5.7 along with the average baseflow value. Storm event details are also shown.

Each event's details are unique and it is important to remember this when assessing and comparing concentrations generated during events.

To determine if rainfall events significantly increase water quality parameters, EMCs were compared to the average baseflow value using the t-test. The results are shown in Table 5.8.

Table 5.7 – Event details and EMCs of parameters sampled during events

		WEST		EAST					
	Units	**Base**	**Event W1**	**Base**	**Event 1**	**Event 2**	**Event 3**	**Event 4**	**Event 5**
Date			31/08/05		11/09/05	15/11/06	27/07/07	11/09/07	21/11/07
24 hr rainfall	*mm*		37.9		58.3	1.6[14]	14.3[15]	18.3	25.1
Peak flow	m^3/s		0.56		0.38	0.14	0.47	0.17	0.14
Antecedent dry period	*Days*		9		12	2	8	7	17
ARI of event	*Years*		<1		<1	<1	<1	<1	<1
Turbidity	*NTU*	5.3	52.8	18.1	179.6	87.3	297.9	235.1	99.0
Nitrate	*mg/L*	0.32	0.43	0.98	1.22	0.92	2.12	0.95	0.86
Phosphorus	*mg/L*	0.02	0.06	0.07	0.47	0.19	0.38	0.50	0.34
Suspended solids	*mg/L*	10	73	36	349	113	463	399	176
TKN	*mg/L*	0.37	1.65	0.51	5.73	2.23	4.40	3.73	12.39
E. coli	*orgs/100mL*	182	92	413	2216	1038	1293	1261	3435
Enterococci	*orgs/100mL*	95	231	355	6810	464	5415	483	1462
Cryptosporidium	*oocysts/L*	0.02	0.00	0.18	0.12	0.00	0.00	1.96	0.00
Giardia	*cysts/L*	0.03	0.00	0.13	0.00	0.00	0.10	0.80	0.00

[14] In the 3 days prior to this sampling period there was 57.13mm of rainfall. The sampling took place on the falling limb of the third peak of the storm.

[15] There was an additional 17.7mm of rainfall in the 12 hours prior to this period.

Table 5.8 – t-test statistics for all captured events highlighting those parameters which were not significantly higher during storms as compared to baseflow

	West	East				
	Event 1	**Event 1**	**Event 2**	**Event 3**	**Event 4**	**Event 5**
Turbidity	17.79	8.31	5.89	6.75	54.67	11.85
Nitrate	6.63	5.78	-1.08	15.24	-0.89	-4.19
Phosphorus	8.65	5.21	4.54	7.86	21.47	10.31
Suspended solids	13.36	5.11	4.04	6.82	20.52	9.90
TKN	10.81	7.68	3.49	8.93	29.95	13.34
E.coli	0.11	6.39	2.53	3.28	3.62	6.49
Enterococci	5.54	8.82	0.49	4.26	0.65	4.63
Cryptosporidium	-1.00	-0.62	-2.89	-2.89	0.44	-2.89
Giardia	-1.40	-2.01	-2.01	1.08	0.01	-2.01

As expected most parameters showed a statistically significant ($\propto = 0.05$) higher concentration during storm events. There were some parameters, however, that were not statistically significantly higher during events (highlighted values) and some that even had a smaller mean during events (negative values). These parameters included *E. coli* in the West, nitrate for East Events 2, 4 and 5 and enterococci in East Events 2 and 4. *Cryptosporidium* and *Giardia* both showed no effect during storm events but this is most likely due to the limitations with the data as explained in Chapter 3. Additionally the lack of response during storms could be due to the event population not being representative, the significant increase in turbidity hampering detection methods or it could be as a result of dilution (Dechesne & Soyeux, 2007).

In terms of the East catchment, nitrate was not significantly different from baseflow values in the three events which had a smaller peak rainfall. This observation may signify that the majority of the nitrogen reaching the stream is doing so via the groundwater and is not affected by rainfall unless the intensity is high. This observation is also consistent with the findings of the FA which showed nitrate not being related to erosion and having a unique transport mechanism, see Table 5.6.

Enterococci concentrations are not significantly different to baseflow values in East Events 2 and 4. It could be hypothesised that the total rainfall that caused these events was not enough to mobilise this indicator. Events 2 and 4 are also preceded by a low number of days without rainfall which could indicate that enterococci did not have time to build up in the catchment.

E. coli was not significantly different to baseflow values in the West catchment but as only one event was captured in this catchment it is not prudent to derive many conclusions from this. It may be that the rainfall during this event was not enough to mobilise this indicator or that the antecedent dry period was too short not allowing contamination to build up in the catchment. It may also be that in the West catchment, which is predominately forested, pathogens and their indicators are not transported in significant numbers during rainfall. It would be necessary to sample and analyse more events in order to confirm the cause of this result.

It is clear, even from just the five events in the East, that the concentrations of pollutants increases significantly during rainfall and it is therefore these times are when the risk to water quality is the greatest. This work highlights the importance of monitoring rainfall events, and also shows that the analysis of the events is not always simple given the number of variables that characterise an event. Given these facts, it is important in a drinking water supply catchment to monitor as many events as possible in order to gain a good understanding of the catchment and its non point source pollution.

Visual analysis

Despite the differences between event details, there were some similarities in terms of parameter behaviour which can help in understanding catchment processes during high rainfall events. The relationships are best shown by plotting relevant data and analysing it visually.

During the majority of events both indicators and physical-chemical parameters showed that the peak concentration occurred before the peak of the hydrograph. Additionally the concentrations all decrease with the falling limb of the hydrograph. An example of this is shown in Figure 5.1 where flow during Event 3 is plotted against the concentration of suspended solids and turbidity.

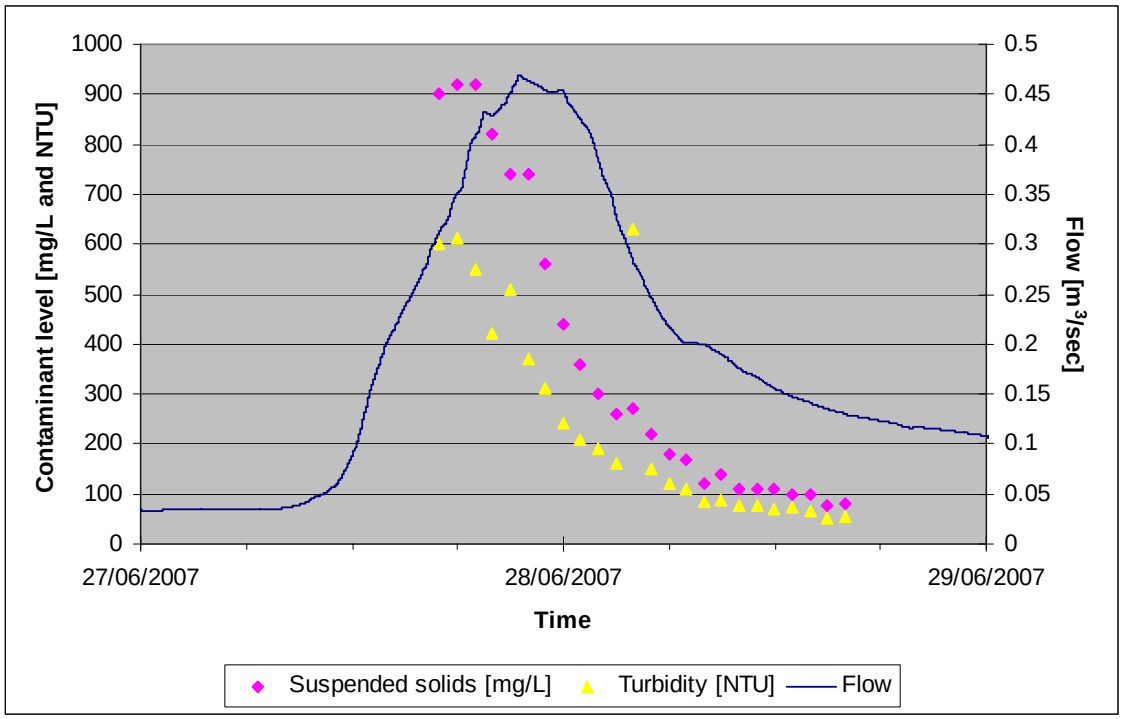

Figure 5.1 – Flow, suspended solids and turbidity in Event 3 in the East catchment

It can be seen that the peak flow occurs after the peak in both contaminants; the time between these two peaks is approximately 3 hours. This first flush phenomenon was evident for most of the water quality data sets; see Appendix D Figures D.1 to D.13 for other contaminants measured during the 5 events in the East catchment. This is consistent with previous work in urban stormwater sampling where it is generally accepted that the concentration of pollutants will be significantly higher during the initial stages of a storm (Gupta & Saul, 1996). Most stormwater analysis is focused on physical-chemical contaminants, such as suspended solids and nutrients, such as nitrogen and phosphorus. In terms of pathogens and pathogenic indicators, there is some debate as to whether the first flush phenomenon occurs. Jenkins et al. (1984, cited in Gannon et al. 2005) suggests that stores of bacteria are depleted as rain falls and runoff is created within the catchment. Roser and Ashbolt (2005) however found when looking at indicator levels throughout an event that there was a seemingly limitless supply of pathogenic organisms within a catchment. A similar observation was made by Davies et al. (2005b). In order to determine how pathogenic indicators behaved in the Tarago catchment Figure 5.2 was plotted. It shows the enterococci levels during Event 1 in the East catchment and demonstrates that there is a first flush phenomenon as opposed to a limitless supply.

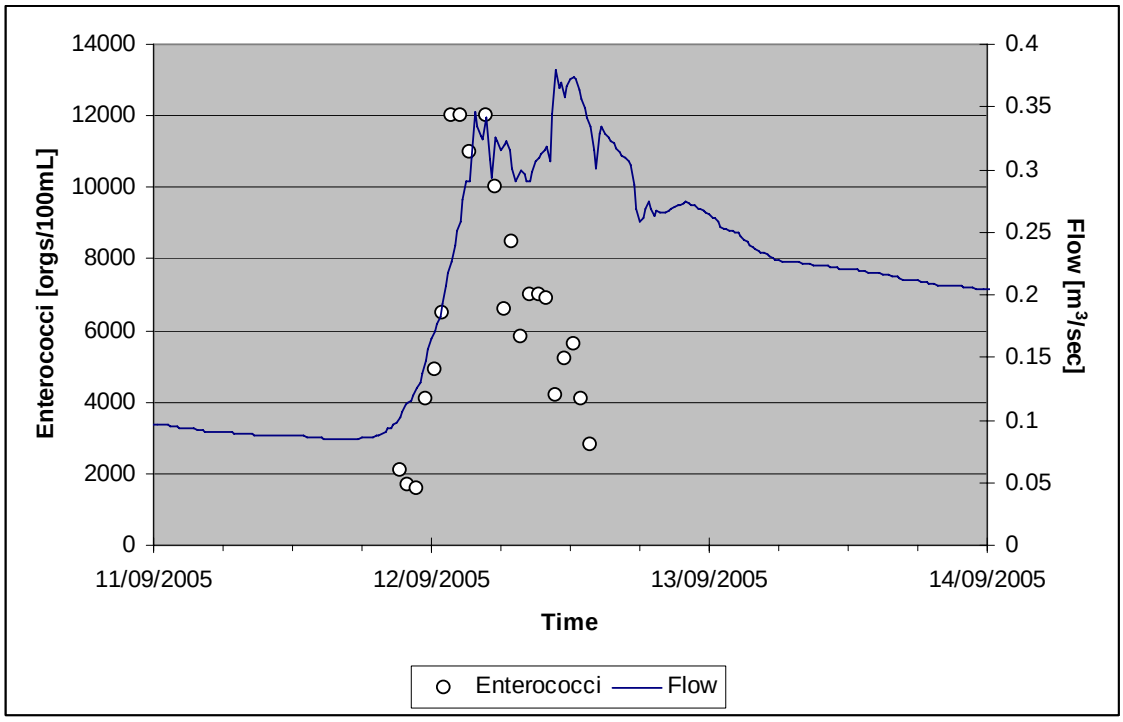

Figure 5.2 – Flow and enterococci concentrations during Event 1 in the East catchment

The limited supply may be due to a lack of contaminant sources within the catchment; a more impacted catchment may be able to contribute more pathogens. Similarly, if the rainfall event had a low number of antecedent dry days, pathogens may not have had enough time to build up in the catchment. It could also be due to the rainfall intensity not being enough to mobilise all available contaminants. It is more likely however that there is a limited supply of pathogens in this catchment as a similar reduction in pathogens on the falling limb of the hydrograph was observed; see Figures D.5, D.7, D.10 and D.13 in Appendix D.

Figure 5.2 also shows that throughout an event there can be large fluctuations in the concentrations of parameters; over approximately 16 hours the concentration of enterococci went from 2,000 orgs/100mL to 12,000 orgs/100mL before going back to about 3,000 orgs/100mL and all prior to the event peaking. These event fluctuations have implications for sampling regimes, especially if knowing the maximum contamination level likely during an event is important. The differences in observed minimum and maximum values depend on when during the event the samples are taken as well as the event characteristics and may not be indicative of the actual minimum and maximum values. Taking a single grab sample during an event and using it to asses the risk to water quality may not give an accurate representation of the maximum concentration, and therefore risk, during that storm.

As a simple validation of the t-test results that there is a significant difference between baseflow and event data, Figure 5.3 was plotted. It shows all of the *E. coli* baseflow and event data for the East catchment. The events are clearly producing larger loads than what is usually seen during normal baseflow conditions.

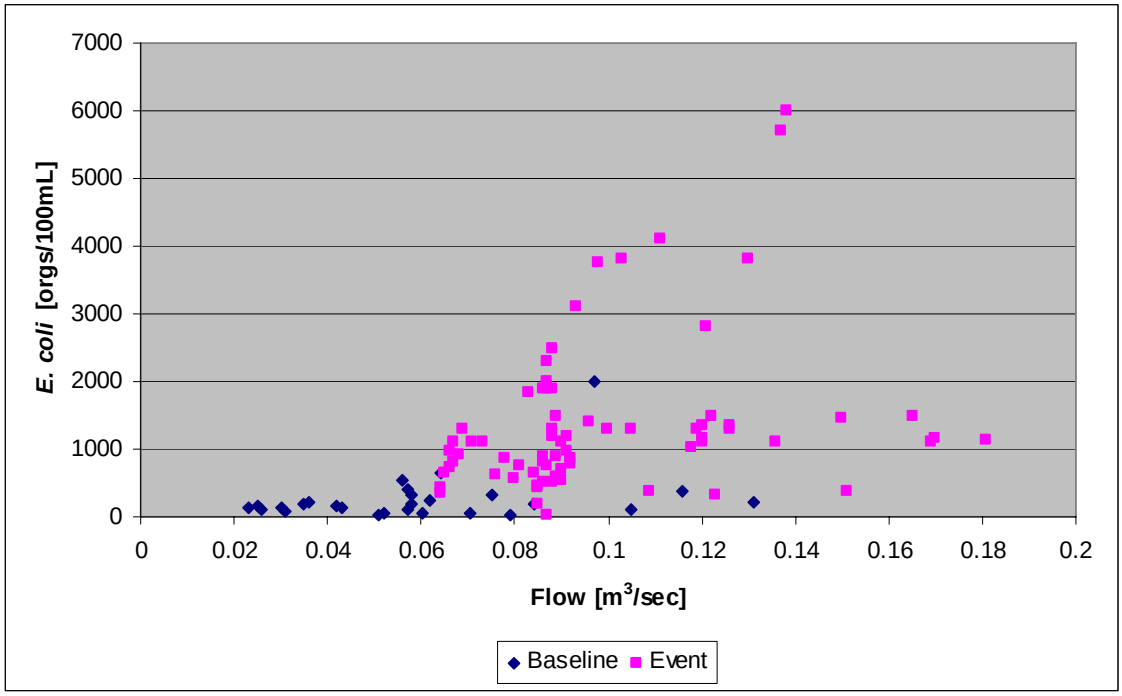

Figure 5.3 – E. coli levels for different instantaneous flows

5.4 Summary and conclusions

The results from the analyses undertaken on the available data show that for the Tarago catchment, erosion is the most dominant process affecting water quality and that rainfall runoff causes this process to occur. Parameters that affect water quality such as turbidity, suspended solids, TKN, phosphorus, *C. perfrigens* and enterococci were mobilised as erosion. This was apparent in both the regression analysis and the FA. It follows that in storm events these parameters would be even more dominant as surface runoff can cause erosion. This was confirmed by the t-tests of the EMCs which found the majority of pollutants sampled during storm events significantly increased during this time. This included *E. coli* and enterococci for most events but did not include *Cryptosporidium* or *Giardia*. The reason for the lack of response from the human infectious pathogens is thought to be the poor data set; 88% of samples were recorded as non-detections due to issues with the data collection, as outlined in

Chapter 3. Given the lack of accurate pathogen data it is fair to assume that human infectious pathogens act similarly to indicators and are transported as part of the erosion process due to surface runoff. Catchment management for the improvement of drinking water quality therefore need to focus on lessening the effect of movement of top soil by reducing pollutants in surface runoff. This could be achieved through the implementation of stream frontage plantings, fencing off stream banks and stabilisation of slopes.

The t-tests of the EMCs showed that storm events significantly increase most contaminants which further highlights that storm periods are the riskiest period for drinking water supplies. It also has implications for water quality sampling regimes. In order to determine the highest contaminant peak, and therefore highest risk, sampling across the entire event is required. Additionally most of the contaminants peaked before the peak of the storm, meaning that taking one or two samples will not be enough to estimate the peak contamination risk. Sophisticated automated sampling equipment is necessary so that water quality samples can be taken over the entire storm flow hydrograph. This will ensure that a thorough understanding of the risk arising from erosion and surface runoff is gained.

The findings of the FA supports the view that total coliforms are inadequate as indicators of pathogens as they differed to the other three indicators in that they were not related to erosion. As a consequence they should not be used as evidence for improvement in stream water quality from a public health perspective.

Nitrate concentrations are not affected by rainfall or by erosion and if a reduction in this parameter in stream is necessary, management techniques other than on-ground physical barriers to flow may be required. The actual transport process would need to be determined to ensure the alternate techniques were successful.

The limited success of the regression analysis in terms of finding a relationship to predict pathogenic indicator levels means that an alternative method for determining the effect of catchment management on drinking water quality and predicting pathogen transport is required. The details of the process of determining an appropriate method are covered in the following chapters.

6. MODEL CHOICE AND MODIFICATION

6.1 Introduction

In Chapter 5 the pathogen and pathogen indicator data was analysed. One of the aims of that work was to determine a method of predicting pathogen numbers from more readily available data so as the impact of different catchment management scenarios on drinking water quality could be quantified. This would allow the risk reduction to public health to also be quantified. Although the regression analysis uncovered some interesting relationships, there were none that related pathogens to physical-chemical parameters. This chapter, therefore, looks at an alternate way of predicting pathogens through the use of a pathogen transport model.

A model that is specifically designed for predicting pathogen movement through catchments is required as this will give the best indication as to the effectiveness of catchment management for the benefit of public health. In order to determine the requirements of that model, to ensure it is adequately modelling the movement of pathogens through a catchment, the characteristics of pathogens needs to first be established. Additionally, knowledge regarding the behaviour of pathogen transport following the implementation of a buffer is necessary. These points are discussed in this chapter. To allow for the modelling of pathogens through buffer strips the chosen pathogen model requires modification and this is significant in the context of this thesis. The literature referenced and the assumptions that were necessary in order to generate a reasonable and useful model are also covered in this chapter.

This chapter will provide details of the necessary hydrologic model used, as well as discuss the importance of baseflow separation.

6.2 Pathogen movement and buffer strips

Catchment management can refer to any method or system that aims to prevent or reduce non-point source pollution, including structural, vegetative or management (Benham, 2005). Based on the multiple benefits that a vegetative method can provide, including enhancing stream stability, providing native habitat and improving visual amenity, they are a popular catchment management tool (Endreny, 2002). Buffer or

riparian strips are one such vegetative method. Riparian land is defined as land immediately alongside a natural watercourse and by promoting vegetation on this land it forms a physical buffer between pollution sources and vulnerable surface water supplies. Buffer strips minimise stream pollution by reducing the momentum and magnitude of surface and sub-surface runoff thereby aiding infiltration into the soil column and promoting entrapment of pollutants (Parkyn, 2004). Specifically the mechanisms involved in pollutant reduction are adsorption, filtration and sedimentation (Tate et al. 2004).

The effectiveness of buffer strips in terms of reducing sediment transport has been well documented; Gharabaghi et al. (2000) report that between 50-98% of sediment is removed. Similarly for nutrients; Gilley et al. (2002) state that buffer strips significantly reduce both concentration and load of nitrogen and phosphorus. Due to the knowledge in this area the design criteria of buffer strips are usually based on trapping sediment and attached nutrients (Prosser & Karssies, 2001). In terms of pathogens, however, the effectiveness of buffers is not as well understood.

A number of laboratory studies have investigated the effect of buffer strips on pathogen movement in both the surface and sub-surface flows. The sub-surface flow is that water which flows directly below the surface; in reality, in a pervious catchment, it is the same as surface flow. This will be further explained in the coming sections. Davies et al. (2004) carried out a laboratory based study that involved placing artificial cow pats seeded with *Cryptosporidium*, on vegetated (grassed) and bare soil plots. A rainfall simulator was used to produce the flow. The runoff produced from each plot was captured and analysed to determine the difference in the number of pathogens. The study concluded that vegetated surfaces were effective in reducing overall transport of *Cryptosporidium* in overland flow; over 99.9% removal was reported during mild to moderate rainfall. This was achieved as the vegetation impeded horizontal flow of water and promoted vertical flow, or infiltration. One limitation of this study was that it only looked at grassed surfaces and not fully vegetated surfaces with established plants. It also did not look at the effect of vegetation on pathogens in the deeper flows, such as groundwater, due to concerns about interrupting the soil matrix.

Various other laboratory based studies (Atwill et al. 2002; Tate et al. 2004; Trask et al. 2004) have looked at the effect of vegetated buffer strips on pathogen numbers in surface and sub-surface flows. They compared pathogen transport over vegetated and non-vegetated soil plots. As with Davies et al. (2004) they found that vegetation was

effective at removing a percentage of pathogens. Each study concluded that pathogens being transported in the surface or sub-surface flows have the potential to be trapped or intercepted by plant roots. Trask et al. (2004) reports that vegetation acts in a number of ways to reduce pathogen transport; pathogens can be trapped by vegetation, they can be adsorbed to vegetation and they can infiltrate the surface due to vegetation restricting overland flow. By impeding horizontal flow and promoting vertical flow, more pathogens will be transported to the deeper groundwater flow. Mawdsley et al. (1995) states, that horizontal movement of pathogens will occur in non-fully saturated and mostly permeable catchments, such as agricultural catchments. Pyke et al. (2003) suggests that pathogens being transported in the deeper groundwater may bypass any interception provided by the plant root zone simply due to the depth of the flow. Groundwater is an important transport mechanism for pathogen transport in catchments and pathogens in this flow will not be affected by a buffer strip.

Based on the outcomes of all of the aforementioned studies, it is clear that in order to determine what effect buffer strips have on total pathogen numbers being transported to the stream, a model that adequately and accurately separates surface, sub-surface and baseflows is imperative.

Buffer strips are a widely implemented form of catchment management, due to their benefits not only for water quality but also for biodiversity and landscape amenity. To determine the effectiveness of buffer strips for the protection of public health through pathogen removal it is clear that the model used needs to be pathogen-specific and that there is capability within the model to separate the different flow paths within the catchment.

6.3 Existing pathogen models

The ability to predict pathogens through catchments would go some way to being able to predict the reduction in pathogens through buffer strips. An extensive review of pathogen research in catchments by Ferguson et al. (2003) found a number of different catchment models that can be used to predict the fate and transport of pathogens. The majority of these models, however, are not suitable for predicting the public health risk related to catchment runoff.

When assessing drinking water quality it is important that high run-off or storm events are considered as this is when the majority of pathogens will be mobilised and transported to the stream (Kistemann et al. 2002). These events are also, therefore, when the highest risk to drinking water and public health occurs. Therefore a model with an appropriate, ie sub-daily, time-step that is able to simulate these events is crucial. Some existing models, such as Generalised Watershed Loading Function (GWLF) (Haith & Shoemaker, 1987), Better Assessment Science Integrating Point and Non-point Sources (BASINS), developed by the US EPA (2001), and PROMISE (Medema and Schijven 2001) have been developed to determine weekly, monthly or even annual contaminant loads which are inadequate for simulating high risk periods. Relative models, such as the Catchment Pathogen Budget model (Ferguson, 2005), were developed to compare different sub-catchments and are useful in prioritising catchment works. They are not, however, able to quantify pathogen concentrations in runoff during specific rainfall events.

Both the BASINS and PROMISE models are also unable to account for non-point source inputs, such as catchment runoff, due to their lack of consideration of hydrologic functions within the catchment. The ability of a model to handle various sources is important as pathogens can be delivered to a stream via either a point source, such as a sewerage treatment plant outlet, or a non-point source, such grazing animals. The influence of each source depends on the type of catchment.

An assumption made by some pathogen transport models is that pathogens behave the same as sediment or nutrients. For example McGechan et al. (2008) used an ammonia transport model to predict transport of *E. coli*. Although it is likely that the majority of the mechanisms for contaminant reduction will be the same, ie filtration, adsorption and infiltration (Tate et al. 2004), there are other processes and characteristics which are unique to pathogens, sediment and nutrients that will influence their transport (Trask et al. 2004). Unlike sediment, pathogens are a living organism and so processes that influence life-cycle stage and their survival mechanisms need to be taken into account. Additionally intrinsic characteristics such as size, shape, density and surface properties will affect pathogen behaviour in the environment (Pachepsky et al. 2006). It is therefore important that the model used to predict pathogens considers pathogens specifically.

In terms of life-cycle stage, a number of pathogen models, including BASINS and GWLF, use a steady state first-order decay function to account for the death of

pathogens. Changes in population based on the environmental conditions are therefore not considered (Shanahan et al. 1998).

An issue that needs consideration when looking at different pathogen models is the issue of scale (Pachepsky et al. 2006). Most models are developed and calibrated using laboratory or field plot scales rather than a whole of catchment scale, most likely due to issues with cost and logistics (Ferguson et al. 2003). Interacting processes and factors that will affect pathogen transport on a smaller scale may not be indicative of what occurs on a catchment scale. Extrapolating between scales, especially up-scaling, will not necessarily give a good indication of the pathogen fate and transport due to variable catchment characteristics. Applying a model that has used catchment scale data for calibration and validation may go some way to addressing this issue.

Research carried out by Haydon (2006) aimed to develop a comprehensive model of waterborne pathogen concentration in runoff from catchments – this model is called EG. The EG model goes some way to addressing the aforementioned limitations of other models as it was developed specifically to predict the fate and transport of pathogens. It therefore takes into consideration the important properties of pathogen including their sources, and how these impact both their survival and movement within a catchment.

6.3.1 The EG model

The EG model was developed by Haydon (2006) and its basic hypothesis is that the fate and transport of pathogens can be largely explained by hydrologic processes (Haydon & Deletic, 2006). It is a simple, lumped conceptual model that predicts pathogen concentrations leaving a catchment and entering a stream on a continuous basis. The model considers non-point source inputs by including pathogen deposition based on land-use. Pathogen elimination through temperature, desiccation or predation is also included. It models pathogen deposition, storage, movement and decay through 3 flow paths - surface, sub-surface and baseflow - making it ideal for modelling pathogen interaction with buffer strips.

Due to it being a recent addition to the available models it has not been extensively applied or tested. During development, however, the model was calibrated with catchment scale data from three different catchments to test its applicability across

different land-uses: a fully forested catchment, a rural catchment and a peri-urban catchment.

With the inclusion of some modifications, EG is thought to have the necessary characteristics to quantify any variation in water quality due to land-use change. These characteristics include: the ability to represent run-off events, specific consideration of pathogen behaviour and consideration of the separate flow paths.

EG is coupled with a hydrologic model, SIMHYD (discussed in Section 6.4), which provides the necessary flows and volumes and is run continuously on an hourly time-step. The hourly time-step ensures that both baseflow and stormflow periods are modelled. Understanding the stormflow periods is imperative when protection of public health is the objective as this is when the majority of pathogens will be mobilised. This is demonstrated both in the literature (Davies et al. 2004; Kistenmann et al. 2002; Signor et al. 2005) and in Chapter 5 where EMCs of pathogenic indicators were shown to be significantly greater than baseflow concentrations. The hydrologic model and EG are run separately with the output from the hydrologic model being an input to the pathogen model. This allows the modeller to gain an understanding of the runoff characteristics and how it affects pathogen behaviour. It also allows the modeller to choose an alternate hydrologic model to that used during development of EG, one which may be more familiar to the modeller or already calibrated to the particular catchment. Additionally separating the models means that the hydrologic model can be used for modelling other water quality constituents if required.

The two major processes affecting pathogen concentration in streams are the number of available pathogens in the catchment, which is primarily a function of faecal deposition, and the ability of those pathogens to be transported. Estimating faecal deposition is done based on land-use, the animals that are present on that land and an understanding of pathogen loads in different animal's faecal matter. The number of available pathogens will also be influenced by elimination processes, such as temperature, desiccation and predation. Pathogen movement is a direct result of kinetic energy of rainfall and the subsequent flow across the catchment (Haydon, 2006). As discussed previously the transportation of pathogens vertically as well as horizontally within a catchment is also important. The EG model simulates these processes by using the outputs from the hydrological model.

A number of assumptions were necessary during development of the model. These are important to note as they can affect the model outputs and may lead to an incorrect assessment of those outputs. The assumptions may also be important when modifying the model as they may influence any necessary additional assumptions. The assumptions made during development include:

- faecal material is distributed uniformly across the catchment and at a fixed monthly rate
- pathogens are mobilised based on rainfall energy which is determined by flow
- pathogen die-off is represented by decaying the pathogen store from the moment of deposition – a linear decay rate is used.

EG is a mass-balance model and is shown schematically in Figure 6.1.

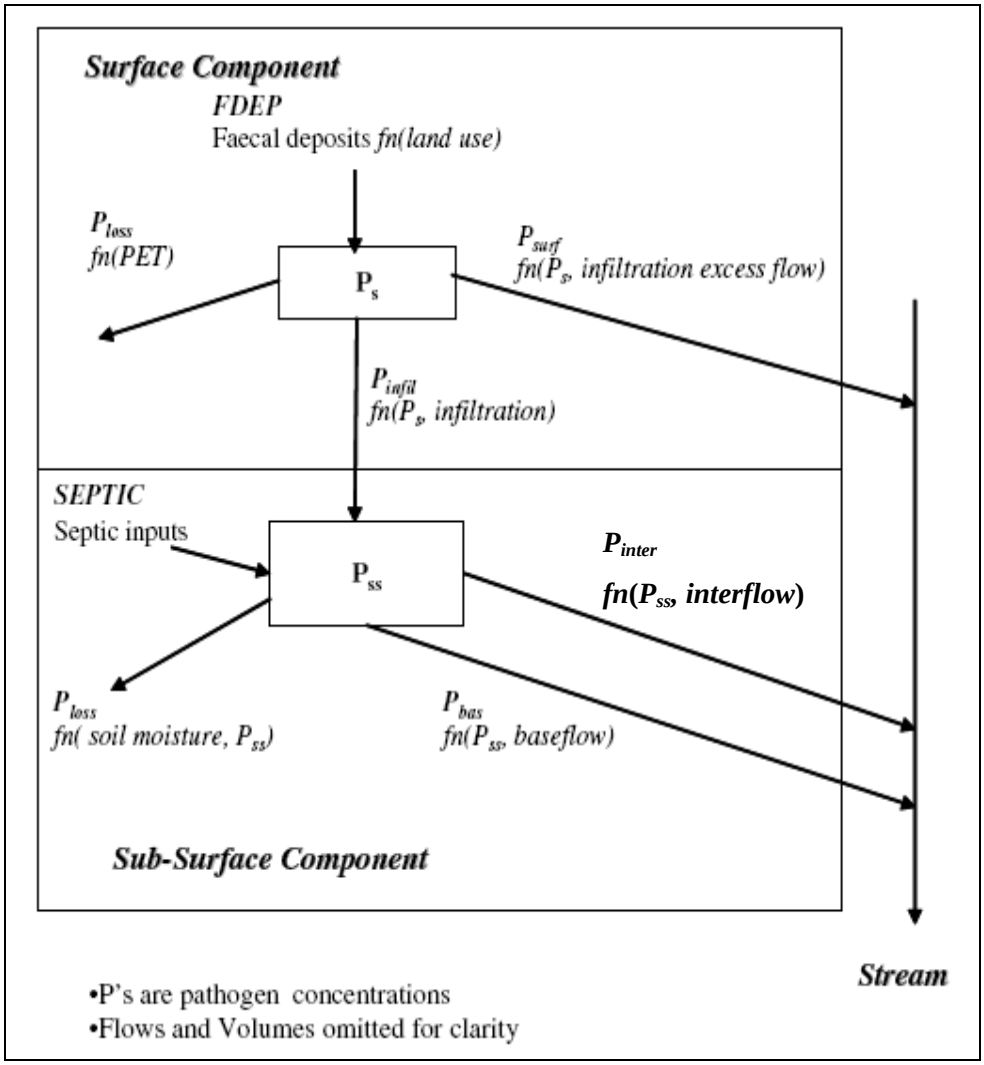

Figure 6.1 – EG model schematic

Pathogens are deposited ($FDEP$) to the surface store (P_s) where pathogens are either eliminated ($P_{s,loss}$), exported to the stream as infiltration excess flow (P_{surf}) or infiltrated to the sub-surface ($P_{in.fil}$). From the sub-surface store (P_{ss}) pathogens are either eliminated ($P_{ss,loss}$) or transported to the stream via interflow ($P_{in.ter}$) or baseflow (P_{bas}).

The governing equations for the model can be seen below.

$$P_{s(t)}v_{s(t)} = P_{s(t-1)}v_{s(t-1)} - P_{in.fiil(t)}Q_{in.fiil(t)}\Delta t - P_{loss(t)}v_{s(t-1)} + FDEP_{(t)}v_{s(t-1)}$$

(*Equation 6.1*)

$$P_{s,loss(t)} = a_1 P_{s(t-1)} PET_{(t)}^{a_2}$$

(*Equation 6.2*)

$$P_{in.fl(t)} = a_5 Q_{in.fl(t)} P_{s(t-1)}$$

(*Equation 6.3*)

$$P_{ss(t)}v_{ss(t)} = P_{ss(t)}v_{ss(t-1)} + P_{in.fil(t)}Q_{in.fil(t)}\Delta t - P_{in.ter(t)}Q_{in.ter(t)}\Delta t \ldots$$
$$- P_{bas(t)}Q_{bas(t)}\Delta t - P_{ss,loss(t)}v_{ss(t-1)}$$

(*Equation 6.4*)

$$P_{bas(t)} = b_1\left(\frac{Q_{bas(t)}\Delta t}{v_{ss(t)}}\right)P_{ss(t-1)}$$

(*Equation 6.5*)

$$P_{in.ter(t)} = b_1\left(\frac{Q_{\mathrm{int}er(t)}\Delta t}{v_{ss(t)}}\right)P_{ss(t-1)}$$

(*Equation 6.6*)

$$P_{ss,loss(t)} = b_2 \frac{P_{ss(t-1)}}{\left(\frac{v_{ss(t-1)}}{SMS}\right)}$$

(*Equation 6.7*)

where:

v_s = volume in surface store at time *t*

$Q_{in.fil}$ = infiltration from the surface at time *t*

v_{ss} = volume in sub-surface flow at time *t*

$Q_{in.ter}$ = interflow volume from the sub-surface at time *t*

Q_{bas} = baseflow volume from the sub-surface at time *t*

SMS = soil moisture store

PET = potential evapotranspiration

Other variables as defined previously

a_1, a_2, a_5, b_1, b_2 are constants

During development of EG the total water generated as surface flow by the hydrologic model was found to be insignificant. This is why the equation calculating P_{surf} has been omitted which is further explained in Section 6.4. The surface model therefore only exists to supply pathogens to the sub-surface store and the surface flow component is represented entirely by $P_{in.ter}$.

There is the capability within the model to add the influence of on-site wastewater management systems, or septic tanks, ($SEPTIC$) to the pathogen sub-surface store, as seen in Figure 6.6. This part of the model was not tested during development and therefore will not be used during this study. It is reasonable to exclude the impact of septic tanks as the pathogen numbers from these influences in a rural catchment would be small compared to those contributed by grazing animals.

The EG model uses streamflow generated from the separately calibrated hydrologic model as an input and requires additional inputs of catchment area and faecal deposition rates. It comprises 5 parameters that require optimisation; 3 which relate to pathogen losses and 2 which relate to pathogen export, these are listed below:

- a_1 - Influences the loss of pathogens from the surface
- a_2 - Determines whether PET has an impact on the losses from the surface
- a_5 - Influences the export of pathogens in the infiltration
- b_1 - Influences the export of pathogens in the surface flow and baseflow
- b_2 - Influences the loss of pathogens in the sub-surface.

During sensitivity testing following development of the model it was determined that the two export parameters had more impact on the final pathogen output than the loss parameters, see Chapter 9 for more detail. This relates well to the concepts involved in buffer strip effectiveness in that it is the transport processes that dominant pathogen removal, not the buffer's ability to kill off pathogens.

The original EG model accounts for some loss of pathogens from the surface and sub-surface store through the effects of temperature, UV exposure and moisture level. However, there is no specific function that relates to loss through filtration due to vegetation. The buildup/washoff process that is assumed in the model will account for pathogen removal by basic groundcover such as grass and for physical trapping by soil particles. It does not, however, consider more complex vegetation and the effect that it might have on pathogen transport. Therefore, in order for the EG model to be used to predict the effects of buffer strips on pathogen transport, some modifications need to be made to the way the model calculates pathogens in the surface flow. This calculation, the required inputs and the necessary assumptions are seen as a considerable advancement in the ability of modelling pathogen movement through catchments and are explained in Section 6.5.

The EG model does not use the total runoff flow from the hydrologic model, instead it uses the partitioned flows, ie surface flow and baseflow. This is a very important part of the model as pathogens will be transported, lost and predated differently depending on the flow path that they are entrained in. When considering the effects of catchment management this flow partitioning becomes even more important because, as discussed above, it is only the surface flow where buffer strips will have an effect on pathogen concentrations. The effectiveness of a buffer strip is highly dependent on the amount of water and the movement of water through it (Correll, 1996) and it is therefore important that the hydrological processes in the catchment are accurately predicted. Haydon (2006) actually states that the performance of the hydrologic model dictates how well the coupled model will perform.

During development EG, was coupled with the rainfall run-off model, SIMHYD (Haydon & Deletic, 2006). SIMHYD was chosen as the conceptual approach used within the model in terms of flow and water storage is the same as that used within the pathogen model. SIMHYD was used as the rainfall runoff model in this research as well.

6.4 The hydrologic model - SIMHYD

SIMHYD is a simple lumped conceptual rainfall runoff model that estimates streamflow from rainfall and areal evapotranspiration. The model was developed by Porter and McMahon (1971) and in its original form was known as HYDROLOG and had 17 parameters. This original version was modified a number of times eventually resulting in a simplified version of the model with just 7 parameters, known as SIMHYD. SIMHYD is one of the most commonly used rainfall runoff models used in Australia (Chiew & Siriwardena, 2005), due mainly to its simplicity and its calibration ease. It also only requires limited input, namely rainfall and potential evapotranspiration (PET). The other benefit of SIMHYD is that it can run on an hourly time-step. The importance of being able to predict peak concentrations during storm events when knowing the risks to drinking water is the objective, has been stated previously. In terms of this study SIMHYD is ideal as it outputs not just total streamflow but surface, sub-surface (interflow) and baseflow for each time-step.

SIMHYD works by filling and emptying three stores, the inception store, the soil moisture store and the groundwater store. Water is added to the interception store by rainfall and emptied either by overflowing the store or by evapotranspiration. Water that overflows the interception store infiltrates the surface and becomes interflow or is diverted to the groundwater store or the soil moisture store. If the infiltration capacity is exceeded any additional flow becomes infiltration excess runoff or surface flow. The groundwater store is fed by groundwater recharge which is a function of the soil wetness. Baseflow occurs when the groundwater store is exceeded. These processes are shown schematically in Figure 6.2.

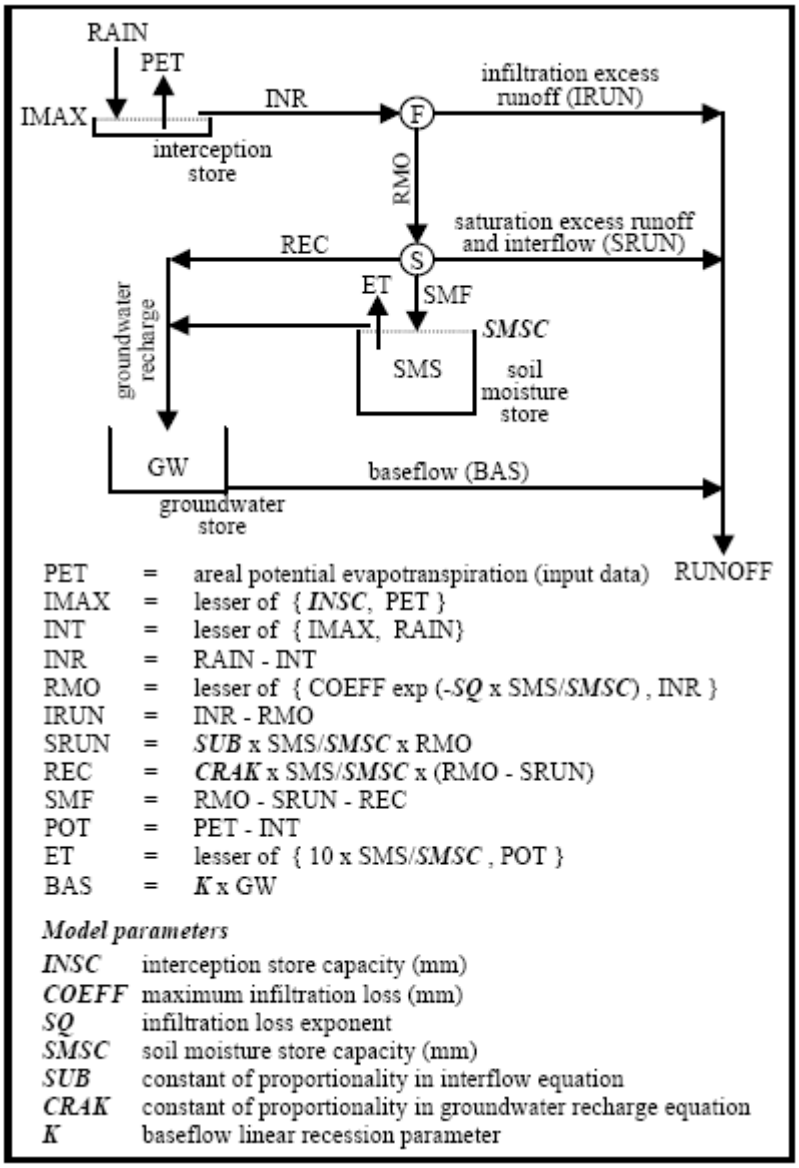

Figure 6.2 – Schematic of SIMHYD model

In the SIMHYD model, infiltration excess (surface flow) and interflow are calculated separately, although in reality the distinction between these two flows is not detectable. Additionally SIMHYD simulates little to no surface flow in most catchments (Chiew & Siriwardena, 2005) meaning that the interflow component in SIMHYD is what would normally be regarded as surface flow. It is therefore reasonable that from this point on in the study interflow will be referred to as surface flow.

As mentioned, there are 7 parameters for calibration, which are indicated in Figure 6.2 in bold italics.

SIMHYD is a lumped conceptual model and therefore it does not contain any hydraulic routing. Routing accounts for the spatial movement of water through the catchment and is therefore usually required where a catchment is large and its characteristics varied. Haydon (2006) added a linear reservoir to SIMHYD to represent routing through the catchment, which is commonly done in hydrology. An additional parameter, *RESCOEFF*, which relates to the reservoir discharge coefficient, was added to the model. This parameter also required calibration.

A literature search failed to find any studies which used the SIMHYD model on an hourly basis to replicate flows, indicating that the use of the model in this way is not common. Additionally, although many studies (Chiew & Siriwardena, 2005; Wang et al. 2008) mention the fact that SIMHYD calculates the total flow through addition of the partitioned flows, surface, sub-surface and baseflow, none actually looked specifically at the partitioned outputs. SIMHYD was developed to give a total flow and it may be beyond its design intent for the partitioned flows to be used in that way they are in the coupled model. Considering that in this work the partitioned flows are going to be used for describing catchment flow characteristics and for pollutant modelling it is important to assess their accuracy and not have blind or absolute faith in the predicted outcomes.

6.4.1 Flow partitioning in SIMHYD

Surface flow is that which occurs above the earth's surface and is usually the direct result of rainfall. Interflow, or sub-surface flow, is defined as infiltrated runoff which moves laterally through the upper soil layers (Ward, 1975). As discussed above, in reality the difference of these two flows is neither detectable nor necessary to separate. Groundwater flow, or baseflow, is that portion of flow which moves vertically through the soil profile, reaches the water table and then moves laterally through the catchment. Baseflow is usually relatively constant, depending on the catchment condition and seasonal rainfall patterns, whereas surface and interflow are highly affected by rainfall. Figure 6.3 explains the processes that will occur with each flow path following a rainfall event.

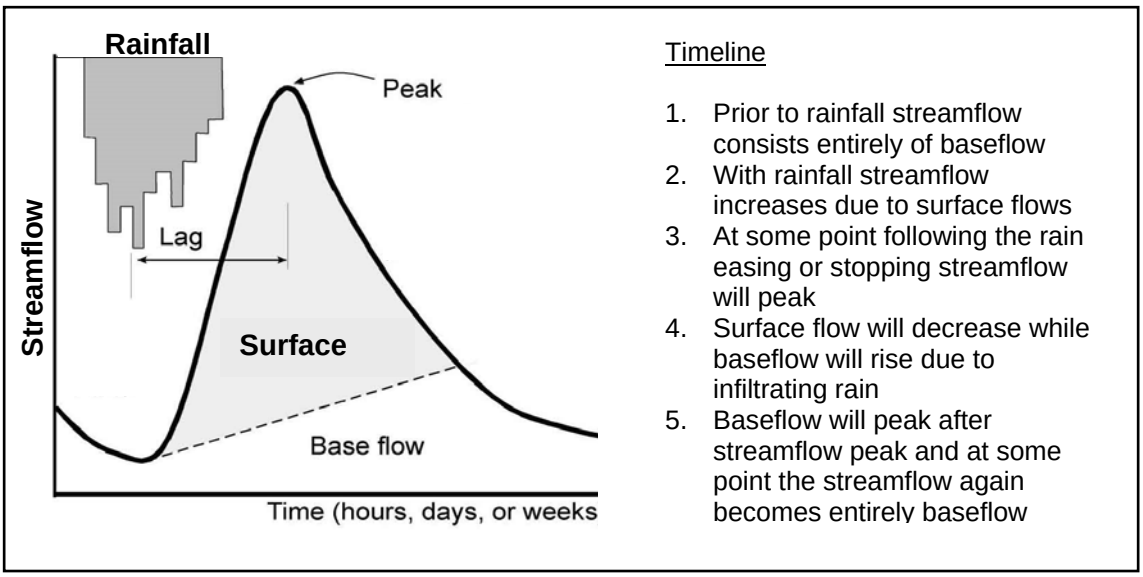

Figure 6.3 – Typical hydrograph following rain

These principles in terms of flow partitioning within a catchment before, during and after a rainfall event are well accepted among hydrologists. Verification of the principles is however difficult due to the complexities in measuring the separate flows in the field.

The conceptual SIMHYD model works on the basic principle that the catchment consists of various "buckets" or stores, which fill based on rainfall and/or overflow from the bucket above and empty due to overflow or losses through evapotranspiration. The problem with this method of mimicking the flow, which is inherent in many rainfall runoff models, is that a spill from the store above will only occur if there is an inflow, either overflow from the store above it or from rainfall. At all other times the store is idle, waiting for spill or rain. As a result SIMHYD tends to overestimate the baseflow during an event or more specifically underestimate the surface and sub-surface flows. This is more easily demonstrated with some examples, which is done in the following section.

6.4.2 SIMHYD outputs

The best fits from SIMHYD for each catchment (reported in Chapter 7) were assessed in terms of their flow partitioning. This was done both on an overall basis and then by focusing on high flow, or rainfall, events. In order to demonstrate the findings in this section concisely, a large single peaked event in February 2005 in the East catchment was chosen as an example. The observations for this event were consistent across all events.

Output for the high flow event from the calibrated hourly SIMHYD model can be seen in Figure 6.4. It shows each of the partitioned flows including the total flow, as well as the rainfall which caused the event.

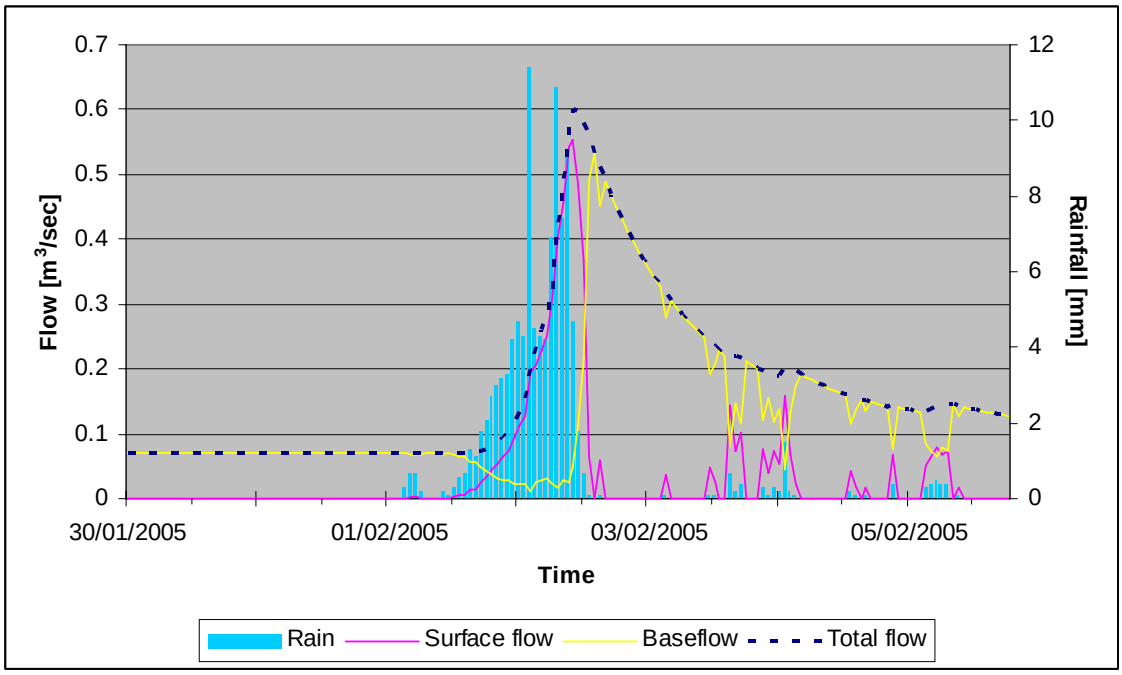

Figure 6.4 – Calibrated hourly SIMHYD output for February 2005 event in the East catchment

The main observation from this graph is that there is only direct runoff, or surface flow (the pink line) when there is rainfall (light blue bars). As discussed previously this is as a result of the way SIMHYD conceptualises the flow partitioning. In reality when rain starts to fall on a catchment there is not an instant impact on the stream and similarly when rain stops falling the stream doesn't instantly go back to being baseflow, although this may be the case in a catchment with a very small area or one with a large percentage of impervious area. From this figure it seems that in order for the SIMHYD model to accurately predict the total flow it increases the baseflow during periods of no rain to compensate for the loss of surface flow.

To confirm that the above results were not catchment specific, calibrated SIMHYD runs for three separate catchments with different land-uses – forested, peri-urban and rural, were obtained from Haydon (2006). The results from these calibrations can be seen in Appendix E, Figures E.1 to E.3 and show similar results to Figure 6.4. Additionally, SIMHYD was calibrated on a daily basis for the East Tarago catchment, as it was hypothesised that the above results may be due to the inability of the model to

adequately manage hourly flows, indicating an issue with the routing parameters. The daily model, however, showed similar results in that there was only surface flow when there was rainfall, see Figure 6.5.

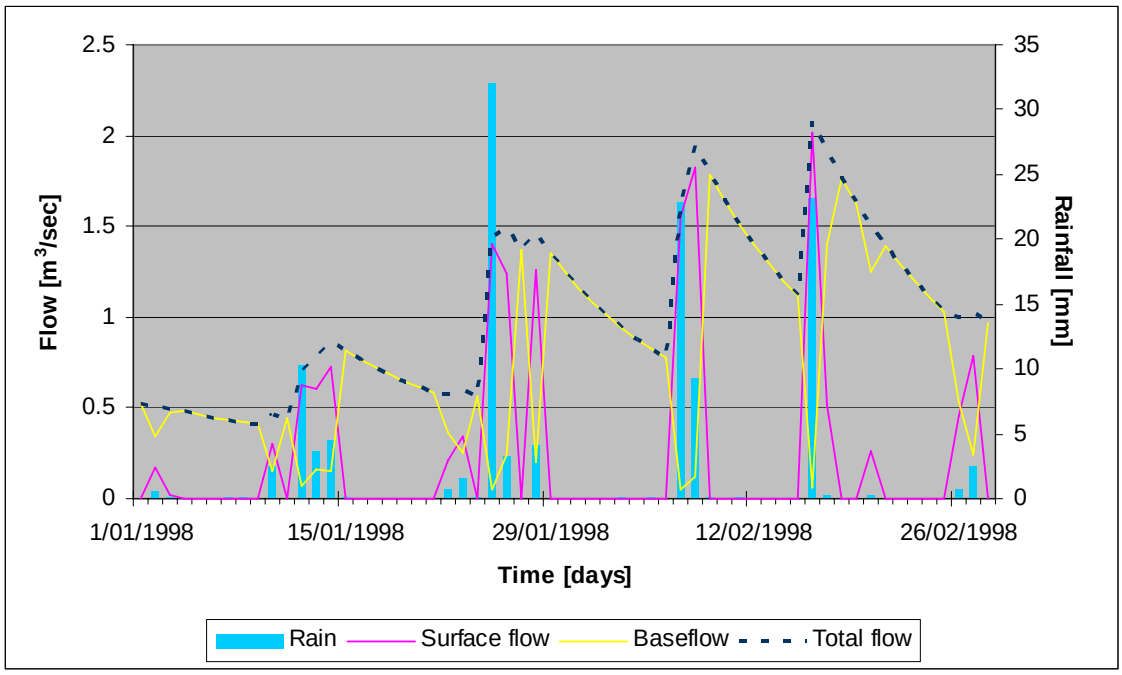

Figure 6.5 – Calibrated daily SIMHYD model in the East catchment

The additional parameter added by Haydon (2006) to the SIMHYD model to allow for hydraulic routing allowed for flows to be attenuated which improves the timing and the smoothness of the peaks. The function was found to be necessary when the model was run with an hourly time-step (Haydon, 2006) as the timing of peaks is important. This routing function did not, however, have any effect on the flow partitioning.

As mentioned previously SIMHYD was not developed to use the different partitioned flows throughout an event, it was initially developed to provide the total flow and on a daily basis. Using it in this way is beyond its design intent. The SIMHYD model will only ever fill its storages, ie produce runoff, when there is input, ie rainfall, whereas in reality runoff from an event lasts beyond that of the rainfall period, as demonstrated in Figure 6.3. Therefore there is the need for better, or more realistic, separation of baseflow to enable accurate constituent modelling in the different components of flow.

6.4.3 Baseflow separation

The above analysis shows the inadequacies of the baseflow separation provided by the hydrologic model SIMHYD. Using the SIMHYD results in the EG model could

potentially influence the outcome in terms of the number of pathogens being delivered to the stream. The importance of accurate separation of the flows within the hydrologic model when determining pathogen numbers has been well established by the aforementioned studies. When assessing the effect of buffer strip planting on pathogen numbers, the pathogens transported in the baseflow will not be affected by vegetation whereas pathogens in the surface flow will. It is therefore necessary to look at alternate methods of separating the baseflow.

Baseflow is defined as that portion of the hydrograph which is not associated with storm runoff and in order to define the contribution from overland flow during storm related run-off, the baseflow must be separated out. Two methods exist for doing this: graphical/manual and filtering/automatic. Manual separation of baseflow was not considered in this study as it can lead to inconsistency in results (Lim et al, 2005) due to the subjective nature of the separation. Additionally with data sets over a long time period, manual techniques are inefficient. An automatic method, known as the digital filter method, was used as it is a fast and objective way of continuous baseflow separation (Nathan & McMahon, 1990).

The digital filter method uses Equation 6.8 (Nathan & McMahon, 1990).

$$q_t = kq_{t-1} + \frac{1+k}{2} \times \left(Q_t - Q_{t-1}\right) \qquad \text{(}\textit{Equation 6.8}\text{)}$$

where:

q_t = filtered direct runoff at time *t*

q_{t-1} = filtered direct runoff at time *t-1*

k = filter parameter

Q_t = total streamflow at time *t*

Q_{t-1} = total streamflow at time *t-1*

Baseflow at time *t* (b_t) is then simply calculated using Equation 6.9.

$$b_t = Q_t - q_t \qquad \text{(Equation 6.9)}$$

The filter parameter, *k*, affects the degree of flow attenuation. Szilagyi (2004) reported that a value between 0.953 and 0.999, with an average of 0.987, gave complimentary results to an alternate physically based method for baseflow separation.

In order to separate the baseflow from the total flow, the Web-based Hydrograph Analysis Tool (WHAT), available from http://pasture.ecn.purdue.edu/~what, was applied. In a study by Jarrar et al. (2007) the WHAT model was found to have satisfactory outcomes when compared to the AWBM model (Boughton, 2004), which is a commonly used rainfall runoff model within Australia. The WHAT tool uses the digital filter method and allows uploading of the users own streamflow data in either a daily or hourly time-step. The user must also enter a filter parameter. For the Tarago catchment a filter parameter of 0.990 was used, which is within the range suggested by Szilagyi (2004). This filter parameter also ensures that the elapsed time between the peak discharge of an event and the streamflow being dominated by baseflow is consistent with the catchment-specific time delay, which is a function of catchment area. The predicted total flow from the calibrated SIMHYD model was entered into WHAT as the streamflow. The results produced by WHAT were found to be more indicative of what would be expected from flow partitioning within a catchment. Figure 6.6 shows the outputs of WHAT for the same February event as shown in Figure 6.4.

The output from WHAT shows the surface flow increasing as it begins to rain, peaking just as the rain stops and then slowly declining. It also shows that the baseflow has a delayed response to the rainfall event which is what would be expected.

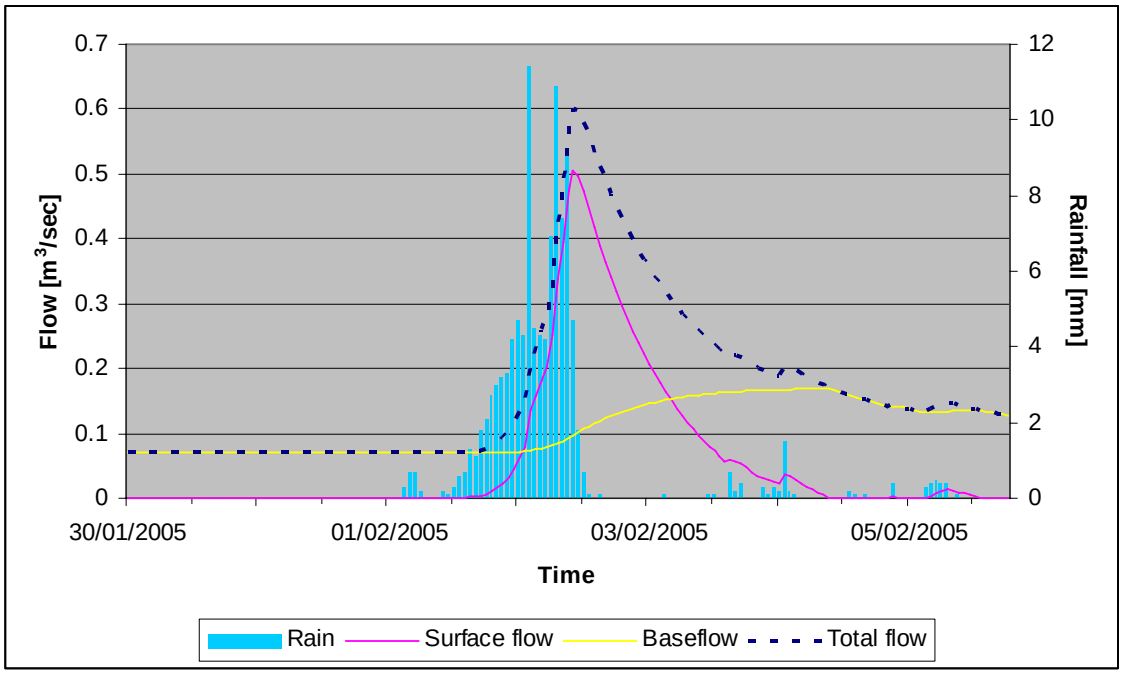

Figure 6.6– Hourly WHAT output for February 2005 event in the East catchment

6.4.4 Summary

The accurate separation of total streamflow into baseflow and surface flow is important when modelling constituent movement and the effect of buffer strips. This is especially important for pathogens as they will be predated, lost and transported differently depending on their flow path. Although the rainfall runoff model, SIMHYD, claims to separate the different flows, on closer visual inspection of the outputs it was determined that the way the model separates the flow is inaccurate, according to accepted thinking. The use of the web-based tool WHAT, which uses the digital filter method to partition the flow, resulted in more reasonable flow separation.

Therefore, going forward in this study, SIMHYD will be calibrated and used to determine the total flow and then WHAT will be used to determine the flow partitioning. The outputs from WHAT will then be used as the input into the pathogen model. Inputting the SIMHYD output as opposed to real flow data into WHAT was done for the following two reasons: firstly the modelled streamflow accounts for missing data within the observed streamflow data set and secondly coupling the two models will provide a better idea as to its overall predictive ability.

SIMHYD has been shown to be more than capable of modelling total flows in a range of catchments across Australia (Peel et al. 2000). This analysis has shown that despite

this, its outputs should be used with caution if the partitioned flows are going to be extracted.

6.5 EG modifications

As shown in the above sections, the need for a pathogen specific model with accurate flow partitioning is required when assessing the public health benefits of catchment management. The EG model, when coupled with a rainfall runoff model that adequately partitions catchment flows, was found to be an acceptable model for determining pathogen movement through catchments. In its current form, however, EG is unable to quantify pathogen reduction due to buffer strip implementation due to its simplified loss functions. To include the effects of buffer strip vegetation on pathogen numbers, the part of the model that calculates the pathogen concentration in the surface flow must be modified, as will be discussed below. The significance of the modification and the details regarding complexity will also be discussed. The modification will mean that the effect of having a buffer strip on pathogen movement can be determined enabling the public health benefits of such works to be estimated.

The pathogen model, EG, separates pathogen movement into three different flow paths: surface flow, sub-surface or interflow and baseflow. Surface flow, as defined and calculated in SIMHYD, is not created in most catchments with the exception being some tropical catchments (Chiew & Siriwardena, 2005). Instead all surface flow, or storm related flow, is termed “interflow” in SIMHYD and as stated previously will be known as surface flow for the remainder of this study. Baseflow and surface flow each have unique qualities and each is affected differently by vegetation. Baseflow, or groundwater, is unlikely to be affected by vegetation due to the depth of the flow (Pyke et al. 2003) and therefore any pathogens reaching this flow path will be unaffected. From the literature and the many studies conducted on pathogen movement (Atwill et al, 2002; Davies et al, 2004; Tate et al, 2004) it is clear that the majority of pathogens from non-point sources will be transported in the surface flow. It is also in this flow path where pathogens are most likely to be intercepted by any vegetation that exists. It is therefore the surface runoff calculation that requires modification.

There have been many studies carried out that have tested the efficiency of vegetated strips for the removal of pathogenic organisms (Atwill et al. 2002; Tate et al, 2004; Trask et al. 2004). Each study varied characteristics of the vegetated strips to

determine what had the greatest effect on their ability to remove pathogens. The majority of studies concluded that although factors such as the kind of vegetation, rainfall intensity and soil type all had some impact on pathogen removal the most influential factors were slope and width of the buffer strip. Tate et al. (2004) states that a 1m buffer strip on a slope of up to 20% can give an average of a 2 log reduction in *Cryptosporidium*. In the same study, it was concluded that on a 20% slope, for every additional metre of vegetated buffer, an extra 1 log reduction in pathogens was achieved. This reduction in pathogens increased with decreasing slope. A study by Atwill et al. (2002) found similar figures. They concluded that a 3m buffer strip with a slope of less than 20% should remove 99.9%, or 3-logs, of *Cryptosporidium*.

The aforementioned studies were carried out in the laboratory using soil boxes, spiked cow faeces and rainfall simulators. The majority of these types of studies are carried out in laboratories and care needs to be taken when up-scaling the results to a sub-catchment or total catchment scale (Ferguson, 2005). Despite the agreeable results from the studies mentioned above there may be characteristics within a real catchment that are not reflected in a laboratory setting but are highly influential to contaminant fate and transport. Characteristics such as: the creation of preferential flow paths promoting the direct transport of pathogens through buffers to streams and/or the potential of re-entrainment of trapped pathogens (Pachepsky et al. 2006), could increase the number of pathogens being transported to the stream. These characteristics could lead to a buffer strip in a catchment having reduced efficiency in terms of removing pathogens.

An additional factor which could decrease the efficiency of a buffer strip in the long-term is the possibility of it “clogging-up”. A plot scale investigation looking at sediment removal through buffer strips found that with time sediment accumulated and totally inundated the buffer reducing its removal efficiency by up to 60% (Dillaha et al. 1986). It is unknown whether a similar process would occur with pathogenic organisms or whether this process would directly affect pathogen transport.

It is possible that the percentage of pathogen reduction caused by buffer strips as stated in the above studies is underestimating the actual reduction. The soil plots used during the experiments were vegetated using grass seed. Although an average vegetation cover of over 85% was achieved the root structure of this immature grass as opposed to more mature grasses and trees would be less complex and therefore less likely to trap as many pathogens.

One of the difficulties with incorporating land-use change, such as buffer strip establishment, into the EG model is that the model does not have a spatial element. It does not require features of the catchment such as topography or groundcover to be known. The model distinguishes between the different land-uses through the differing faecal deposition rates and pathogen loads which are based on animal population. To incorporate a spatial element into EG, such as a buffer strip, some assumptions regarding characteristics of the buffer and its location are necessary.

Assumptions

Based on an understanding of the available studies, referenced above, and their limitations, it is reasonable to suggest a pathogen percentage reduction for buffer strips assuming a minimum width and maximum slope. The suggestion is as follows: for a buffer strip of at least 1m width and on a slope of less than 20% a 99%, or 2-log, reduction in pathogens is achieved. This figure is conservative, due to the limitations of the studies and the reduction rate chosen, is realistic, given knowledge of pathogen movement in catchments, and is justifiable, based on literature.

Incorporating the spatial element of buffer location into EG requires a fairly basic assumption. That is, that any buffer strip is in-between the agricultural practices, or the pathogen source, and the stream. This will ensure that the buffer is affecting pathogen movement for the entire sub-catchment and assumes that there is no catchment, and therefore no pathogen sources, below the buffer.

The actual buffer position along the stream requires an even distribution be assumed. For example if 30% of the total stream length has a buffer, regardless of it being continuous or not, then 30% of the catchment will be affected by a buffer. This assumption of even distribution is similar to that of the faecal deposition, in that it is assumed to be evenly distributed across the catchment. For each catchment, therefore, the total length of stream reach will need to be determined, followed by determining the percentage of stream covered by buffer strips. This will be displayed as a ratio and it will be this portion of the total catchment area which will be affected by the buffer strip and therefore have a reduction in pathogen numbers.

Once pathogens are intercepted by the buffer they are not likely to remain there perpetually but instead be available to be re-entrained in subsequent flows (Chadwick et al. 2008). *Cryptosporidium*, as well as other pathogens, are known to be relatively

robust in the environment and can remain infective for many months once leaving the host (Davies et al. 2005a). Remobilisation from soil is therefore an important factor when determining dispersion and transport as they may still be viable and therefore a risk to public health. For the purposes of the model modification it is assumed that the pathogens trapped by the buffer will be available for transport by the surface flows following the next rainfall events. Additionally, trapped pathogens have the potential to reach the groundwater and be transported by this flow. A study by Mawdsley et al. (1995) stated that vertical movement of pathogens through the soil column will occur providing the soil is not completely saturated or impermeable. Hekman et al. (1995) also showed that soil cores with vegetation had increased vertical microorganism transport as compared to those soil cores without vegetation. This means that pathogens trapped by the vegetation will have the ability to be transported vertically via infiltration and then laterally by the baseflow. To ensure trapped pathogens can be transported by either of surface flow or baseflow, any trapped pathogens will be placed back into the sub-surface store.

In summary, to enable the effects of buffer strips on pathogen numbers to be included in the existing EG model the following assumptions are necessary:

- pathogens in the baseflow are not affected by buffer strips
- the width and slope of the buffer are more than 1m and less than 20% respectively
- buffer strips provide a 99% reduction in pathogens
- the location of buffer strips is always in-between the pathogen source and the stream
- the ratio of vegetated stream reach to total stream reach is equivalent to the portion of catchment affected by the buffer
- of the 99% of total pathogens in the surface flow trapped in the buffer, all will be put back into the sub-surface store.

With these assumptions in mind, it is now possible to identify the equations within EG which require modification to allow for buffer strip effectiveness to be predicted. This, along with the structure of the modifications, is outlined in the following section.

6.5.1 The buffer effectiveness equation

The above discussion has shown that buffer strips will only affect the transport of pathogens in the surface flow. It is therefore the equation in EG which calculates the pathogen concentration in the surface flow ($P_{in.ter}$) which is the focus of this section.

Assumptions regarding spatial variables such as width, slope and location of the buffer mean that they are not necessary to consider in the calculation. The percentage pathogen reduction rate through the buffer and buffer ratio in the catchment must, however, be included.

The percentage pathogen reduction has been assumed to be 99%, or 2-log.

In terms of buffer ratio, this figure will be catchment specific and therefore needs to be an input into the model. It can be calculated using Equation 6.10.

$$B_R = \frac{L_B}{L_{TS}} \qquad \text{(Equation 6.10)}$$

where:

B_R = buffer ratio

L_B = length of the buffer

L_{TS} = length of the total stream

To calculate the ratio correctly the location of the stream within the catchment is important. For example, if the stream runs through the middle of the catchment, which would usually be the case, then it is necessary to record the buffer length on both sides of the stream and add them together. It is also then necessary to multiple the total stream length by 2, in effect, to include both "sides" of the stream. If the catchment boundary is formed by the stream then it will only be necessary to include one "side" of the stream in the ratio calculation.

The ratio determines the portion, or percentage, of the catchment that is affected by the buffer. The pathogens transported in the surface flow for this portion of the catchment will be reduced by 99%. For the remaining portion of the catchment the pathogens transported in the surface flow will be unaffected.

The pathogens in the original EG model in the surface flow ($P_{in.ter}$) are calculated using Equation 6.6. To include the effect of the buffer, the pathogens being transported to the stream, $P^*_{in.ter}$, are calculated using Equation 6.13, see below.

$$P_{in.ter(t)} = b1\left(\frac{Q_{in.ter(t)}\Delta t}{v_{ss(t)}}\right)P_{ss(t-1)} \qquad \text{(Equation 6.6)}$$

$$P^{*}_{in.ter(t)} = \left(P_B\right) + \left(P_{NB}\right) \qquad \text{(Equation 6.11)}$$

$$P^{*}_{in.ter(t)} = \left(B_R P_{in.ter(t)}\left(1-R\right)\right) + \left(\left(1-B_R\right)P_{in.ter(t)}\right) \qquad \text{(Equation 6.12)}$$

$$P^{*}_{in.ter(t)} = \left(B_R P_{in.ter(t)} 0.01\right) + \left(\left(1-B_R\right)P_{in.ter(t)}\right) \qquad \text{(Equation 6.13)}$$

where:

P_B = pathogens transported through the buffered catchment

P_{NB} = pathogens transported through the non-buffered catchment

Other variables as defined previously

The re-calculated $P^{*}_{in.ter}$ is used throughout the model to predict pathogen transportation to the stream.

As discussed, any pathogens which are not transported as $P^{*}_{in.ter}$ need to be available for transport by the next surface flow event or by the baseflow. To ensure this can occur, pathogens not transported initially remain in the sub-surface store.

6.6 Summary and conclusions

This chapter has discussed why it is required to have a pathogen specific model for the accurate prediction of their fate and transport in the environment. This is especially the case when the effects of establishing buffer strips need to be determined.

In terms of modelling pathogens, the EG model was found to have the necessary characteristics for modelling the fate and transport of pathogens in the environment. That is, it has the ability to represent rainfall runoff events, along with a specific consideration of pathogen behaviour and the separation of different flow paths.

An important consideration when looking at the effects of buffer strips is the accurate partitioning of the different flows in the catchment. The hydrologic model used during development, SIMHYD, was found to be inadequate in this regard and an alternate method for separating the baseflow was devised. This method used the digital filter method via WHAT. The outputs from WHAT were shown to be more realistic based on knowledge of a typical rainfall runoff hydrograph. The outputs from SIMHYD and WHAT formed the transport component to the pathogen model.

In order for EG to be used to show the effects of having buffer strips in the catchment modifications to the model calculations were necessary. This involved consideration of various pathogen transport studies. The modifications made are significant, in that they allow pathogens being transported in the surface flow to be trapped by a vegetative buffer strip and be put back into the sub-surface store. This model advancement improves the applicability of the model by giving catchment managers the ability to quantify the benefits of having a buffer strip. Any decrease in pathogen numbers as a result of buffer strip implementation can be used as an input to a QMRA and therefore be expressed as a reduction in disease burden to the community. This type of quantitative assessment will essentially allow the public health benefits of these works to be estimated.

The EG model is limited in that it does not have a spatial element. This meant that a number of assumptions were required to allow for the inclusion of the effect of the buffer strip. The assumptions made are reasonable based on literature and will be further tested, where necessary, in Chapter 9.

The modified EG model will allow catchment managers and water quality professionals to predict a reduction in pathogens following buffer strip implementation. The following chapter will look at calibrating both models defined in this chapter, the hydrologic and the pathogenic. Due to the number of assumptions necessary when modelling pathogen movement it is not recommended that modelling results alone are used to drive management decisions but that they are used in a suite of evidence based research. With this in mind, Chapter 8 will look at what effect the modifications made to EG have on pathogen numbers with an aim to quantifying the buffer's effectiveness and giving drinking water quality managers a validated buffer to pathogenic contamination.

7. MODEL CALIBRATION

7.1 Introduction

Following on from determining the appropriate models for modelling pathogen movement within a catchment, it is now necessary to calibrate them to the study catchment, the Tarago Reservoir catchment. This chapter presents the calibration and validation of both the hydrologic model, SIMHYD and the pathogen model, EG (both described in Chapter 6). It will present calibration and validation statistics as well as discuss what is acceptable in terms of model fit.

Only the East branch and the West branch catchments are represented here as there is no streamflow data for Crystal Creek making calibration impossible for this catchment.

7.1.1 Calibration procedure

Calibration is a necessary and important step in any form of modelling as it checks the accuracy of the predictions and assesses the performance of the model. It is the process by which parameters within the model are changed until the differences between the predicted data and the observed data is minimal. Following calibration it is important to validate the model by testing it on a section of independent data that was not used in the calibration process; this is known as a split sample test. This process further confirms, or otherwise, that the model parameters can adequately predict the observed conditions over a range of circumstances.

There is no common method for assessing model performance as it depends on the type of model and the expected or required outcomes. It is agreed, however, that is important to have a clear outline of how model outcomes will be compared prior to starting modelling. Two of the most frequently used measurements to assess model performance are the coefficient of determination, R^2, and the Nash-Sutcliffe coefficient of efficiency, E, which will together give a good indication of the goodness of fit (Krause et al. 2005). These objective functions can be used for both the hydrologic and the pathogen models. An additional statistic used in hydrologic modelling is the calculation of the percentage difference in the total streamflow volume (*TVOL*) outputted by the

observed and the predicted data, which is a good basis for comparison between data sets.

The coefficient of determination, R^2, is one of the most commonly used indicators of "goodness-of-fit" of a model. It estimates the combined dispersion against the single dispersion of the observed and predicted series (Krause et al. 2005). Equation 7.1 shows how R^2 is calculated.

$$R^2 = \left(\frac{\sum_{i=1}^{n} \left(O_i - \overline{O}\right)\left(P_i - \overline{P}\right)}{\sqrt{\sum_{i=1}^{n} \left(O_i - \overline{O}\right)^2} \sqrt{\sum_{i=1}^{n} \left(P_i - \overline{P}\right)^2}} \right)^2 \qquad \text{(Equation 7.1)}$$

where:

O_i = i^{th} observed value

P_i = i^{th} predicted value

$\overline{O}$ = mean observed values

$\overline{P}$ = mean predicted values

n = number of values

Values of R^2 range between 0 and 1, with 1 indicating the dispersion of the predicted is equal to that of the observed. This coefficient, although widely used, can give a false impression of fit as it assesses the ability of the model to follow a trend and is not always a good indication of how well the observed series is predicted by the model; it is based on correlation only (Krause et al. 2005). As an example a model can have an R^2 of 1 and have a relationship $y = 2x$, which means the model will be over-predicting by a factor of 2. It should therefore not be used alone but in conjunction with other indicators of fit.

This deficiency is somewhat addressed by the use of the coefficient of efficiency, *E*, or the Nash-Sutcliffe model efficiency coefficient, which is also used to assess the predictive power of various types of models. The Nash-Sutcliffe is defined as one minus the sum of the absolute squared differences between the predicted and observed values normalised by the variance of the observed values (Krause et al. 2005), see Equation 7.2.

$$E = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}\left(O_i - \overline{O}\right)^2} \qquad \text{(Equation 7.2)}$$

Variables as defined previously

Values of *E* range from negative infinity to 1 with values closer to 1 indicating good agreement between the observed and predicted data. A value of zero indicates that the observed mean is a predictor equally as good as the model, whereas a negative value indicates that the observed mean is a better predictor than the model (Parajuli et al. 2008).

Both the coefficient of determination, R^2, and the coefficient of efficiency, *E*, tend to fit peaks at the expense of other parts of the time series (Beven, 2001). This is acceptable or even preferred when modelling rainfall events as these peaks, or events, will be when the majority of contaminants will be mobilised. Peak values are what are of most interest to suppliers of drinking water as they indicate the time at which public health is at greatest risk and how big that risk is. Additionally it will indicate the maximum challenge that a water treatment plant is likely to face.

TVOL is the comparison of the total predicted and total observed streamflow values as a percentage of the total observed streamflow (Peel, et.al., 2000). While both R^2 and *E* can be used for both hydrologic and water quality model assessment, *TVOL* is only used on the hydrologic data as both the observed and predicted data sets are continuous. The equation for *TVOL* is presented below:

$$TVOL = \left| \frac{\sum_{i=1}^{n} P - \sum_{i=1}^{n} O}{\sum_{i=1}^{n} O} \right| \times 100 \qquad \text{(Equation 7.3)}$$

Variables as defined previously

TVOL gives a measure of the difference in the overall total predicted streamflow from the observed. A value close to zero indicates that the two data sets are very similar.

The final, and perhaps most important, indication of whether a predicted result is matching the observed result is to visually observe the data in a time series graph. Visual inspections should always accompany model calibrations as it helps to subjectively judge the ability of the model to predict observed values (Legesse, 2003). It can reveal areas of concern sometimes not evident in calibration statistics such as poor matching of recessions or unacceptable flow biases (Hogue, 2006). Additionally, and especially with pathogen modelling, the peak of an event can sometimes not be given the focus that is required. When visually observing model results, all of these issues can be addressed.

Calibration statistics are calculated after running the model for an initial warm up period of 6 months. This allows the stores within the models, both hydrologic and pathogenic, to reach equilibrium.

The assessment of model performance should be based on all calibration measures. Table 7.1 gives an indication of hydrologic model performance based on calibration statistics and visual fit. It is based on the classifications used by Peel et al. (2000).

Table 7.1 – Classification of hydrologic model performance based on calibration findings

Classification	R^2	*E*	*TVOL*	Visually
Excellent	> 0.80	> 0.75	Within 5%	All peaks and baseflows are similar
Good	> 0.70	> 0.55	Within 10%	Most of the data is similar
Passable	> 0.60	> 0.35	Within 15%	General pattern is similar
Poor	> 0.40	> 0.10	Within 20 %	Limited data is similar
Unacceptable	< 0.40	< 0.10	Beyond 20%	Very limited to no similar

In terms of water quality modelling, however, assessing model performance is not as simple. Donigian (2000) produced a table quoting tolerances for percent mean errors between predicted and observed water quality values but with a caveat that they were only relevant for monthly and daily values. They are therefore not relevant here where hourly data is being used. The uncertainty inherent in water quality measurements and the variations in data caused by random and episodic events can greatly affect calibration statistics (Shen et al. 2006). Therefore an absolute criterion for assessing water quality modelling especially on an hourly time scale is inappropriate. Dorner et al. (2006) reports that it is acceptable for predicted results to be within an order of magnitude of observed data. An order of magnitude, or more, is also stated by Novotny (2003) as the expected level of accuracy for deterministic models of water

quality in a large catchment. This range is reasonable as drinking water treatment plants are operated according to the magnitude of the peak pathogen concentration as this tells operators what log-reduction is required to provide safe drinking water. This study will report calibration statistics for water quality modelling performance, but it will be the examination of predicted versus observed graphs and the comparison of magnitudes of these results that will be of most interest.

There are two ways in which models can be calibrated, manually or by using an automated optimising package. Manual calibration is a good first step when calibrating a model as it allows the modeller to get an appreciation of the parameters and how they will affect the model outcome. Although this method usually leads to conceptually realistic parameters and good model performance in the validation period, it is time-consuming and requires extensive expertise (Hogue et al. 2006). Manual calibration also does not guarantee an optimal solution is reached but it can provide a reasonable set of starting parameters for the automatic calibration. Automatic calibration means running the model through an optimisation package which adjusts the parameters until previously defined criteria are met. The knowledge gained from attempting to calibrate the model manually should ensure that the automatic calibration provides optimal as well as logical outcomes.

One such automatic calibration package is PEST, which stands for Parameter ESTimation model. It is an optimisation tool that assists in data interpretation, model calibration and predictive analysis (Doherty, 2004). PEST works by taking control of the model, adjusting the parameters and running and re-running the model until modeller defined criteria are met. The criteria may include minimizing the difference between the modeled and observed data sets, reaching a certain number of iterations or a combination of different criteria. As the criteria are determined by the modeller the method by which the package has determined the optimum result is known. PEST is a fast and convenient tool, as compared to other optimization packages, as it does not require any recoding or modification of the existing model.

Having determined the calibration methods by which each model will be assessed against, the following sections report on the calibration process and the results.

7.2 Calibration of SIMHYD

As discussed above, SIMHYD was first run manually in order to gain some appreciation of the model parameters as well as gain a reasonable set of starting parameters for the automatic calibration. Although the parameters within SIMHYD seemingly relate to on ground features, such as the capacity of the soil to store water, studies trying to relate the parameters to catchment characteristics have been relatively unsuccessful (Boughton & Chiew, 2007; Chiew & Siriwardena, 2005). Therefore the starting parameters for the manual calibration were chosen randomly. The results for both the East and West catchments manual and automatic calibrations are presented below.

7.2.1 East branch

Manual calibration of SIMHYD for the East branch was carried out over a 5 year period from 1999 to the end of 2003. The rainfall values used for the manual calibration were an average of all four gauges, Reservoir, Bunyip, Drouin and Nayook, which is deemed an acceptable way of spatially distributing rainfall (Ward & Trimble, 2004), see Chapter 3. For all parameter sets and results from the manual calibration, see Appendix F, Table F.1. The runs from the manual calibrations were sorted according to their calibration statistics, specifically, by adding the values of R^2 and E for each run. The details of the run that gave the highest total of R^2 and E is given in Table 7.2.

Table 7.2 – Best manual calibration run for SIMHYD in the East catchment (excerpt from Table D.1)

Run #	Rainfall[16]	Factor[17]	R^2	E	*TVOL*
7	N+B+R+D	None	0.56	0.49	6.29

According to Table 7.1, these calibration statistics classify the run as (approximately) “Passable”.

During manual calibration it became evident that the two parameters that dealt with infiltration loss, namely COEFF and SQ, had no effect on the final outcome in terms of fit, see the results from Runs 2–4 in Table D.1. Apart from in tropical catchments, SIMHYD produces little to no infiltration excess, so optimisation of these parameters is

[16] N = Nayook, B = Bunyip, R = Reservoir and D = Drouin rainfall gauges

[17] The factoring is explained in Section 3.5.2, Chapter 3

not required (Chiew & Siriwardena, 2005). These two parameters are therefore insensitive and can be fixed during automatic calibration allowing the optimisation process to focus on the more influential parameters.

Automatic calibration was carried out using the same period of data that was used for the manual calibration. The criteria used during automatic calibration were based on those set out in the PEST manual (Doherty, 2004). During automatic calibration, it was found that the final parameters were not significantly influenced by the variables in the PEST model but were highly influenced by the parameter starting values. Therefore it is important that the modeller is confident that the starting parameters are close to the "best-fit" parameters. The best parameters from the manual calibrations were used as the starting values in PEST.

As discussed in Chapter 3, there are four different rainfall gauges which are available for use within the hydrologic model. This large amount of data meant that determining the average rainfall for the catchment could be done using one, two, three or all four gauges in any combination. It was unknown which combination of gauges would give the most representative estimation of rainfall and therefore streamflow in the catchment. Therefore all possible combinations of rainfall gauges were trialled. Additionally each combination was scaled by a factor of 0.8 and 1.2 (see Chapter 3), which accounted for errors in rainfall measurements and also allowed for catchment specific losses and gains, respectively. Some rainfall combinations were unable to be used for modelling due to an incomplete data set during the calibration period chosen. 30 automatic calibration runs were carried out, see Table F.2 in Appendix F.

The best output from the automatic calibration was achieved when an average of Nayook and Reservoir rainfalls were factored by 0.8, see Table 7.3.

Table 7.3 – Best automatic calibration run for SIMHYD in the East catchment (excerpt from Table D.2)

Run #	Rainfall	Factor	R^2	*E*	*TVOL*
21	N+R	0.8	0.74	0.70	1.60

This classifies the run as "Good" and compared to the best fit from the manual run. Visually the fit is also a lot better. An example of this can be seen in Figure 7.1, where a period of about 20 days is used to illustrate the different fits.

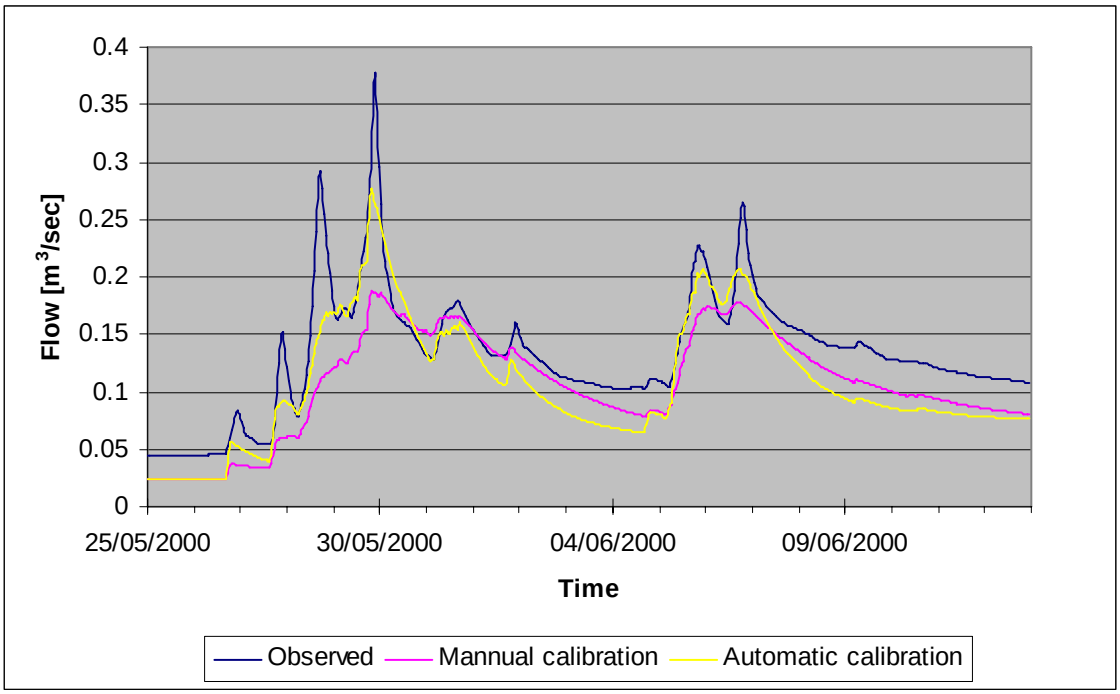

Figure 7.1 – East branch hydrograph for June 2000 showing the better fit from the automatic calibration

The automatic calibration is not only hitting the peaks more accurately but is also following the general trend of the observed flow much better than the manual calibration.

Interestingly the top 7 calibrated runs from the automatic calibration - Runs 21, 12, 24, 3, 30, 9 and 27, see Table D.2 - all used rainfalls scaled by a factor of 0.8. This indicates that the gauged measurements are overestimating of rainfall within the East catchment. This could be as a result of water being captured and not allowed to runoff as a result of dams within the catchment for example. It could also be accounting for the assumed underestimation at the East branch streamflow gauge due to silting as discussed in Chapter 3. The need for scaling is, however, most likely due to errors in the tipping bucket measurement which tends to overestimate rainfall during low intensity periods (Molini et al. 2005). The period can be considered low intensity due to the low number of large storms. Additionally it is reported that using point rainfall values to estimate rainfall over an area usually results in an overestimation of the area-averaged rainfall (WMO, 1994).

Validation

The parameter sets from the best 5 runs were used during validation as a way of determining which parameter set gave the best overall fit. Data from the start of 2004

to the end of 2006 was used as the validation period. The results of the validation can be seen in Table 7.4.

Table 7.4 – SIMHYD validation results for the East branch

Run #	Rainfall	Factor	Calibration Statistics			Validation Statistics		
			R^2	*E*	*TVOL*	R^2	*E*	*TVOL*
21	N+R	0.8	0.71	0.70	1.60	0.63	0.51	18.80
12	N+R+B	0.8	0.74	0.70	1.88	0.60	0.49	15.44
24	N+B	0.8	0.71	0.67	3.00	0.56	0.45	12.75
3	N+D+R+B	0.8	0.71	0.65	2.02	0.60	0.58	0.25
9	N+D+R	0.8	0.70	0.65	2.06	0.60	0.59	5.36

The statistics for all 5 validation runs indicate that any of the 5 data sets could be used to model this catchment using SIMHYD. A decision about the best run, and the reasons for it, will be made in Section 7.2.3.

7.2.2 West branch

As discussed in Chapter 3 there is no direct gauging of the streamflow on the West branch of the Tarago River. The West branch streamflow can, however, be predicted (see Equation 3.2) using data from the streamflow gauge on the East branch and the gauge after the confluence of the East and West branches, along with abstraction data for the Tarago Main Race (TMR).

$$Q_W = Q_C - Q_E + Q_{TMR} \qquad \text{(Equation 3.2)}$$

where:

Q_W = West branch streamflow

Q_C = Confluence streamflow

Q_E = East branch streamflow

Q_{TMR} = Abstraction for the TMR

Data for the TMR was only available as a daily total. This was converted into hourly data by simply dividing the total daily figure by 24. This will lead to some inaccuracies in the "observed" flow and this is important to keep in mind when viewing calibrated statistics and results.

The same calibration and validation periods as used in the East branch hydrologic modelling were used, namely 1999-2003 and 2004-2006 respectively. An average of all for rain gauges was used for the manual calibrations, see Table F.3 in Appendix F. PEST was then employed using different rainfall combinations with scaling, see Table D.4. Runs were ranked according to their calibration statistics as for the East. Table 7.5 gives the best results from the manual and automatic runs.

Table 7.5 – Best calibration runs for SIMHYD in the West catchment (excerpt from Tables D.3 and D.4)

Calibration mode	Run #	Rainfall	Factor	R^2	*E*	*TVOL*
Manual	19	N+B+R+D	None	0.50	0.49	0.20
Automatic	9	N+D+R	0.8	0.60	0.58	9.15

According to Table 7.1 the manual calibration is classified as “Passable” and the automatic calibration as “Good”. Figure 7.2 shows an example of the difference in fit between the manual and automatic calibrations.

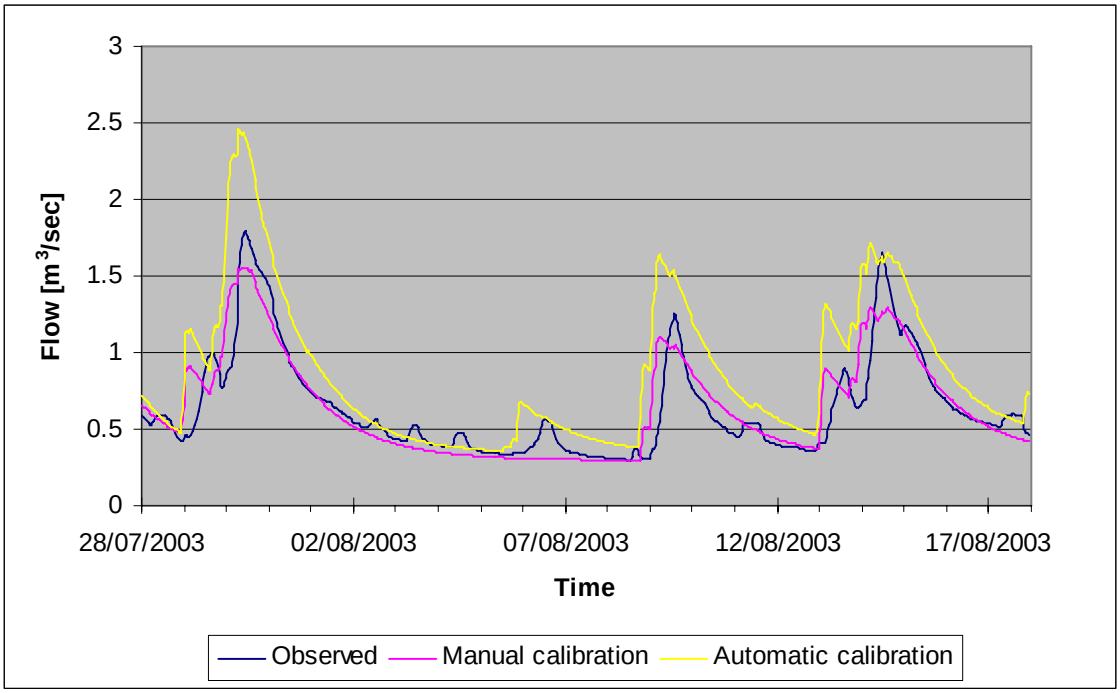

Figure 7.2 – West branch hydrographs in August 2003 showing the better fit from the automatic calibration

The main difference between these two fits is mainly in the timing of the peaks. For the manual calibration they are early whereas the peaks in the automatic calibration are similar to the observed peaks. The general overall fit of the automatic calibration is similar to that of the manual but the total volume is being overestimated.

Validation

Validation was undertaken on the top five calibrated runs which were ranked according to their calibration statistics. The results of this can be seen in Table 7.6.

Table 7.6 – SIMHYD validation results for the West branch

Run #	Rainfall	Factor	Calibration Statistics			Validation Statistics		
			R^2	*E*	*TVOL*	R^2	*E*	*TVOL*
9	N+D+R	0.8	0.60	0.58	9.15	0.66	0.59	28.78
15	D+R+B	0.8	0.60	0.58	10.67	0.63	0.60	17.01
3	N+B+R+D	0.8	0.59	0.56	10.46	0.60	0.57	17.96
18	N+D	0.8	0.57	0.55	10.05	0.56	0.54	2.70
6	N+D+B	0.8	0.55	0.54	6.02	0.56	0.53	2.33

As in the East, the rainfall combinations that gave the best fits in the West were those that were scaled by a factor of 0.8. The influence of farm dams was suggested as a possible cause of the overestimation of rainfall in the East but as there are no known dams in the West this is now thought to be an unlikely cause as the effect is catchment-wide. The necessary scaling is more likely to be due to catchment-wide features such as a dry catchment, due to the drought, promoting infiltration and reducing runoff. It is most likely, however, that the reason for the overestimation in rainfall in both catchments is due to errors in measurement and/or the inherent errors in using an area-averaged rainfall, as explained above.

As discussed in Chapter 3, the Theissen polygon method was able to be used in the West catchment to spatially distribute the rainfall. Given the above results in Table 7.3 it is not surprising that the Theissen predicted rainfall scaled by a factor of 0.8 gave the best calibration statistics of the three Theissen runs. What was surprising, however, was that calculating the rainfall using this method did not produce the best, or one of the best, calibration runs, it was ranked 11th. The Theissesn method in this catchment did not include the Drouin gauge due to its location, however, the top five results for the West catchment the Drouin gauge was included. In this catchment the Theissen method rainfall as an input to SIMHYD does not seem to give the best streamflow estimation as compared to a simple averaging method.

7.2.3 Best rainfall combinations

Having a good fit for the hydrologic model before undertaking the pathogen modelling was highlighted in Haydon (2006), where it is stated that as the transport aspects of the pathogen model are the most sensitive, focusing on a good hydrologic fit is important.

It is therefore necessary that before moving onto the pathogen model the best fitting hydrologic model for each catchment is chosen.

From the calibration/validation process detailed above the best 5 runs for each catchment were examined. The statistics from these 5 runs along with a visual inspection of each of the runs led to one rainfall combination being chosen for each catchment as giving the most accurate representation of streamflow, the results of which can be seen in Table 7.7.

Table 7.7 – Best SIMHYD calibration runs for the East and West catchments

Catchment	Run #	Rainfall	Factor	Calibration statistics			Validation statistics		
				R^2	*E*	*TVOL*	R^2	*E*	*TVOL*
East	9	N+D+R	0.8	0.70	0.65	2.06	0.60	0.59	5.36
West	15	D+R+B	0.8	0.60	0.58	10.67	0.63	0.60	17.01

The results obtained from these two runs classify them as "Good" according to Table 7.1. Figures 7.3 and 7.4 show the results for each catchment, for the same periods as is the previous sections.

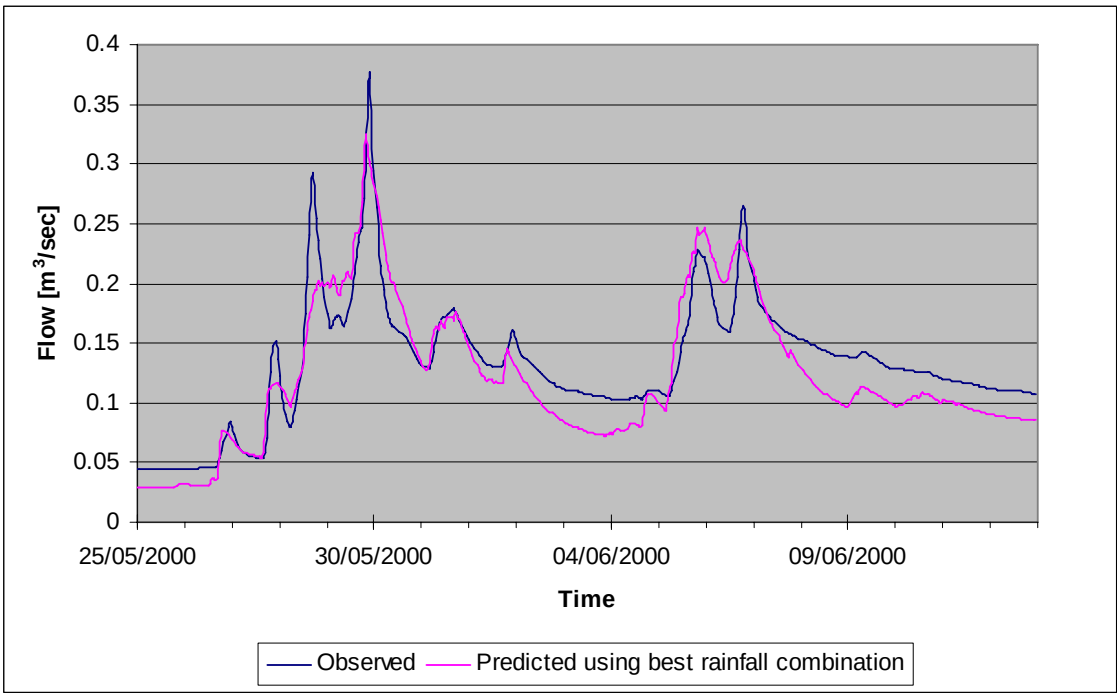

Figure 7.3 – Best calibration run for the East branch (Run 9) in June 2000

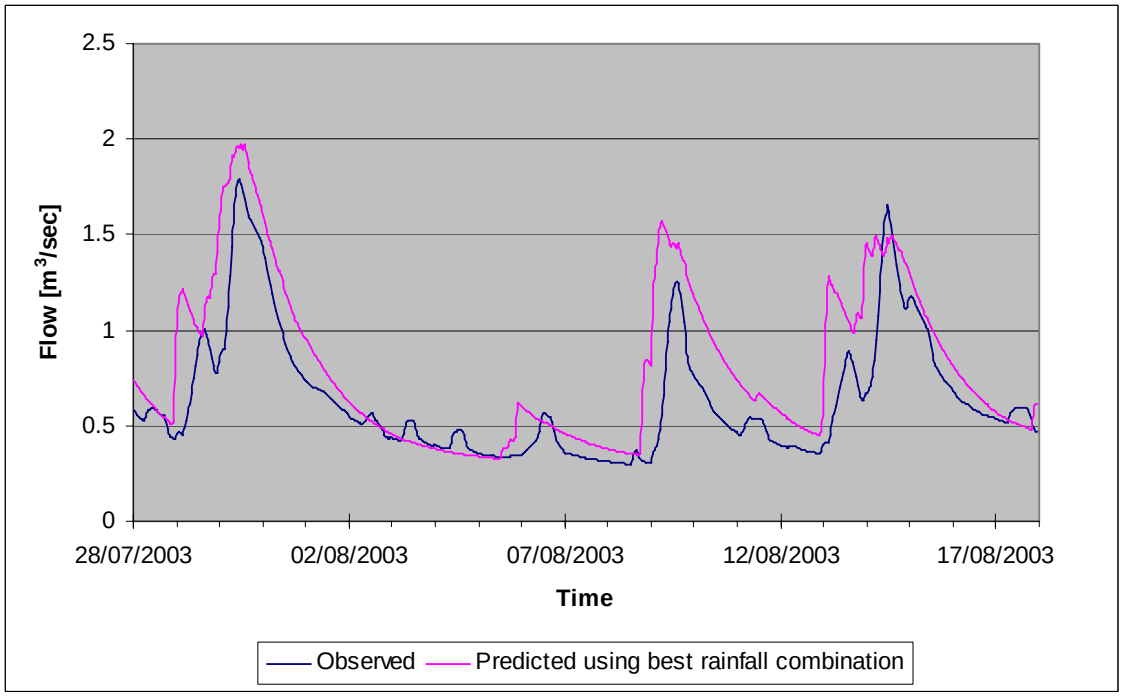

Figure 7.4 – Best calibration run for the West branch (Run 15) in August 2003

The difference between the two catchments in terms of the rainfall gauges that resulted in the best runs corresponded very well to the streamflow gauges in terms of location. This is not surprising given there can be substantial differences in rainfall over short distances which can directly influence observed flow. The Nayook rain gauge which is included in the best run for the East is located within the East catchment and is only 3 km north of the streamflow monitoring site. In the West's best run the Bunyip gauge was included. This gauge is located only 3 km west from the boundary of the West catchment. The Reservoir and Drouin gauges are included in both catchments best run.

From this point on in the study, the rainfall combinations stated in Table 7.7 will be the ones used for each catchment for modelling streamflow.

7.3 Calibration of EG

The EG model was calibrated using *E. coli* data, which is an indicator of pathogenic contamination. As discussed in Chapter 3, the field data that represents observed human-infectious pathogenic data is insufficient for modelling purposes. Although the baseflow *E. coli* data is essential for calibration, it is the *E. coli* data during events that will be the focus of the calibration. It is important for the model to be accurate during

these times. The events are of most interest to drinking water quality managers as they represent the biggest risk and give an indication as to what level of treatment is required to ensure safe drinking water. It is therefore the captured events, 5 in the East and the 1 in the West, where the majority of the focus will be during the pathogen model calibration/validation process.

EG produces a time-series of pathogen concentrations, or pathogen pollutograph. It shows the rate at which pathogens suspended in runoff are transported.

As with SIMHYD, EG was first run manually to enable an appreciation of the key input parameters and their effect on the model and calibration outcomes. Following manual calibration EG was run through the automatic calibration tool, PEST. Both R^2 and E were recorded for each calibration run. Additionally, and more so than in the hydrologic modelling, visual checks were done for each model run. This is particularly important when modelling pathogens, as it is not necessarily exact predictions that are necessary but rather the right order of magnitude and a similar trend during events. These characteristics are often better determined visually than from statistics.

To enable the modelling of the effect of buffer strips in catchment the EG model was modified to allow for a reduction in pathogen concentration according to the amount of buffer in the catchment, see Chapter 6. The model requires a buffer ratio be specified and as it is necessary to calibrate the model to existing conditions, the current buffer ratios for each catchment were determined. For the East, a buffer ratio of 0.85 was determined based on aerial photos. This means that sufficient vegetation existed between the agricultural land and the East branch along 85% of its length. The uncertainty related to this number will be discussed in Chapter 9. As the West catchment is fully forested a buffer ratio of 1.00 was appropriate.

7.3.1 East branch

In the East Tarago catchment, calibration statistics were recorded for the overall fit of the model and also specifically for the 4 of the 5 events captured. The fifth event was reserved for validation purposes. In order to further emphasise the importance of the peaks and the models ability to fit them, during the automatic calibration process using PEST an increased weighting was given to each event peak. This ensures that those values take precedence in the estimation process within PEST (Doherty, 2004).

Manual calibration was undertaken and the calibration statistics were recorded. Over 40 runs were completed to enable an understanding of how the model responded to different parameter changes and also to obtain starting values for the automatic calibration run. The results can be seen in Appendix F, Table F.5. An observation made during manual calibration was that parameters a_1, a_2 and b_1 had an effect on the magnitude of the pathogen pollutograph whereas a_5 and b_2 had more effect on the shape of the pollutograph. Equations 6.1 to 6.7 show the role of these parameters in the EG model.

Automatic calibration was undertaken using the program PEST and the best parameter set and overall calibration statistics as well as the calibration statistics for the four events are presented in Table 7.8.

Table 7.8 – EG calibration results for the East branch including events

Parameters		***a*$_1$**	***a*$_2$**	***a*$_5$**	***b*$_1$**	***b*$_2$**
		$8x10^{-1}$	0	$5x10^{-6}$	400	$7x10^{-3}$
Calibration Statistics		**Overall**	**Event 1**	**Event 2**	**Event 3**	**Event 4**
	***R*^{2}**	0.50	0.99	0.10	0.71	0.01
	E	0.28	0.34	-0.06	0.22	-6.14

As discussed previously it is important when modelling pathogens that the graphs are looked at to determine how suitable the fit actually is. Figures 7.5 to 7.9 show the fit for both the flows and the pathogen concentrations in the East catchment for the entire calibration period and for the four events respectively. Note the different scales for each of the graphs.

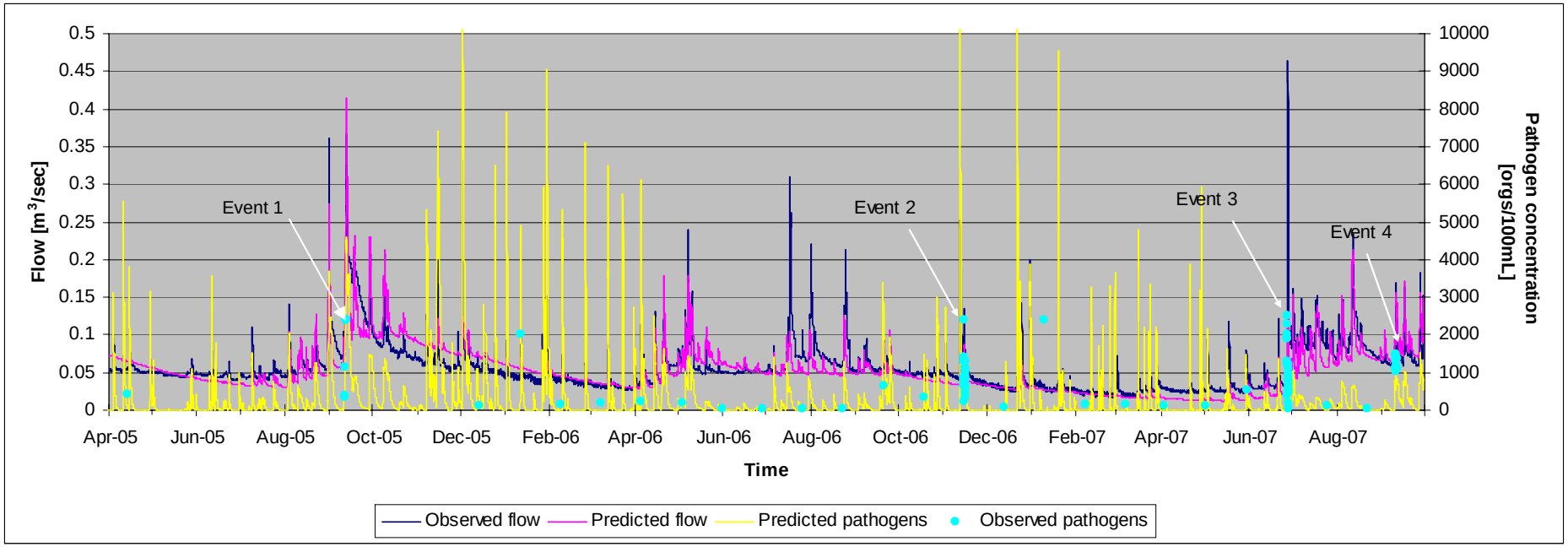

Figure 7.5 – East branch predicted versus observed flows and pathogens for the calibration period

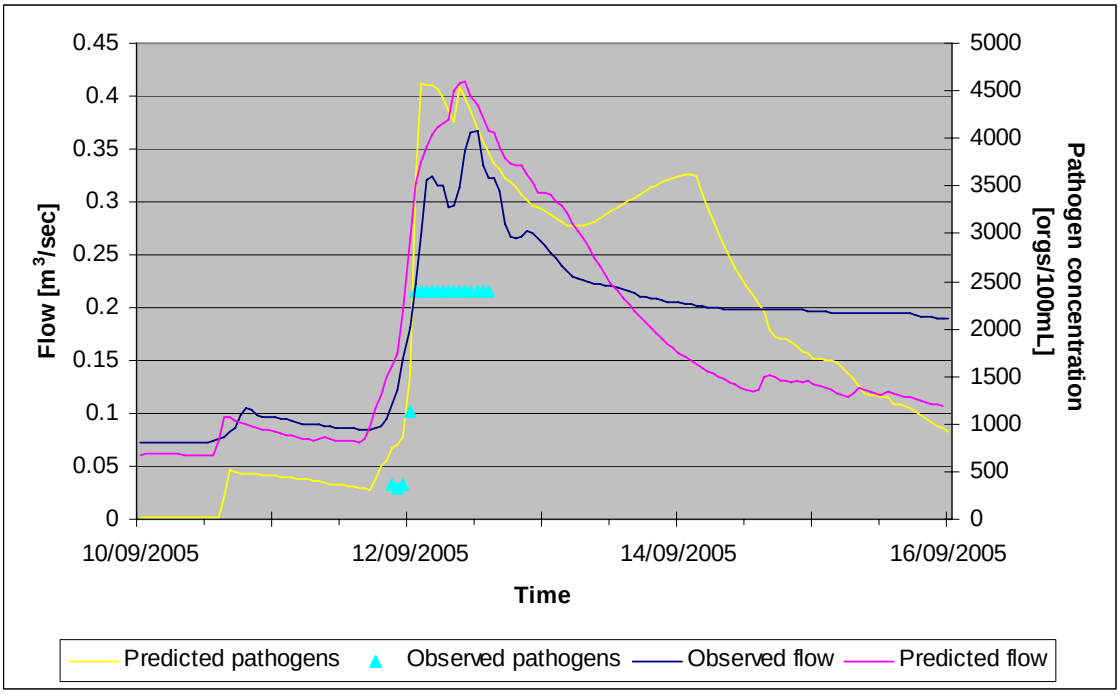

Figure 7.6 – Best EG calibration runs for Event 1

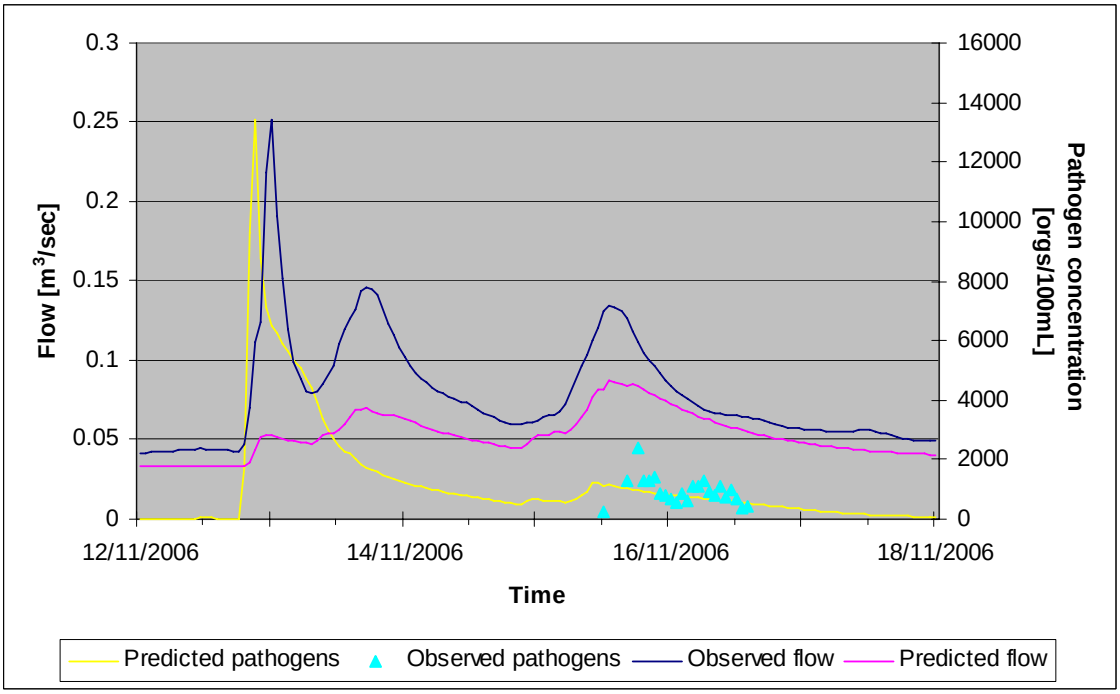

Figure 7.7 – Best EG calibration run for Event 2

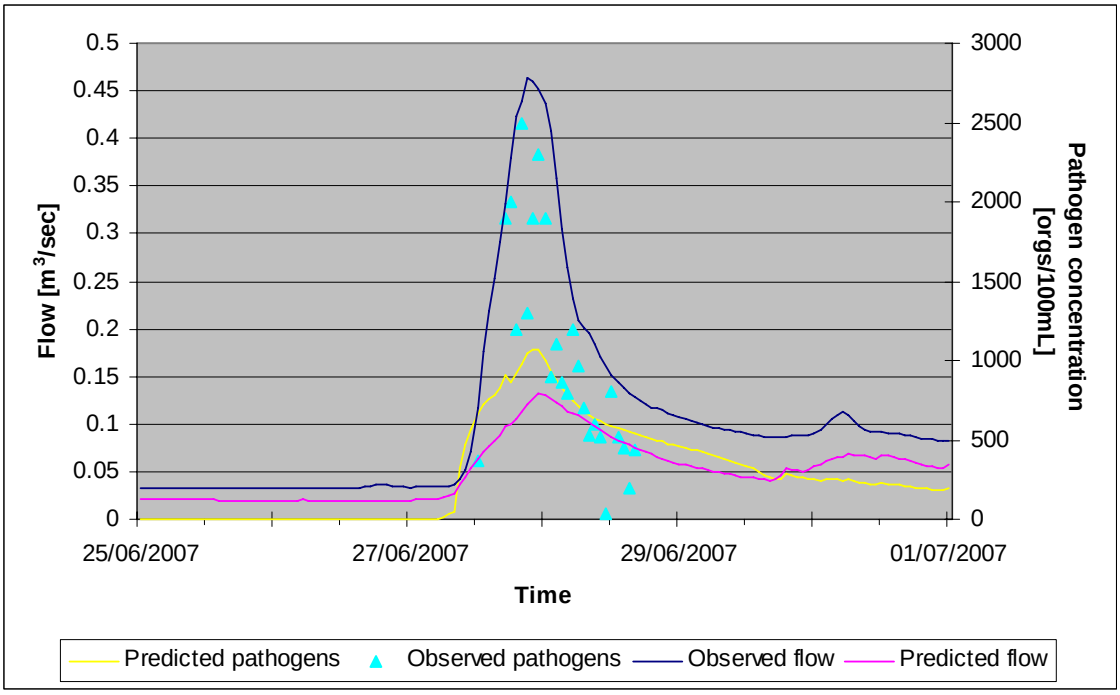

Figure 7.8 – Best EG calibration run for Event 3

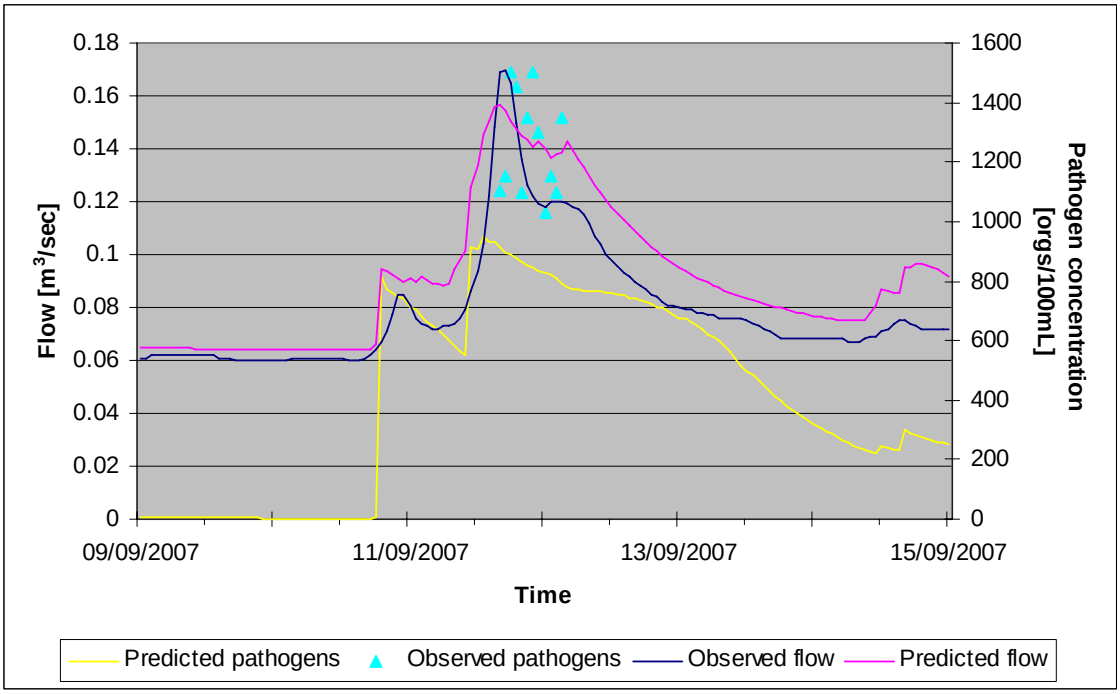

Figure 7.9 – Best EG calibration run for Event 4

As the four events are being looked at in detail it is relevant to also give the calibration statistics for the fit of the hydrologic model in each case, see Table 7.9.

Table 7.9 – SIMHYD calibration results for the East branch including events

Run #	Rainfall	Factor	Calibration statistics					
				Overall	Event 1	Event 2	Event 3	Event 4
9	N+D+R	0.8	R^2	0.70	0.78	0.41	0.83	0.86
			E	0.65	0.57	-0.21	0.17	0.68

The calibration statistics were very good for the Overall fit as well as for Events 1 and 4. The flows for Events 2 and 3 were underestimated which will obviously impact on the pathogen modelling.

In terms of the pathogen model, Event 1 had very good correlation statistics but this is due to only the first 4 observations being taken into consideration. The observations recorded as "above the detection limit" were ignored as they are not a true indication of the pathogen levels at that time. The observed values in Event 2 were only sampled on the falling limb of the hydrograph. The predicted results appear to pass through the middle of those numbers so this is regarded as a good fit despite the poor calibration statistics. Event 3 was the opposite in that the calibration statistics were more than acceptable but the visual fit is poor. The event was not predicted very well by the hydrologic model in that it underestimated the peak, and as the EG model is heavily reliant on the calibration of the hydrologic model the pathogen model is also underestimating the observed peak. For Event 4 the observed pathogen numbers were low, compared to the other 3 events, and therefore the difference between predicted and observed is exaggerated making the fit look visually unacceptable. The predicted results were, however, within the right order of magnitude, with the highest difference between predicted and observed being 0.28 of an order of magnitude. It is therefore important to always view the predicted versus observed results as the statistics alone may not give a good indication of the fit.

Overall the ability of the EG model to fit the observed data as shown in Figure 7.5 is relatively good. To further demonstrate the models overall ability to predict values within an order of magnitude, a regression relationship is plotted on a log scale with a 1:1 line and error bars at ±1 order of magnitude, see Figure 7.10.

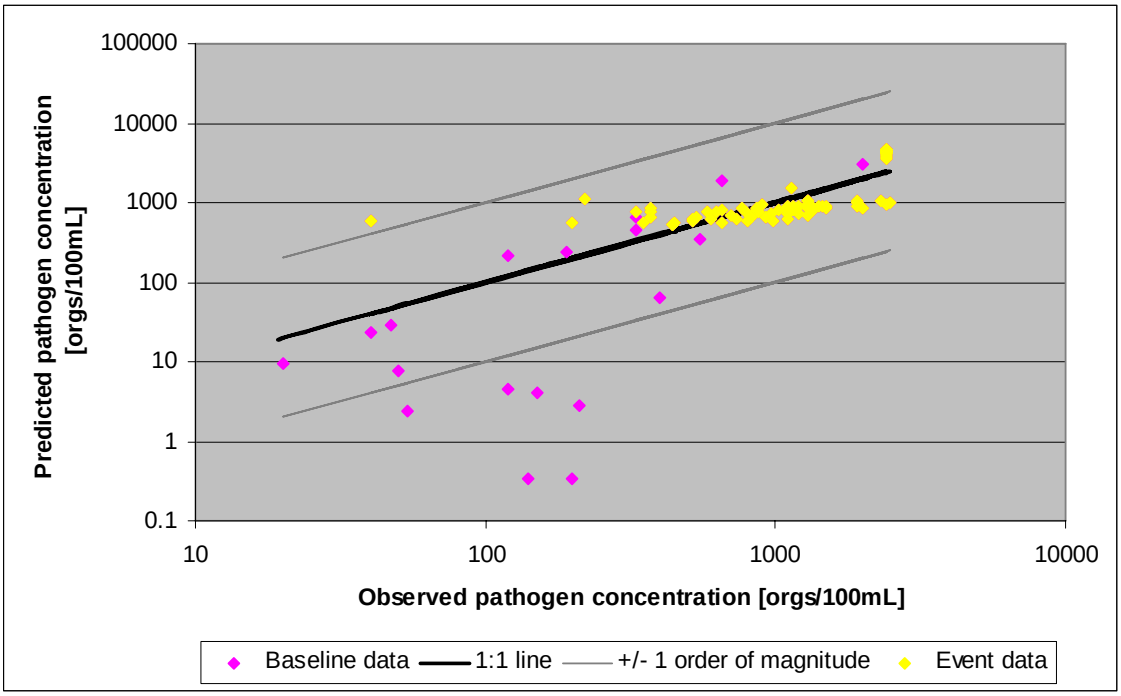

Figure 7.10 – East branch predicted pathogen concentrations versus observed concentrations showing the 1:1 line and ±1 order of magnitude

This graph clearly shows that the event data, and generally data with higher values, are very well represented by the model and that the majority of predicted results are within 1 order of magnitude of the observed results. When assessing pathogens it is a change in magnitude rather than an absolute change that is important to drinking water quality practitioners. A higher magnitude may mean that a more advanced treatment technology is required to ensure safe drinking water. The majority of the values outside of this 1 magnitude range are at the lower end of the observed pathogen concentration data set and are being underestimated – there are 4 additional points not shown in Figure 7.10 that were observed to be around 100 orgs/100mL and predicted to be below 0.1 orgs/100mL. This indicates that the baseflow concentrations in the model are not being predicted as well. This is most likely a result of the model being calibrated with a focus on the events.

Validation

Validation of the calibrated EG model was carried out using data from October 2007 to December 2007, which included Event 5. The results are shown in Table 7.10.

Figure 7.11 shows the visual fit of the calibrated model for Event 5 and Figure 7.12 shows that the majority of the predicted results throughout the period were within an order of magnitude of the observed results.

Table 7.10 – Validation statistics for EG in the East branch

Parameters						Calibration	Validation	
a_1	a_2	a_5	b_1	b_2		Overall	Overall	Event 5
$8x10^{-1}$	0	$5x10^{-6}$	400	$7x10^{-3}$	R^2	0.50	0.64	0.79
					E	0.28	0.46	0.11

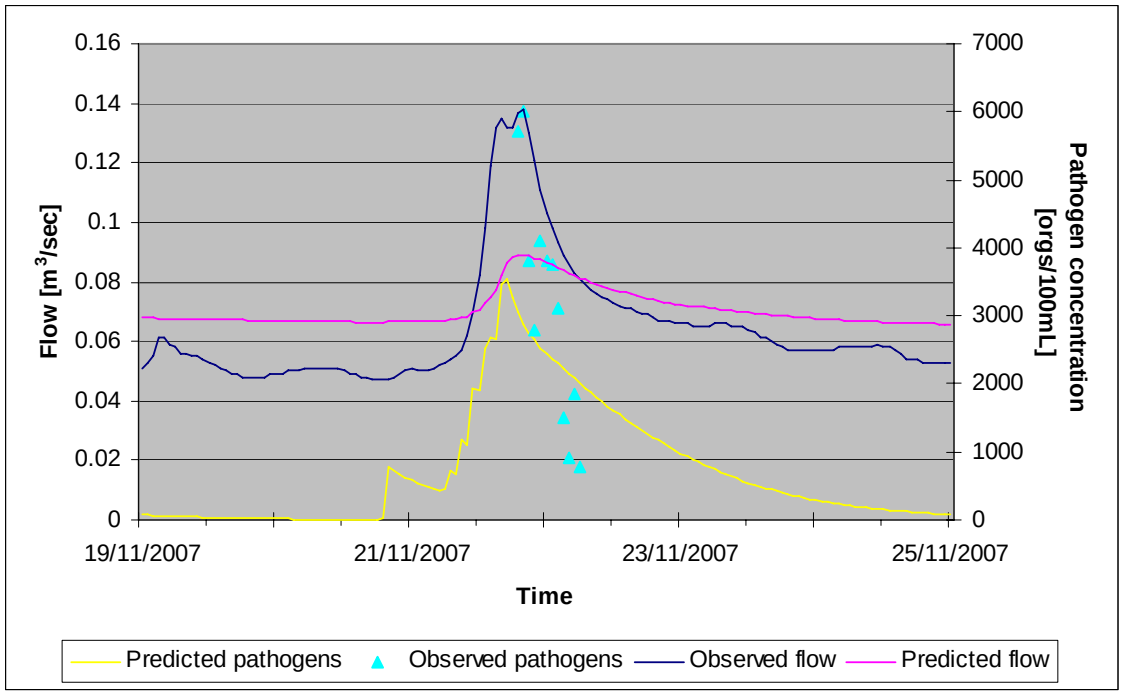

Figure 7.11 – EG validation results for the East branch during Event 5

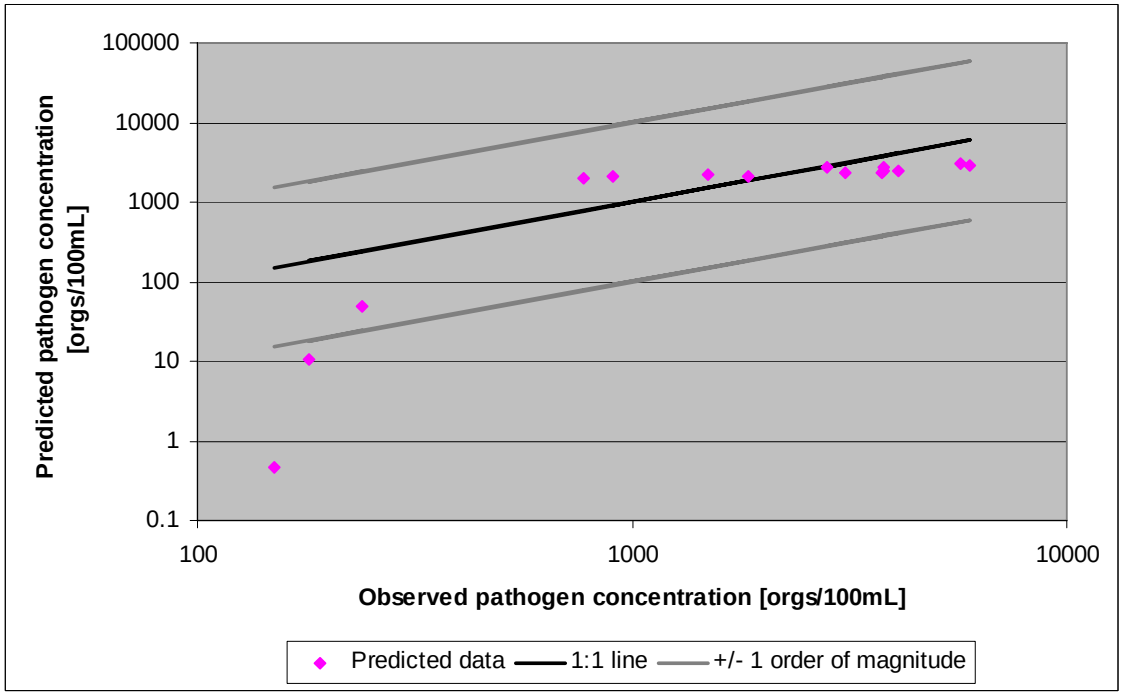

Figure 7.12 – East branch predicted pathogen concentrations versus observed pathogen concentration during the validation period

The calibrated EG model is slightly under-predicting the pathogen numbers during Event 5, most likely due to the hydrologic model under-predicting the size of the event. They are still, however, well within the required 1 order of magnitude. This is confirmed by Figure 7.12 where it can be seen that all data in the validations period, excluding 2 points, were within an order of magnitude.

Flux, load and EMCs

To further assess the performance of the validated model some additional comparisons were carried out between the predicted and the observed results. This is not meant as further validation but rather as a test of the models overall predictive ability. These included looking at fluxes as well as focusing on the Event Mean Concentrations (EMC) as the events are where the model fit is most important.

Pathogen fluxes are calculated by multiplying the concentration by the corresponding flow and then adjusting for units. Both flux and concentration data were compared for predicted and observed pathogen numbers. This was done for three different sets of data: the first was using all of the available data, the second was using all of the data without the values that were recorded as above the detection limit and the third was just the peaks from four events (Events 2, 3, 4 and 5) plus another date, where an *E. coli* sample was taken when the flow was relatively high (11/01/2006). Additionally the event loads for the sampling period of each of the 5 captured events were compared. The correlation statistics can be seen in Table 7.11.

Table 7.11 – Correlation statistics from additional assessments of the East branch EG model

		R^2	*E*
All data	***Concentration***	0.50	0.28
	Flux	0.49	-0.57
Without readings recorded as above detection limit	***Concentration***	0.68	0.62
	Flux	0.30	0.09
Peaks only (5 data points)	***Concentration***	0.45	0.23
	Flux	0.10	-0.70
Event load (5 data points)		0.56	0.45

This table shows that the concentration statistics improve when the censored data (data recorded as above the detection limit) is removed. Although the statistic related to flux decreased in terms of R^2, the *E* value increased indicating a better fit in terms of magnitude was being obtained without the censored data. For the “Peaks only” having

only 5 data points results in lower correlation statistics and this is most likely due to slight timing issues which will be more pronounced when looking at a limited number of points. The correlation statistics for the load data showed that the model performance was more than satisfactory with relatively high values for both R^2 and E. Overall, the flux, load and concentration data sets are represented reasonably well by the predicted data. Without including the data above the detection limit, 87% of the predicted concentration data was within an order of magnitude of the observed value. For the flux data, the figure was just as good with 88% within an order of magnitude. These additional tests confirm that the model is performing reasonably well.

To enable a comparison of the overall impact of the event, EMCs for all five events were evaluated. The five events plus the routine sample taken on the 11/01/2006 were looked at. The graph in Figure 7.13 shows the results of the predicted versus observed EMCs on a log scale graph.

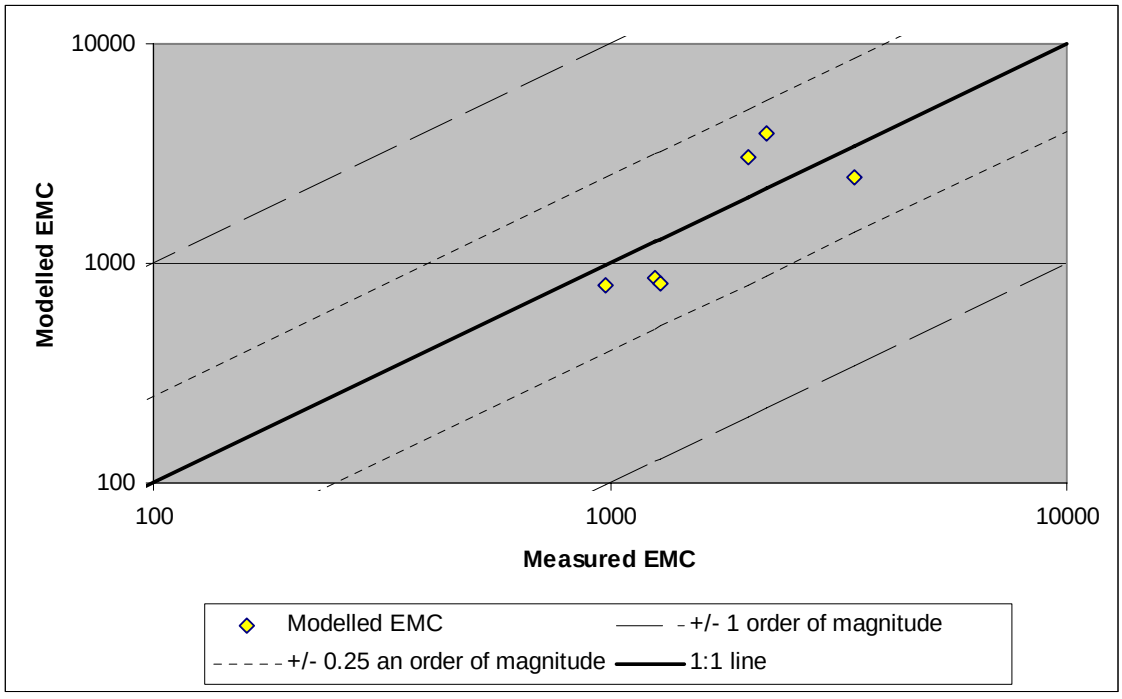

Figure 7.13 – Observed and predicted EMCs for the East branch

The above graph has error lines which represent 1 order of magnitude difference and 0.25 an order of magnitude difference from the observed results and shows that all predicted EMC results are within 0.25 an order of magnitude of the observed results. The model, therefore, is able to accurately predict the average pathogen concentration over an event. Given the highly varied pathogen concentrations likely over an event,

EMCs can describe overall event water quality and determine the effect of events as compared to baseflow conditions.

7.3.2 West branch

The quality of the *E. coli* field data from the West branch made calibration of the EG model more difficult, in terms of finding a satisfactory fit, than for the East branch. There are 67% less data points for the West site as compared to the East for the same time period. Additionally the *E. coli* levels in the West are an order of magnitude or more lower than those in the East. The low values are most likely the result of low deposition rates within the catchment due to its predominately native and therefore sparse animal population. During the one event that was captured in the West catchment *E. coli* numbers did not increase significantly from baseflow indicating that either the forested catchment is acting as a buffer during high rainfall or that there is a lack of available pathogenic contaminants. It may also be that the event was not large enough to mobilise large values of contaminants. These factors: number of data points, magnitude of values and limited variation, combined made calibrating the EG model more challenging.

The calibration period for the West was from 2005 to May 2007, which included the one event that was captured. The results from the manual calibration runs can be seen in Appendix F, Table F.6.

Results of the best run can be seen below in Table 7.12 and visually in Figures 7.14 and 7.15.

Table 7.12 – EG calibration results for the West branch

Parameters	a_1	a_2	a_5	b_1	b_2
	9.9×10^{-1}	0	8.1×10^{-4}	1000.9	3.7×10^{-2}
Calibration Statistics		**EG**		**SIMHYD**	
		Overall	**Event 1**	**Overall**	**Event 1**
	R^2	0.40	0.17	0.60	0.76
	E	0.31	-6.31	0.58	0.59

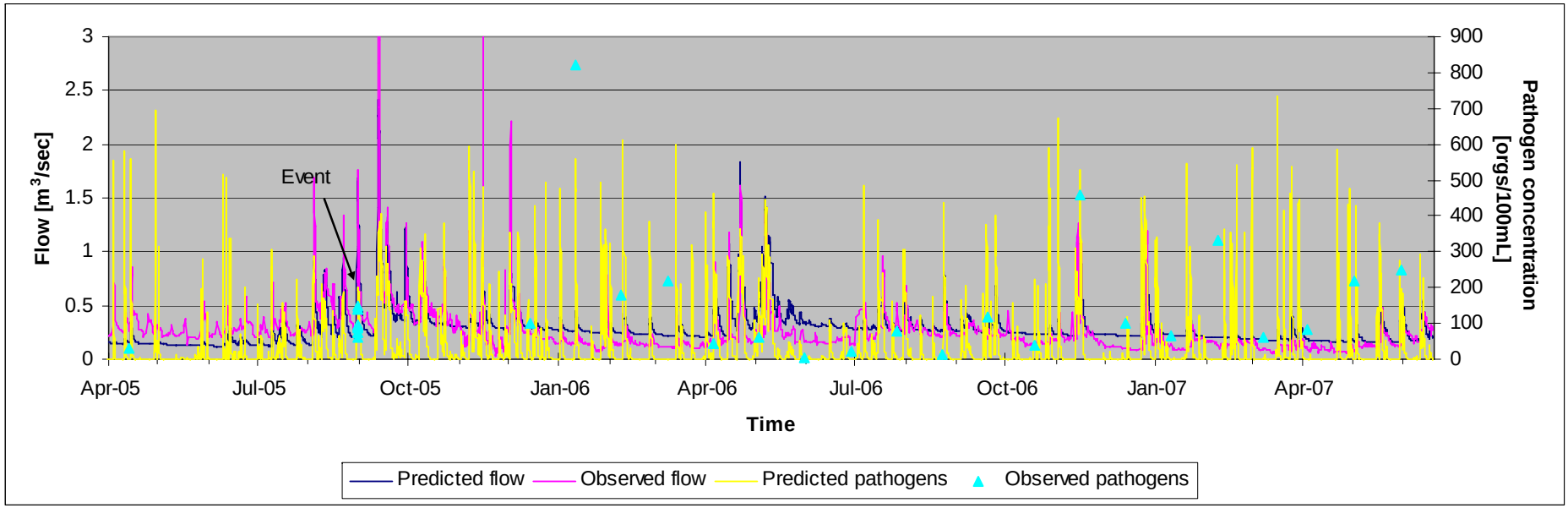

Figure 7.14 – West branch predicted versus observed flows and pathogens for the calibration period

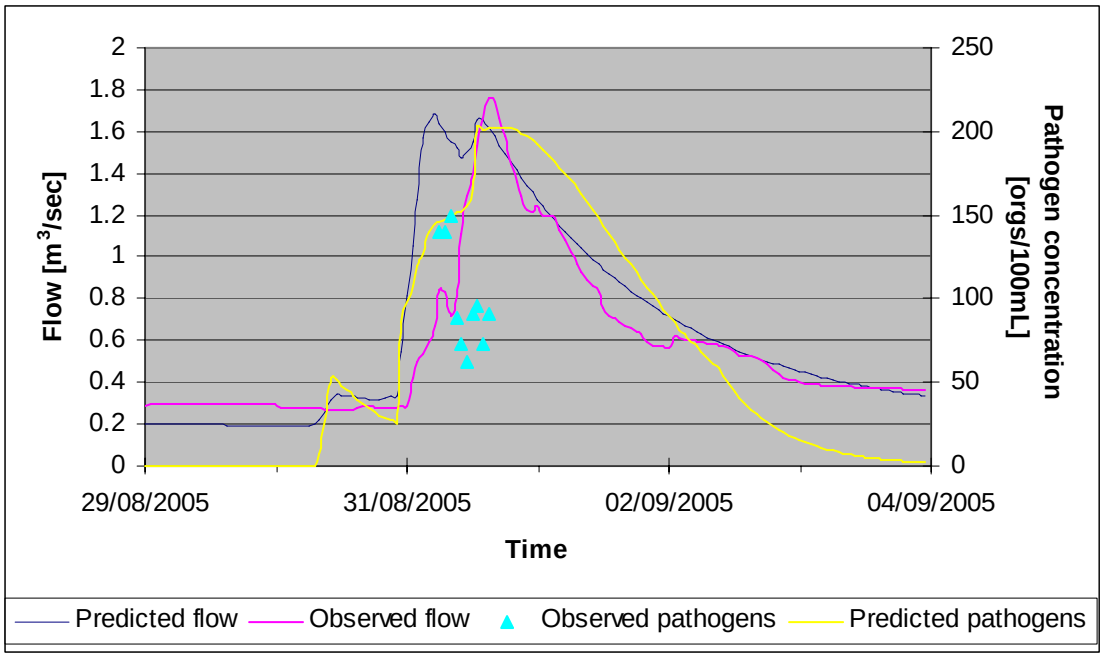

Figure 7.15 – Best EG calibration run for the event for the West branch

Despite the calibration statistics indicating a poor fit, visually the fit of the EG model to the observed pathogen data is acceptable. Figure 7.14 shows that, for the most part, the model is predicting the rise and fall of pathogens at the correct time and at the correct magnitude. The Event shown in Figure 7.15 is also acceptable as the predicted peak is within 50 orgs/100mL of the observed peak.

Validation

As the one captured high flow event in the West was used to calibrate the model, validation of the model was undertaken using baseflow data from May 2007 to December 2007. This period consisted of monthly samples resulting in 7 data points and equated to approximately 18% of the total *E. coli* data set for the West branch. Table 7.13 gives the results and visually in Figure 7.13.

Table 7.13 – EG validation results for the West branch

Parameters						Calibration		Validation
a_1	a_2	a_5	b_1	b_2		Overall	Event 1	Overall
9.9×10^{-1}	0	8.1×10^{-4}	1000.9	3.7×10^{-2}	R^2	0.40	0.17	0.06
					E	0.31	-6.31	-1.54

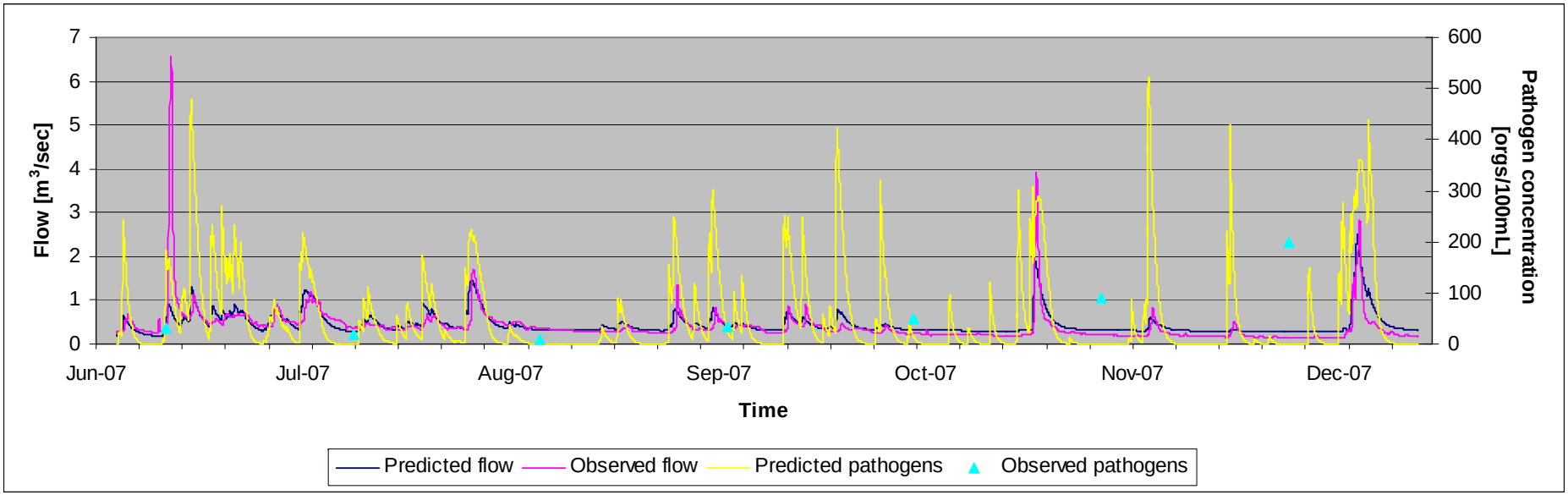

Figure 7.16 – EG validation for the West branch

Although the validation statistics are poor, the visual fit is generally satisfactory. The final two observed data points are being underestimated by the model which will greatly affect the statistics given the limited amount of data being used for validation.

Flux

A comparison of fluxes was undertaken for the West branch. It showed an acceptable correlation between predicted and observed fluxes: R^2 of 0.91 and E of -1.79 were achieved. Figure 7.17 shows how well the model is predicting pathogen fluxes in terms of order of magnitude (note the log scale on both axes).

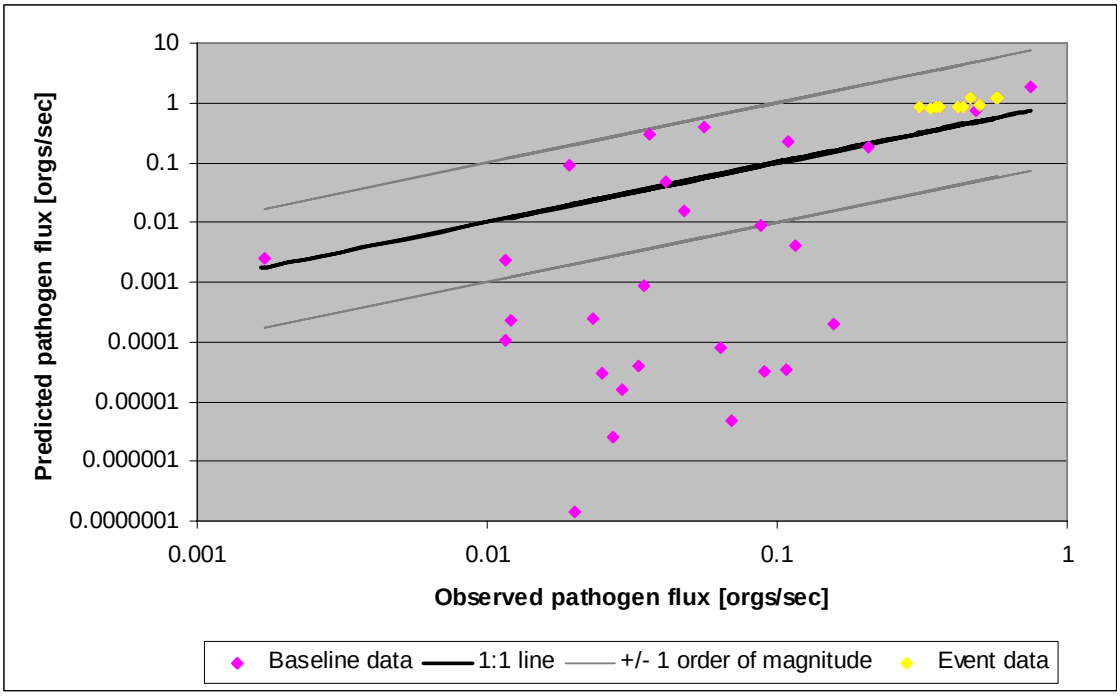

Figure 7.17 – West branch predicted versus observed pathogen fluxes showing 1:1 line and ±1 order of magnitude

This graph again shows that the model is under-predicting the lower observed fluxes. When the fluxes are higher, however, the predicted values are slightly above the observed. Although a perfect fit would be the ideal outcome, a model which slightly over-predicts the pathogen fluxes in high risk periods is an acceptable outcome. Over-estimating this risk when it comes to protecting public health is better than under-estimating it as it provides a greater margin of safety.

7.4 Summary and conclusions

The calibration of the hydrologic model for the East catchment of the Tarago was reasonably successful due to the high quality rainfall and streamflow data sets for the site. The calibration statistics for the West branch indicated that the predicted flow was not as accurate as the East and this was in part due to there being no direct measurement of the streamflow at that site.

A large number of calibration runs were done for each catchment using SIMHYD, and this allowed the rainfall combination and rainfall scaling that gave the best calibration statistics to be chosen. For each catchment, the rainfall gauges that combined to give the best fit corresponded well in terms of location to the streamflow gauging sites. The calibration runs which gave the best fits, in both catchments, were those that used a rainfall scaled by a factor of 0.8. As this result was catchment wide it is likely to be the result of drier than usual ground promoting infiltration. Alternatively, as both the East and West branches use streamflow data from the East gauge, the scaling could be due to an overestimation of streamflow in the East branch caused by silting up of the weir. Another factor could be the uncertainty related to rainfall measurement with tipping-bucket rain gauges as reported by Molini et al. (2001).

Modelling pathogens is more difficult than modelling hydrology due to the many uncertainties related to monitoring and detection. The inherent uncertainty due to sampling or laboratory error, along with the variations due to random and episodic events mean that predicted pathogen values within an order of magnitude of observed is acceptable. Given this, the overall performance of the EG model in the East and West Tarago catchments was satisfactory. The model for the West catchment did not perform as well as for the East which could be due to the smaller variation in *E. coli* numbers, the land-use within the catchment or the minimal data available with which to calibrate it with. The modelled fit for the West was still visually satisfactory as it is predicting pathogen values within an order of magnitude, especially the higher values. The pathogen fluxes in the West were well predicted which was also the case in the East.

In general the EG model is able to predict pathogen numbers within an order of magnitude. Given this, any quantification of the effectiveness of the buffer will be reported in a similar way.

The number of events captured in the East catchment allowed an assessment of how well the model predicted event peaks to be carried out. The censored pathogen data, that is data above the detection limit, was removed from the calibration, which improved the model performance. As discussed in Section 7.3 it is the events that are of most importance when modelling pathogens as this is when the majority of pathogens will be mobilised and therefore it is when the receiving water body is at the highest risk. It is therefore important that both the peaks and the event means are represented well by the model. Figure 7.10 shows that the EG model performs very well for these high runoff/high risk periods.

It is evident from this assessment of the EG model that it is important to not trust the calibration statistics implicitly without visually assessing the results in graphical form. What may seem like a bad fit from the R^2 and E numbers may just have some timing or variation anomalies which although affecting the calibration statistics may still follow the trend and predict the peak adequately.

Both SIMHYD and EG have been successfully calibrated for both catchments. The effectiveness of the buffer strip can now be assessed using these models by changing the buffer ratio. It will be important that when assessing the outcomes of a model to be aware of the quote from Box and Draper (1987) that “all models are wrong, but some are useful”. The usefulness of the coupled SIMHYD/EG model will be discussed in detail in the following Chapter.

8. BUFFER EFFECTIVENESS

8.1 Introduction

Both the hydrologic model and the EG model have now been calibrated for both the East and West branches of the Tarago River. The coupled SIMHYD/EG model can now be used to assess the effectiveness of buffer strips on reducing pathogen transport and improving drinking water quality. Additionally, a way of predicting any pathogen reduction following buffer implementation will be investigated.

In this chapter, only the East branch catchment is being considered due to two reasons: one being that the number of pathogens in the East is far greater than in the West meaning that there are more pathogens available to remove making the different scenarios easier to assess. The second reason relates to the superior calibration achieved in the East catchment compared to the West, as reported in Chapter 7.

A number of different analyses are undertaken with different buffer ratios to determine the overall effect of having a buffer. Both baseflow and storm flow conditions, will be assessed to confirm at which stage, or stages, during the hydrological process the buffer is having the most effect on pathogen numbers. This will assist any further analysis.

The relationship between storm characteristics and the effect of the buffer strips will be examined. Studies have shown that the transport of pathogens through catchments is related to runoff and storm intensity (Davies et al. 2004). The effectiveness of the buffer as transport of pathogens increases is of interest. The ability of the buffer strip to remove pathogens during large events is crucial for it to be a valuable and worthwhile investment in the catchment.

The ability to quantify the water quality benefits of implementing buffer strips along streams is of interest to most catchment managers. Being able to do this will mean they are able to more easily compare the investment requirements for catchment management to treatment costs. Although modelling alone should not be used to direct management decisions the outcomes can be useful in assessing the risk

reduction benefits of different options. To enable any benefits to be quantified, different buffer ratios will be assessed against each other.

It is not only an ability to quantify the benefits of buffer strips for pathogen removal that will be useful to catchment managers, but also a better understanding of how and when to sample for pathogens. This will also be discussed.

The EG model was calibrated in the East catchment with a buffer ratio of 0.85, as discussed in Chapter 7, it will be re-run with the same data, and calibrated parameters, with a buffer ratio of 0.00, or no buffer, and the effects of the different scenarios will be reported. Additionally EG will be run with other buffer ratios to determine if there are any trends or patterns related to buffer ratio. If trends or patterns do occur then these could potentially form the basis of a quantitative assessment and be of real benefit to catchment managers, landowners within the catchment and drinking water suppliers.

8.2 Overall buffer effectiveness

Within the modified EG model, pathogens transported in the baseflow are unaffected by buffer strips. Coupled with this, pathogens trapped by the buffer in the surface flow are not eliminated completely but put back into the sub-surface store. Once in the sub-surface store they are available for transport in the baseflow, re-entrainment in the surface flow or they can be eliminated as part of the sub-surface loss function. Therefore, although it seems most likely that the effect of the buffer will only be seen when there is surface runoff, ie during storm events, there may be some impact on the pathogen numbers in the other flow paths.

In order to determine the extent to which the trapped pathogens affect pathogen numbers in the baseflow, the stores and the loss functions the calibrated model was run with a buffer ratio of 0.00 and compared to the results from the original calibrated model, which had a buffer ratio of 0.85. The model was run over a 4 year period, from 2004 to 2007 inclusive and the percentage difference in summed pathogen numbers in each flow path over the whole time period is investigated.

The output from EG gives pathogen numbers at all stages of the modelling process; that is for each of the flow paths, storages and loss functions for each time step, allowing an assessment of the effect on the buffer on each of the model components.

A comparison between 0.85 buffered and non-buffered model runs in terms of the summed total of each of the EG modelling outputs for the specified time period was carried out. The 4 year time period includes both baseflow and stormflow periods. Table 8.1 shows the percentage decreases in pathogen numbers when comparing a non-buffered catchment to a buffered one.

Table 8.1 – Comparison of total summed pathogen numbers between non-buffered catchment and 0.85 buffered catchment scenarios

Variable	Definition	% decrease[18]
$P_{s,loss}$	Pathogens lost from the surface	0.00%
$P_{in.fil}$	Pathogens being transported from the surface to the sub-surface	0.00%
P_{ss}	Pathogens in the sub-surface store	-0.04%
$P_{ss,loss}$	Pathogens lost from the sub-surface	-0.02%
$P_{in.ter}$	Pathogens transported in the storm flow	83.67%
P_{bas}	Pathogens transported in the baseflow	-0.05%
P_{total}	Total pathogens in the stream	23.07%

The slight increases, for the summed totals of P_{ss}, P_{bas} and $P_{ss,loss}$, is due to the fact that the pathogens trapped by the buffer are deposited back into the sub-surface store. This therefore increases the pathogen numbers in that store and means that there are more pathogens that can be lost and that are available for transport in the baseflow. The increases are however very minor and is practically insignificant. $P_{in.fil}$ and $P_{s,loss}$ were not impacted at all by the buffer. This is expected as they relate to the movement of pathogens from the surface store. The relatively large percentage differences in $P_{in.ter}$ and P_{total} indicates that the buffer strip is having a significant effect on pathogen numbers in the storm flow and subsequently in the total pathogen numbers. These results are not unexpected given that the buffer is only really affecting pathogen numbers in the storm flow.

The percentage differences seem large and the significance of the differences was further confirmed with the use of a t-test. It was performed to ensure that the total

[18] Negative values in this table represent an increase in pathogen numbers

pathogen numbers from a buffered catchment as compared to a non-buffered catchment were statistically significantly different. Equation 5.2 is again used.

$$t = \frac{\overline{X}_E - \overline{X}_B}{\sqrt{\frac{SD_E^2}{n_E} + \frac{SD_B^2}{n_B}}} \qquad \text{(Equation 5.2)}$$

where:

$\overline{X}_E$ = mean P_{total} in a 0.85 buffered catchment

$\overline{X}_B$ = mean P_{total} in a non-buffered catchment

SD_E = standard deviation P_{total} in a 0.85 buffered catchment

SD_B = standard deviation P_{total} in a non-buffered catchment

n_E = number of predicted points

n_B = number of predicted points

The test was carried out over a 4-year time period and resulted in a value of 8.8. This large positive value means that overall the total pathogen numbers being transported to the stream in a buffered catchment are significantly lower ($\propto$ >0.05) to those transported in a non-buffered catchment. It is therefore worthwhile investigating this difference.

An initial step was to confirm that the stage of the hydrological cycle when the buffer is most effective was during storm events. To do this, a time series of the results for a buffered and non-buffered catchment was plotted along with the corresponding flows. Figure 8.1 shows a sub-set of the total time period used.

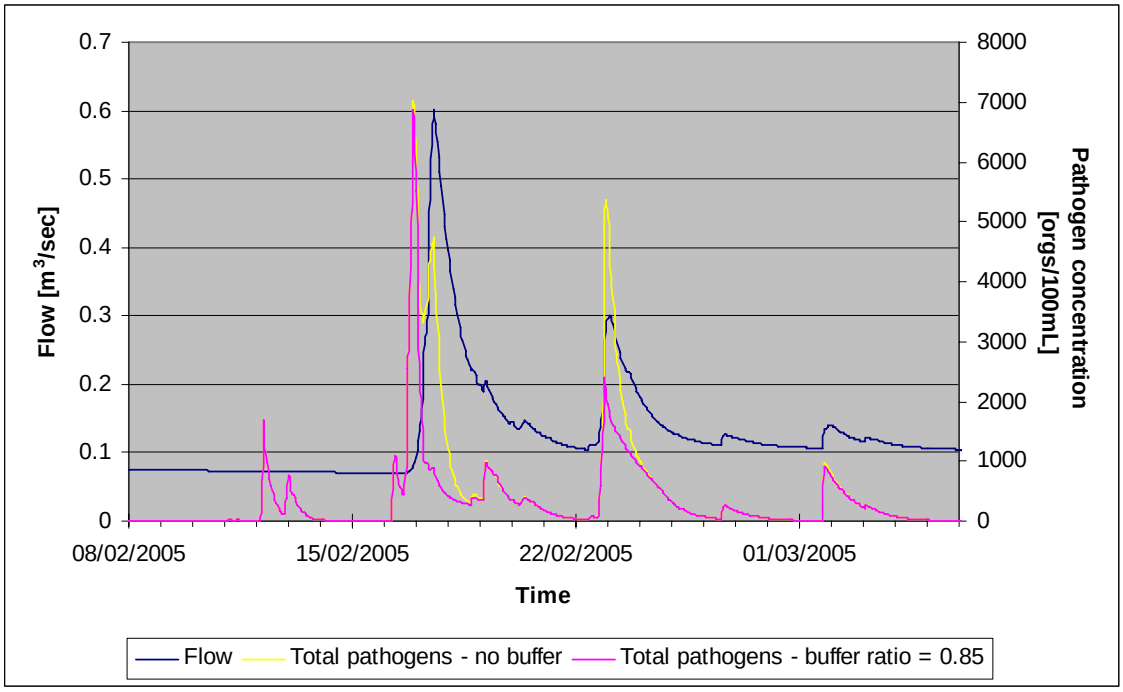

Figure 8.1 – Total pathogen concentrations for a buffered and non-buffered catchment showing both baseflow and stormflow periods

It is clear from this figure that total pathogen numbers, for the majority of the time, are the same regardless of whether there is a buffer present or not. It is only large increases in flow that result in a difference in the total pathogen numbers. This verifies that it is only during storm events that the buffer is having any effect on pathogen movement. Total pathogen numbers during baseflow are virtually the same for buffered and non-buffered catchments. This result essentially confirms that the modifications made to EG are affecting the model outcomes as expected.

The outcomes has implications for water quality sampling regimes when the objective of sampling is to determine the decrease in pathogens due to on-ground works. Collecting routine samples only during baseflow conditions is not likely to show any difference in pathogen numbers. It is necessary to collect storm samples both before and after any works to determine the magnitude of the effect and to show that the buffer is an effective barrier.

It is clear from the literature, that having a buffer will only impact pathogen numbers during storm events and the modified EG model is also showing this. An assessment of this impact is now necessary with a focus on determining the magnitude of that affect. In order to do this a number of storm events that occurred during the modelling period were extracted to be looked at in detail. These storms will be used to determine

by how much pathogens can be reduced during large events, if this reduction is related to storm characteristics and what effect different buffer ratios can have on pathogen reduction during storms.

8.2.1 Choice of storms to analyse

A total of 15 storm events were chosen to be analysed, including the 5 storm events for which water quality samples were taken and used for the model calibration and 10 randomly chosen events. The chosen storm events covered both high and low flow events as well as events of short and long duration, see Appendix G, Figure G.1. A mixture of different storm events was important to allow any relationships between pathogen number reduction and storm characteristics to be revealed. The storm characteristics that were assessed were:

- peak flow during the event [m^3/sec]
- the total event volume [ML]
- the average flow throughout the event [m^3/sec].

A summary of each of the storm events, along with their Average Return Interval (ARI), can be seen in Table 8.2.

Table 8.2 – Storm characteristics for events chosen for analysis

Storm date	Event duration [*hours*]	Peak flow [m^3/*sec*]	Event volume [*ML*]	Average flow [m^3/*sec*]	ARI [*years*]
September 2004	46	0.29	31.69	0.20	<1
February 2005	46	0.51	53.83	0.28	5
August $2005_{(1)}$	73	0.10	19.25	0.08	<1
August $2005_{(2)}$	57	0.30	31.90	0.16	<1
September 2005 (Event 1)	57	0.39	53.76	0.25	<1
May 2006	40	0.18	19.77	0.13	<1
August 2006	64	0.17	20.34	0.10	<1
November 2006 (Event 2)	50	0.09	11.56	0.07	<1
December 2006	40	0.08	7.51	0.06	<1
June 2007 (Event 3)	52	0.17	14.19	0.09	<1
August 2007	68	0.26	37.26	0.17	<1
September $2007_{(1)}$ (Event 4)	47	0.22	20.51	0.15	<1
September $2007_{(2)}$	53	0.21	22.60	0.14	<1
November $2007_{(1)}$	39	0.36	22.51	0.24	1
November $2007_{(2)}$ (Event 5)	38	0.15	10.67	0.11	<1

As is evident from the ARI values, the majority of the chosen storms were not particularly large (ARI < 1), the exceptions being the November 2007 storm (ARI = 1) and the February 2005 storm (ARI = 5). No larger storms occurred during the sampling period. This is a result of the time in which this study was undertaken, which was during the driest period on record; Victoria's driest 11-year period in history was

between 1997 and 2007 (Australian Government, 2008). The storm events will be referred to as large or small based on a relative comparison.

During analysis, the pathogen data during the storm events was summarised in a number of different ways, these included:

- average pathogen concentration [orgs/100mL]
- peak pathogen concentration [orgs/100mL]
- average pathogen flux [orgs/hour]
- peak pathogen flux [orgs/hour]
- Event Mean Concentration (EMC) [orgs/100mL]
- total pathogen event load [orgs].

Each of these data sets will give different information as to how well the buffers work and under what flow conditions. The different information will also be relevant to different stakeholders, which will be explored in the Section 8.6.

In order to allow a more complete evaluation of the effect of different buffer ratios during storm events on the different pathogen data sets, the EG model was run with a ratio of 1.00 and 0.50 to add to the results from buffer ratios of 0.85 and 0.0.

8.3 Relationship between flow and buffer effectiveness

Looking at Figure 8.1 along with the hydrographs of the other chosen events, which can be seen in Appendix G, Figures G.2 to G.16, it seemed that there was a relationship between the storm size and the effect of the buffer on pathogen numbers. The larger the peak flow of the event the larger the difference between the pathogen numbers transported in a buffered to those in a non-buffered catchment. The validity of this observation was tested using regression analysis.

Two different analyses related to storms and pathogen numbers were carried out; the first simply looked for a relationship between storm characteristics and pathogen transport, and the second considered the difference between a buffered and non-buffered catchment and the size of this difference as it related to the different storm characteristics.

The total pathogen numbers for each event for the four different buffer scenarios - ratios of 1.00, 0.85, 0.50 and no buffer - were plotted against the storm characteristics

(see Table 8.2) for that event. A number of different regression types were trialled in an attempt to find a significant relationship between pathogen numbers and storm characteristics. For example, Appendix G, Table G.1, shows the results of these regressions. Both power and logarithmic relationships were disregarded due to their poor correlation statistics in comparison to the other relationships. The 2nd order polynomial relationships, although they resulted in good correlation values, were also disregarded due to the shape of the best fit lines being unsatisfactory. Appendix G, Figure G.20 shows that this relationship would return a negative value for pathogen numbers which is not possible. Of the two relationships remaining, linear and exponential, the latter had the better correlation statistics.

Of the three storm characteristics, and using an exponential relationship, peak flow resulted in the highest R^2 values. Table 8.3 shows the correlation statistics for each pathogen data set and each buffer ratio.

Table 8.3 – R^2 values for exponential relationships between peak flow and pathogen numbers for different buffer ratios

	1.00	0.85	0.50	0.00
Average concentration	0.44	0.53	0.61	0.64
Peak concentration	0.34	0.40	0.57	0.64
Average flux	0.73	0.78	0.82	0.83
Peak flux	0.67	0.79	0.82	0.83
EMC	0.46	0.56	0.64	0.67
Event load	0.80	0.85	0.86	0.86

The relationship between peak flow and peak pathogen flux resulted in good correlation statistics across the different buffer ratios. This relationship is in part due to peak flow being represented on both axes and therefore the two variables are not independent (Sanders et al. 1980). This is known as cross correlation. It is important to be aware of this issue throughout all of the regression analyses. The same issue may also be slightly influencing the statistics for the other pathogen data sets concerned with flux and load.

Figure 8.2 illustrates the exponential relationship between peak flow and event load for each buffer ratio; note the log scale on the “y” axis. It also shows the equation for each relationship (equations for the other exponential relationships with peak flow can be found in Appendix G, Table G.2).

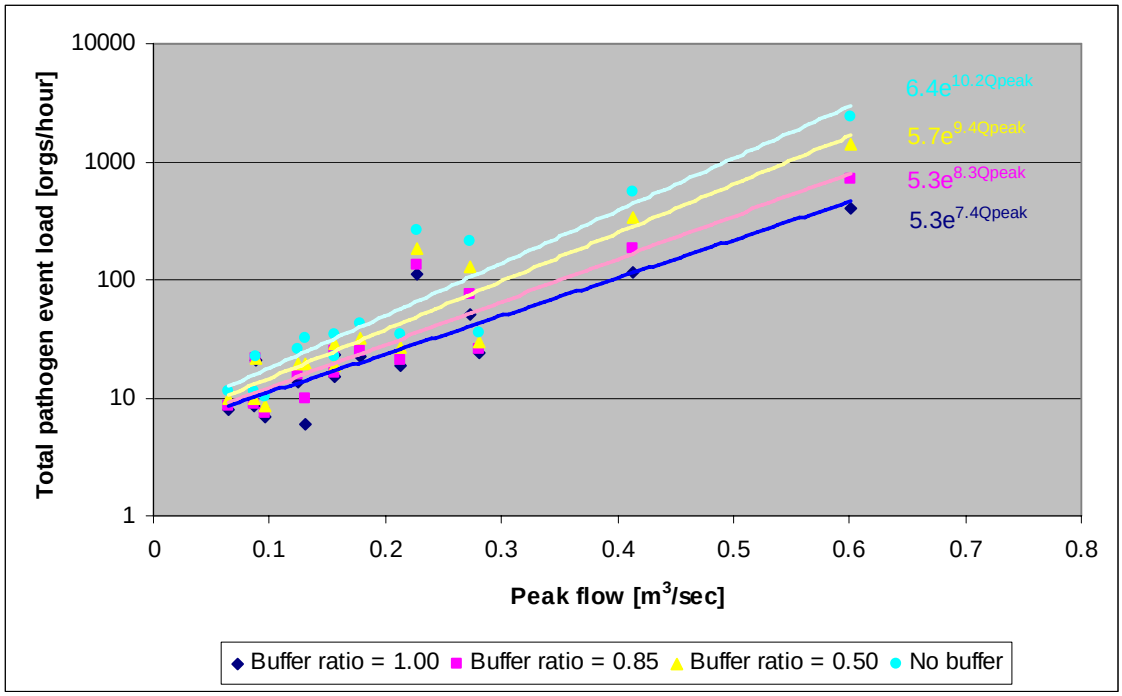

Figure 8.2 – Relationships between peak flow and event load for different buffer ratios

The exponential relationship implies that the pathogen transport rate increases very rapidly for large peak flow values. The significance of the exponential relationship is most likely the result of the data set being weighted towards smaller storms.

The second analysis in relation to storm characteristics, looked at the difference between a catchment with a buffer ratio of 1.00 and a non-buffered catchment. In analysing this relationship, it is important to appreciate the way that the difference is expressed. It can be absolute, which is a simple subtraction of the total pathogen numbers between different buffer scenarios, or as a percentage difference. The benefit of using percentage difference is that it removes the effect of the magnitude of the event from the difference. This means that the percentage difference figure can be used in regression analysis against storm characteristics without the issue of cross correlation. Both absolute and percentage differences were assessed.

Regression was trialled using linear, exponential and logarithmic relationships. The results for the exponential regression for the absolute difference between total pathogen numbers and storm size showed the strongest relationship. This relationship is not unexpected given that the bigger storms will mobilise a larger number of pathogens in the catchment and transport them in the storm flow. This in turn gives the buffer the opportunity to filter out more pathogens as more are available, compared to a smaller event. In terms of the percentage difference correlations, the relationships

were not as strong but they still showed a general trend that indicated that the larger an event the more affect the buffer will have on pathogen numbers. As explained above, these relationships are independent of flow. Table 8.4 shows these results.

Table 8.4 – R^2 values for exponential relationship for the difference in pathogen numbers in a non-buffered catchment compared to one with a buffer ratio of 1.00 and storm characteristics

	Absolute difference			Percentage difference		
	Peak flow	**Total volume**	**Average flow**	**Peak flow**	**Total volume**	**Average flow**
Average concentration	0.67	0.48	0.60	0.39	0.37	0.32
Peak concentration	0.68	0.54	0.62	0.32	0.35	0.28
Average flux	0.80	0.64	0.75	0.42	0.39	0.41
Peak flux	0.80	0.65	0.75	0.47	0.46	0.35
EMC	0.68	0.50	0.61	0.42	0.39	0.41
Event load	0.80	0.68	0.75	0.42	0.39	0.41

The equations for each of these relationships are displayed in Table E.3. They show for example, that the absolute difference in pathogen event load between a catchment with no buffer and a catchment with a buffer ratio of 1.00 can be calculated using Equation 8.1.

$$\Delta_{EL} = 1.43e^{12.99Q_{peak}} \qquad \text{(Equation 8.1)}$$

where:

Δ_{EL} = difference in event load

Q_{peak} = peak flow

With a peak flow of, for example, 0.40 m^3/sec the difference in event load between a buffered and non-buffered catchment would be 258 organisms.

The best correlation figures from the relationships that looked at storm characteristics, for both pathogen transport and the difference in transport between different catchment scenarios, were obtained between peak flow and total pathogen event load. The applicability of these relationships in a practical sense relies on having an accurate prediction of the peak flow, which may be difficult to obtain, and has implications for monitoring strategies as discussed in Section 8.6.

The following section focuses on comparing the predicted results of a catchment with no buffer, to a catchment with some known buffer ratio. This will allow the benefits of having a buffer to be quantified, independent of flow and lead to outcomes and recommendations which are useful for stakeholders within the catchment.

8.4 Comparison of different buffer ratios

Comparing the absolute pathogen numbers that are transported through a catchment with different buffer ratios will determine the reduction in pathogen numbers given a change in buffer ratio. This will quantify the benefits of having a buffer.

Regression analysis was undertaken in order to find a relationship between pathogen numbers in the non-buffered catchment and pathogen numbers in catchments with different buffer ratios. As done previously, linear, exponential and logarithmic relationships were trialled, Table G.4 in Appendix G shows these results. A linear relationship gave the best correlation statistics and Table 8.5 shows the equations and the R^2 values. These relationships have been forced through the origin, which is logical, as it represents a situation where there are no available pathogens in the catchment, meaning that neither the buffered nor the non-buffered catchment would be transporting pathogens. Forcing the relationship through the origin means that the gradients can be recorded and compared as they represent the change in pathogen numbers between the different scenarios.

Table 8.5 – Equations and R^2 values for linear relationship between pathogen numbers in a non-buffered catchment and pathogen numbers in a buffered catchment[19]

	1.00 buffer ratio		0.85 buffer ratio		0.50 buffer ratio	
	Equation	**R^2**	**Equation**	**R^2**	**Equation**	**R^2**
Average concentration	y=0.26x	0.83	y=0.37x	0.94	y=0.63x	0.99
Peak concentration	y=0.15x	0.67	y=0.21x	0.83	y=0.53x	0.99
Average flux	y=0.18x	0.95	y=0.30x	0.99	y=0.59x	1.00
Peak flux	**y=0.06x**	0.88	y=0.19x	0.99	y=0.52x	1.00
EMC	y=0.19x	0.75	y=0.31x	0.94	y=0.60x	0.99
Event load	y=0.18x	0.96	y=0.30x	0.99	y=0.59x	1.00

where:

y = difference in pathogen numbers

x = pathogen numbers in a non-buffered catchment

[19] The relationships are forced through zero

The gradients signify the difference in pathogen numbers expected in a buffered catchment during a storm event compared to the same catchment without a buffer in the same storm event. As an example, for the same storm event the peak pathogen flux in a catchment with a buffer ratio of 1.00 will be 0.06 times that in a non-buffered catchment, see bold equation in Table 8.5. This can be expressed in a number of other ways:

- a 94% reduction in peak pathogen flux in the buffered catchment
- inverting 0.06 reveals that peak pathogen flux will increase by almost 17 times in the non-buffered catchment compared to a buffered one
- taking the $\log_{10}$ of this figure gives a magnitude difference between the different scenarios of 1.22.

The results from the regression analysis in Table 8.5 for peak flux are plotted in Figure 8.3; note the log scale on both axes.

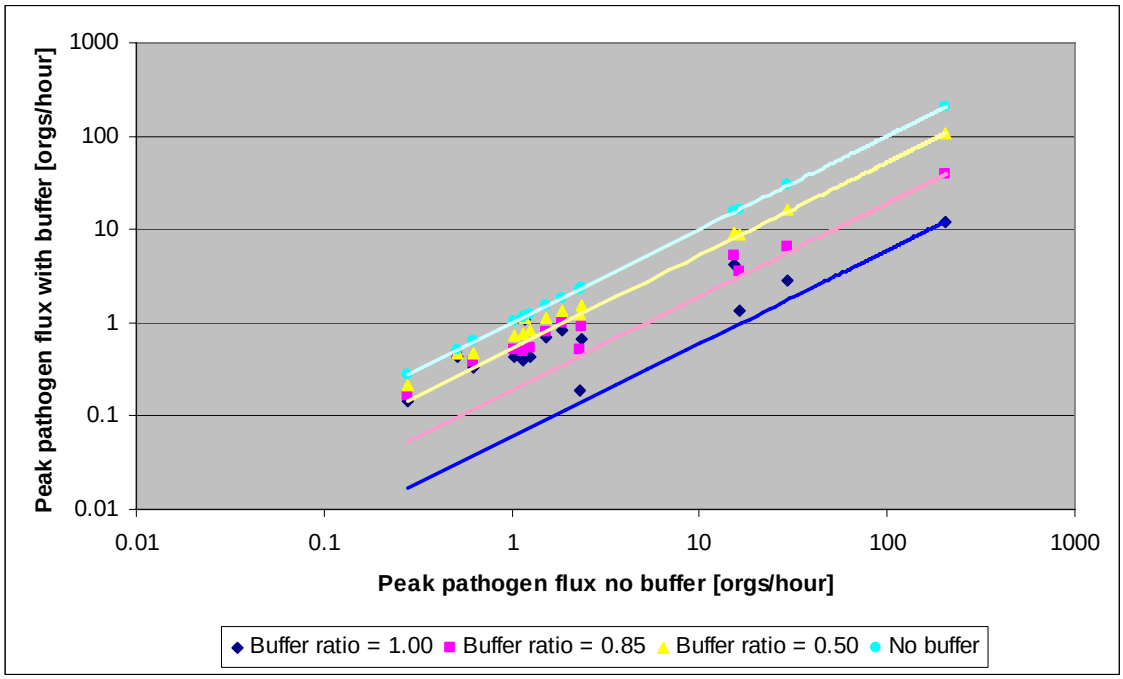

Figure 8.3 – Peak pathogen flux in a non-buffered catchment compared to peak pathogen flux in catchments with different buffer ratios

Given the relatively good correlation statistics calculated above and the meaningful gradients of these relationships, more work was done in an attempt to determine a practical and useful relationship between different buffer scenarios. One of the main aims of this work is to determine whether it is possible to quantify the benefits, in terms

of pathogen transport, of having a buffer as compared to not having one. Similarly catchment managers want to know how much improvement they could expect in their catchment, which may already have some amount of buffering, if they were to increase its buffer ratio.

Table 8.5 was created comparing a catchment with no buffer to catchments with differing buffer ratios. The same analysis was done comparing catchments with some buffer to those with a higher buffer ratio. These results can be seen in Appendix G, Tables G.5 to G.7. Overall the correlation statistics were very good. As discussed previously, the gradients of the linear regression equations represent the change in pathogen numbers between scenarios with different buffers. Gradients higher than 1.00 indicate that there is an increase in pathogen numbers; this occurs when the buffer ratio is decreased. Peak flux was the pathogen data set most influenced by a change in buffer ratio as it returned the smallest gradients indicating the largest change.

For each pathogen data set, a matrix containing the rate of change (the gradients) for pathogen numbers between two scenarios with different buffer ratios were constructed, see Table 8.6 for the peak flux results. Tables G.8 to G.12 in Appendix G show the gradient matrices for each of the other pathogen data sets. In order to make things clearer the gradients were inverted so instead of representing the increase in pathogen numbers between catchments they now represented the decrease in pathogen numbers, with a number above 1.00 indicating a decrease.

Table 8.6 – Peak flux matrix showing gradients of linear relationships between different buffer ratios

		Final buffer ratio			
		0.00	**0.50**	**0.85**	**1.00**
Starting buffer ratio	**0.00**	1.00	1.92	5.26	16.67
	0.50	0.52	1.00	2.78	9.09
	0.85	0.19	0.36	1.00	3.13
	1.00	0.07	0.12	0.34	1.00

The numbers in these matrices were plotted and it was evident that as expected there was a linear relationship for each final buffer ratio. Figure 8.4 shows the relationship between the starting buffer ratio and the expected reduction in peak pathogen flux. The different lines represent different final buffer ratios in the catchment. The figure also displays the linear relationships and their correlation statistics.

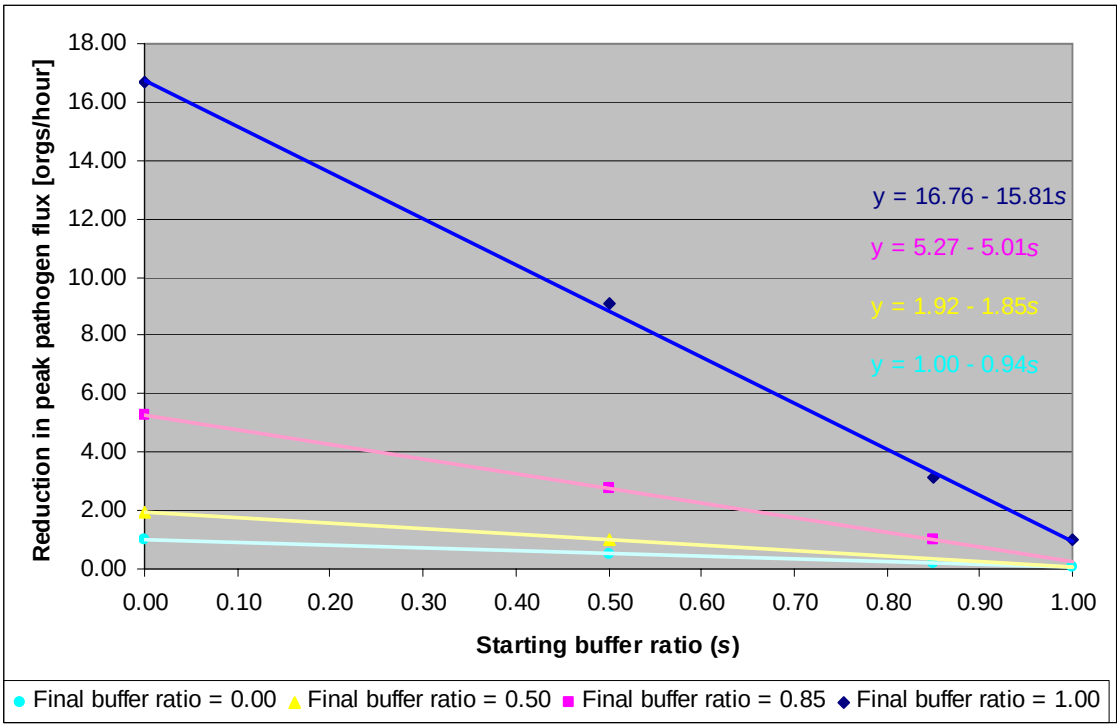

Figure 8.4 – Starting buffer ratio and reduction in peak pathogen flux given different final buffer ratios

Figure 8.4 is useful for determining the likely reduction in pathogen flux between the four buffer ratios represented. However, an understanding of the reduction in pathogen numbers between a varied range of buffer ratios is considered more useful. A relationship that relates a change in pathogen numbers to a change in buffer ratio, not necessarily the buffer ratios investigated, may be more beneficial to catchment and drinking water quality managers. Feasible questions that may be asked could include:

- "What magnitude of pathogen reduction could be expected if the existing buffer ratio in the catchment was increased?" or
- "To achieve a 1-log reduction in pathogen numbers, what does the existing buffer ratio need to be increased to?"

In order to answer these questions it was necessary to further develop the relationships gained from the matrices.

For each final buffer ratio linear equations relating starting buffer to a change in pathogen numbers were produced, each with a unique gradient and an intercept, as shown on Figure 8.4. These intercepts and gradients were collated and plotted for each pathogen data set. Although no strong mathematical relationship was evident, plotting the points and connecting them formed a smooth line, which can be used to construct useful equations. Figure 8.5 shows these lines for peak flux.

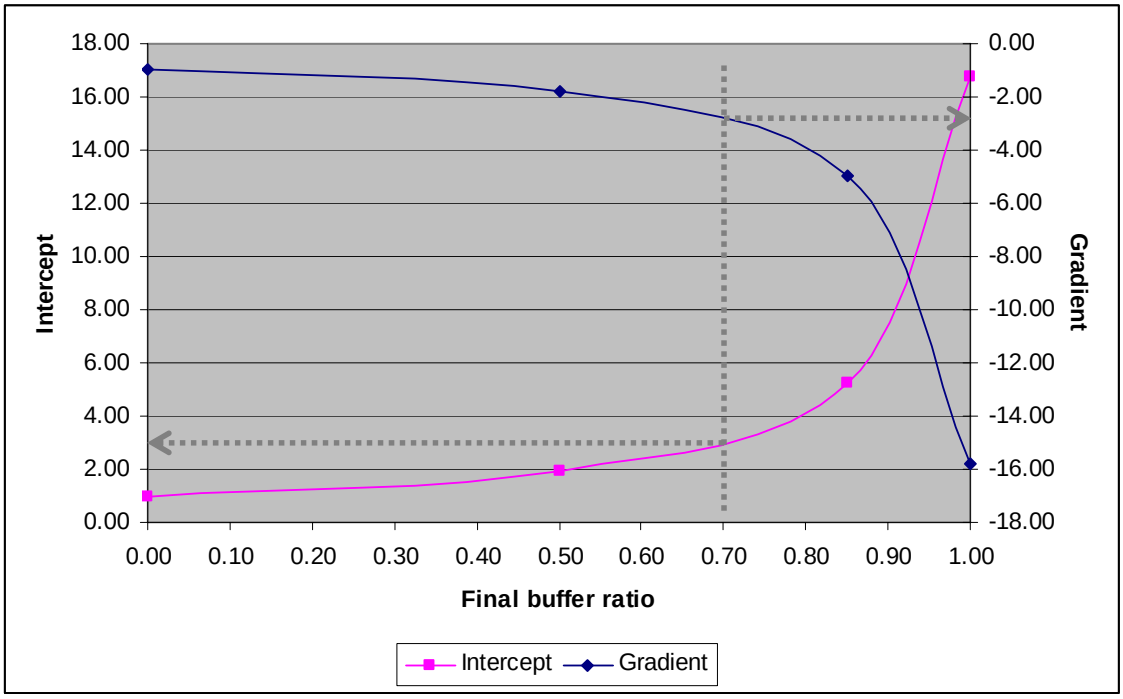

Figure 8.5 – Determining the equations for peak flux for different final buffer ratios[20]

The shape of the gradient line in Figure 8.5 indicates that as the final buffer ratio increases so too does the effect of that buffer on pathogen numbers (the larger negative numbers represent a bigger reduction).

Graphs similar to Figure 8.5 were created for each of the pathogen numbers. From these graphs it is possible to construct useful equations by reading off values for the gradient and intercept for any final buffer ratio. The equation created, Equation 8.2, relates the starting buffer ratio with a reduction in pathogen numbers.

$$y_{(f)} = I - Gs \qquad \text{(}\textit{Equation 8.2}\text{)}$$

where:

$y_{(f)}$ = reduction in pathogen number of a final buffer ratio *f*

I = intercept

G = gradient

s = starting buffer ratio

[20] Note the negative values on the "Gradient" axis

For example, as shown by the dotted lines in Figure 8.5, a final buffer ratio of 0.70 would result in the Equation 8.3.

$$y_{(0.7)} = 2.95 - 2.80s \qquad \text{(Equation 8.3)}$$

where:
$y_{(0.7)}$ = reduction in peak flux

These equations were created for final buffer ratios of 0.20, 0.40, 0.60, 0.80, 0.90 and 1.00 for each pathogen data set.

Using pathogen flux as an example, the gradients and intercepts were obtained from Figure 8.5 and resulted in the following equations:

$$y_{(0.2)} = 1.25 - 1.20s \qquad \text{(Equation 8.4)}$$

$$y_{(0.4)} = 1.58 - 1.48s \qquad \text{(Equation 8.5)}$$

$$y_{(0.6)} = 2.38 - 2.22s \qquad \text{(Equation 8.6)}$$

$$y_{(0.8)} = 4.10 - 3.95s \qquad \text{(Equation 8.7)}$$

$$y_{(0.9)} = 7.45 - 7.05s \qquad \text{(Equation 8.8)}$$

$$y_{(1.0)} = 16.76 - 15.81s \qquad \text{(Equation 8.9)}$$

Figure 8.6 plots these equations. It shows the decrease in pathogen flux that would be expected during a storm event against the starting buffer ratio for different final buffer ratios. Note that the “y axis” starts at 1.00. Any value below 1 indicates an increase in pathogen numbers and is not relevant if the buffer ratio is being increased.

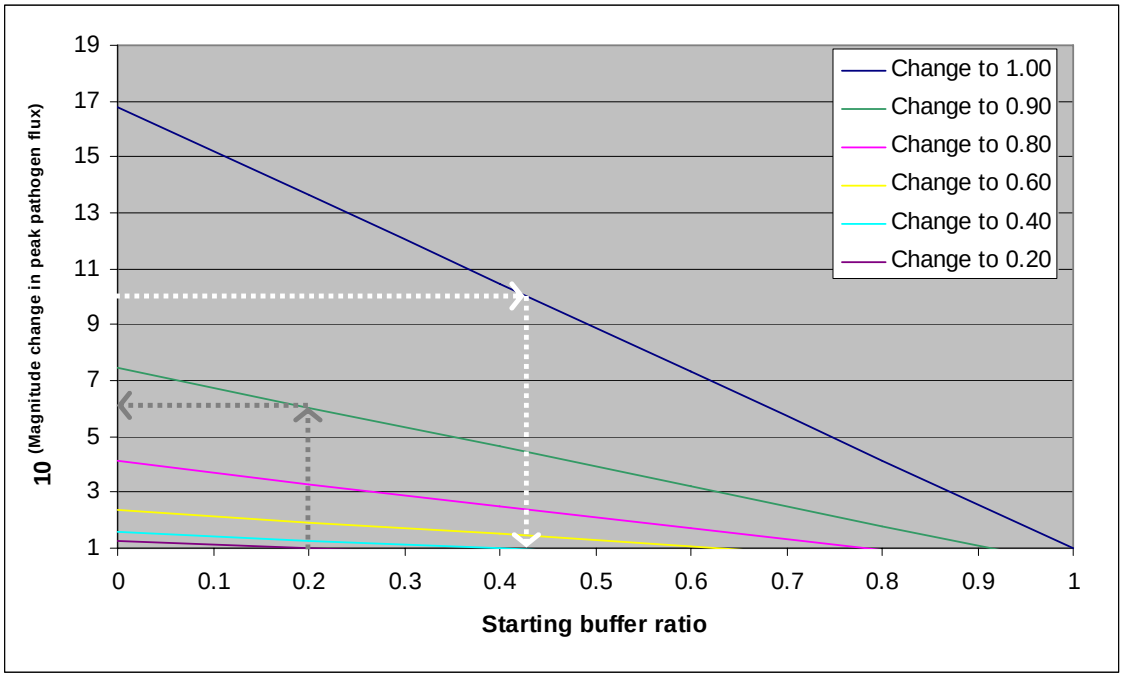

Figure 8.6 – Starting buffer ratio against change in pathogen flux for different final buffer ratios

The above analysis was carried out for all the other pathogen data sets and the equations are shown in Table 8.7.

The plots for each of the pathogen data sets can be found in Appendix H, Figures H.1 to H.5.

Table 8.7 – Equations to determine the decrease in pathogen numbers (*y*) for selected final buffer ratios (*f*)

$y_{(f)}$	Average concentration	Peak concentration	Average flux	Peak flux	EMC	Event load
$y_{(0.2)}$	1.20 – 0.85s	1.23 – 1.05s	1.22 – 1.00s	1.25 – 1.20s	1.22 – 0.94s	1.22 – 1.00s
$y_{(0.4)}$	1.42 – 1.02s	1.55 – 1.35s	1.48 – 1.22s	1.58 – 1.48s	1.48 – 1.15s	1.48 – 1.20s
$y_{(0.5)}$	1.58 – 1.14s	1.85 – 1.59s	1.69 – 1.39s	1.92 – 1.81s	1.66 – 1.31s	1.69 – 1.39s
$y_{(0.6)}$	1.82 – 1.30s	2.45 – 2.10s	2.00 – 1.64s	2.38 – 2.22s	2.00 – 1.55s	2.00 – 1.62s
$y_{(0.8)}$	2.47 – 1.82s	4.21 – 3.70s	2.98 – 2.48s	4.10 – 3.95s	2.90 – 2.30s	3.00 – 2.42s
$y_{(0.85)}$	2.70 – 1.98s	4.70 – 4.11s	3.33 – 2.74s	5.26 – 4.96s	3.21 – 2.58s	3.33 – 2.74s
$y_{(1.0)}$	3.83 – 2.86s	6.54 – 5.85s	5.57 – 4.56s	16.76 – 15.81s	5.23 – 4.28s	5.57 – 4.56s

Applying the results

The plots and equations created are both useful and easily understood. To demonstrate the usefulness of the equations and the graph the following examples for peak flux are given, using Figure 8.6 and Equations 8.4 to 8.9.

If a particular catchment had a buffer ratio of 0.20 and the catchment manager planned to increase it to a ratio of 0.90 they would use Equation 8.8.

$$y_{(0.9)} = 7.45 - 7.05s \qquad \text{(}\textit{Equation 8.8}\text{)}$$

$$y_{(0.9)} = 7.45 - 7.05 \times 0.2$$

$$y_{(0.9)} = 6.04$$

The catchment manager could, therefore, expect to see a reduction in pathogen flux during storm events of around 6 times, or a magnitude change of 0.78 (see dark gray dotted line on Figure 8.6).

Another way to use these equations and graphs is if the catchment manager wanted to achieve a certain log reduction in peak flow. For example a 1-log reduction would require the buffer ratio to be increased to 1.00 and the necessary maximum starting buffer could be determined with Equation 8.9.

$$y_{(1.0)} = 16.76 - 15.81s \qquad \text{(}\textit{Equation 8.9}\text{)}$$

$$if \rightarrow y_{(1.0)} = 10^{10}$$

$$then \rightarrow s = \frac{10^{1.0} - 16.76}{-15.81}$$

$$\therefore s = 0.43$$

Therefore in order to achieve a 1-log reduction in pathogen flux the starting buffer ratio would need to be no more than 0.43. If it were any more than that and it would not be possible to achieve the required reduction by implementing a buffer strip (see white dotted line on Figure 8.6).

These equations and graphs have shown that there is an impact on pathogen numbers following implementation of a buffer strip and that this reduction can be predicted and

quantified. They have also proven to be useful for looking at different scenarios and could assist in assessing the overall benefits of carrying out catchment management works. As an example the pathogen reduction likely from increasing the size of an existing buffer could be compared to the treatment technologies that would be required if the barrier was not there. Comparisons could be done in terms of public health benefits, the likelihood of failure and/or the costs. Additionally the benefits to the community of implementing catchment works, as a landowner, resident or a visitor to the catchment, could be taken into consideration. The risks, costs and benefits for all stakeholders and for various options can be assessed with the aid of an analysis such as the one above.

8.5 Verification of findings

The relationships obtained above will be verified by testing them on a section of data that was not used in the calibration, or in this case relationship building, process. The relationships applicability across a range of events is tested using 3 randomly chosen storm events from the predicted data, separate from those 15 used in the development of the relationships. Storm events with varying ranges of size and duration were chosen.

The characteristics of the 3 storm events chosen to verify the relationships are shown in Table 8.8.

Table 8.8 – Storm characteristics of events chosen for verification

Storm date	**Event duration** *(hours)*	**Peak flow** *(m^3/sec)*	**Event volume** *(ML)*	**Average flow** *(m^3/sec)*	**ARI** *(years)*
November 2004	51	0.35	44.06	0.24	1
October 2005	25	0.21	17.41	0.19	<1
August 2006	53	0.11	16.25	0.09	<1

During calibration an exponential relationship was found between peak flow and pathogen numbers for the different buffer ratios. See Tables 8.3 and E.2. The relationship indicated that as the peak flow of the storm increased so too the pathogen numbers. The relationships were used to predict the pathogen numbers in the verification events and these results were then correlated against the observed numbers to determine the validity of the relationship. The calculations for event load with a buffer of 0.85 are shown in Table 8.9 as an example.

Equation 8.10 was obtained from Table E.2 and used to obtain the values.

$$EL_{(f)} = 5.3e^{8.3Q_{peak}} \qquad \text{(Equation 8.10)}$$

where:

EL = event load

f = buffer ratio

Q_{peak} = peak flow

Table 8.9 – Predicted event load with a buffer ratio of 0.85 for verification events

Verification event	Peak flow	Observed event load	Predicted event load
November 2004	0.35	190.10	96.81
October 2005	0.21	22.18	30.29
August 2006	0.11	8.50	13.21
		***R*²**	0.98
		E	0.57

Table 8.10 shows the correlation statistics for all of the buffer ratios and pathogen data sets.

Table 8.10 – Correlation statistics of verification events for the exponential relationships with peak flow

	1.00 buffer		0.85 buffer		0.50 buffer		No buffer	
	***R*²**	***E***	***R*²**	***E***	***R*²**	***E***	***R*²**	***E***
Average concentration	0.99	0.40	0.99	0.62	0.99	0.85	1.00	0.95
Peak concentration	0.96	0.68	0.97	0.81	0.97	0.86	0.97	0.80
Average flux	1.00	0.29	1.00	0.53	1.00	0.80	1.00	0.94
Peak flux	0.99	0.41	0.99	0.79	0.99	0.96	0.99	0.98
EMC	0.98	0.42	0.99	0.69	0.99	0.92	0.99	0.94
Event load	0.97	0.57	0.98	0.57	0.99	0.80	0.99	0.92

It is reasonable to report the *E* values here as a predicted result is being compared with an observed result. The high values of R^2 in this validation indicate that the exponential relationship between peak flow and pathogen numbers is very well supported. The *E* values are acceptable however they do decrease the larger the buffer ratio is. This indicates that the variation in pathogen numbers may be slightly broader than that estimated by a simple equation. To further investigate this, an order of magnitude plot of the concentration results was created, see Figure 8.7. The flux and event load results are shown in Figures 8.8 and 8.9 respectively.

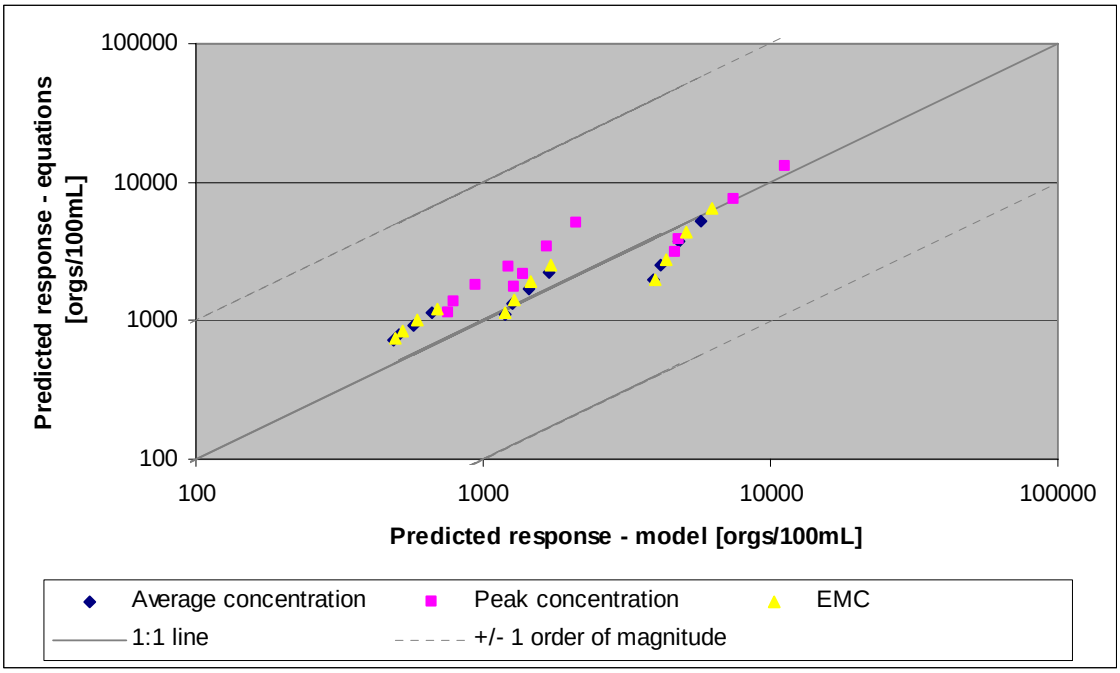

Figure 8.7 – Verification events - predicted pathogen concentrations against the predicted pathogen concentrations using the equations from Table E.2

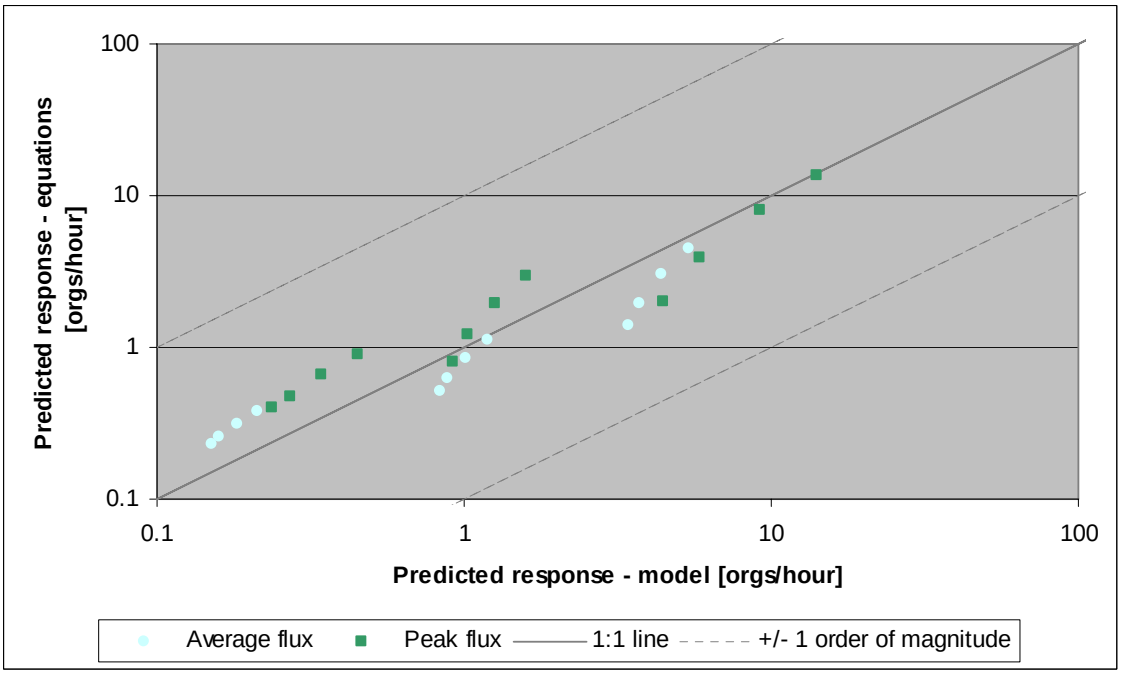

Figure 8.8 – Verification events - predicted pathogen fluxes against the predicted pathogen fluxes using the equations from Table E.2

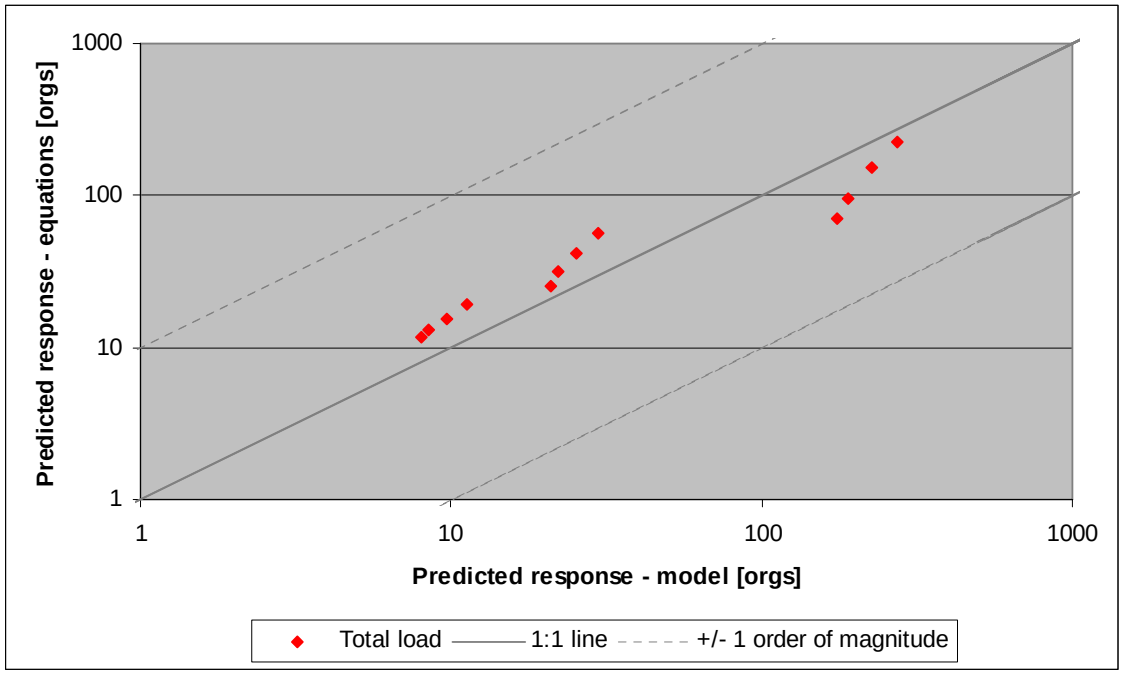

Figure 8.9 – Verification events - predicted pathogen event load against the predicted pathogen event load using the equations from Table E.2

As can be seen all of the data is sitting close to the 1:1 line confirming that the equations using peak flow are capable of predicting pathogen numbers within the right order of magnitude for varying buffer ratios.

The effect of the buffer as it relates to having no buffer resulted in strong correlation statistics. The equations derived from the gradients of the regressions, shown in Table 8.5, are important findings as they form the basis of the quantification work and they therefore require verification. The equations were applied to the three validation storm events. The calculations for peak flux are shown in Table 8.11.

Table 8.11 – Peak flux calculations for verification events using equations from Table 8.5

Final buffer ratio	Equation (from Table 8.5)	Verification event	Non-buffered catchment Peak flux (x)	Predicted Peak flux	Observed Peak flux
1.00	0.06x	November 2004	14.05	4.45	0.84
		October 2005	1.59	0.93	0.10
		August 2006	0.45	0.24	0.03
0.85	0.19x	November 2004	14.05	5.85	2.67
		October 2005	1.59	1.03	0.30
		August 2006	0.45	0.27	0.09
0.50	0.52x	November 2004	14.05	9.23	7.31
		October 2005	1.59	1.26	0.83
		August 2006	0.45	0.34	0.23
				R2	0.85
				E	0.82

This was done for each of the pathogen data sets and the correlation statistics can be seen in Table 8.12.

Table 8.12 – Correlation statistics of verification events for the equations shown in Table 8.5

	R^2	*E*
Average concentration	0.86	0.72
Peak concentration	0.88	0.80
Average flux	0.81	0.69
Peak flux	0.85	0.82
EMC	0.80	0.66
Event load	0.83	0.73

The values in Table 8.12 show that the ability of the equations in Table 8.5 to predict pathogen numbers is reasonably good. The relationships in Table 8.5 were used to develop the relationships that can be used to quantify the pathogen reduction expected when moving from one buffer ratio to another. As the verification has shown the initial relationships to be accurate, it can be said that the equations formed from them are also accurate.

The verification process has confirmed the relationships obtained during the calibration between storm characteristics and pathogen numbers. In terms of the applicability of Figure 8.6 for quantifying any reduction, the verification process gives confidence in the ability of the equations in Table 8.7 to be able to predict the pathogen numbers likely during large events.

8.6 Discussion

The analysis of the pathogen numbers coming from buffered and non-buffered catchments indicated that it is only during storm events that the buffer is effective. This is consistent with the published literature as cited in Chapter 2. During baseflow conditions there is virtually no difference between total pathogen numbers in the receiving water of a catchment with buffer ratio of 1.00 and a catchment with no buffer at all. This outcome is due to the initial assumption that pathogens transported via baseflow are unaffected by buffer strips as the flow path is too deep and therefore too far away from the filtering effect of plants or their root systems. There is also practically no effect on loss function, surface or sub-surface, regardless of the flow conditions. Buffers are only effective at reducing pathogens in the storm flow which occurs during and directly following a rainfall event. A rainfall event is likely to mobilise a large number of pathogens and so it is important that this is when the buffer is reducing pathogen numbers.

The initial observations regarding pathogen movement have implications for pathogen and indicator sampling programs, especially when the objective of those programs is to show change in water quality due to catchment management. Traditionally, sampling is undertaken on a routine basis which means that the frequency of sampling is set regardless of weather conditions in the catchment. The majority of the time routine sampling will occur in baseflow conditions. In some situations sampling is purposely only taken in dry weather due to safety concerns for samplers during rainfall, meaning that all samples are baseflow samples. Pathogen concentrations during baseflow conditions both before and after any implementation of buffer strips are likely to remain largely unchanged, assuming no other works have been carried out in the catchment. To enable any changes or improvements to be observed in the sampling data, sampling during storm events, both before and after works, is imperative.

The pathogen data was summarised in a variety of ways which allowed for various relationships to be explored. In any catchment there are likely to be a number of different stakeholders each with their own priorities and knowledge bases. Summarising the pathogen data in several different ways allows all groups with an interest in the catchment to determine the best manner for them to express any likely benefits from buffer strip implementation. For example, drinking water treatment plant operators talk in terms of peak pathogen flux being delivered to the treatment plant

whereas land managers may be more interested in pathogen concentrations in the stream independent of flow.

Of the three storm characteristics investigated, peak flow of an event was found to be the one that was the best predictor of pathogen transport during an event. Additionally peak flow was able to predict the difference in pathogen numbers between different catchment scenarios. The average flow and event volume did not correlate as well as peak flow to the pathogen data sets indicating that the effectiveness of the buffer is less related to the duration or overall magnitude of an event, and that it is the peak intensity which dominates the number of pathogens that are mobilised. This is consistent with Ferguson et al. (2003) who state that the intensity of the storm is a key factor in mobilising pathogens from faecal material and transporting them in through the catchment. This finding, again, has implications for monitoring programs. To enable the relationships formed in Section 8.3 to be used, an indication of the peak flow of events within the catchment is necessary, which requires continuous monitoring of the streamflow.

The good correlations between buffered and non-buffered catchments pathogen numbers, shown in Table 8.5, give an indication as to the amount of improvement that could be expected following a buffer being implemented. The relationships shown in Table 8.7 allow catchment managers to quantify the actual reductions that could be expected following on-ground works. The analysis shows that peak flux is the pathogen number most affected by buffers, with a magnitude difference for a buffer ratio of 1.00 compared to a non-buffered catchment of 1.22 (see discussion following Table 8.5). The relationships formed are expected to be useful in determining the pathogen reduction likely in certain circumstances given a particular increase in buffer size. Catchment managers could for example, as an initial assessment, use the predicted magnitude decrease in pathogen numbers from the implementation of a buffer strip and the cost of those works and compare it to the cost of an increase in the capability of the treatment plant. By quantifying the benefits in this way on-ground works may be able to be comparable to other treatment options and therefore more easily justifiable. It also provides a form of validation as to the barrier's effectiveness.

The pathogen data set least impacted by having a buffer was the average concentration, as indicated by the lower numbers in the equations in Table 8.7. Although there is still a reduction in the average pathogen concentration during storm events, it is the least affected of the pathogen data sets considered. This indicates that

following implementation of a buffer in a catchment, traditional methods of sampling and reporting may fail to pick up a significant change in pathogens in the receiving water body. In terms of showing the benefits of buffers through pathogen sampling, peak pathogen concentration and peak pathogen flux during storm events are the best indicators as they are the values that will show the greatest magnitude of change. Determining these values requires a sophisticated sampling program incorporating continuous flow measurements and a number of pathogen samples taken throughout storm events. To enable change to be detected, this needs to be done both before and after any catchment works. Sampling only pathogen concentration during baseflows on a routine basis is not acceptable as it does not give the catchment manager much useful information.

8.7 Summary and conclusions

The relationships formed in the above analyses are useful for quantifying the likely benefits in terms of pathogen numbers from implementing a buffer strip within a catchment. The analysis also resulted in some interesting results that can be related directly to pathogen sampling.

Quantification of the benefits of buffer strips through modelling may assist catchment managers and water quality managers in planning works in the catchment and in securing funding for such works. The ability to show that the on-ground works can have a positive and measurable affect on drinking water quality is important for various stakeholders including regulators and the community. For the protection of public health drinking water quality managers need to be certain that they are achieving a specific pathogen log-reduction across their barriers prior to distribution. The ability to quantify the reduction gives a validated barrier to contamination. Having confidence in catchment management initiatives to provide a reduction in pathogen numbers may lead to more on-ground works and less conventional treatment. This has benefits for the community on a number of different levels including, but not limited to, the following: a reduced cost of treating their drinking water, a more aesthetic landscape and healthier streams.

In terms of sampling, the above analysis has shown the inadequacies of traditional sampling programs with regards to showing the positive impacts on water quality of buffer strip implementation. The importance of continuous flow measurements and

multiple pathogen and pathogenic indicator samples throughout large rainfall events both prior to and after buffer strip implementation was clearly evident. This kind of sampling is complicated and time consuming as it involves flow triggered samplers and on-call collection of samples. It is, however, necessary if the real impact of catchment management is to be expressed in terms of improving water quality.

The calibrated EG model with its modifications have been used in this analysis to assess the effect of having a buffer strip on pathogen transport. The modifications and the additional inputs to the model to allow the buffer effect to be predicted need to be assessed. The next chapter deals with the uncertainty related to the estimation of the buffer ratio and the percentage reduction in pathogens through buffer strips.

9. UNCERTAINTY ANALYSIS

9.1 Introduction

Following on from obtaining model predictions, devising relationships and validating those relationships it is necessary to next undertake uncertainty assessments (Refsgaard & Henriksen, 2004). Uncertainty is defined by Walker et al. (2003) as being "any departure from the unachievable ideal of complete determinism". Uncertainty analysis is an important part of modelling and model development as it leads to a greater understanding of the behaviour of the model, can give an indication of the models limitations and benefits and may assist in model refinement.

Uncertainty analysis ties in well with the precautionary principle, which aims to protect humans and the environment from uncertain risks by understanding all of the risks. In relation to the supply of safe drinking water the precautionary principle is explained in Chapter 2 and is implicit in many policies that relate to drinking water management including the European Union's Water Framework Directive (European Community, 2000) and the ADWG (2004). Uncertainty analysis ensures that a wide range of possibilities is covered by the model and that the impact of those possibilities is demonstrated.

This chapter will provide some background on uncertainty analysis, including a definition of sources and types of uncertainty. The uncertainty analysis that was undertaken on the EG model during its initial development is then covered. It is not within the scope of this work to repeat or check the work done during model development, only to report on it for completeness and to aid understanding of the model. The uncertainty work carried out on the modified EG model, in particular, buffer ratio and pathogen reduction rate through the buffer, is presented in detail along with a discussion and overall summary.

9.2 Background

The terminology and typology of uncertainties within a management or modelling framework is not widely agreed upon (Walker et al. 2003), it is therefore necessary to

define uncertainty analysis in order to provide a consistent context as it relates to the work carried out in this chapter.

In a modelling framework, uncertainty relates to errors in values or the degree of confidence in an outcome which Walker et al. (2003) describes as coming from five separate sources:

- modelling context uncertainty
- model structure and technical uncertainty
- input data uncertainty
- parameter value uncertainty
- model outcome uncertainty.

Sensitivity analysis, in this thesis, refers to a method of uncertainty analysis. It assesses the variation in output attributed to different sources of variation (Refsgaard et al. 2007), it aims to determine the most important or influential parameters. In particular, uncertainty analysis quantifies the overall uncertainty, while sensitivity identifies the key contributors to uncertainty (Scott, 1996).

There are two types of uncertainty: those that relate to natural variability, or random errors, and those which are theoretical or systematic. Random errors, in environmental modelling, are usually associated with the inherent unpredictability of natural processes, where as systematic errors are due to imperfect knowledge and can result in entire data sets being either above or below the true value (Walker et al. 2003). Input values such as rainfall can have both systematic and random errors. For example, random errors in catchment rainfall estimation may be due to site variation in rainfall at a point giving errors at the catchment scale; that is the spatial variability of catchment rainfall is misrepresented by a specific sites rainfall variation. In terms of systematic errors in rainfall values these could occur due to poor gauge siting, for example under a tree or at the bottom of a valley, or poor instrument calibration (both over and underestimation are possible) which will be constant over the whole data set. Errors associated with nature are not possible to reduce as they are related to the stochastic and chaotic nature of natural phenomena, such as weather (Refsgaard et al. 2007). Errors based on theoretical or imperfect knowledge have the ability to be reduced by collecting more data or conducting more studies. Sensitivity analysis can be used in this instance to identify the most influential inputs or parameters and direct research towards minimising their uncertainty.

In addition to the five sources of uncertainty already mentioned, there is uncertainty in the actual calibration of the model as it is possible that a number of different parameter sets and model structures may produce a similar model outcome. This is known as equifinality (Refsgaard & Henriksen, 2004), and it can occur when two or more parameters are well correlated and are compensating for each other or are compensating for inadequacies in the model structure. If equifinality is occurring then uncertainty analysis can be used to reduce the complexity of the model by deleting the need for certain parameters.

9.3 Summary of uncertainty analysis during original EG model development

As mentioned previously there is no agreed or common way, among modellers, in which uncertainty is defined. During the development of the EG model the terms uncertainty and sensitivity were defined as follows:

- sensitivity related to non-measurable factors and their impact on the model outcomes
- uncertainty related to measurable inputs and their impact on model uncertainty (Haydon, 2006).

These definitions meant that the model parameters and the input data were assessed separately. In order to be consistent with the definitions stated in the above section, the work done during development can be very simply redefined as:

- parameter uncertainty and
- input data uncertainty respectively.

During development work was also undertaken on model structural uncertainty, model outcome uncertainty and context uncertainty and these are discussed separately below. The aim of this thesis is not to repeat or check the uncertainty work done during the model development only to summarise the results and the conclusions so as a comprehensive understanding of the model can be gained. For a detailed description of the work that was undertaken the reader is referred to the original work (Haydon & Deletic, 2007; Haydon & Deletic, 2009).

Model context uncertainty was not explicitly examined during the uncertainty analysis although it is acknowledged that there is considerable uncertainty related to the simplified representation of the pathogen transport process. Despite this it could be said that the contextual uncertainty was evaluated as part of the development as 3

different hydrological-pathogen models were developed and trialled. Each model framed the problem of pathogen transport differently and each was calibrated and assessed in terms of their ability to fit to the observed data. Of the 3 models the EG model preformed the best and was therefore chosen to be the model used for modelling pathogen movement through catchments.

Model structure uncertainty was tested by varying the amount of data used in model calibration. As expected the more events included in the process, the better the model's predictive performance. This was not true, however, with one of the catchments where it was concluded that an ill-performing model will not improve with more data. The work highlighted the danger of obtaining a seemingly well fitted model with too few events and using it for predictive purposes. It was stated that in order to increase the likelihood of a successful calibration a total of 3 or more events are needed.

Input data uncertainty during model development refers to the uncertainty in observed data. That is, rainfall, catchment area, PET and pathogen deposition. Although these inputs are catchment specific it can be assumed that the errors or uncertainty reported in Haydon and Deletic (2009) are generic for these types of measurements or, in the case of pathogen deposition, generic for this type of land-use. The systematic errors in the input data, specifically rainfall and PET, were assessed using local sensitivity analysis, explained in Section 9.4.1. It was found that uncertainty related to rainfall measurements had a large impact on load calculations, up to a 264% difference in model outcomes with only a 30% increase in rainfall, whereas the effect of PET uncertainty was generally damped through the model, ie the variation was larger than the average difference, and therefore less significant, see Table 9.1. A standard Monte Carlo simulation was used to assess the random errors in the input data. The most influential input was found to be catchment area as any uncertainty in that figure was amplified through the model, especially in terms of the load calculations. Table 9.1 shows that a 12.5% increase in catchment area resulted in a 30% increase in pathogen load from the base case. Random errors related to rainfall had less affect on the load but more affect on the peak than systematic errors. In terms of pathogen deposition rate, any change in this figure was reflected one-to-one in the output concentrations, ie a 1000% change in deposition rate gave a 1000% change in model outcomes. Such large input variations, ie more than $\pm$1-log, would require re-calibration of the model.

Table 9.1 – Results from uncertainty analysis of the original EG model

Error type	Input	Input variation	Difference in model outcomes from the base case	
			Peak	Load
Systematic	Rainfall	-30%	-22%	-67%
		30%	7%	264%
	PET	-30%	13%	38%
		30%	-9%	-18%
Random	Rainfall	-50%	-29%	-13%
		50%	51%	27%
	Catchment area	-12.5%	-7%	-24%
		12.5%	8%	30%
	Pathogen deposition rate	10%	10%	10%
		1000%	1000%	1000%

Parameter uncertainty using global sensitivity analysis (as explained in Section 9.4.1) was undertaken during development in order to determine the most sensitive, and therefore the most influential, parameters within the model and also to establish if cross-correlation was a factor. The model was found to be most sensitive to the two parameters that related to pathogen transport (a_5 and b_1) as compared to those parameters that influenced decay or loss of pathogens (a_1 and b_2). As the pathogen transport processes in EG are based on the outputs of the hydrologic model, a good calibration of the attached hydrologic model is clearly very important. In an attempt to reduce the number of parameters that required calibration the two least sensitive parameters, the loss parameters, were held constant at their optimal value and the model was rerun. This resulted in a large change in the objective function, over 200%, and it was concluded that all of the parameters are required to successfully calibrate the EG model.

In terms of model outcome uncertainty, this relates to the data used for calibration. The uncertainty related to streamflow and pathogen concentrations, is important as this data is being used to assess the model outcomes. Although timing issues can be a factor in calibration, they were not included in the analysis, as they were considered less significant than those related to the observed measurements of flow and pathogen concentration. Uncertainty in streamflow measurement may occur due to a poorly placed staff gauge or pressure sensor, errors in the rating curve or issues with data handling. In terms of pathogen measurements, the uncertainty can be categorised as either sampling errors, such as contamination and representativeness, or laboratory errors, such as identification and enumeration. These errors were discussed previously in more detail, see Chapter 3.

The uncertainty analyses carried out during EG model development showed that the more data, and especially event data, available to calibrate the model the better the final fit and that it is necessary to calibrate all five parameters to achieve the best fit. In terms of input data uncertainty, the analysis showed that the modeller should focus on ensuring that the catchment area and the rainfall measurements are correct, as these have the most influence on the model outcomes.

9.4 Uncertainty assessment for the modified EG model

The modified EG model contains two additional values as compared to the original model: the buffer ratio and the pathogen reduction rate. According to Walker et al. (2003) the buffer ratio would be defined as an input and therefore subject to either random or systematic errors. The buffer ratio is most likely affected by random errors as there is direct measurement of the entered value and it is a single value so a systematic error is illogical. The pathogen reduction rate is a constant in the model and is therefore defined as a parameter by Walker et al. (2003). Their different definitions mean that they need to be dealt with differently in terms of estimating their likely errors.

This section explains the methods for exploring errors and discusses the uncertainties related to both buffer ratio and pathogen reduction rate. It also presents the results from the uncertainty analysis.

9.4.1 Methodology

There are a number of methods that can be used as a way of exploring the sensitivity of a model to uncertainties in the data. They are generally categorised into one of two methods:

- local sensitivity analysis
- global sensitivity analysis.

Local sensitivity analysis involves determining the response of the model around the calibrated dataset by changing one parameter, or input, at a time. Global sensitivity analysis, on the other hand, assesses the model response within the confines of the parameter or input boundaries and varies all model inputs/parameters simultaneously. It can be used to reduce the number of inputs/parameters required in a model by determining if there is any cross-correlation. Undertaking global sensitivity analysis

usually requires some type of Monte Carlo simulation which involves generating random errors for each of the inputs/parameters and running the model after each change. This generates a large number of model runs and therefore a large number of model outputs which are examined using a statistical distribution.

For the uncertainty analysis related to the buffer ratio and the pathogen reduction rate it is thought that only local sensitivity analysis is required. The global sensitivity technique is necessary when the model under investigation is complex and its inputs/parameters are likely to range over several orders of magnitude (Manache & Melching, 2008). As discussed in the following section the uncertainties in the values being investigated do not cover this kind of range. It is more appropriate to use local sensitivity analysis when there is only one value being analysed because the interest lies in how that values sensitivity affects the model outcomes (Castillo et al. 2008). Therefore the errors associated with the buffer ratio and the pathogen reduction rate are propagated through the model separately producing two separate sets of results.

Reporting the outcomes of uncertainty analysis consists of studying the effects of variation in parameter or input values on the performance of the model (Simon, 1988), either through the value of the objective function or through the deviation of model output from the calibrated model. Both of these methods are utilised here. The changes in the modelled outcomes following propagation as they relate to the measured, or observed, values, is done by looking at the objective functions, R^2 and E, and comparing them to those that were achieved with the calibrated model. Both the overall results and the results for the 5 events sampled in the East catchment are reported on. The second reporting method involves assessing the change in pathogen numbers of the error propagated model from the calibrated model – both absolute, or actual, and percentage change are investigated. For this assessment the changes in both summed pathogen load over the entire calibration period and the peak pathogen concentration during a large event in February 2005 were examined.

9.4.2 Sources and magnitude of uncertainties

As discussed above, there are two new values in the modified EG model that require assessment in terms of their uncertainty; namely the buffer ratio and the pathogen reduction rate. The buffer ratio is a variable in that it is a value which is input by the modeller and is based on knowledge about the catchment. How important the accuracy of this number is to model outcomes will be assessed here. The pathogen

reduction rate is a fixed parameter and not a variable, in that the modeller can not choose the reduction rate they think is the most appropriate. A number has been chosen based on literature as explained in Chapter 6. There is still, however, uncertainty related to this number. Different literature quotes different figures and the differences are often based on varied spatial elements, which EG is unable to manage. The possible sources of errors for the two values and their likely magnitudes are reviewed in detail below.

Buffer ratio

The buffer ratio is calculated by dividing the total stream length in the catchment by the total length of stream that is protected by an established vegetated buffer. If the stream runs through the middle of the catchment, and there is catchment on both sides of the stream, then the stream length needs to be doubled. As an alternate way of calculating the buffer ratio the area of catchment directly upstream of the buffer, which can be determined using contour maps, can be divided by the total catchment area. Although the latter method is more accurate, it is also more difficult to determine than the first method without the appropriate expertise, knowledge and software.

The simplest method of determining the percentage of stream protected by a buffer is by examining a recent aerial photograph. There are uncertainties in using aerial photography for this purpose, these include encountering issues with:

- interpretation and identification methods
- accurate representation of land cover
- how current the aerial photo is.

Obviously field validation is recommended to assist in reducing any uncertainty, but the practicality of this needs to be assessed on a catchment-by-catchment basis; that is for a large catchment the time required to complete an accurate ground survey may be limiting. Engaging local people to verify aerial photos may be of some help, but misunderstanding regarding what actually constitutes a buffer and miscommunication of figures could also be an issue here.

The accuracy of classifying land-cover from interpreting aerial photos has been quoted at 90% (Lambert et al. 2002), or 10% error. This value is based on an expert undertaking the interpretation. Assuming the worst case scenario that an expert is not involved and to account for any objectiveness that is likely in the interpretation, an additional 5% error is added. It is, therefore possible that the buffer ratio may be misinterpreted by up to $\pm$15%. The error distribution is assumed to be symmetric

around the inputted value. Therefore to determine the effect of the uncertainty in buffer ratio on the model outcomes, the model will be run with errors of ±5%, ±10% and ±15% from the original buffer ratio.

Reduction rate

The pathogen reduction rate is incorporated into the model and is a parameter that is unable to be changed by the modeller. It is, however, a value that has uncertainty associated with it and therefore requires investigation. The pathogen reduction rate through a buffer of 2-logs, or 99%, is based on literature from various laboratory studies and is an indicative value from those studies, see Chapter 6. Chapter 6 states that this figure is conservative, realistic and justifiable based on the various studies quoted. It is also, however, open to discussion as some studies give a range of likely reduction rates. As an example Tate et al. (2004) states that a 1m buffer strip on a slope of up to 20% gives between 1 and 3-log reduction in *Cryptosporidium*. While in a study by Atwill et al. (2002) it was found that a 3m buffer strip with a slope of less than 20% should remove 99.9%, or 3-logs, of *Cryptosporidium*.

An additional observation from these studies is that the range of likely pathogen reduction rates through buffer strips is based on the width and slope of the buffer. One of the necessary assumptions when modifying the EG model was that the slope and width of the buffer adhered to certain measurements regarding slope and width. It is feasible that the catchment being modelled will have a different slope or width therefore increasing the uncertainty related to the pathogen reduction rate and therefore potentially changing the buffer's overall effectiveness.

The error distribution for the pathogen reduction rate requires discussion as unlike the buffer ratio, it is not symmetrical. In reality the pathogen reduction rate through a buffer strip is clearly bounded in terms of its logical range in that it will not remove more than 100% of pathogens nor will it remove less than 0%. According to the above literature, however, it can be said that the likely range of pathogen reduction rates is between 99.9% and 90%, or 3-logs and 1-log. The uncertainty is therefore on a log-normal scale and is not symmetrical. Microbiologists generally only discuss pathogen numbers, and especially pathogen reduction rates, in terms of order of magnitude. This is due to the many uncertainties surrounding pathogen monitoring and the fact that water treatment plant design and operation only requires this level of accuracy (Dorner et al. 2006). It is therefore reasonable to reflect this in the error distribution

and assume an uninformed prior of an error of ±1-log around the reduction rate of 2-log.

Therefore to examine the effect of different pathogen reduction rates the modified EG model will be amended and two new models created; one with a reduction rate of 90%, or 1-log, and the other 99.9%, or 3-log. The outcomes from these models will be assessed against the outcomes of the original modified EG model to determine the sensitivity of the uncertainty in the pathogen reduction rate on model outcomes.

9.4.3 Results and discussion

Changes in the objective functions

Presented first are the results obtained for the changes in objective functions, R^2 and E, given a change in either the buffer ratio or the pathogen reduction rate. Results are best displayed visually as a percentage change, see Figures 9.1 to 9.4 and Tables I.1 and I.2 in Appendix I show the numerical results. The set of graphs displaying the changes in R^2 values have been plotted on the same scale to allow for an easier comparison of sensitivities. This was also done for the set of graphs showing the E values.

When assessing these graphs it is appropriate to recall each objective functions role in assessing model outcomes. R^2 reports on the ability of the model to follow a similar trend to the observed data with less consideration for predicting observed data point values. Both R^2 and E tend to fit the peaks at the expense of the other parts of the time series and as the focus is on the events, using these objective functions to assess uncertainty is deemed acceptable.

Looking at Figures 9.1 to 9.4 together it seems that the buffer ratio has more influence on the model outcomes than the change in pathogen reduction rate. The relatively flat lines seen in Figure 9.2 indicate that any change in the pathogen reduction rate will have very little effect on the model outcomes. This is in contrast to Figure 9.3 where over a 500% decrease in E is seen for Event 1 following only a 15% decrease in the buffer ratio.

The uncertainty related to buffer ratio, generally, had a lot more influence on E (Figure 9.3) than it did on R^2 (Figure 9.1). Event 4 was an exception in that the percentage improvement in R^2 was significant following an increase in the buffer ratio, see Figure

9.1. In terms of an absolute number, however, the change was very small. Event 4 had a very low initial R^2 value of 0.01 which increased by a trivial amount to 0.04 with a 15% increase in buffer ratio, see Table I.1, Appendix I. When this improvement is expressed as a percentage change a very large number is obtained, exaggerating the actual effect of the change. If this event is ignored, it can be said that any error in the buffer ratio will affect the peak values (E) more than the trend (R^2). Therefore, if the outcome of the modelling process that is of most interest is peak pathogen concentration, as would be the case if a high risk scenario was being modelled, then it will be important to have an accurate estimate of the buffer ratio. In this situation, field validation of the ratio may be warranted. If, on the other hand, overall pathogen load is of more interest, then less effort and time can be put into determining an exceedingly accurate buffer ratio.

The seemingly random nature of the percentage change in E after a change in buffer ratio (Figure 9.3) can be explained. Both the 'Overall' and 'Event 1' lines, which show up to a 100% increase in E following an increase in the buffer ratio, are representing mainly baseflow pathogen values. The increase in E means that any increase in buffer ratio may improve the overall fit of the model but at the expense of fitting the peaks. Conversely, a decrease in buffer ratio results in an increase in E for Event 3 where the peak was significantly underestimated, see Figure 7.8. These results highlight the importance of looking specifically at events during the calibration/validation process. This is especially important when the pathogen peaks are of most interest. If no events are included then the modeller faces the likely scenario that the final calibrated model will underestimate the peaks.

In comparison to the percentage change in buffer ratio the models sensitivity to the magnitude change in the pathogen reduction rate was quite dull, that is the lines are relatively flat; see Figures 9.2 and 9.4 and Tables I.3 and I.4 in Appendix I. The maximum change in R^2 was only 36.8%, which was from a value of 0.008 to 0.005, a relatively small change, with the next highest change being 15.5% from an R^2 of 0.50 to 0.42. For values of E the largest change was 267.4%, which was from a value of 0.41 to -0.69. Although this seems like a big difference, compared to a change in buffer ratio which gave a maximum change of 523.8%, it is relatively small. These relatively small changes in model outcomes indicate that any further justification or refinement of the reduction rate of pathogens through buffer strips is unnecessary. Although it seems like a large error band, whether the buffer strip provides a 1-log or 3-log reduction in pathogens the model fit is relatively stable.

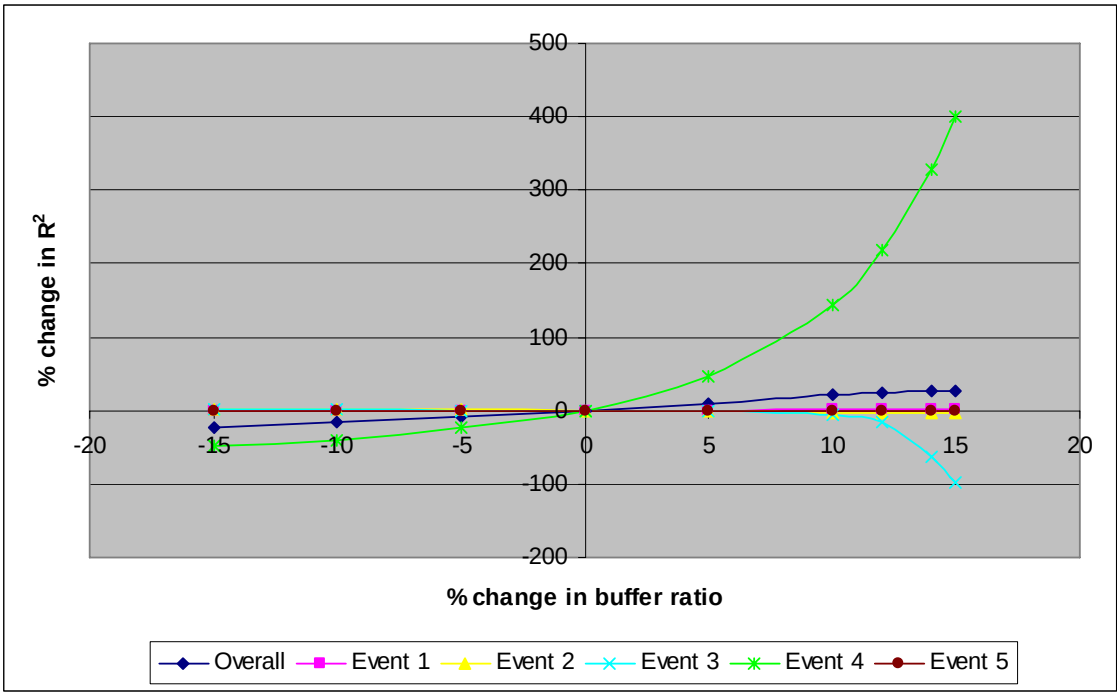

Figure 9.1 – The effect of % change in buffer ratio on R^2

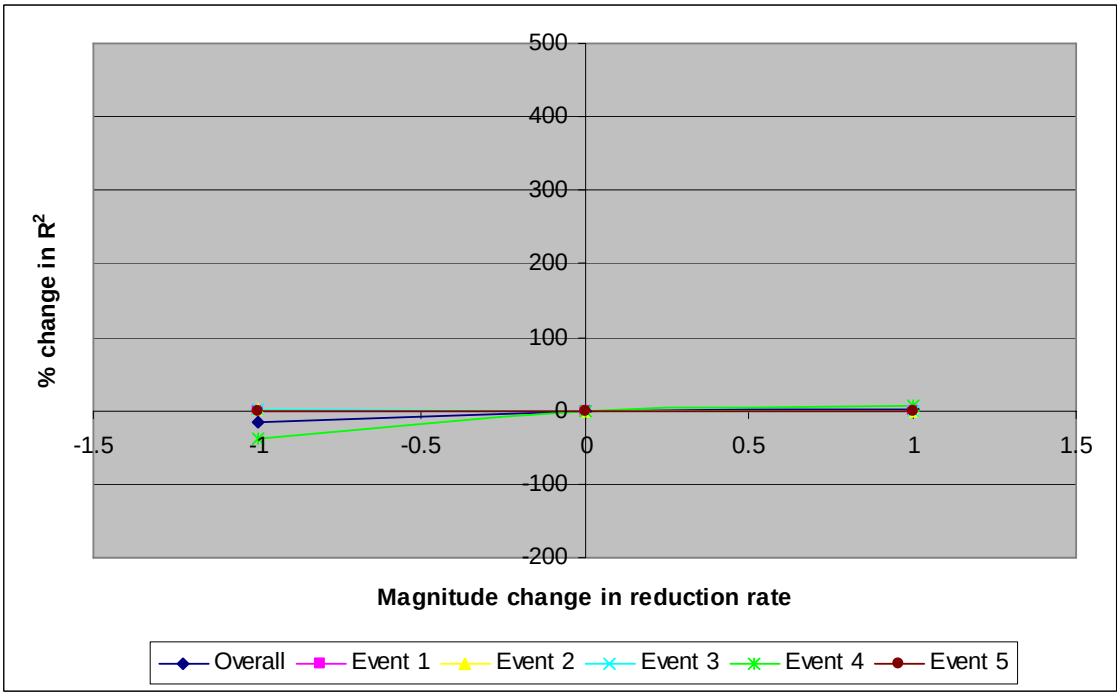

Figure 9.2 – The effect of magnitude change in pathogen reduction rate on R^2

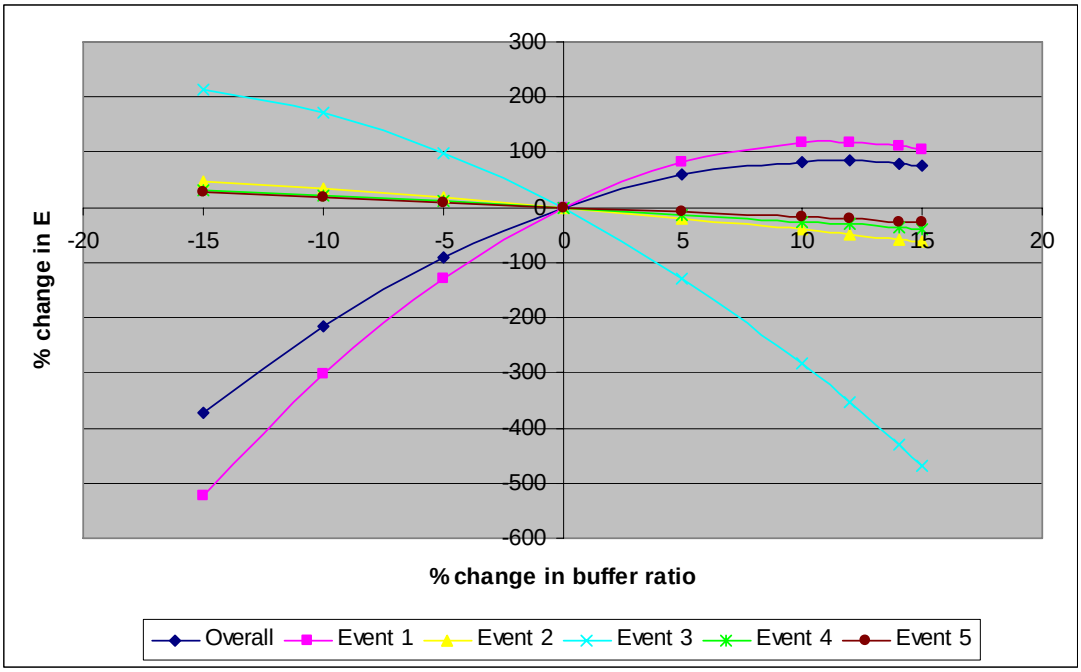

Figure 9.3 – The effect of % change in buffer ratio on E

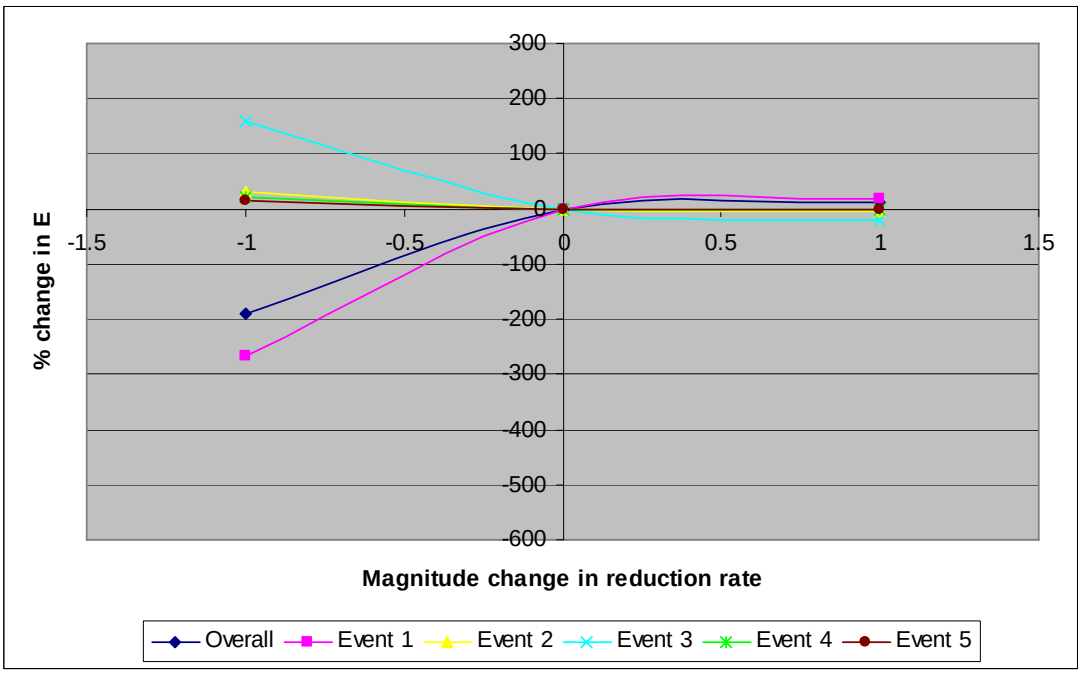

Figure 9.4 – The effect of magnitude change in pathogen reduction rate on E

Changes in pathogen numbers

The second set of results that are presented are looking at the final pathogen numbers being produced by the model, and the change seen as compared to the initial calibrated model. Graphs are shown for a percentage change in buffer ratio and a

magnitude change in pathogen reduction rate, Figures 9.5 and 9.6 respectively. The actual and percentage changes can be found in Appendix I, Table I.5 and I.6. The results are for the total pathogen load for the whole calibration period (2005-2007, inclusive) and the peak pathogen concentration during a large event in February 2005. The Appendices also show the results for the peak values from a smaller event. As done previously, both graphs are shown with the same scale on the 'y' axis to aid comparison.

The difference in overall pathogen load produced by the models for both the change in buffer ratio and the change in pathogen reduction rate compared to the calibrated model was relatively minimal; the maximum load change for a buffer ratio change of 15% and was less than 10%, see Figure 9.5, which was less than 500 orgs.

In terms of the pathogen peak, the model was much more sensitive, especially when the buffer ratio was changed. Figure 9.5 shows that with a 15% increase in the buffer ratio, there is over a 60% decrease in pathogen peak which was a reduction in peak from 18,424 orgs/100mL to 6,560 orgs/100mL. Figure 9.5 also shows that there was a 4-fold change in the pathogen peak with buffer ratio change, meaning that for every unit of change of the buffer ratio there was 4 times as much change in the pathogen peak. This large amplification of error through the model indicates that having an accurate estimation of the ratio of stream covered by buffer is crucial in determining the peak pathogen concentration. It was found, however, that for an event with a smaller peak the amplification of error was not as large, see Table I.5 in Appendices I.

As was the case in the analysis above for the objective functions (Figures 9.2 and 9.4), the magnitude change in the reduction rate had a relatively limited impact on the pathogen numbers, see Figure 9.6. The insensitivity of the model to this change should help to reassure the modeller that the inconsistencies in the literature regarding this number are of little concern. Providing the modeller is satisfied that the pathogen reduction rate through the buffer being within the range of 1-log and 3-log then any further investigation or justification is unwarranted.

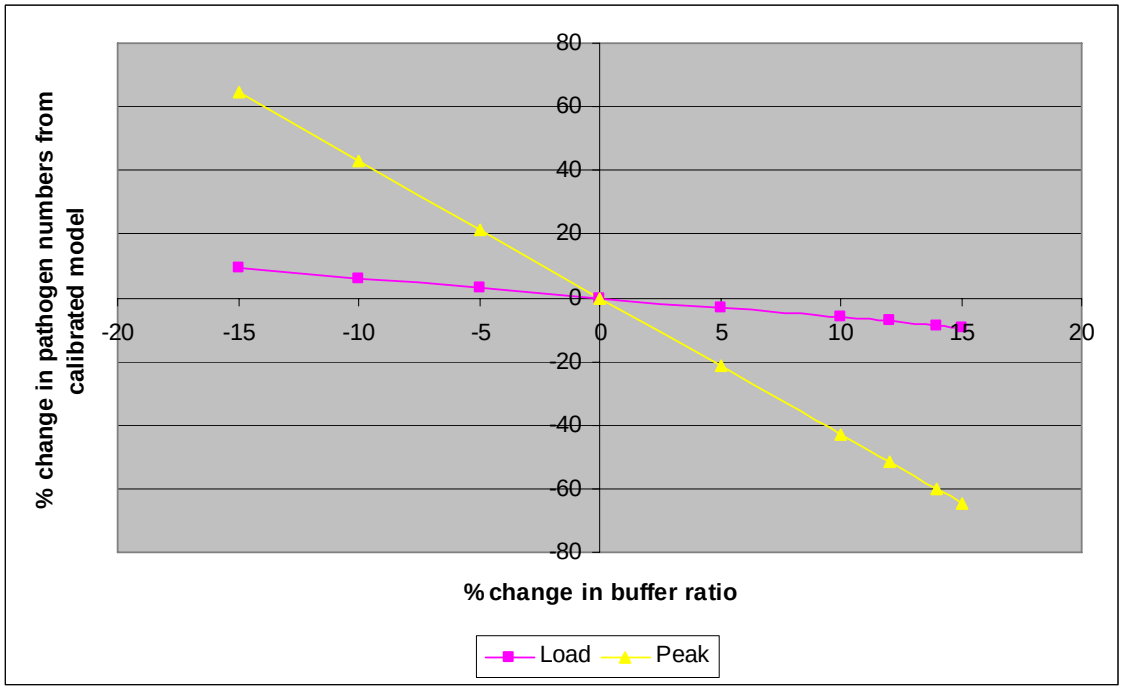

Figure 9.5 – The effect of % change in buffer ratio on pathogen concentration and peak

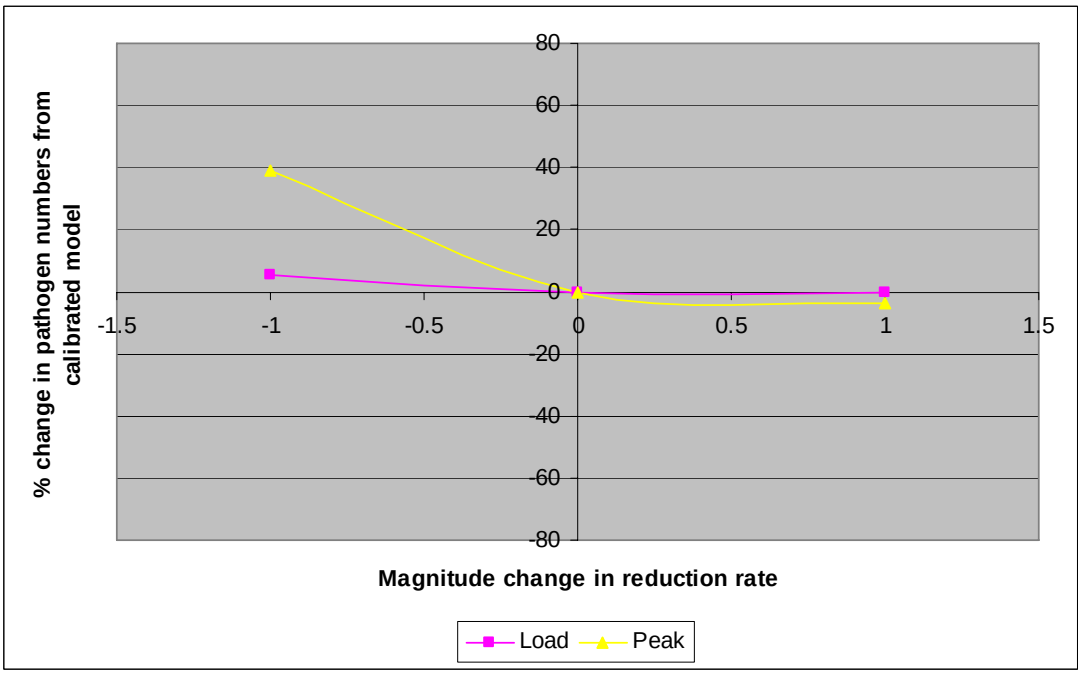

Figure 9.6 – The effect of magnitude change in reduction rate on pathogen concentration and peak

9.5 Summary and conclusions

The initial uncertainty analysis on the EG model found that the transport parameters were more influential to model outcomes than the decay parameters and that both

rainfall and catchment area were the most important input values to get right. These findings lead to an increased understanding of the model, and can assist modellers in knowing where to focus their efforts in order to get a better calibrated and more useful model.

In the modified EG model, it was the pathogen peaks that were most sensitive to changes in the input values, specifically the buffer ratio, with a 15% change in buffer ratio giving over a 60% change in peak pathogen concentration. Ensuring that the buffer ratio is determined with up to date and accurate information is critical if the model is being used to determine the pathogen peak concentration during an event. Obviously this criticality is exaggerated when the model is being used for its specific task; that is estimating the reduction in pathogens during events with an increase in buffer ratio.

It was determined that for a large event there was a 4-fold change in peak pathogen concentration with a change in buffer ratio. This means that in order to ensure that the peak concentration is within an order of magnitude, ie 90%, the buffer ratio has to be within 90% divided by 4, or 22.5%, of its actual value.

It was concluded in the original EG uncertainty analysis that the more events used to calibrate the model the better its performance. So too in this analysis it was shown that the inclusion of, and particular focus on, events in the calibration process was very important. If, during calibration, only the overall objective function is assessed, the modeller would most likely underestimate the pathogen peaks.

In terms of prioritising research, the uncertainty analysis has shown that it is unnecessary to further refine the pathogen log reduction likely through a buffer strip. This is due to the outcomes of the model, both objective functions and actual predictions, not changing considerably when the reduction rate was altered. The pathogen reduction rate of 99% obtained from the literature is adequate for the purposes in this model.

As discussed in Chapter 6 the modified EG model required a number of assumptions due to EG not being a spatial model. These included assumptions about the minimum width and maximum slope of the buffer. A buffer that did not fit into these criteria may provide more or less pathogen reduction, depending on its make-up. For example Tate et al. (2004) concluded in their study that on a 20% slope, for every additional metre of

vegetated buffer, an extra 1 log reduction in pathogens was achieved. The results obtained from the uncertainty analysis indicate, however, that the make-up of the buffer and its subsequent reduction rate will have little effect on the model outcomes. This therefore validates these initial assumptions made in the EG model modification.

Undertaking local sensitivity analysis on each of the two inputs is justified based on the objectives of the analysis; that is to determine the sensitivity of the model to their individual uncertainties. There is, however, an opportunity to carry out global sensitivity analysis to determine if there is any cross-correlation occurring either with the parameters within the model or with other inputs. This could be an area for further investigation.

10. CONCLUSIONS

The overall aim of this research was to determine if it is possible to see a change in water quality following the implementation of catchment management and to quantify that change with respect to drinking water quality. The applicability of this aim was illustrated by literature and current regulations both of which clearly advocate the implementation of multiple barriers to ensure the protection of public health, but fail to provide evidence of their actual benefits at a catchment scale.

The catchment management technique which was the focus of the research was buffer strips, due to their increasing popularity as a method of controlling constituent movement through catchments. Despite their popularity, there is a lack of catchment scale research to justify to regulators or catchment managers that buffer strips are impacting on or improving drinking water quality, in particular with respect to the transport of pathogenic organisms.

Pathogens have been shown to be the biggest risk to public health and therefore their absence from drinking water is required. This research investigated the impact of diffuse pathogen pollution sources in an agricultural catchment and determined the impact buffer strip implementation had on pathogen numbers in drinking water.

This chapter summarises the findings and conclusions detailed throughout the research. It is set out by first discussing the relevance of the findings for resource mangers, regulators and for water quality sampling. These are then related back to the research questions posed in Chapter 1. It also looks at the strengths and weaknesses of the research as well as possible areas for further investigation.

10.1 Relevance of findings

An important consideration while undertaking this research was that the final conclusions or findings be relevant to managers of catchments and/or drinking water, who may want to implement buffer strips but are unsure of their real benefit, and/or drinking water quality regulators, who may be specifying acceptable contaminant barriers. These two groups are discussed separately below. Some conclusions related to drinking water quality sampling and possible ways to increase its value follows.

Catchment and/or water quality managers

- The most dominant processes that affect water quality within the study catchment were erosion and surface runoff. It follows then that rainfall would mobilise and transport contaminants and this would be the time that poses the greatest risk. Therefore, in the study catchment, management techniques that intercept or in some way treat surface runoff, or storm event runoff, will improve water quality.

- The EG model was able to be calibrated successfully in the study catchment which indicates that it could be a useful tool in similar catchments.

- The EG model showed the likely number of pathogens in a stream given a particular buffer ratio. It was also able to quantify the decrease in pathogen numbers given an increase in buffer ratio. This capability makes the model valuable as it allows drinking water quality and catchment mangers to predict the likely pathogen log-reduction through a buffer strip.

- The modified EG model showed that as a barrier to contamination, buffer strips are only effective during storm events. They reduce both the pathogen peak and the total number of pathogens. This in turn reduces both the risks to drinking water quality and the reliance on the downstream barriers.

- The outcomes of the modelling validate buffer strips as a barrier and gives managers confidence in the technique as a barrier. Additionally it allows buffer strips as a management technique to be compared against other more conventional techniques, such as treatment in terms of both cost and risk reduction.

- The model gives a quantifiable outcome which means that buffers could be included in a QMRA with some confidence. This may lead to a reduction in the level of treatment needed downstream without impacting on public health. Such an outcome could, in fact, be of benefit to public health due to less chemical interference with the water and less by-product formation.

- In terms of land-use within a drinking water catchment the model could be used to determine the difference in expected pathogen loads between a fully agricultural catchment with a buffer and a pristine or non-impacted catchment. Additionally it

could be used to evaluate the impact of increasing development on pathogen loads and the likely impact of having a buffer.

Regulators

- This research has shown buffers alone have the ability to reduce pathogens by over 1-log, and up to 1.22-logs, indicating that the assumed reduction rates in the LT2 Rule and ADWG may be underestimating the actual overall benefits of catchment management. Both the LT2 Rule and the ADWG lump all catchment management techniques together in terms of allocating an overall pathogen log reduction capability; they are 0.5 and 1-log respectively.

- The modified EG model could be used as a basis for developing guidelines for managing the introduction of recreational activities into an otherwise pristine catchment.

Water quality sampling

- The data analysis was unable to show any consistent trends or clear measurable impact that catchment management had had on the quality of drinking water. This was due to the majority of available data being obtained during routine water quality sampling and therefore, mostly, during baseflow conditions.

- Any form of risk assessment on a system should be based on the sampling results of storm events as this will clearly show the highest level of risk that the system is likely to be challenged with. Additionally storm event sampling is imperative to be able to show changes in water quality due to buffer strip implementation. Storm event sampling should be undertaken as part of routine testing, not just for pathogens but for all important water quality constituents.

- The best predictor of pathogen transport during events was peak flow indicating that the peak intensity of a storm, rather then storm duration or magnitude, gives the best information. This means that in order to predict pathogen transport, it is necessary to have continuous streamflow monitoring as this will allow the peak flows to be determined.

- Buffer strips had the least affect on average pathogen concentration which is traditionally the way in which pathogens are reported in the drinking water industry. This data may be inadequate in terms of showing any change in water quality due

to catchment management. A reduction in the pathogen peak is much more likely to show the real benefits, and this again shows the value in storm sampling.

10.2 Research questions

In the introduction, a set of research questions were posed which were directly related to the research hypothesis. In this section those questions are answered based on the findings of the research and ultimately prove the hypothesis to be correct.

- *Is there a measurable impact on water quality following catchment management?*
  Based on the results of the statistical analysis it is difficult to provide a definitive answer to this question. However, further analysis of the results shows that catchment management will impact water quality during rainfall events and that this impact is measurable if the appropriate data is collected, ie storm data. Showing the effects of catchment management using routine or baseflow data is effectively unachievable.

- *How effective are buffers at reducing pathogen transport and improving drinking water quality?*
  Buffers are reasonably effective at trapping pathogens in the surface flow and preventing their transport to streams. It is only therefore only during storm events that a buffer is effective; pathogens entrained in the baseflow are unaffected by buffers. The modelling showed that the peak flux of an event decreases by a magnitude of 1.22 with the introduction of a buffer.

- *Can a reduction in pathogens following buffer implementation be predicted?*
  Not only can a reduction in pathogens following buffer implementation be predicted but that reduction can also be quantified. The quantification is in terms of magnitude change, which is the level of accuracy required when pathogens are being discussed. To enable accurate prediction of pathogen transport, the EG model must be successfully calibrated and this requires reliable pathogen data from the catchment streams and, most importantly, must include event data.

- *Does the quantification of buffer effectiveness give drinking water quality managers a validated barrier to contamination?*

Yes, although more correctly it gives drinking water quality managers evidence that buffer strips can work as a barrier in terms of reducing pathogen contamination. Verification of the model results with field data may be required to show regulators that the barrier is validated.

- *Are the resources necessary to implement catchment management justifiable based on the risk reduction to drinking water quality?*
  Given the ability of the modified EG model to successfully predict the likely pathogen reduction due to buffer strip implementation, it would be possible to carry out a QMRA as well as a cost-benefit analysis comparing buffer strips to more conventional downstream treatment options. Ultimately and based on the risks in the catchment, this may lead to more informed decisions about the appropriate treatment and the appropriate level of treatment.

10.3 Strengths and weaknesses of the research

It is important to identify the strengths and weaknesses of any research as it helps to put the outcomes in perspective and also assists in highlighting any areas for future investigation. This section is split into the following two areas: data and model application.

Data

- One of the strengths of this research is that a number of different techniques were trialled to determine if there was a measurable impact on water quality following catchment management. The techniques were complementary in that they resulted in similar outcomes further strengthening the final conclusions and assumptions which were necessary in modifying the model.

- A considerable amount of data - over 145,000 data points - was available for the test catchment, including: before and after catchment works, during different flow conditions and covering a range of parameters. A specific strength of the data was that there were a number of storms which were sampled in the period classified as after catchment management implementation. These events included physical-chemical parameters as well as pathogens and pathogenic indicators.

- Despite the extensive data set, the most important data set for indicating that catchment management was improving water quality was storm event data. This uncovered a weakness in the research in that there was not enough water quality data sampled during events prior to any works to demonstrate the effects of catchment management with basic statistical analysis.

- The paucity of pathogen event data in the West branch was a limitation when it came to calibration of the EG model. It was determined during the original sensitivity analysis that the quantity of event data could impact the final fit of the model and that the more data there was the better the chances of achieving a satisfactory fit. It meant that confidence in the model outcomes and therefore the predictive power of the model was reduced in this catchment.

- The five storm events sampled in the East are a strength of this research as they allowed the successful calibration and validation of the EG model in this catchment. More events would, however, undoubtedly improve the calibration.

- The EG model was calibrated using *E. coli* data as opposed to specific pathogen data. The reasons for this were explained in the thesis and were mostly related to poor pathogenic data availability due to inadequate sampling and detection techniques. Until advancements in pathogen monitoring occurs, pathogenic indicators are the best way of indicating the presence of faecal contamination in drinking water.

Model application

- A need was identified for a pathogen transport model that could quantify the benefits of having a buffer strip. No such model existed previously and now that one has been created and successfully calibrated the true benefits of implementing catchment management, in particular buffer strips, can be realised and be used to inform QMRAs.

- The range of catchments that EG has been successfully calibrated in indicates that the model is relatively robust. The modified EG model has, however only been calibrated in one catchment and therefore the results obtained pertaining to buffer effectiveness may be catchment-specific. Based on the model set up it is expected that the effect of the buffer on pathogen numbers would remain the same but that the actual change in numbers may be different.

- The modified EG model is relatively simple, with only one additional input compared to the original EG model. The model requires data that is accessible in most catchments or is easy to ascertain. This simplicity is considered a strength as it means the model is relatively quick to run and calibrate. This makes it appealing to modellers who require immediate outcomes to aid decision making or who want to model and compare outcomes of different scenarios.

- The pathogen reduction rate chosen as it was based on laboratory studies and then applied to a catchment scale model, which may be seen as a weakness. The sensitivity analysis showed that the reduction rate had only a minor impact on the model outcomes and objective functions and that further refinement of the actual rate would not greatly influence the model fit. Consequently, the extrapolation between scales with respect to reduction rate is not a concern.

- The accuracy of the calibrated model in terms of predicting observed pathogen values is considered a strength of this research. Predicting pathogens is widely acknowledged as a difficult task and a model that can predict pathogens within a 1-log range is considered accurate, which the modified EG model was able to do. This range is reasonable as drinking water treatment plants are operated according to the magnitude of the peak pathogen concentration.

10.4 Further investigation

This research has uncovered a number of areas where further investigation could be carried out.

- *Model calibration*
  The EG model has been developed and used throughout this thesis using *E. coli* as a pathogenic indicator. It would be desirable to calibrate the model using actual pathogen data to determine if the outcomes are similar. Ideally protozoan data should be used as it is the biggest threat to drinking water quality. Future versions of the model could concentrate on viruses and bacteria; although this would require a sophisticated and focused monitoring program to provide the necessary calibration data. Additional areas for further investigation in this area include

consideration of emerging pathogens, viability/infectivity of the modelled pathogens and consideration of other constituents of concern such as pesticides.

A better performing hydrological model could potentially improve the performance of the EG model as the results of the former impact on the results of the latter. Hydrological models other than SIMHYD should be tested with the EG model.

The EG model was successfully calibrated with data that was classified as being after catchment works. It was then used to predict the likely pathogen transport before catchment works. Ideally, data would be available both before and after catchment management so as the models predictive power could be verified.

Ideally the modified EG model would be tested in a variety of catchments to verify the buffer effectiveness results and determine the effect of different catchment types on pathogen transport.

- *Changing buffer characteristics over time*
  There is very little research on how buffer strips may change over time and what this might mean for their effectiveness as a contaminant barrier. There is the possibility of the buffer clogging up or of the creation of preferential flow paths; both actions would result in a reduction in the capability of the buffer as a barrier. Compaction, through animal access or other issues related to animal access, such as direct faecal deposition, could also reduce the buffers effectiveness. Alternatively, there is the possibility that buffer strips may become more effective over time due to an increase in understory vegetation and/or existing vegetation having more established root systems.

  An associated question relates to how long it takes for a buffer to become established and whether in its early stages of growth there is some benefit in terms of contaminant reduction or if there is a specific time before its true benefits are realised.

- *Effectiveness of other catchment management techniques*
  Only one catchment management technique was investigated in this research. A gap still remains in terms of the effectiveness of other techniques for the reduction of pathogen transport and the improvement of drinking water quality. Additional studies could undertake research on particular techniques with a focus on

pathogens. Following this additional research, techniques could be compared and implemented based, in part, on their risk reduction abilities.

- *Cross correlation*

  The issue of parameter cross correlation was not addressed within this thesis. It is possible that a global sensitivity analysis may reveal that two or more of the inputs into the modified EG model are correlated. The need for this type of analysis is however not clear as the model is relatively simple and its inputs and parameters do not range over more than 1 order of magnitude.

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APPENDICIES

Appendix A – IFD curve for Tarago catchment

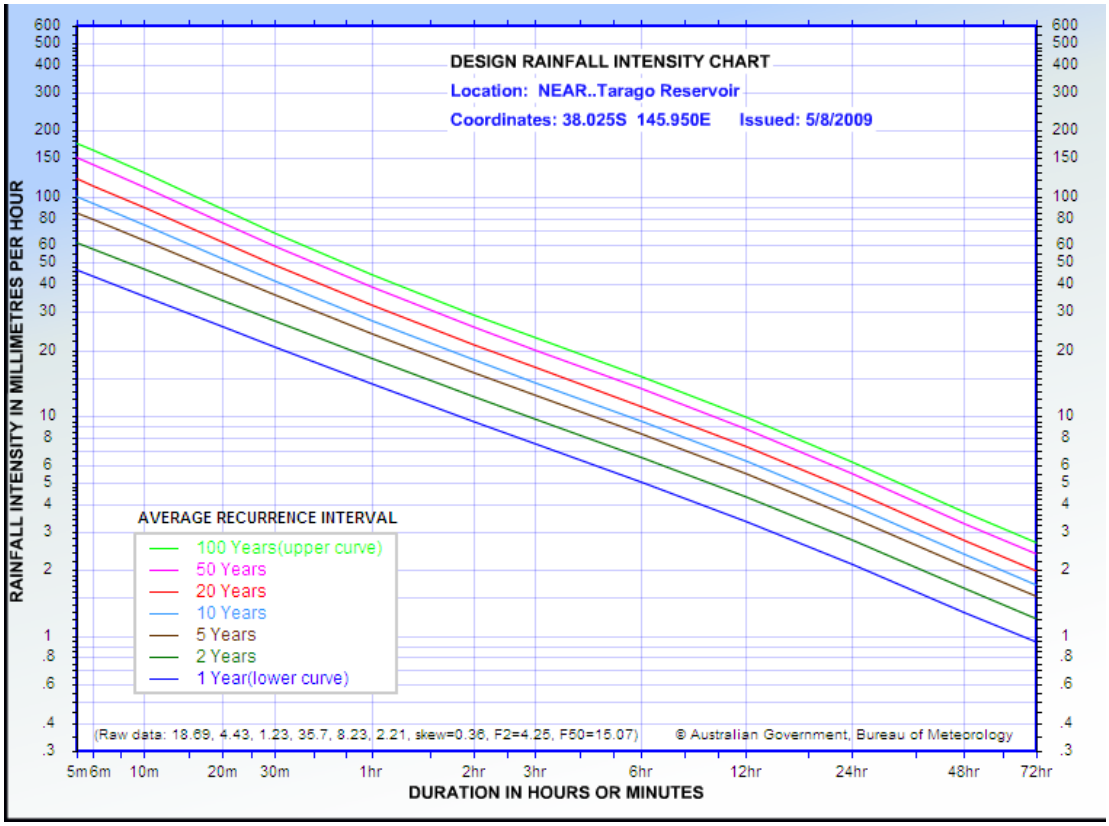

Figure A.1 – IFD curve for near the Tarago Reservoir

Appendix B – 3-year rolling averages

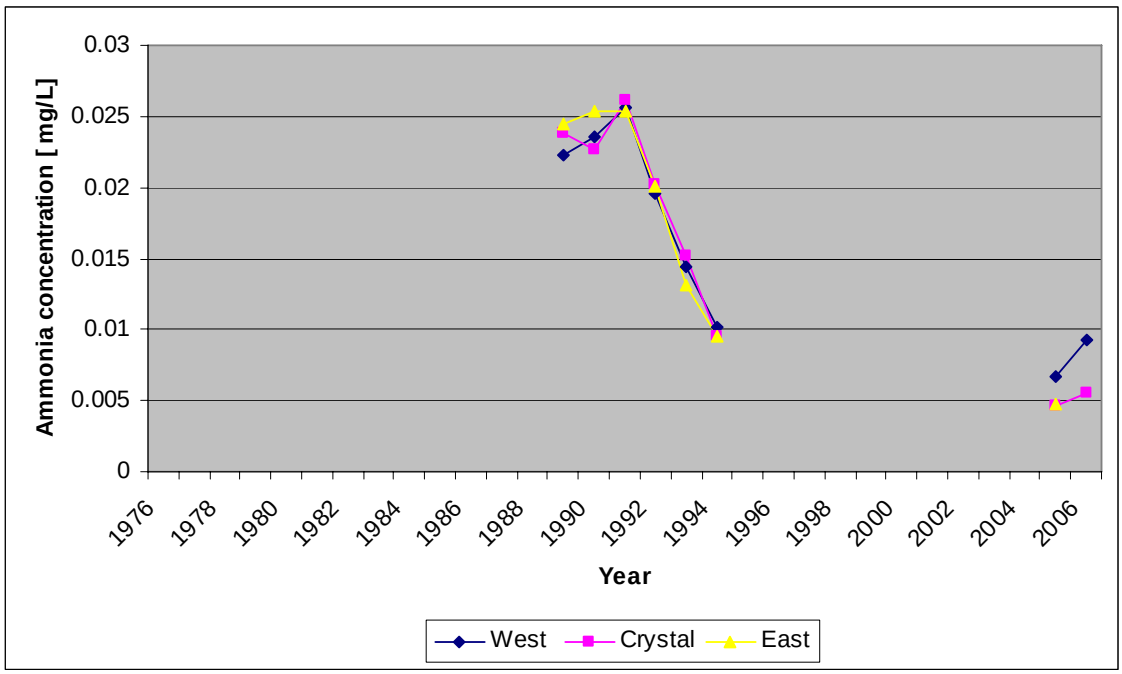

Figure B.1 – 3-year rolling averages for ammonia

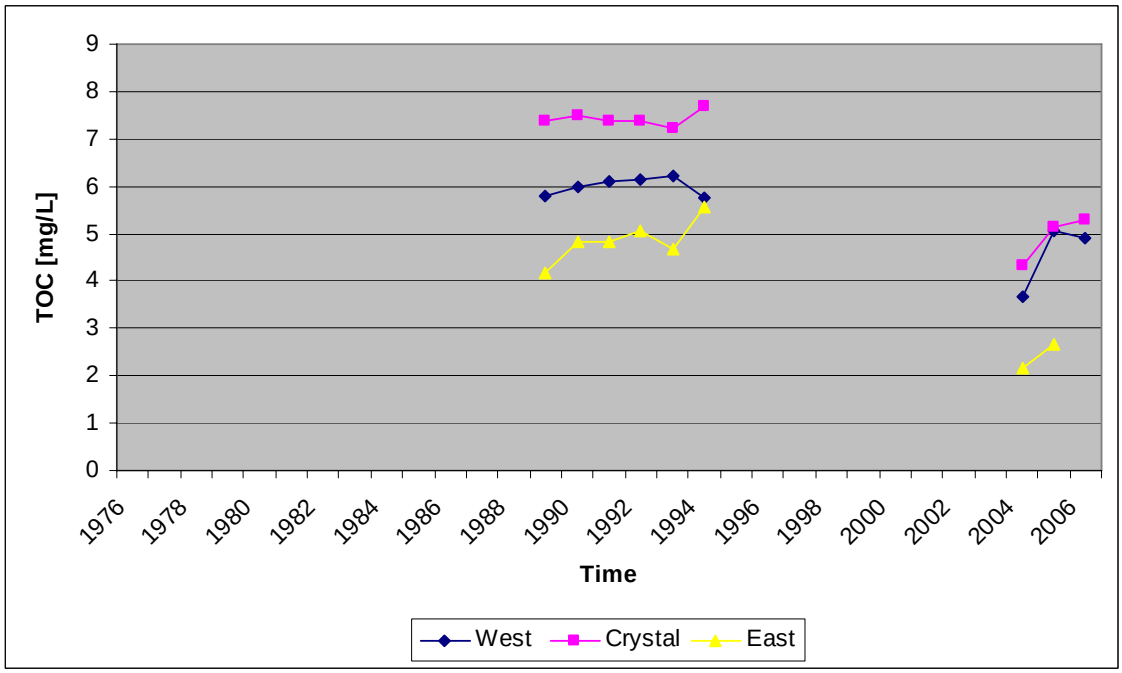

Figure B.2 – 3-year rolling averages for TOC

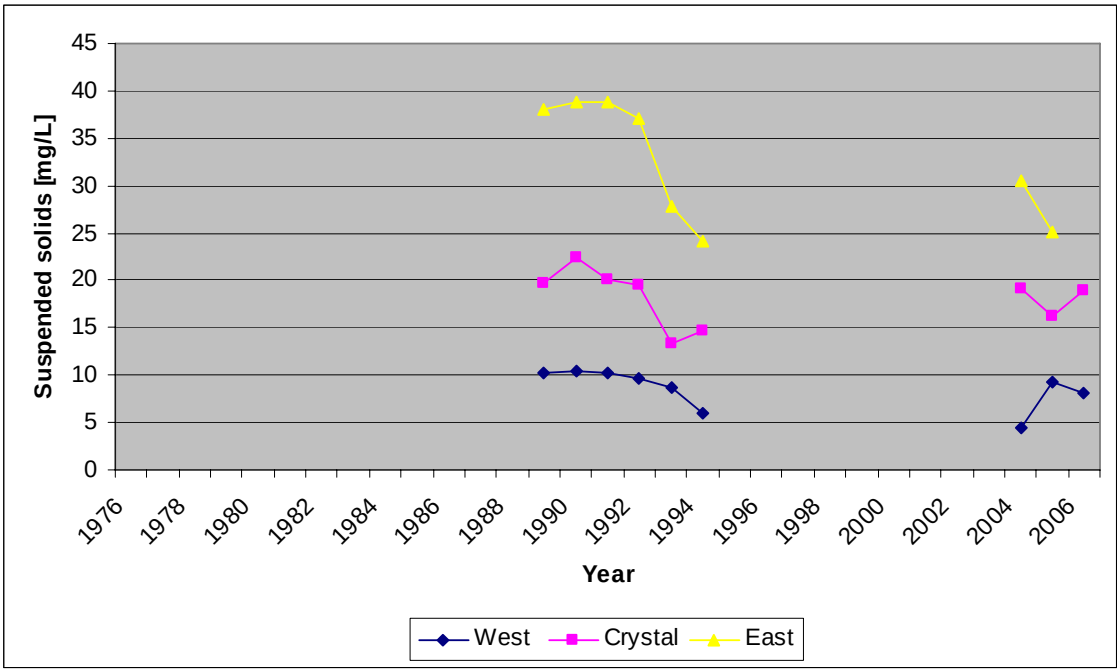

Figure B.3 – 3-year rolling averages for suspended solids

Appendix C – Correlation matrices

Table C.1 – Linear regression R^2 statistics for parameters in the West catchment

	EC	Colour	Turbidity	Iron	Manganese	Nitrate	Phosphorus	Ammonia	TOC	Suspended solids	TKN	Total coliforms	*E. coli*	Enterococci	*C. perfrigens*	Flow
pH	0.11	0.05	0.03	0.00	0.00	0.01	0.00	0.01	0.08	0.03	0.03	0.16	0.11	0.01	0.00	0.00
EC		0.05	0.03	0.00	0.00	0.03	0.02	0.00	0.03	0.05	0.06	0.05	0.07	0.12	0.20	0.10
Colour			0.29	0.25	0.14	0.02	0.02	0.00	0.52	0.29	0.20	0.06	0.01	0.01	0.00	0.01
Turbidity				0.42	0.22	0.07	0.09	0.02	0.31	0.86	0.80	0.05	0.03	0.30	0.00	0.08
Iron					0.45	0.01	0.02	0.00	0.31	0.25	0.31	0.22	0.15	0.13	0.00	0.04
Manganese						0.01	0.01	0.00	0.17	0.15	0.17	0.36	0.20	0.19	0.00	0.00
Nitrate							0.00	0.03	0.00	0.05	0.04	0.18	0.04	0.00	0.01	0.16
Phosphorus								0.05	0.07	0.19	0.12	0.13	0.06	0.01	0.00	0.00
Ammonia									0.01	0.05	0.07	0.16	0.00	0.02	0.00	0.05
TOC										0.30	0.45	0.04	0.33	0.00	0.15	0.03
Suspended solids											0.83	0.06	0.05	0.21	0.00	0.02
TKN												0.28	0.02	0.53	0.01	0.03
Total coliforms													0.48	0.45	0.01	0.21
E. coli														0.40	0.01	0.01
Enterococi															0.00	0.11
C. perfringens																0.00

Table C.2 – Linear regression R^2 statistics for parameters in the Crystal catchment

	EC	**Colour**	**Turbidity**	**Iron**	**Manganese**	**Nitrate**	**Phosphorus**	**Ammonia**	**TOC**	**Suspended solids**	**TKN**	**Total coliforms**	***E. coli***	**Enterococci**	***C. perfrigens***
pH	0.07	0.07	0.00	0.00	0.00	0.00	0.00	0.01	0.14	0.00	0.01	0.09	0.09	0.03	0.00
EC		0.08	0.02	0.01	0.01	0.00	0.00	0.14	0.13	0.01	0.02	0.16	0.29	0.40	0.25
Colour			0.31	0.34	0.18	0.04	0.05	0.00	0.54	0.44	0.18	0.19	0.07	0.11	0.50
Turbidity				0.71	0.24	0.00	0.14	0.01	0.33	0.45	0.37	0.19	0.04	0.11	0.69
Iron					0.30	0.00	0.06	0.03	0.20	0.32	0.31	0.30	0.11	0.18	0.59
Manganese						0.05	0.17	0.03	0.13	0.43	0.19	0.52	0.39	0.51	0.23
Nitrate							0.03	0.05	0.00	0.04	0.02	0.08	0.01	0.00	0.00
Phosphorus								0.00	0.05	0.29	0.13	0.16	0.20	0.27	0.06
Ammonia									0.00	0.00	0.01	0.03	0.01	0.00	0.02
TOC										0.27	0.14	0.24	0.96	0.45	0.03
Suspended solids											0.46	0.26	0.16	0.32	0.38
TKN												0.26	0.27	0.41	0.29
Total coliforms													0.30	0.12	0.15
E. coli														0.66	0.03
Enterococci															0.09

Table C.3 – Linear regression R^2 statistics for parameters in the East catchment

	EC	Colour	Turbidity	Iron	Manganese	Nitrate	Phosphorus	Ammonia	TOC	Suspended solids	TKN	Total coliforms	*E. coli*	Enterococci	*C. perfrigens*	Flow
pH	0.29	0.09	0.00	0.03	0.00	0.00	0.00	0.08	0.05	0.01	0.00	0.01	0.01	0.00	0.00	0.08
EC		0.06	0.00	0.08	0.03	0.01	0.02	0.04	0.03	0.01	0.00	*[*]	*	*	0.49	0.16
Colour			0.29	0.05	0.18	0.00	0.14	0.00	0.68	0.69	0.39	0.00	0.02	0.09	0.00	0.01
Turbidity				0.43	0.37	0.01	0.48	0.01	0.61	0.76	0.76	0.14	0.17	0.34	0.13	0.01
Iron					0.54	0.00	0.32	0.04	0.57	0.43	0.43	0.17	0.21	0.52	0.14	0.00
Manganese						-0.03	0.59	0.04	0.62	0.77	0.66	0.41	0.47	0.78	0.39	0.02
Nitrate							0.00	0.02	0.04	0.01	0.01	0.04	0.47	0.23	0.01	0.23
Phosphorus								0.00	0.32	0.57	0.41	0.05	0.20	0.45	0.28	0.03
Ammonia									0.01	0.00	0.01	0.07	0.05	0.04	0.03	0.02
TOC										0.59	0.48	*	*	0.13	0.15	0.27
Suspended solids											0.81	0.16	0.13	0.24	0.12	0.02
TKN												0.16	0.26	0.27	0.33	0.03
Total coliforms													0.22	0.13	0.02	0.00
E. coli														0.67	0.35	0.24
Enterococi															0.31	0.32
C. perfringens																0.00

[*] Insufficient data to perform regression

Appendix D – Contaminant levels during events

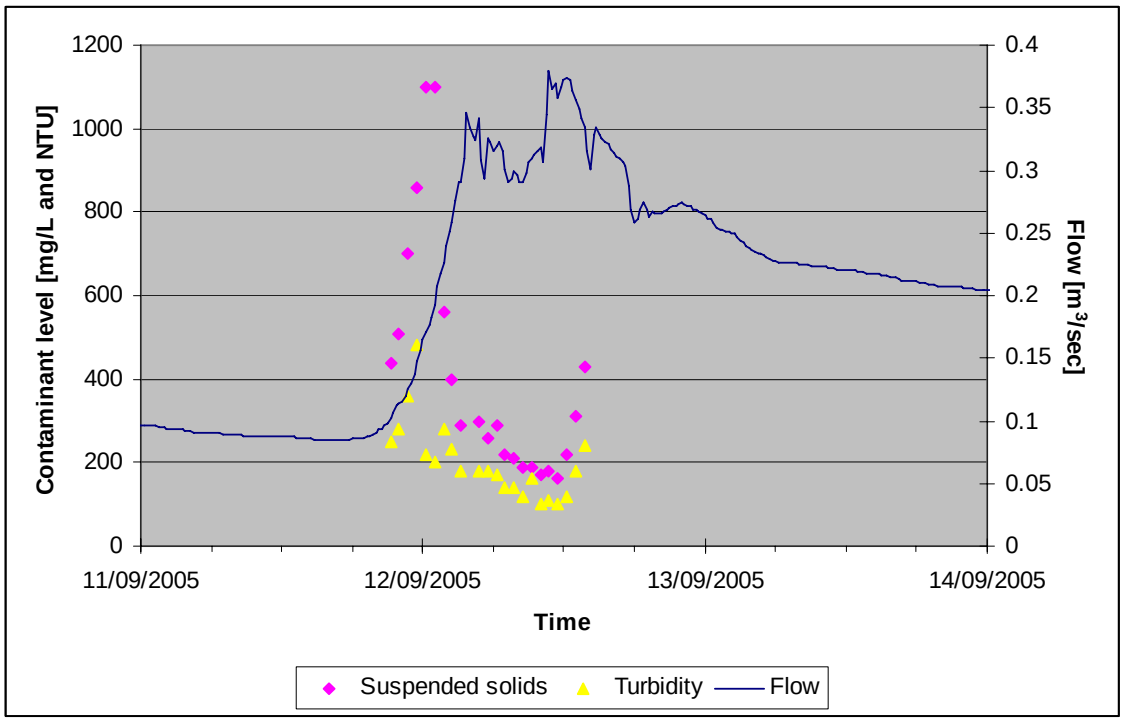

Figure D.1 – Flow, suspended solids and turbidity for Event 1 in the East catchment

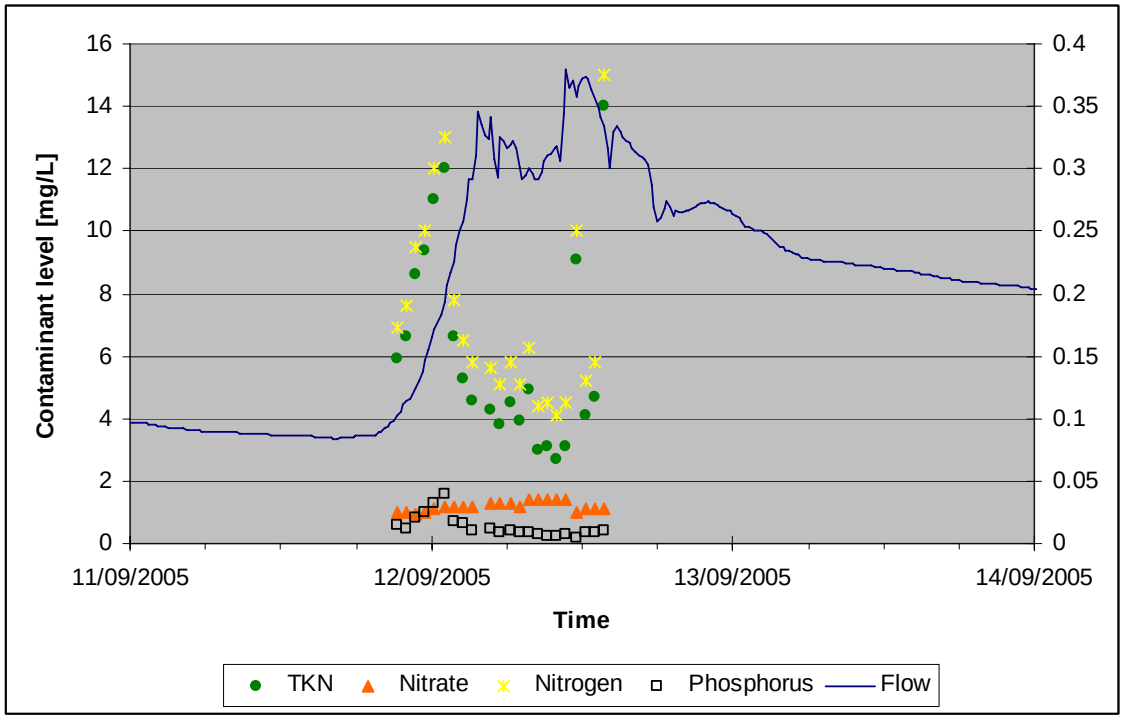

Figure D.2 – Flow and nutrients for Event 1 in the East catchment

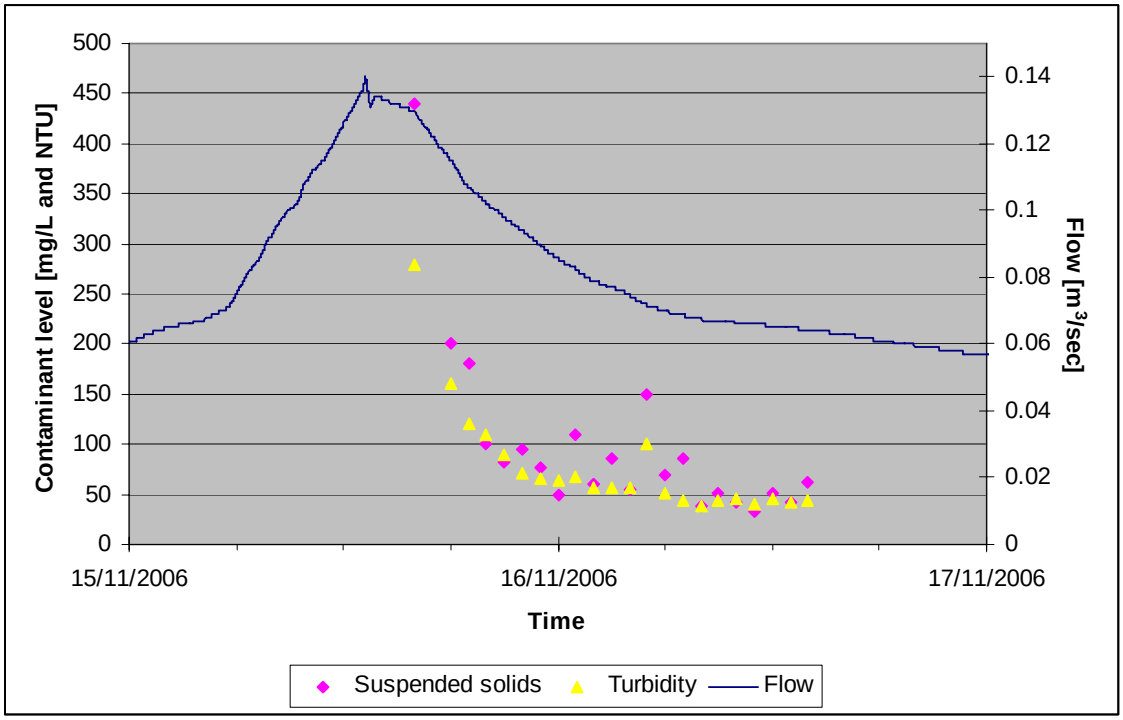

Figure D.3 – Flow, suspended solids and turbidity for Event 2 in the East catchment

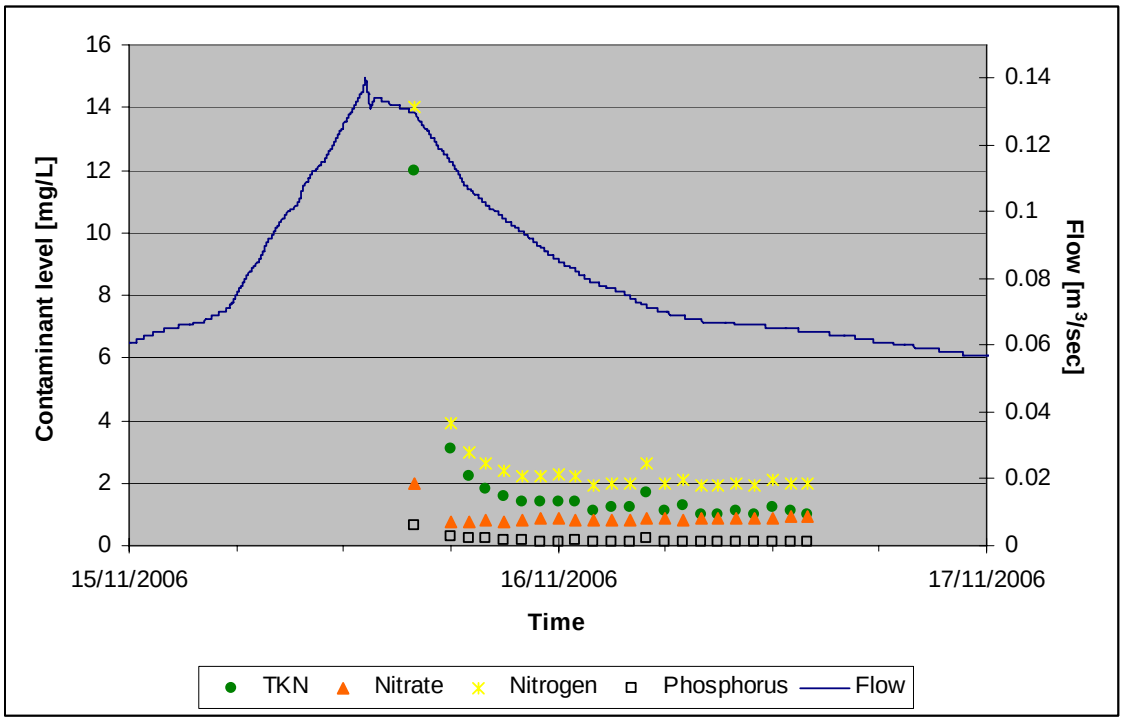

Figure D.4 – Flow and nutrients for Event 2 in the East catchment

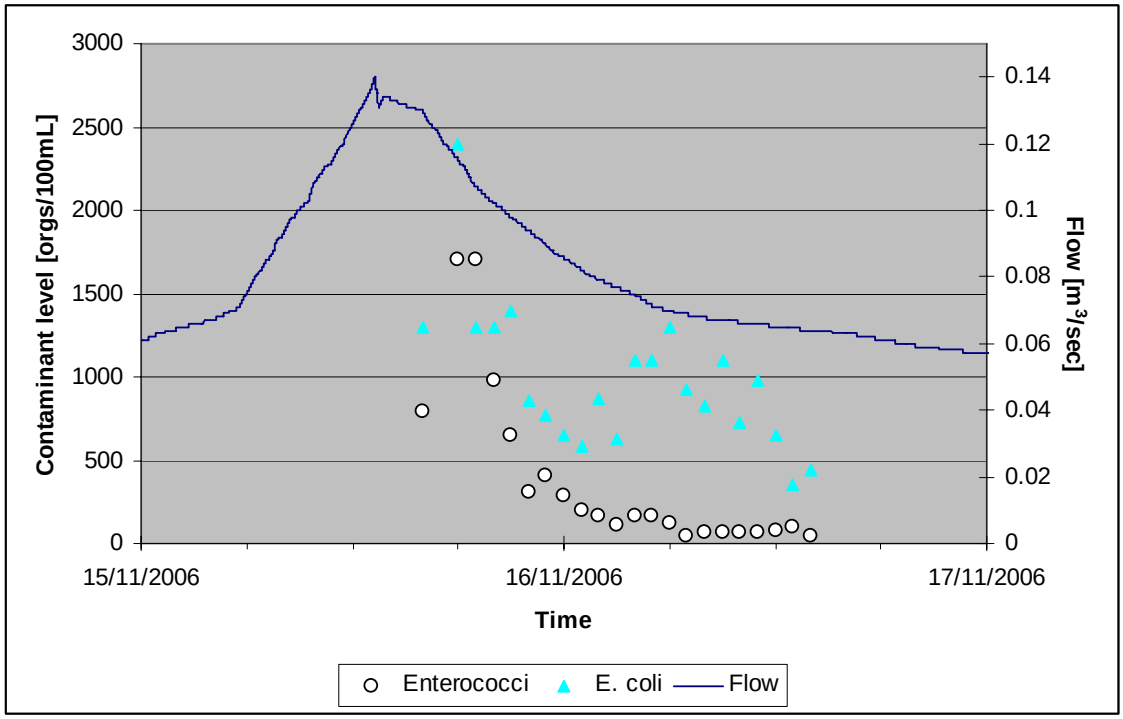

Figure D.5 – Flow and indicators for Event 2 in the East catchment

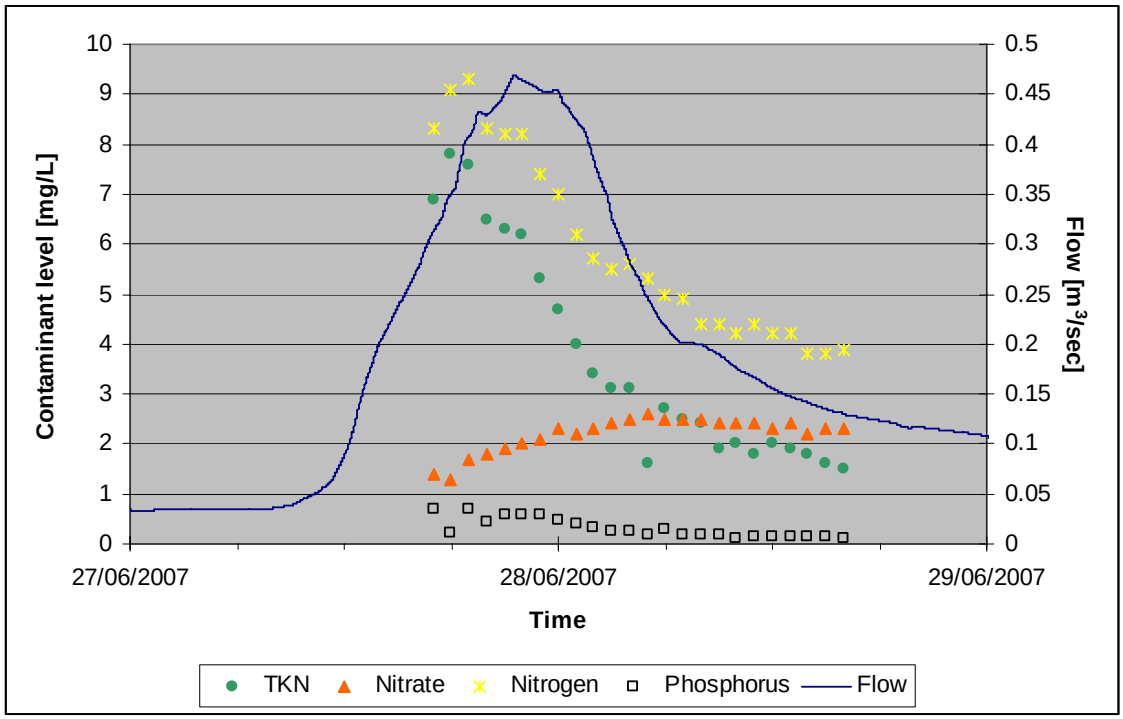

Figure D.6 – Flow and nutrients for Event 3 in the East catchment

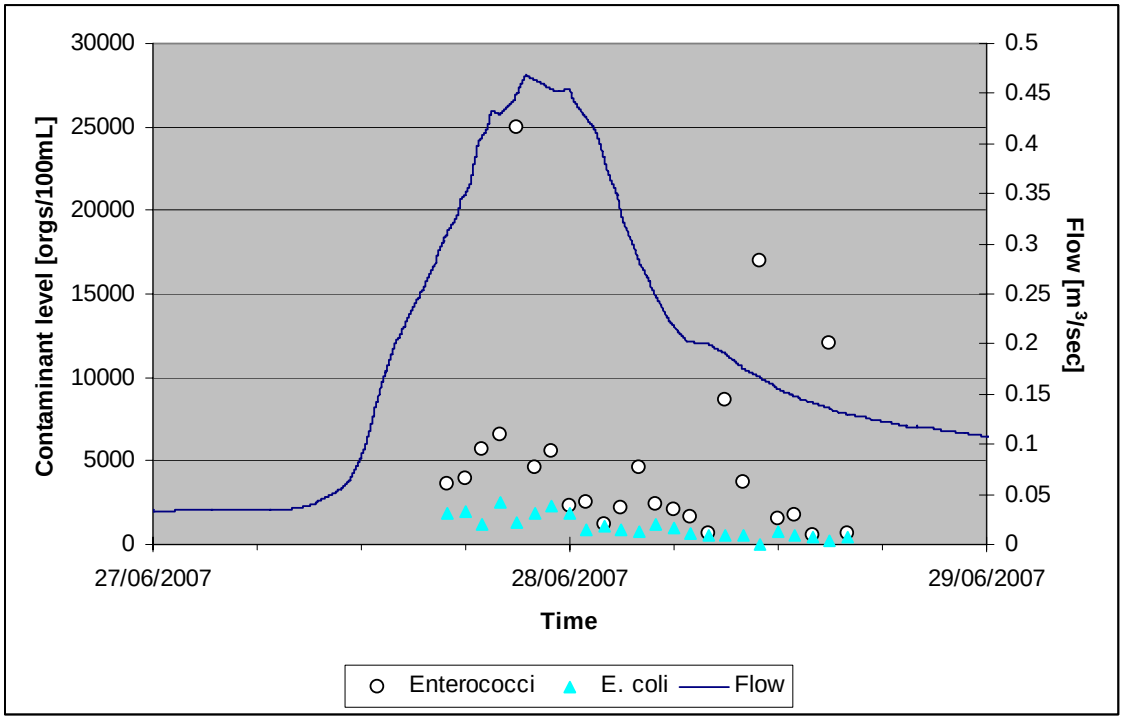

Figure D.7 – Flow and indicators for Event 3 in the East catchment

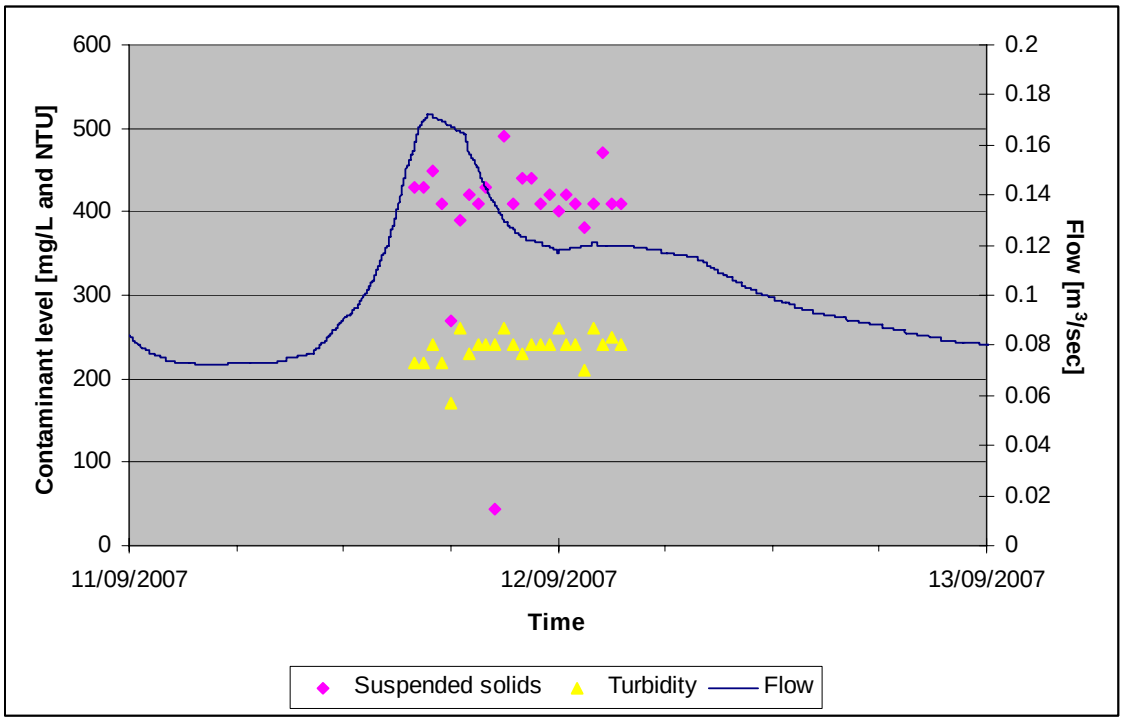

Figure D.8 – Flow, suspended solids and turbidity for Event 4 in the East catchment

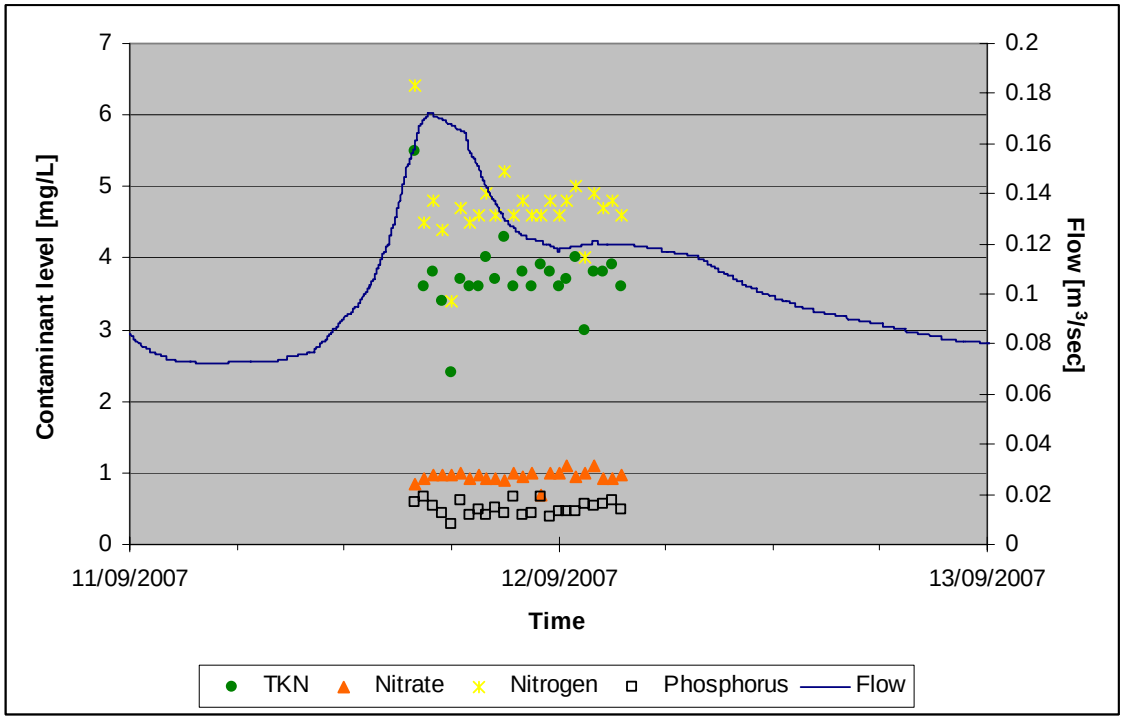

Figure D.9 – Flow and nutrients for Event 4 in the East catchment

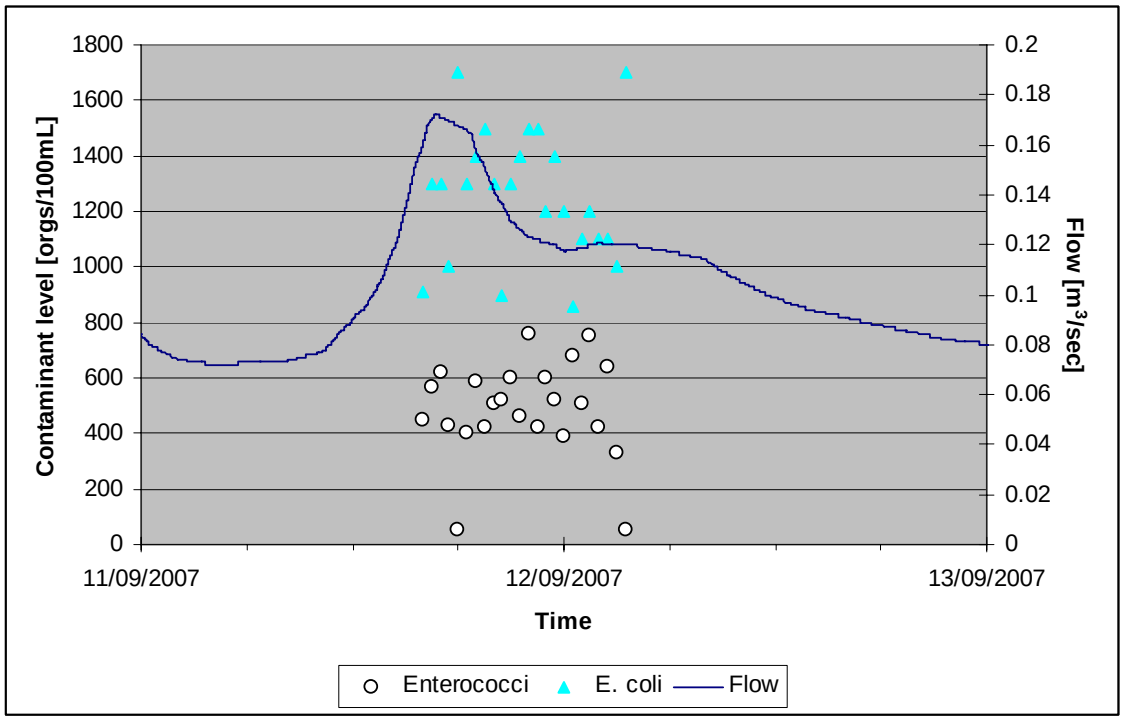

Figure D.10 – Flow and indicators for Event 4 in the East catchment

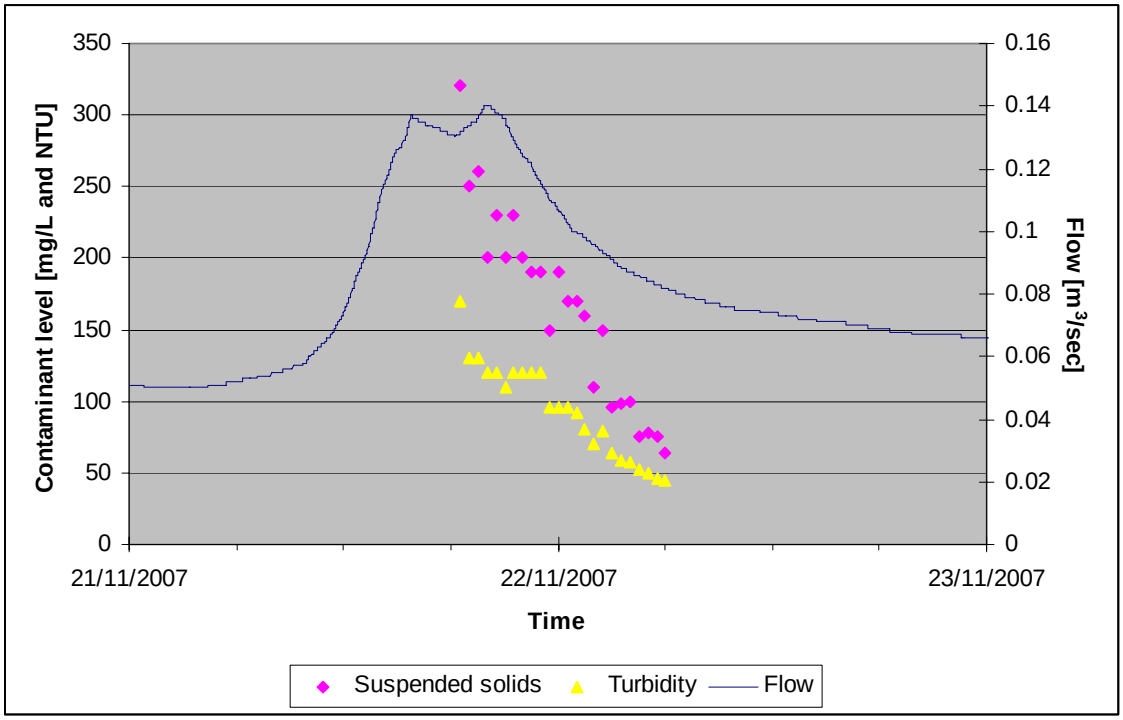

Figure D.11 – Flow and suspended solids and turbidity for Event 5 in the East catchment

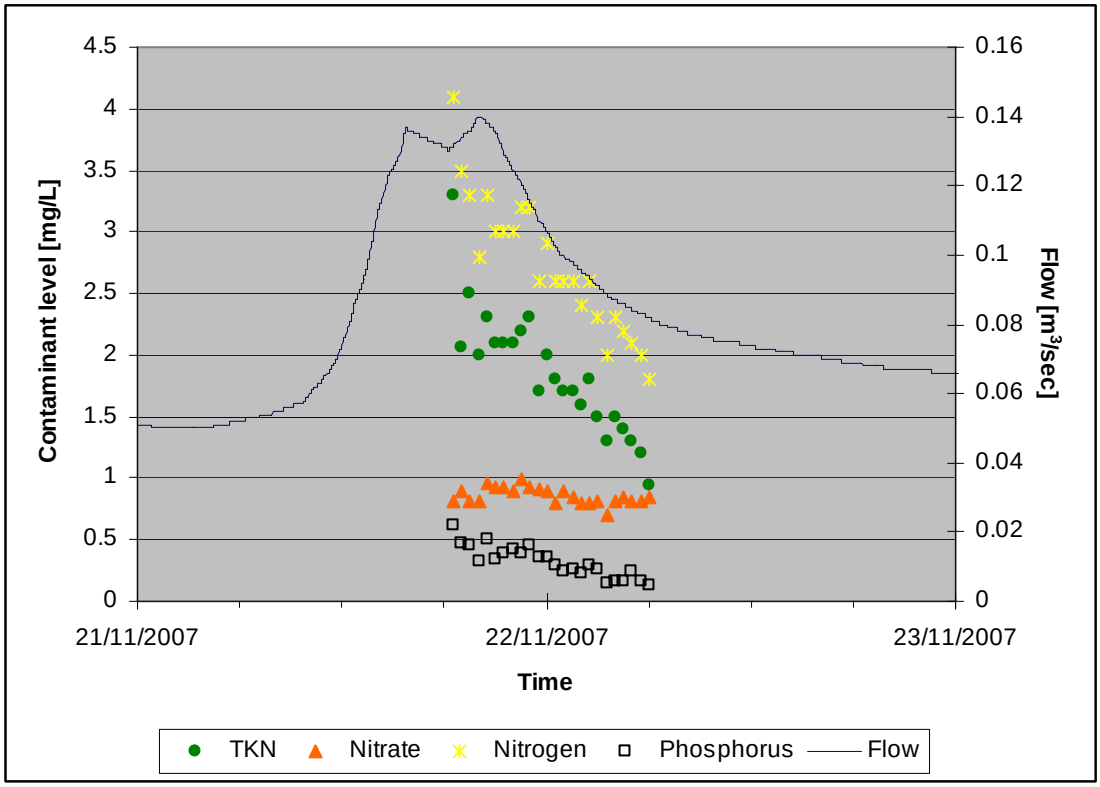

Figure D.12 – Flow and nutrients for Event 5 in the East catchment

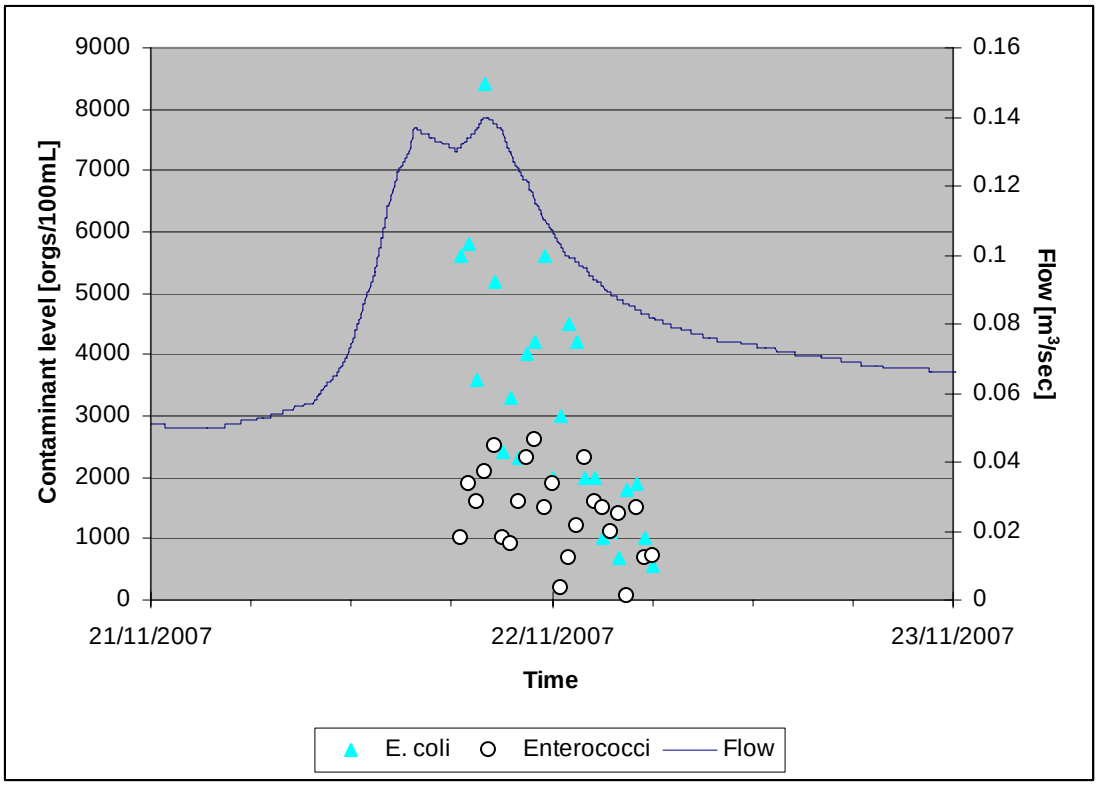

Figure D.13 – Flow and indicators for Event 5 in the East catchment

Appendix E – SIMHYD hourly outputs for different catchments

Forested catchment

- area = 11,900 ha
- no human or domestic animal habitation
- deep stable soils
- high quality runoff

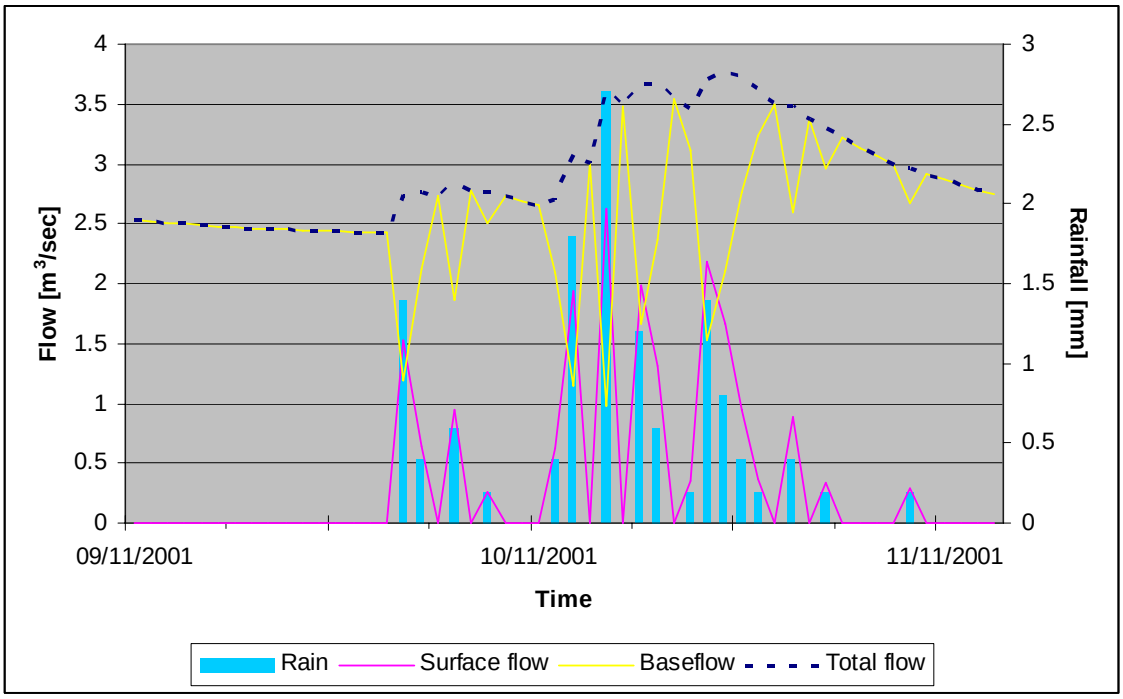

Figure E.1 – SIMHYD hourly output for a forested catchment

Peri-urabn catchment

- area = 780 ha
- 61% urban, majority on septic systems

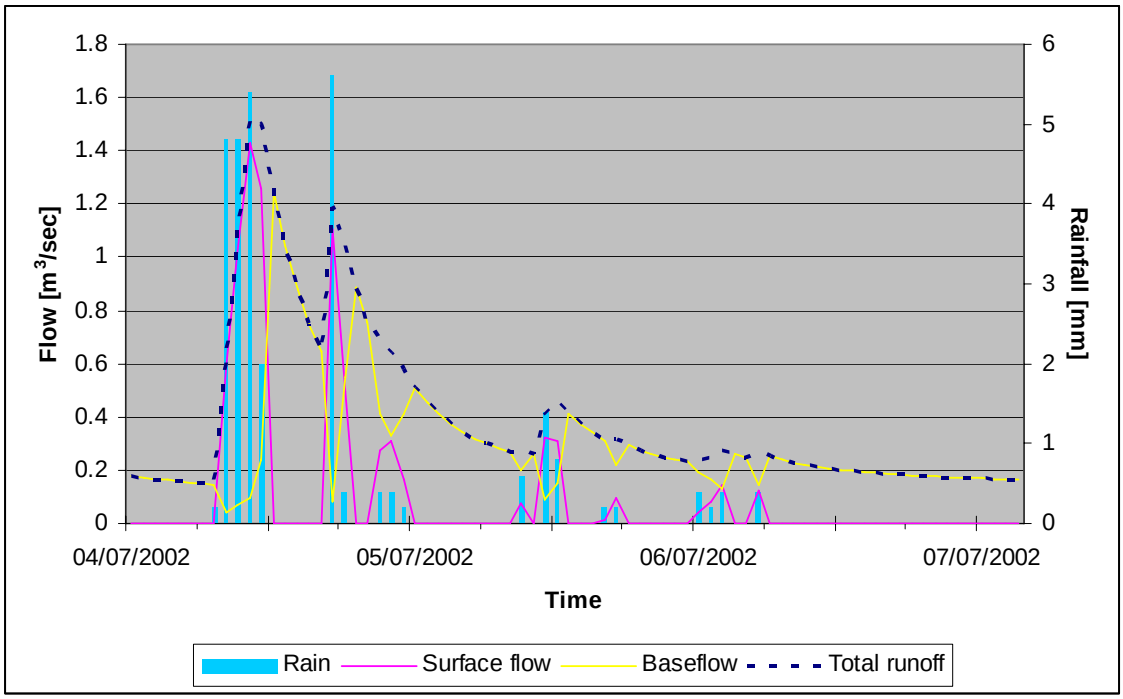

Figure E.2 – SIMHYD hourly output for a peri-urban catchment

Agricultural catchment

- area = 7,668 ha
- 86% grazing land

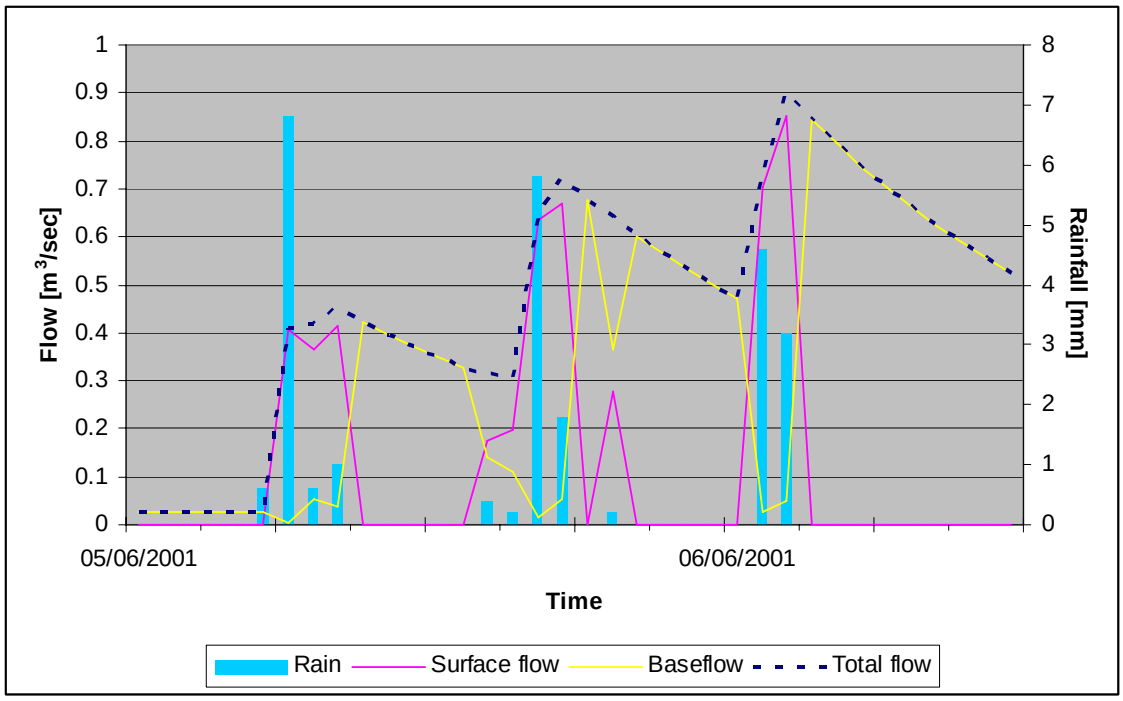

Figure E.3 – SIMHYD hourly output for an agricultural catchment

Appendix F – Calibration statistics

Table F.1 – SIMHYD manual calibration runs for the East catchment – data from 1999-2003

(highlighted row is the best run)

Run #	Rainfall	Factor	SIMHYD parameters								Objective functions		
			INSC	COEFF	SQ	SMSC	SUB	CRAK	RK	RESCOEFF	R^2	*E*	*TVOL*
1	N+B+R+D	none	0.0001	35	5	1000	0.5	2.5	0.0005	0.02	0.62	-1.07	61.41
2			5	200	"	"	"	"	"	"	0.64	0.27	24.89
3			"	100	"	"	"	"	"	"	"	"	"
4			"	"	0.01	"	"	"	"	"	"	"	"
5			"	"	"	50	"	"	"	"	0.68	-7.86	144.93
6			"	"	"	500	"	"	"	"	0.71	-1.23	62.53
7			"	"	"	1500	"	"	"	"	0.56	0.49	6.29
8			"	"	"	1000	1	"	"	"	0.66	-0.39	31.77
9			"	"	"	"	0.75	"	"	"	0.66	0.03	28.39
10			"	"	"	"	"	0.01	"	"	0.39	-2.31	20.95
11			"	"	"	"	"	3	"	"	0.68	-0.13	36.19
12			"	"	"	"	"	"	0.05	"	0.42	-11.35	41.22
13			"	"	"	"	"	"	0.0001	"	0.45	0.20	16.18
14			"	"	"	"	"	"	"	0.8	0.11	-7.27	16.29
15			"	"	"	"	"	"	"	0.001	0.16	0.04	13.27
16			"	"	"	"	"	"	"	0.05	0.43	-0.22	16.26
17			"	"	"	"	"	"	"	0.03	0.45	0.06	16.23

Table F.2 – SIMHYD automatic calibration runs for the East catchment – data from 1999-2003

Run #	Rainfall	Factor	SIMHYD parameters								Objective functions		
			INSC	COEFF	SQ	SMSC	SUB	CRAK	RK	RESCOEFF	R^2	E	TVOL
1	N+D+R+B	None	5.0000	*Fixed at 200*	*Fixed at 5*	539.42	0.0635	0.5969	0.0012	0.0986	0.66	0.60	6.88
2		1.2	5.000			100.00	0.1170	0.4757	0.0003	0.0041	0.27	-0.65	39.90
3		0.8	4.7600			398.05	0.3403	3.0000	0.0004	0.0481	0.71	0.65	2.02
4	N+D+B	None	0.0009			500.00	0.1992	0.0003	0.0001	0.0053	0.44	-1.17	15.45
5		1.2	0.0009			535.2	0.2017	0.3842	0.0001	0.0032	0.35	-4.68	118.69
6		0.8	0.0001			540.73	0.4754	1.1123	0.0002	0.0102	0.56	0.51	0.35
7	N+D+R	None	3.3300			395.57	0.5950	0.6363	0.0001	0.0023	0.59	0.54	2.59
8		1.2	5.0000			1000.00	0.4238	0.0002	0.0001	0.0011	0.42	0.29	2.36
9		0.8	0.0001			504.17	0.4713	3.0000	0.0004	0.0524	0.70	0.65	2.06
10	N+R+B	None	4.2100			627.31	0.0633	0.6135	0.0010	0.0893	0.64	0.57	1.58
11		1.2	06328			1000.00	0.4165	0.0001	0.0135	0.0001	0.01	-0.92	15.94
12		0.8	5.0000			451.64	0.3117	2.8611	0.0004	0.0557	0.74	0.70	1.88
13	D+R+B	None	0.0030			499.87	0.1566	0.0004	0.0024	0.0131	0.34	-0.78	34.7
14		1.2	0.0009			498.23	0.0002	0.0001	0.0002	0.0074	0.43	-7.56	71.85
15		0.8	0.0001			503.97	0.4860	2.0800	0.0004	0.0219	0.62	0.54	0.46
16	N+D	None	0.0009			500.45	0.1616	0.0001	0.0001	0.0056	0.38	-0.62	16.33
17		1.2	0.0004			500.71	0.5434	0.9668	0.0002	0.0071	0.55	-6.16	134.05
18		0.8	0.0001			503.49	0.6547	1.4756	0.0002	0.0079	0.54	0.49	0.43
19	N+R	None	5.0000			501.53	0.0968	0.8828	0.0009	0.0819	0.71	0.63	4.61
20		1.2	5.0000			1000.00	0.1700	0.4441	0.0002	0.0018	0.19	-0.26	16.64
21		0.8	0.9818			478.97	0.4389	3.0000	0.0004	0.0400	0.71	0.70	1.6

cont…

cont…

Run #	Rainfall	Factor	SIMHYD parameters								Objective functions		
			INSC	COEFF	SQ	SMSC	SUB	CRAK	RK	RESCOEFF	R^2	E	TVOL
22	N+B	None	2.1000			499.90	0.3196	1.8527	0.0004	0.0263	0.67	-2.95	99.31
23		1.2	2.1000			501.44	0.3338	20.351	0.0004	0.0267	0.68	-14.69	212.51
24		0.8	5.0000			505.19	0.5294	1.8037	0.0004	0.0368	0.71	0.67	3.00
25	R+B	None	5.0000			552.34	0.0658	0.6556	0.0001	0.0911	0.64	0.56	2.83
26		1.2	5.0000			1000.00	0.2634	0.5102	0.0001	0.0016	0.19	-0.68	37.54
27		0.8	3.1500			493.37	0.4048	3.0000	0.0004	0.0361	0.70	0.65	2.38
28	N	None	0.0009			500.01	0.0602	0.2002	0.0010	0.0100	0.42	-1.59	24.71
29		1.2	0.0009			500.00	0.0601	0.2003	0.0010	0.0100	0.56	-19.46	158.3
30		0.8	0.0001			481.81	0.3208	1.0243	0.0003	0.0174	0.69	0.66	0.65

Table F.3 – SIMHYD manual calibration runs for the West catchment – data from 1999-2003

(highlighted row is the best run)

Run #	Rainfall	Factor	SIMHYD parameters								Objective functions		
			INSC	COEFF	SQ	SMSC	SUB	CRAK	RK	RESCOEFF	R^2	*E*	*TVOL*
1	N+B+R+D	none	5	200	5	1000	0.5	2.5	0.0005	0.02	0.41	0.39	7.69
2			0.0001	"	"	"	"	"	"	"	0.33	-0.03	39.17
3			0.01	"	"	"	"	"	"	"	0.33	-0.02	38.11
4			0.0001	"	"	50	"	"	"	"	0.60	-2.95	148.47
5			"	"	"	500	"	"	"	"	0.40	-0.60	69.71
6			"	"	"	50	1	"	"	"	0.65	-4.41	153.73
7			"	"	"	"	0.75	"	"	"	0.64	-3.51	151.08
8			"	"	"	"	0.01	"	"	"	0.17	-3.15	143.43
9			"	"	"	"	0.75	0.01	"	"	0.58	-12.34	102.88
10			"	"	"	"	"	3	"	"	0.64	-3.62	159.00
11			"	"	"	"	"	"	0.05	"	0.50	-21.33	161.46
12			"	"	"	"	"	"	0.0001	"	0.56	-2.10	126.33
13			"	"	"	"	"	"	"	0.8	0.06	-13.09	126.35
14			"	"	"	"	"	"	"	0.001	0.09	-2.17	122.63
15			"	"	"	"	"	"	"	0.05	0.56	-2.76	126.33
16			"	"	"	"	"	"	"	0.03	0.58	-2.29	126.28
17			5	"	"	"	"	"	"	"	0.59	-1.17	88.87
18			"	"	"	750	"	"	"	"	0.51	0.47	11.72
19			"	"	"	1000	"	"	"	"	0.50	0.49	0.20
20			"	"	"	"	"	0.1	"	"	0.53	-0.23	30.81
21			"	"	"	"	"	"	0.005	"	0.54	-0.24	29.19
22			"	"	"	"	"	"	"	0.1	0.32	-2.84	29.19
23			"	"	"	"	"	"	"	0.01	0.50	0.26	29.22

Table F.4 – SIMHYD automatic calibration runs for the West catchment – data from 1999-2003

Run #	Rainfall	Factor	SIMHYD Parameters								Objective functions		
			INSC	COEFF	SQ	SMSC	SUB	CRAK	RK	RESCOEFF	R^2	E	TVOL
1	N+D+R+B	None	0.0001	*Fixed at 200*	*Fixed at 5*	1000.00	0.6370	0.9346	0.0002	0.0204	0.51	0.49	0.59
2		1.2	0.2810			1000.00	0.1963	0.4376	0.0001	0.0167	0.34	0.17	23.14
3		0.8	0.0001			353.56	1.0000	3.0000	0.0002	0.0294	0.59	0.56	10.46
4	N+D+B	None	0.0009			1000.00	0.3367	0.7322	0.0001	0.0165	0.43	0.43	1.98
5		1.2	5.0000			1000.00	0.1753	0.7148	0.0001	0.0183	0.33	-0.19	49.01
6		0.8	0.0001			612.11	1.0000	2.5210	0.0001	0.0254	0.55	0.54	6.02
7	N+D+R	None	0.0001			1000.00	0.8317	1.5733	0.0002	0.0222	0.50	0.48	0.65
8		1.2	2.8290			1000.00	0.3280	0.7584	0.0001	0.0176	0.41	0.33	11.46
9		0.8	0.0001			196.44	0.8516	3.0000	0.0003	0.0344	0.60	0.58	9.15
10	R+N+B	None	0.0001			1000.00	0.5273	0.7582	0.0002	0.0204	0.47	0.44	1.67
11		1.2	0.0001			992.48	0.1368	0.8697	0.0001	0.0596	0.18	-0.43	52.77
12		0.8	0.0001			1000.00	0.5663	0.6780	0.0003	0.0503	0.43	0.06	51.09
13	D+R+B	None	0.0009			249.87	0.2258	0.5398	0.0001	0.0209	0.48	0.42	12.67
14		1.2	0.0009			219.96	0.1389	0.8987	0.0001	0.0286	0.38	-0.85	88.71
15		0.8	0.0001			205.30	0.7384	2.4806	0.0002	0.0311	0.60	0.58	10.67
16	N+D	None	3.6428			512.67	0.4294	0.9630	0.0002	0.0203	0.53	0.52	0.77
17		1.2	0.0009			199.97	0.4912	1.4787	0.0001	0.0300	0.57	-3.05	137.40
18		0.8	0.0001			203.90	0.5877	1.7940	0.0001	0.0288	0.57	0.55	10.05
19	N+R	None	0.0009			203.47	0.1068	0.5791	0.0001	0.0277	0.29	0.24	11.41
20		1.2	0.0005			199.66	0.2647	0.8720	0.0001	0.0291	0.46	-1.44	97.77
21		0.8	0.0001			204.04	0.7176	2.5179	0.0002	0.0327	0.55	0.52	11.05
22	N+B	None	0.0027			199.73	0.3703	1.1685	0.0001	0.0294	0.52	-1.09	90.99
23		1.2	1.9683			1000.00	0.2800	1.1568	0.0001	0.0206	0.33	-1.25	93.40
24		0.8	0.0001			203.91	0.2462	0.5831	0.0002	0.0243	0.50	0.48	4.40

cont…

cont…

Run #	Rainfall	Factor	SIMHYD Parameters								Objective functions		
			INSC	COEFF	SQ	SMSC	SUB	CRAK	RK	RESCOEFF	R^2	E	TVOL
25	R+B	None	0.0001			488.53	0.2938	0.4502	0.0002	0.0203	0.47	0.45	0.27
26		1.2	0.0009			1000.00	0.1959	0.5293	0.0001	0.0188	0.29	-0.05	36.35
27		0.8	0.0001			389.03	1.0000	3.0000	0.0002	0.0281	0.55	0.53	8.73
28	N	None	0.0009			200.13	0.3000	0.5016	0.0002	0.0300	0.48	-1.59	72.34
29		1.2	0.0009			200.06	0.3000	0.5013	0.0002	0.0300	0.46	-9.18	160.50
30		0.8	0.0001			199.20	0.2786	0.7193	0.0002	0.0260	0.49	0.48	4.71
31	Theissen	None	0.0009			199.18	0.0002	0.0001	0.0001	0.0191	0.30	-1.88	29.83
32		1.2	0.0009			199.74	0.0002	0.0001	0.0001	0.0200	0.42	-9.35	128.50
33		0.8	0.0001			199.60	0.2637	0.6468	0.0002	0.0254	0.50	0.48	4.07

Table F.5 – Manual calibration statistics for EG in the East catchment

Run #	EG parameters					R^2					E				
	a_1	a_2	a_5	b_1	b_2	All	Event 1	Event 2	Event 3	Event 4	All	Event 1	Event 2	Event 3	Event 4
1	0.1	1	5.00E-06	200	6.80E-03	0.32	0.99	0.10	0.71	0.01	-11987.30	-26956.10	-4397.59	-20239.50	-134513.73
2	0.5	“	“	“	“	0.29	0.99	0.10	0.71	0.01	-342.15	-779.51	-76.35	-634.54	-3462.62
3	0.9	“	“	“	“	0.26	0.99	0.10	0.71	0.01	-71.05	-162.88	-5.39	-148.05	-607.69
4	1	“	“	“	“	0.25	0.99	0.10	0.71	0.01	-51.56	-118.02	-2.28	-111.05	-415.22
5	“	1	“	“	0.068	0.11	0.98	0.03	0.55	0.03	-2.35	-23.18	-4.46	-0.54	-42.27
6	“	“	“	“	0.01	0.25	0.99	0.09	0.70	0.01	-38.17	-104.31	-0.27	-58.31	-213.62
7	“	“	“	1000	“	“	“	“	“	“	-1239.25	-3291.01	-93.79	-2057.36	-10734.36
8	“	“	“	100	“	“	“	“	“	“	-6.53	-18.13	-1.02	-8.16	-12.43
9	“	“	5.00E-02	“	“	“	“	“	“	“	“	“	“	“	“
10	“	“	5.00E-04	“	“	0.25	0.99	0.09	0.70	0.01	-92323.52	-298526.12	-13105.72	-197540.56	-1184218.22
11	0.9	1	3.00E-09	200	0.006	0.25	0.99	0.10	0.70	0.01	-1.24	-1.31	-4.52	-2.40	-58.74
12	0.8	0	5.00E-06	200	0.0068	0.50	0.99	0.10	0.71	0.01	0.16	0.82	-1.57	-0.78	-26.32
13	“	1	“	“	“	0.26	0.99	0.10	0.71	0.01	-98.80	-226.46	-10.84	-199.68	-888.17
14	1	0	1.50E-05	200	0.048	0.17	0.98	0.01	0.56	0.00	-1.25	-1.29	-4.53	-2.42	-58.94
15	0.8	0	5.00E-06	160	0.0068	0.50	0.99	0.10	0.71	0.01	-0.02	0.59	-2.04	-1.05	-31.81
16	“	“	“	400	0.009	0.48	0.99	0.10	0.71	0.01	0.30	0.54	-0.82	0.00	-11.26
17	“	“	“	600	0.05	0.16	0.98	0.01	0.55	0.01	-0.59	0.65	-4.38	-1.78	-48.63
18	“	“	“	300	“	“	“	“	“	“	-0.79	0.76	-4.45	-2.09	-53.63
19		1	“	“	“	0.50	0.99	0.10	0.71	0.01	-441.69	-1002.43	-76.65	-899.47	-4525.76
20	0.08	0	“	“	“	“	“	“	“	“	-5356.39	-10834.87	-6117.86	-2785.14	-53298.43
21	0.8	“	5.00E-07	“	“	“	“	“	“	“	-0.87	-0.69	-3.82	-2.04	-51.43
22	“	“	5.00E-05	“	“	“	“	“	“	“	-214.31	-443.42	-226.43	-98.69	-1881.34
23	“	“	1.00E-06	“	“	“	“	“	“	“	-0.54	-0.16	-3.17	-1.68	-44.37
24	“	“	7.00E-06	“	“	“	“	“	“	“	-0.50	-1.76	0.03	0.48	-0.33
25	“	“	“	“	0.008	“	“	“	“	“	-0.33	-1.54	0.01	0.49	-1.42
26	“	“	“	“	0.01	0.47	0.99	0.09	0.70	0.01	-0.17	-1.23	-0.50	0.39	-4.31
27	“	“	“	350	“	“	“	“	“	“	0.10	-0.25	-0.74	0.21	-7.63
28	“	“	“	450	“	“	“	“	“	“	-0.55	-2.48	-0.32	0.52	-1.99
29	“	“	“	“	0.02	0.35	0.99	0.03	0.64	0.00	-0.23	-1.15	-2.86	-0.37	-19.35
30	0.5	“	“	“	“	“	“	“	“	“	-25.81	-109.10	-3.50	-1.12	-44.20
31	0.65	“	“	“	“	“	“	“	“	“	-5.19	-24.34	-2.09	0.59	-3.11
32	0.8	0	5.00E-06	400	0.0075	0.49	0.99	0.10	0.72	0.01	0.29	0.39	-0.27	0.17	-7.55
33	“	“	“	450		“	“	“	“	“	0.14	-0.13	-0.08	0.32	-4.56
34	“	“	“		0.008	0.49	0.99	0.10	0.71	0.01	0.16	-0.08	-0.22	0.28	-5.47
35	“	“	“	400		“	“	“	“	“	0.29	0.42	-0.43	0.13	-8.58
36	0.9	0	“	“	“	0.49	0.99	0.10	0.71	0.01	0.01	0.71	-2.18	-1.01	-30.99
37	“	“	“	“	0.0007	0.12	0.95	0.20	0.05	0.01	-1.92	-0.09	-11.14	-0.22	-5.67
38	0.9	0	5.00E-06	400	0.07	0.11	0.98	0.03	0.55	0.03	-1.06	-0.02	-4.52	-2.32	-57.54
39	0.7	“	“	“	“	“	“	“	“	“	-0.76	0.73	-4.48	-2.04	-53.52
40	0.4	“	“	“	“	“	“	“	“	“	-2.76	-29.38	-4.37	-1.24	-41.88
41	“	“	“	“	0.03	0.26	0.99	0.00	0.60	0.00	-13.28	-78.58	-3.44	0.36	-8.60
42	0.8	0	5.00E-05	400	“	0.26	0.99	0.00	0.61	0.00	-2.19	-13.41	-3.31	-0.05	-14.74
43	“	“	“	“	0.05	0.16	0.98	0.01	0.55	0.01	-1.06	-6.66	-4.26	-1.21	-39.41
44	0.65	“	“	“	“	“	“	“	“	“	-6.49	-58.36	-4.12	-0.30	-24.57
45	“	“	1.50E-06	“	“	“	“	“	“	“	-0.83	0.63	-4.46	-2.13	-54.26

Table F.6 – Manual calibration statistics for EG in the West catchment

Run #	EG parameters					R^2		*E*	
	a_1	a_2	a_5	b_1	b_2	All	Event	All	Event
1	0.0088	0	2.30E-05	243933.3	0.00009	0.09	0.02	<-1000	<-1000
2	0.8	"	"	"	"	0.11	0.63	<-1000	<-1000
3	"	"	"	200	"	0.00	0.65	<-1000	-100.52
4	"	"	"	"	0.09	0.20	0.66	-0.59	-6.12
5	"	"	"	1000	"	"	"	-0.08	0.01
6	"	"	2.00E-02	"	"	0.39	0.12	-271.82	<-1000
7	"	"	2.00E-04	"	"	0.28	0.70	-9.59	-590.12
8	"	"	1.00E-05	"	"	0.19	0.66	-0.40	-1.84
9	0.9	"	"	"	"	"	"	-0.60	-1.60
10	0.7	"	"	"	"	"	"	-0.19	0.59
11	"	"	1.00E-06	"	"	"	"	-0.71	-9.16
12	0.5	"	"	"	"	"	"	-0.61	-6.64
13	"	1	"	"	"	0.03	0.66	-0.71	-5.77
14	0.1	0	"	"	"	0.19	0.66	0.03	-10.20
15	"		5.00E-07	"	"	"	"	-0.17	0.65

Appendix G – Buffer effectiveness

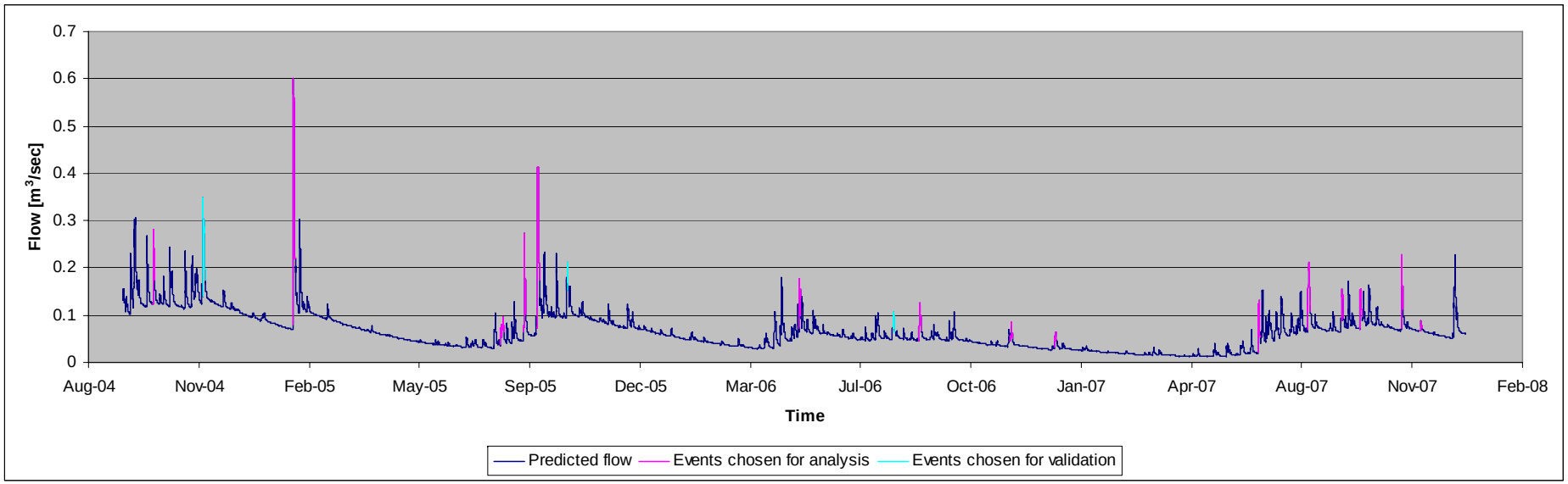

Figure G.1 – Predicted flow for the East branch showing events chosen for buffer effectiveness analysis and events chosen for validation

Figures G.2 to G.16 – Events chosen for calibration[21]

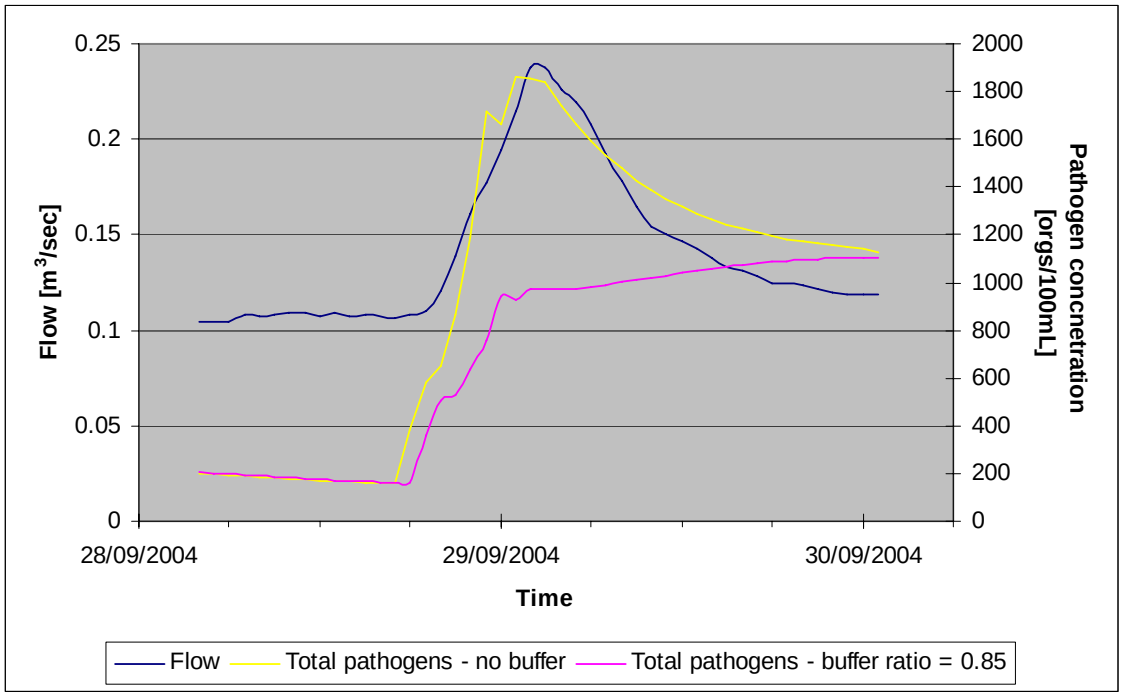

Figure G.2 – Flow and pathogen concentrations for September 2004 event

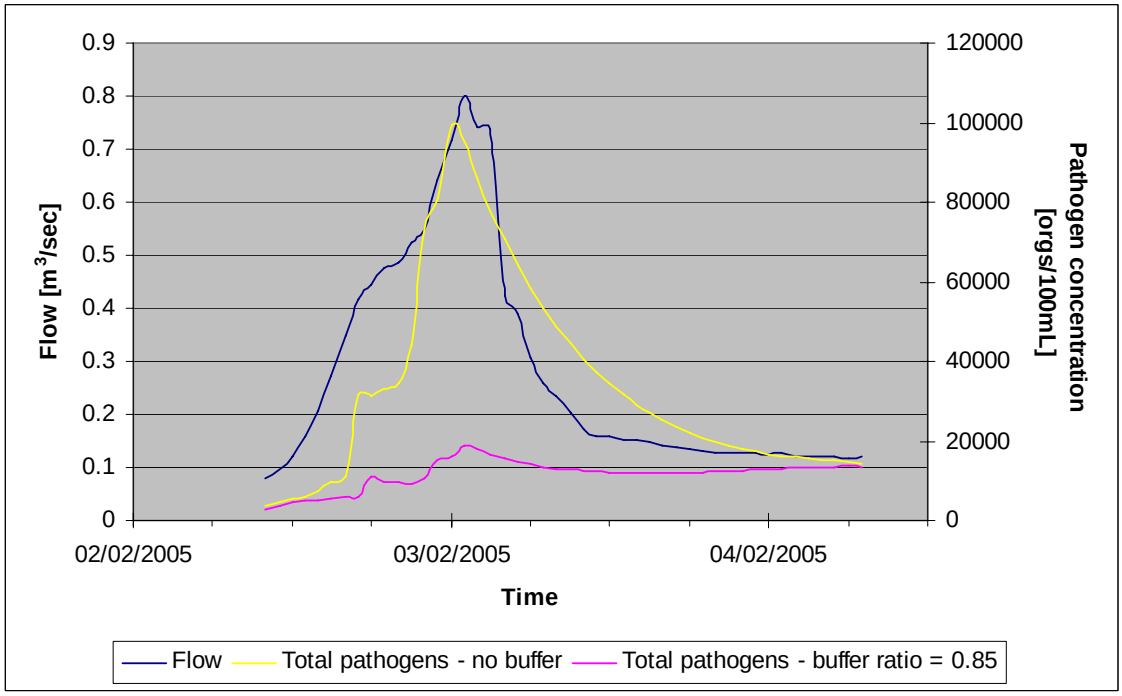

Figure G.3 – Flow and pathogen concentrations for February 2005 event

[21] Note the different axis on each graph

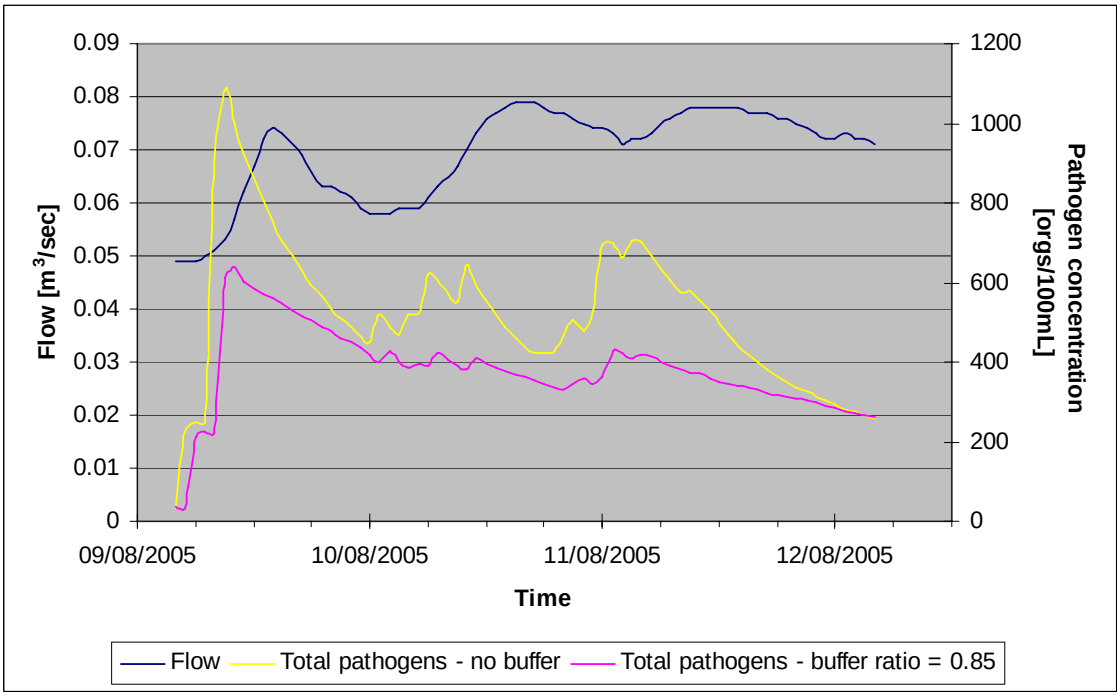

Figure G.4 – Flow and pathogen concentrations for August 2005 (1) event

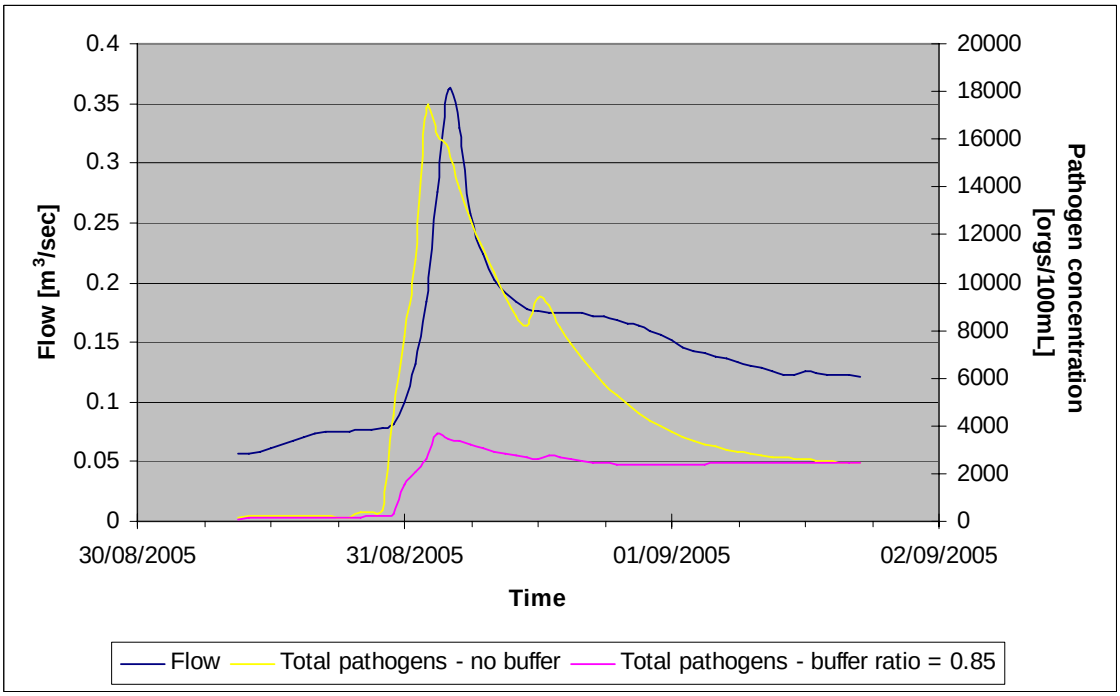

Figure G.5 – Flow and pathogen concentrations for August 2005 (2) event

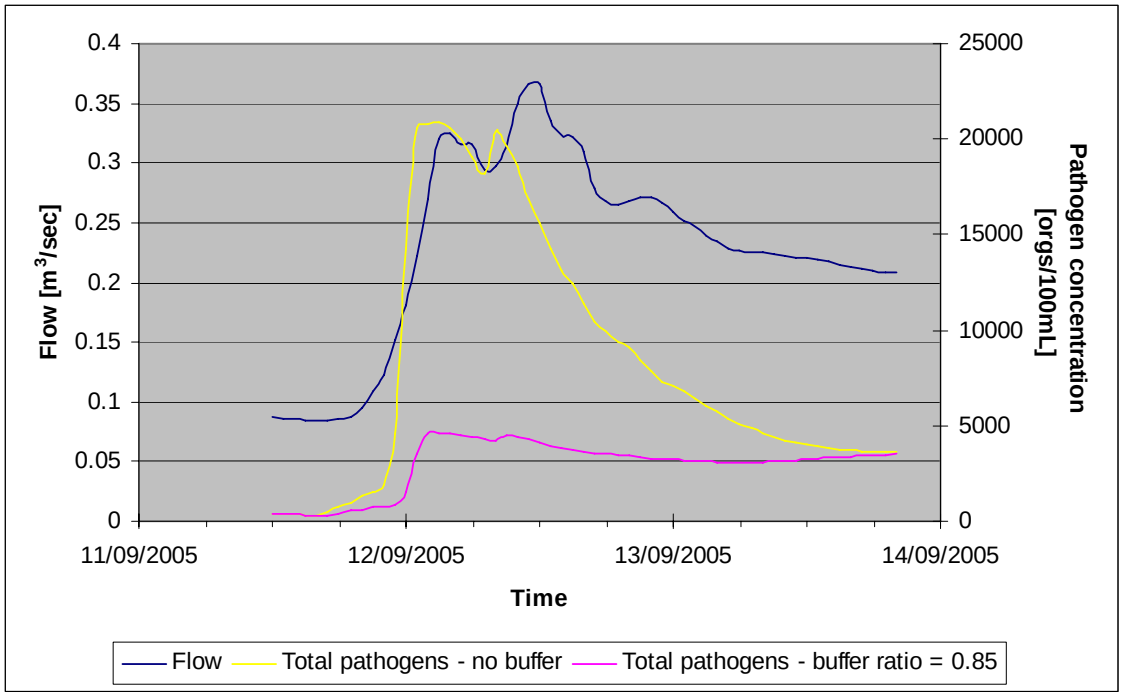

Figure G.6 – Flow and pathogen concentrations for September 2005 event (Event 1)

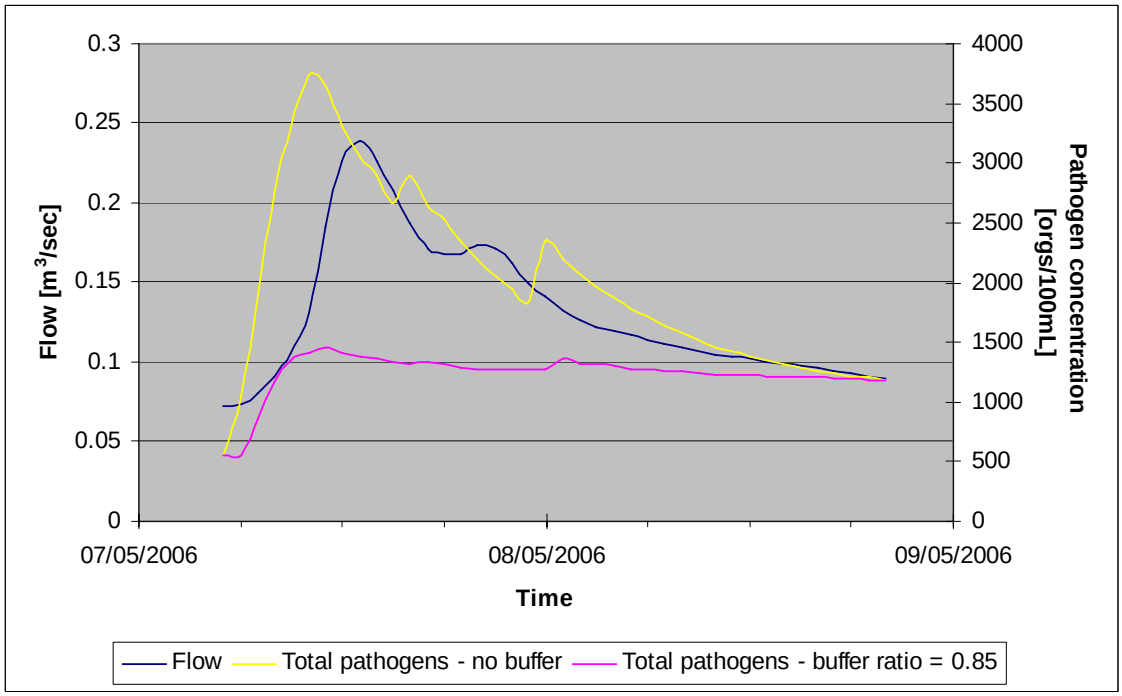

Figure G.7 – Flow and pathogen concentrations for May 2006 event

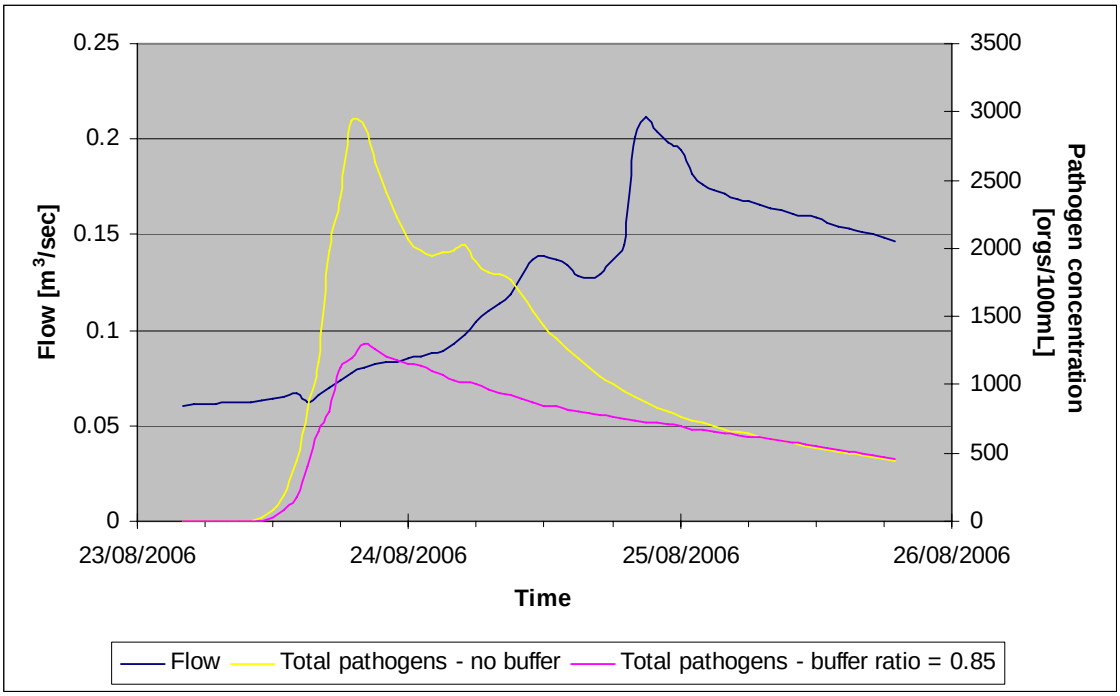

Figure G.8 – Flow and pathogen concentrations for August 2006 event

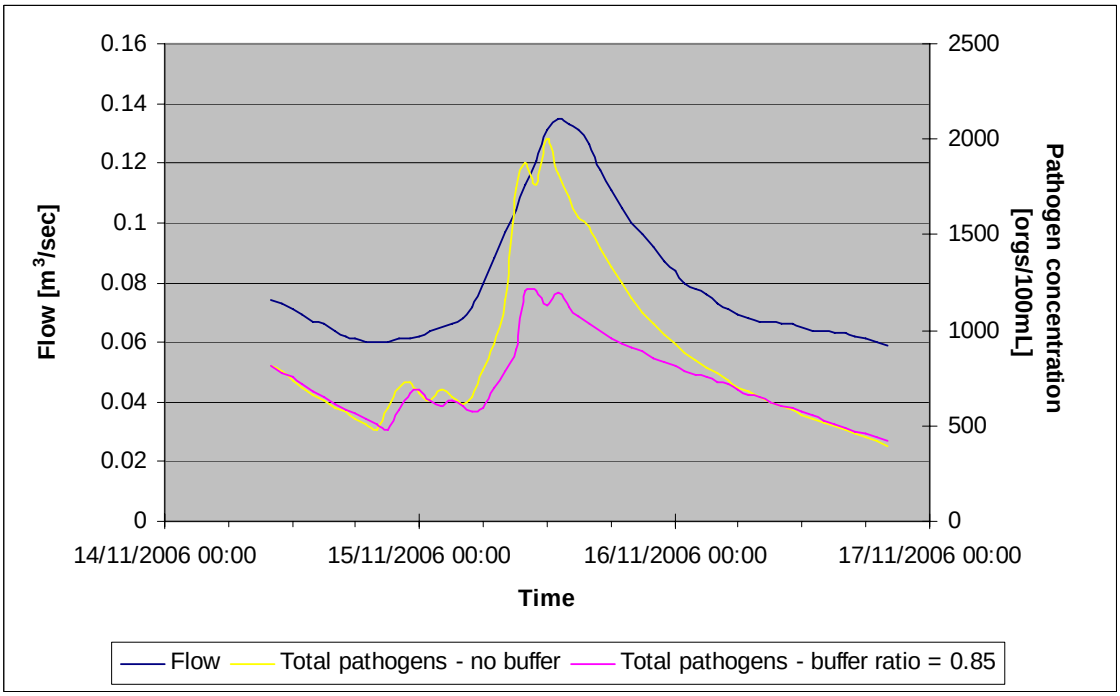

Figure G.9 – Flow and pathogen concentrations for November 2006 event (Event 2)

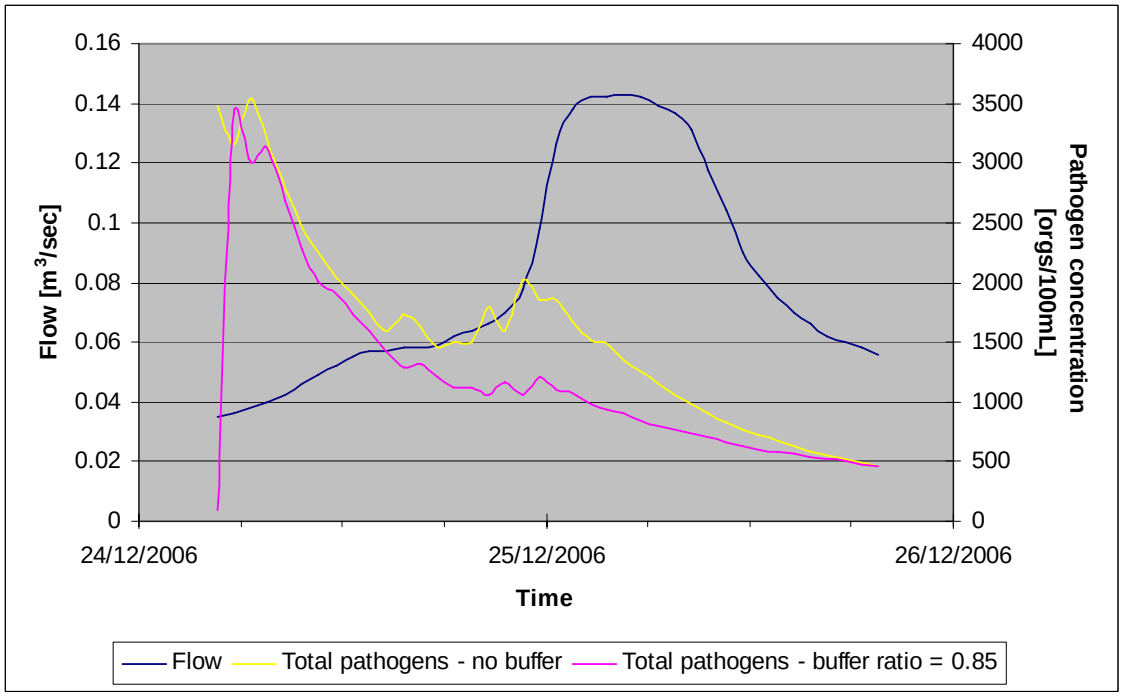

Figure G.10 – Flow and pathogen concentrations for December 2006 event

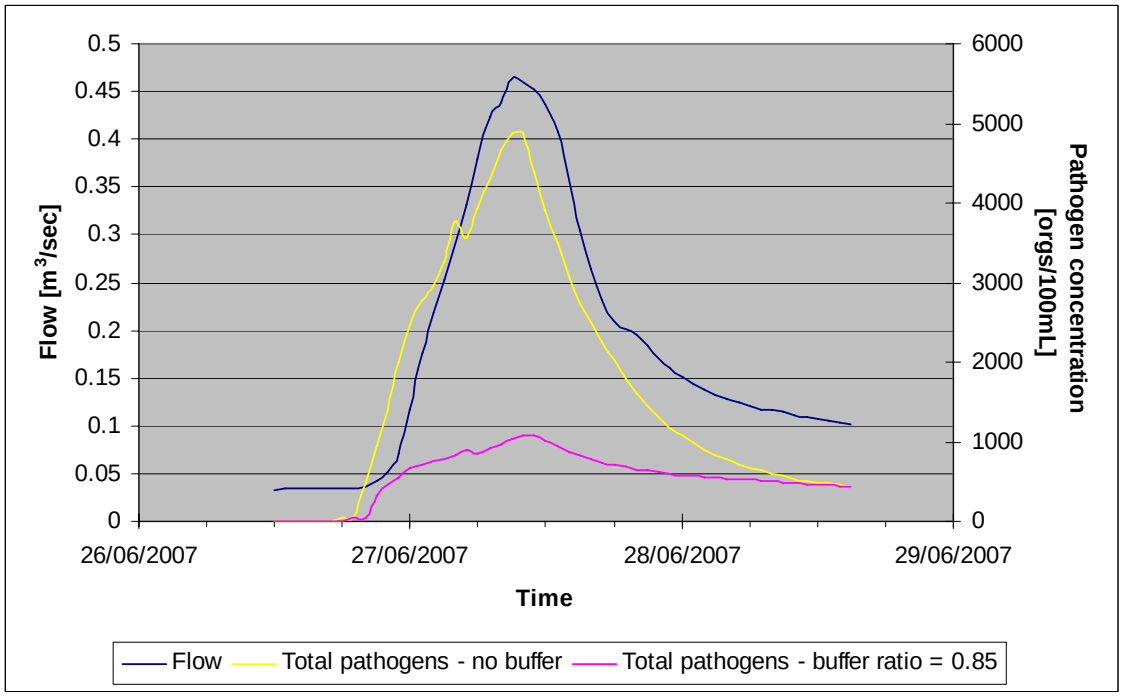

Figure G.11 – Flow and pathogen concentrations for June 2007 event (Event 3)

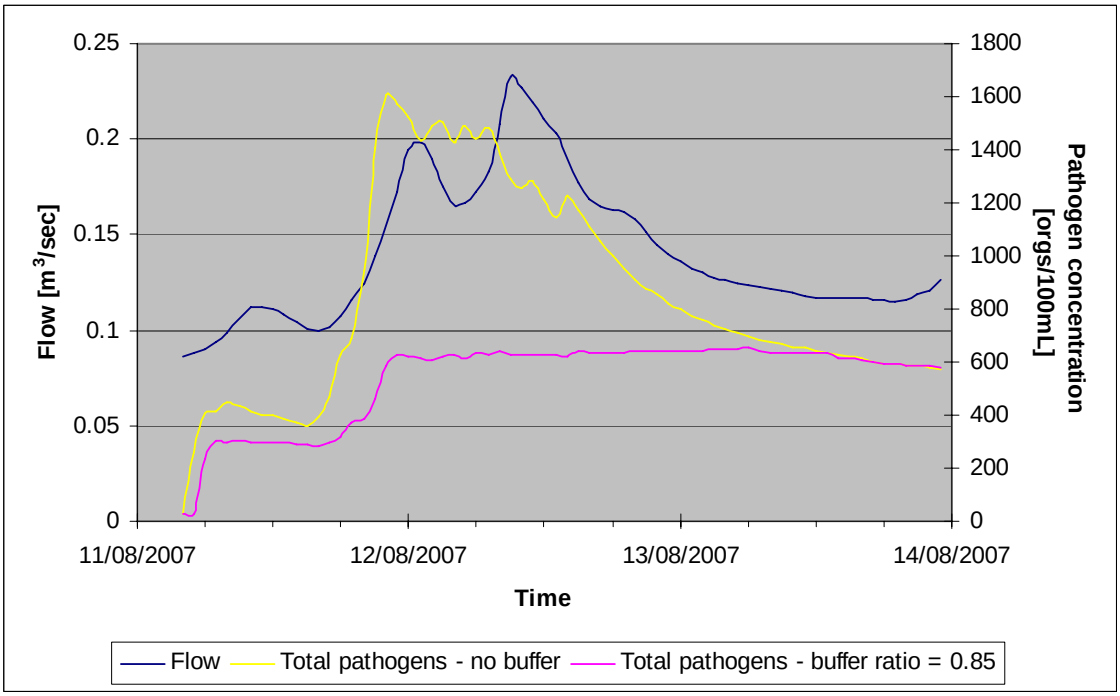

Figure G.12 – Flow and pathogen concentrations for August 2007 event

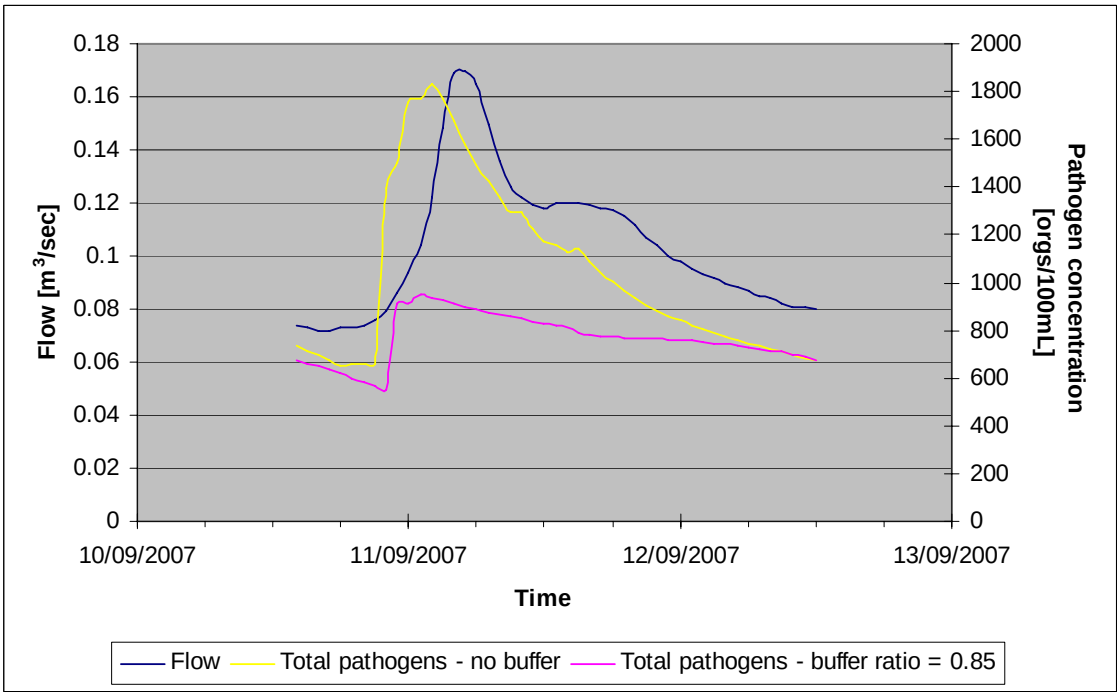

Figure G.13 – Flow and pathogen concentrations for September 2007 (1) event (Event 4)

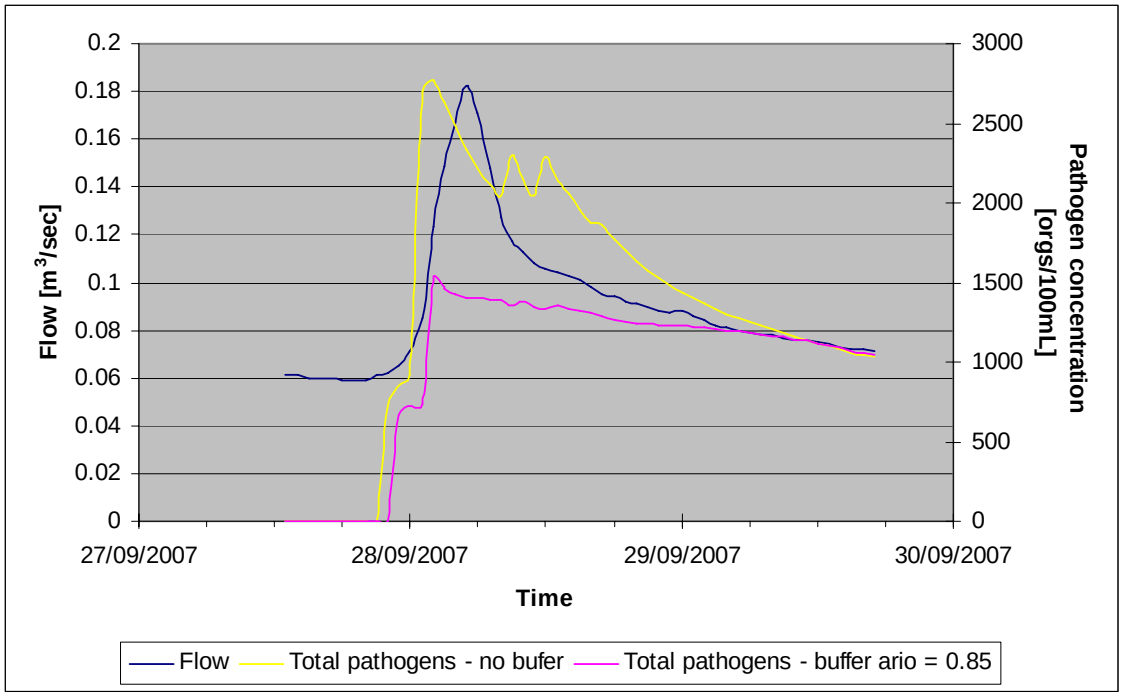

Figure G.14 – Flow and pathogen concentrations for September 2007 (2) event

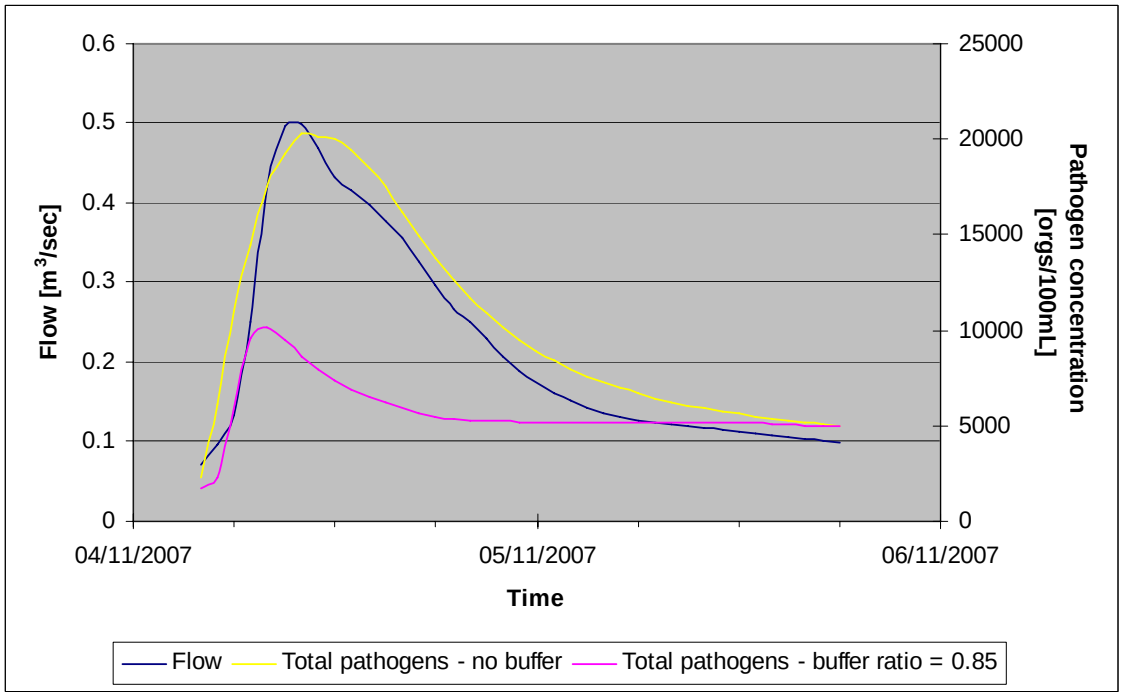

Figure G.15 – Flow and pathogen concentrations for November 2007 (1) event

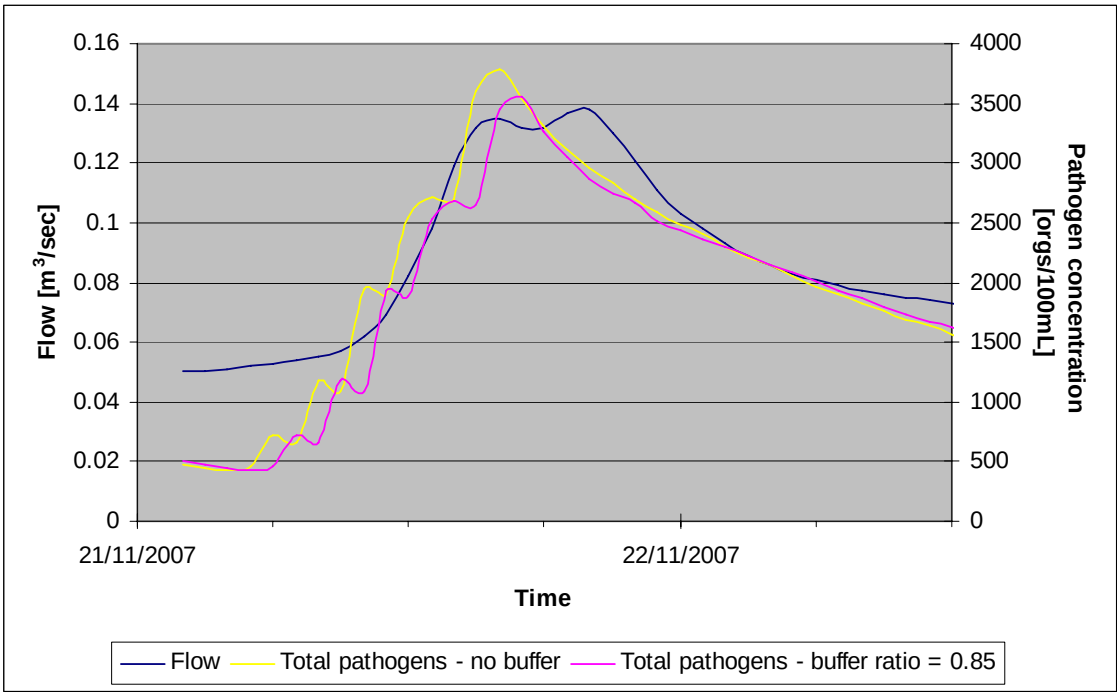

Figure G.16 – Flow and pathogen concentration for November 2007 (2) event (Event 5)

Figures G.17 to G.19 – Events chosen for validation

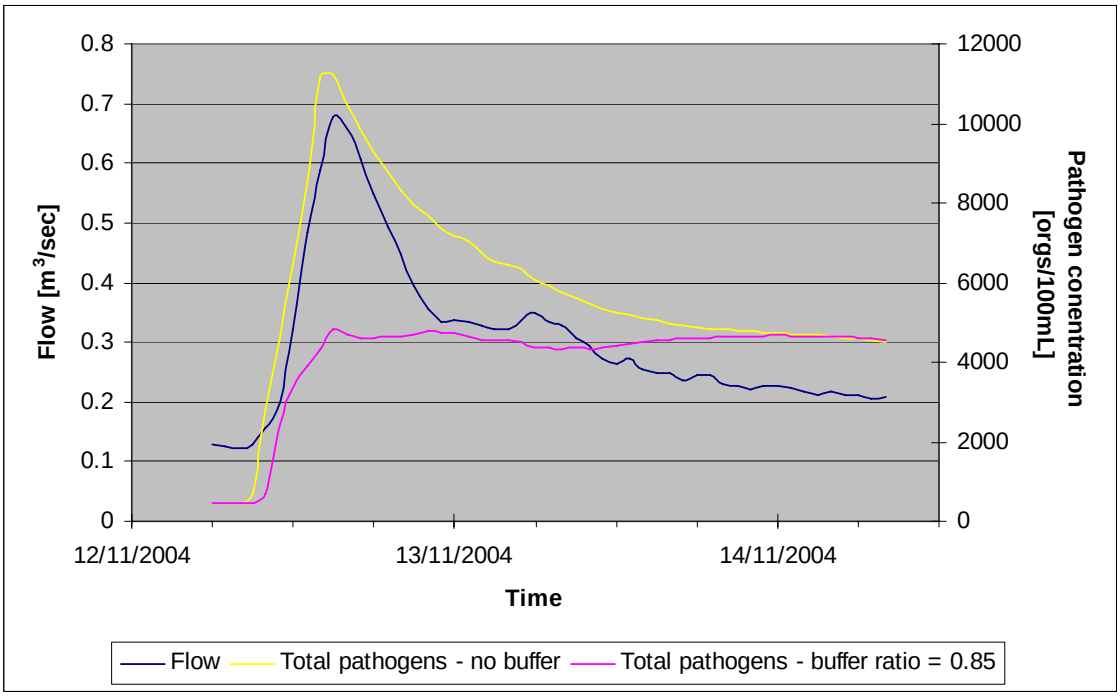

Figure G.17 – Flow and pathogen concentrations for November 2004 event

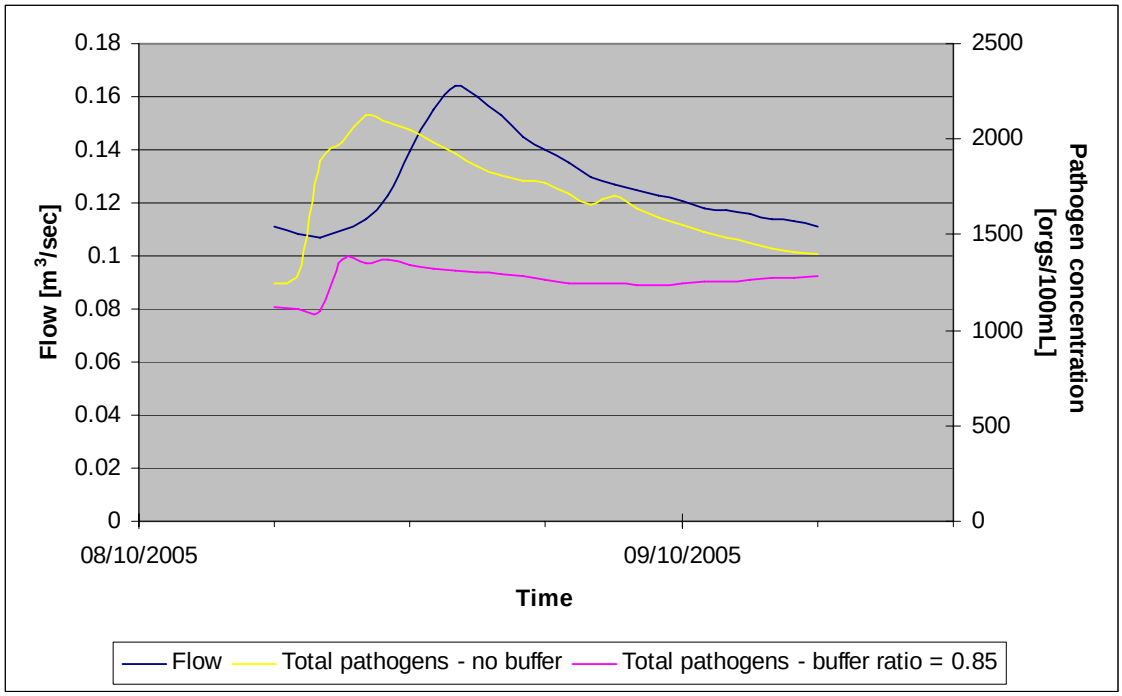

Figure G.18 – Flow and pathogen concentrations for October 2005 event

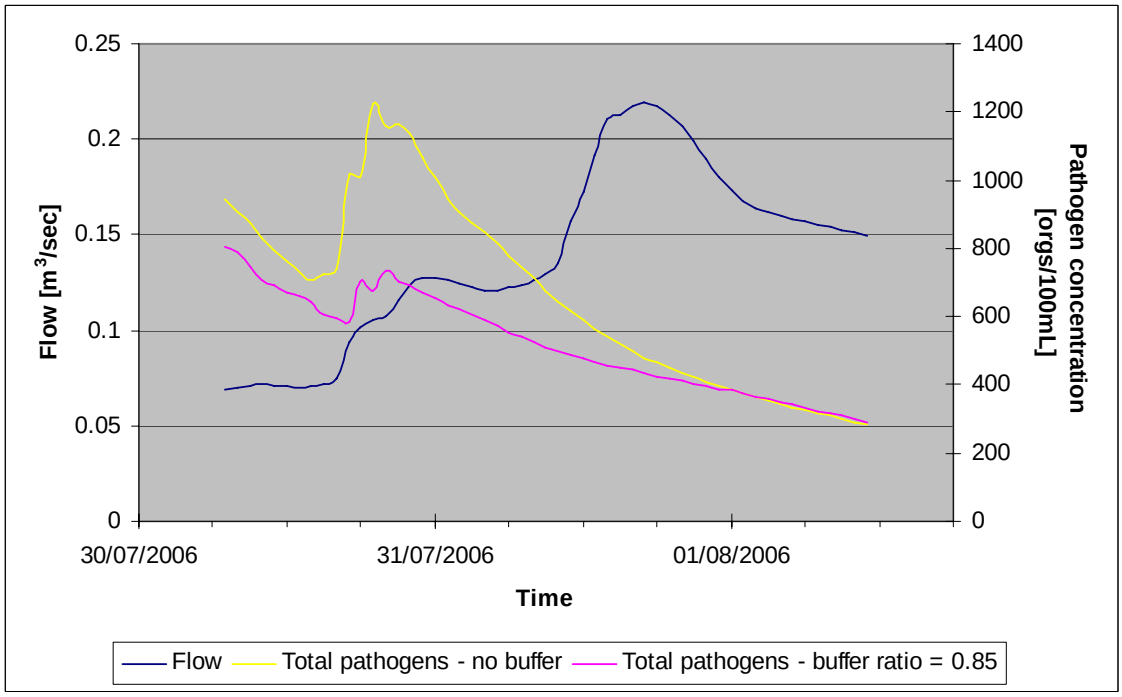

Figure G.19 – Flow and pathogen concentrations for August 2006 event

Table G.1 – Correlation statistics for different relationship types between storm characteristics and pathogen numbers[22]

		Peak flow				Event volume				Average flow			
		1.00	**0.85**	**0.54**	**0.00**	**1.00**	**0.85**	**0.50**	**0.00**	**1.00**	**0.85**	**0.50**	**0.00**
Linear	**Average concentration**	0.56	0.65	0.71	0.73	0.27	0.34	0.40	0.43	0.50	0.56	0.61	0.62
	Peak concentration	0.49	0.58	0.72	0.74	0.22	0.29	0.41	0.44	0.43	0.50	0.60	0.61
	Average flux	0.74	0.74	0.74	0.73	0.44	0.44	0.45	0.45	*0.65*	*0.64*	*0.62*	*0.62*
	Peak flux	*0.73*	*0.72*	*0.71*	*0.70*	0.42	0.43	0.42	0.42	0.64	0.60	0.59	0.58
	EMC	0.57	0.68	0.73	0.74	0.28	0.37	0.42	0.44	0.51	0.59	0.62	0.63
	Event load	0.79	0.78	0.76	0.76	*0.50*	*0.49*	*0.49*	*0.48*	0.69	0.67	0.65	0.64
Exponential	**Average concentration**	0.44	0.53	0.61	0.64	0.21	0.27	0.34	0.38	0.43	0.50	0.56	0.58
	Peak concentration	0.34	0.40	0.57	0.64	0.14	0.17	0.31	0.38	0.32	0.35	0.49	0.55
	Average flux	0.73	0.78	0.82	0.83	0.50	0.55	0.59	0.60	*0.75*	*0.79*	*0.80*	*0.80*
	Peak flux	*0.67*	*0.79*	*0.82*	*0.83*	0.44	0.54	0.58	0.60	0.68	0.75	0.77	0.77
	EMC	0.46	0.56	0.64	0.67	0.22	0.30	0.37	0.41	0.45	0.53	0.58	0.60
	Event load	0.80	0.85	0.86	0.86	*0.63*	*0.67*	*0.68*	*0.69*	0.82	0.84	0.84	0.83
Logarithmic	**Average concentration**	0.37	0.42	0.46	0.48	0.18	0.23	0.27	0.29	0.36	0.40	0.42	0.43
	Peak concentration	0.29	0.36	0.45	0.47	0.12	0.17	0.27	0.29	0.28	0.33	0.40	0.41
	Average flux	0.49	0.48	0.46	0.45	0.30	0.30	0.30	0.30	*0.40*	*0.41*	*0.43*	*0.46*
	Peak flux	*0.48*	*0.45*	*0.43*	*0.43*	0.29	0.29	0.28	0.28	0.37	0.38	0.40	0.45
	EMC	0.38	0.45	0.48	0.48	0.19	0.25	0.29	0.30	0.37	0.41	0.43	0.43
	Event load	0.53	0.51	0.49	0.48	*0.35*	*0.34*	*0.33*	*0.32*	0.49	0.46	0.43	0.42
2nd order polynomial	**Average concentration**	0.68	0.79	0.87	0.91	0.37	0.46	0.53	0.56	0.63	0.73	0.81	0.84
	Peak concentration	0.62	0.75	0.92	0.93	0.35	0.42	0.55	0.57	0.58	0.69	0.85	0.86
	Average flux	0.9	0.94	0.96	0.96	0.55	0.58	0.59	0.59	*0.84*	*0.87*	*0.89*	*0.89*
	Peak flux	*0.88*	*0.95*	*0.96*	*0.96*	0.54	0.57	0.56	0.56	0.83	0.88	0.88	0.88
	EMC	0.68	0.83	0.90	0.92	0.38	0.49	0.55	0.57	0.63	0.77	0.84	0.86
	Event load	0.94	0.96	0.97	0.98	*0.62*	*0.63*	*0.64*	*0.64*	0.89	0.91	0.92	0.92

cont…

[22] Numbers in Italics are influenced by cross-correlation

cont…

		Peak flow				Event volume				Average flow			
		1.00	**0.85**	**0.54**	**0.00**	**1.00**	**0.85**	**0.50**	**0.00**	**1.00**	**0.85**	**0.50**	**0.00**
Power	**Average concentration**	0.31	0.38	0.46	0.51	0.12	0.16	0.22	0.25	0.34	0.39	0.44	0.46
	Peak concentration	0.20	0.25	0.41	0.50	0.05	0.07	0.18	0.25	0.21	0.23	0.35	0.42
	Average flux	0.66	0.71	0.74	0.76	0.41	0.45	0.48	0.49	*0.69*	*0.71*	*0.72*	*0.71*
	Peak flux	*0.57*	*0.68*	*0.74*	*0.76*	0.33	0.41	0.47	0.50	0.60	0.65	0.67	0.69
	EMC	0.33	0.43	0.51	0.55	0.13	0.19	0.25	0.29	0.36	0.42	0.46	0.49
	Event load	0.74	0.78	0.80	0.81	*0.54*	*0.57*	*0.58*	*0.59*	0.77	0.77	0.76	0.75

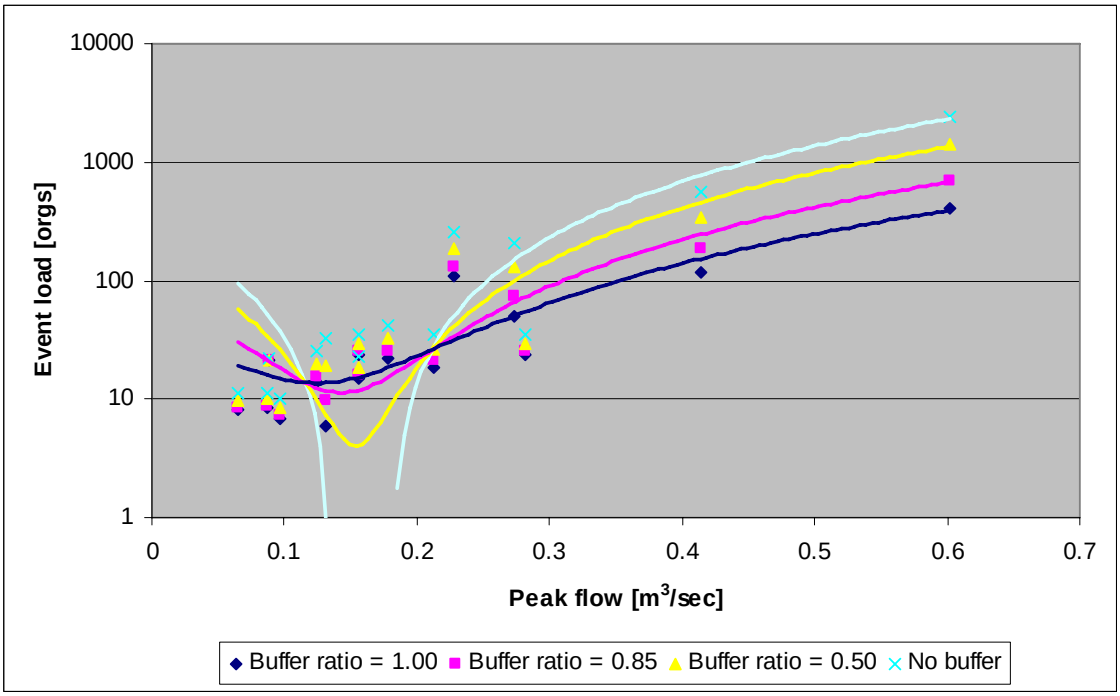

Figure G.20 - Example of a 2nd order polynomial relationship between peak flow and event load

Table G.2 – Equations for exponential relationships between peak flow (Q_{peak}) and pathogen numbers for different buffer ratios

	1.00	0.85	0.50	0.00
Average concentration	$466.7e^{4.1Qpeak}$	$474.9e^{4.8Qpeak}$	$509.4e^{5.7Qpeak}$	$570.0e^{6.4Qpeak}$
Peak concentration	$745.0e^{4.1Qpeak}$	$845.5e^{4.4Qpeak}$	$942.0e^{6.0Qpeak}$	$1147.2e^{7.0Qpeak}$
Average flux	$0.1e^{7.41Qpeak}$	$0.1e^{8.3Qpeak}$	$0.1e^{9.4Qpeak}$	$0.1e^{10.2Qpeak}$
Peak flux	$0.2e^{6.7Qpeak}$	$0.2e^{8.7Qpeak}$	$0.2e^{10.4Qpeak}$	$0.3e^{11.3Qpeak}$
EMC	$489.2e^{4.1Qpeak}$	$489.3e^{5.0Qpeak}$	$523.5e^{6.1Qpeak}$	$590.7e^{6.9Qpeak}$
Event load	$5.3e^{7.4Qpeak}$	$5.3e^{8.3Qpeak}$	$5.7e^{9.4Qpeak}$	$6.4e^{10.2Qpeak}$

Table G.3 – Equations for exponential relationship between the difference in pathogen numbers in a non-buffered catchment compared to one with a buffer ratio of 1.00 and storm characteristics

	Absolute difference			Percentage difference		
	Peak flow	**Total volume**	**Average flow**	**Peak flow**	**Total volume**	**Average flow**
Average concentration	$117.57e^{9.16x}$	$108.35e^{0.08x}$	$84.35e^{16.22x}$	$25.18e^{5.05x}$	$20.34e^{0.05x}$	$22.01e^{8.58x}$
Peak concentration	$276.45e^{9.96x}$	$228.42e^{0.09x}$	$191.32e^{17.68x}$	$37.11e^{5.88x}$	$25.82e^{0.06x}$	$30.53e^{10.28x}$
Average flux	$0.03e^{12.99x}$	0.02e0.12x	$0.02e^{23.62x}$	$26.96e^{5.57x}$	$21.67e^{0.05x}$	$23.23e^{9.47x}$
Peak flux	$0.08e^{13.90x}$	$0.06e^{0.13x}$	$0.05e^{25.23x}$	$42.30e^{7.17x}$	$30.79e^{0.07x}$	$33.40e^{12.52x}$
EMC	$131.90e^{9.53x}$	$119.54e^{0.08x}$	$93.52e^{17.00x}$	$26.96e^{5.57x}$	$21.67e^{0.05x}$	$23.23e^{9.47x}$
Event load	$1.43e^{12.99x}$	$1.00e^{0.12x}$	$0.83e^{23.55x}$	$26.96e^{5.57x}$	$21.67e^{0.05x}$	$23.23e^{9.47x}$

Table G.4 – R^2 values for relationships between pathogen numbers in a non-buffered catchment and pathogen numbers in a buffered catchment

	Linear			Exponential			Logarithmic		
	1.00	**0.85**	**0.50**	**1.00**	**0.85**	**0.50**	**1.00**	**0.85**	**0.50**
Average concentration	0.90	0.97	1.00	0.64	0.71	0.75	0.80	0.80	0.78
Peak concentration	0.78	0.89	1.00	0.51	0.59	0.70	0.72	0.77	0.73
Average flux	0.97	0.99	1.00	0.85	0.62	0.64	0.73	0.69	0.65
Peak flux	0.93	1.00	1.00	0.52	0.62	0.61	0.71	0.63	0.60
EMC	0.86	0.97	1.00	0.61	0.69	0.73	0.79	0.79	0.75
Event load	0.98	0.99	1.00	0.61	0.66	0.67	0.74	0.70	0.67

Table G.5 - R^2 values for linear relationship for pathogen numbers in final catchment with a starting buffer of 0.50

	Final buffer ratio					
	1.00		0.85		0.00	
	R^2	Gradient	R^2	Gradient	R^2	Gradient
Average concentration	0.89	0.42	0.98	0.59	0.99	1.58
Peak concentration	0.75	0.29	0.88	0.39	1.00	1.88
Average flux	0.96	0.30	0.99	0.51	1.00	1.70
Peak flux	0.89	0.11	1.00	0.36	1.00	1.91
EMC	0.82	0.33	0.97	0.53	0.99	1.67
Event load	0.97	0.30	0.99	0.51	1.00	1.70

Table G.6 - R^2 values for linear relationship for pathogen numbers in final catchment with a starting buffer of 0.85

	Final buffer ratio					
	1.00		0.50		0.00	
	R^2	Gradient	R^2	Gradient	R^2	Gradient
Average concentration	0.97	0.72	0.98	1.66	0.95	2.59
Peak concentration	0.97	0.77	0.90	2.35	0.86	4.35
Average flux	0.99	0.59	0.99	1.95	0.99	3.31
Peak flux	0.93	0.32	1.00	2.74	0.99	5.22
EMC	0.94	0.64	0.97	1.85	0.95	3.06
Event load	0.99	0.59	1.00	1.95	0.99	3.32

Table G.7 - R^2 values for linear relationship for pathogen numbers in final catchment with a starting buffer of 1.00

	Final buffer ratio					
	0.85		0.50		0.00	
	R^2	Gradient	R^2	Gradient	R^2	Gradient
Average concentration	0.98	1.37	0.91	2.23	0.87	3.47
Peak concentration	0.97	1.27	0.80	2.89	0.75	5.30
Average flux	0.99	1.67	0.97	3.24	0.95	5.47
Peak flux	0.94	2.98	0.91	8.06	0.90	15.32
EMC	0.95	1.52	0.87	2.74	0.82	4.49
Event load	0.99	1.68	0.97	3.26	0.96	5.52

Table G.8 – Average concentration matrix showing gradients of linear relationships between different buffer ratios

		Final buffer ratio			
		0.00	0.50	0.85	1.00
Starting buffer ratio	0.00	1.00	1.59	2.70	3.85
	0.50	0.63	1.00	1.69	2.38
	0.85	0.39	0.60	1.00	1.39
	1.00	0.29	0.45	0.73	1.00

Table G.9 – Peak concentration matrix showing gradients of linear relationships between different buffer ratios

		Final buffer ratio			
		0.00	**0.50**	**0.85**	**1.00**
Starting buffer ratio	**0.00**	1.00	1.89	4.76	6.67
	0.50	0.53	1.00	2.56	3.45
	0.85	0.23	0.43	1.00	1.30
	1.00	0.19	0.35	0.79	1.00

Table G.10 – Average flux matrix showing gradients of linear relationships between different buffer ratios

		Final buffer ratio			
		0.00	**0.50**	**0.85**	**1.00**
Starting buffer ratio	**0.00**	1.00	1.69	3.33	5.56
	0.50	0.59	1.00	1.96	3.33
	0.85	0.30	0.51	1.00	1.69
	1.00	0.18	0.31	0.60	1.00

Table G.11 – EMC matrix showing gradients of linear relationships between different buffer ratios

		Final buffer ratio			
		0.00	**0.50**	**0.85**	**1.00**
Starting buffer ratio	**0.00**	1.00	1.67	3.23	5.26
	0.50	0.60	1.00	1.89	3.03
	0.85	0.33	0.54	1.00	1.56
	1.00	0.22	0.36	0.66	1.00

Table G.12 – Event load matrix showing gradients of linear relationships between different buffer ratios

		Final buffer ratio			
		0.00	**0.50**	**0.85**	**1.00**
Starting buffer ratio	**0.00**	1.00	1.69	3.33	5.56
	0.50	0.59	1.00	1.96	3.33
	0.85	0.30	0.51	1.00	1.69
	1.00	0.18	0.31	0.60	1.00

Appendix H – Relationships between starting and final buffer ratios

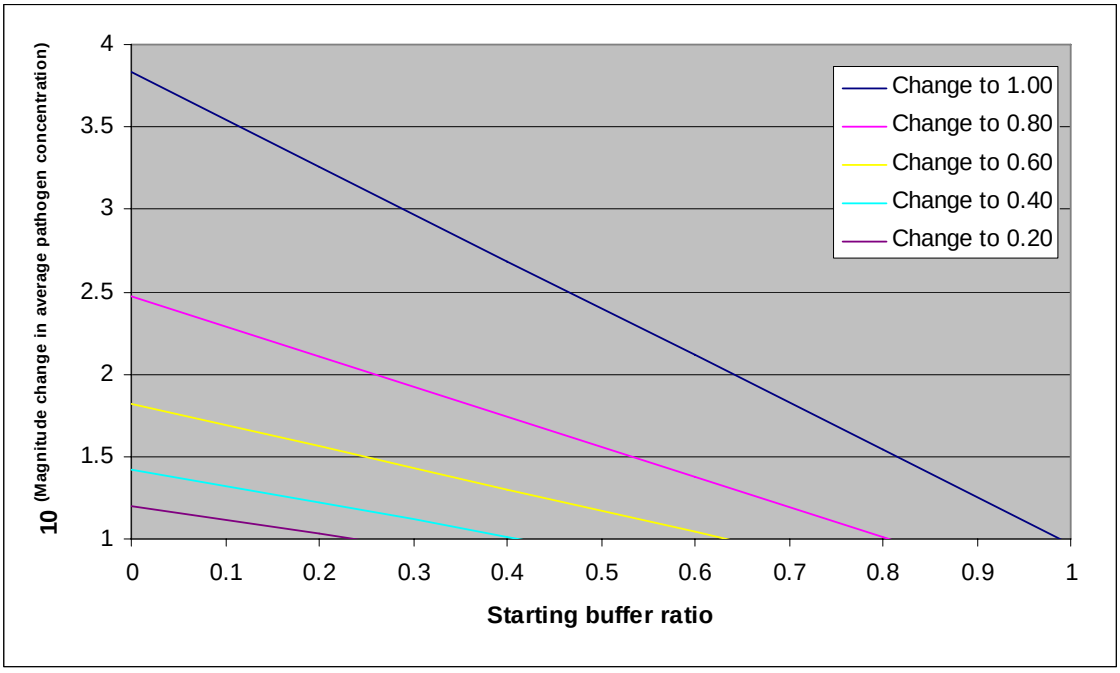

Figure H.1 - Starting buffer ratio against change in average pathogen concentration for different final buffer ratios

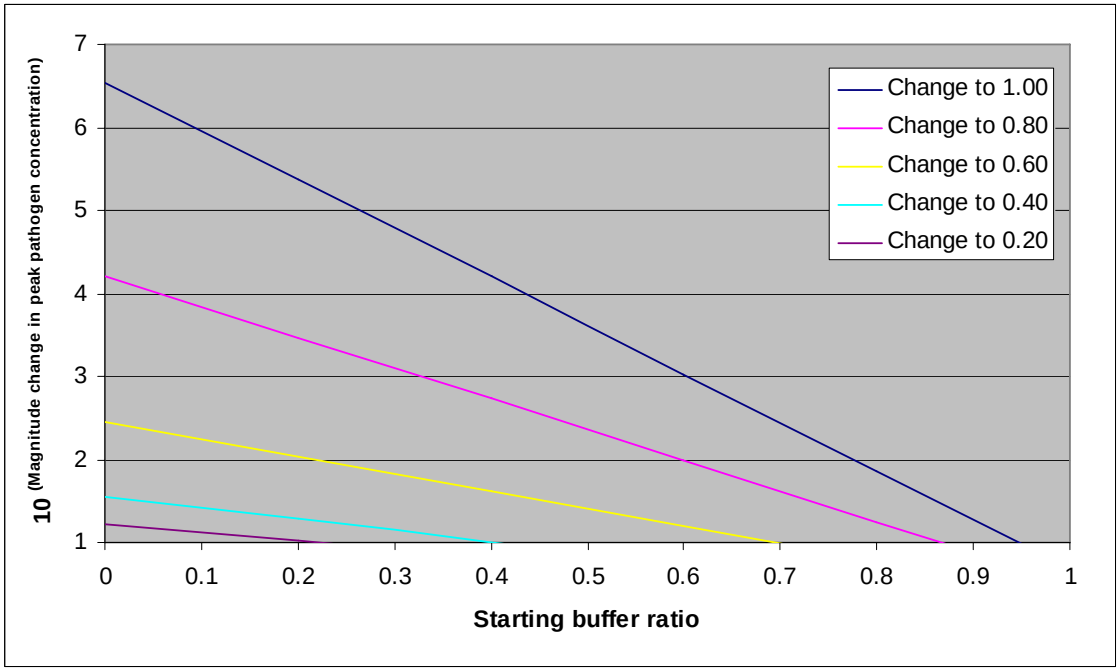

Figure H.2 – Starting buffer ratio against change in peak pathogen concentration for different final buffer ratios

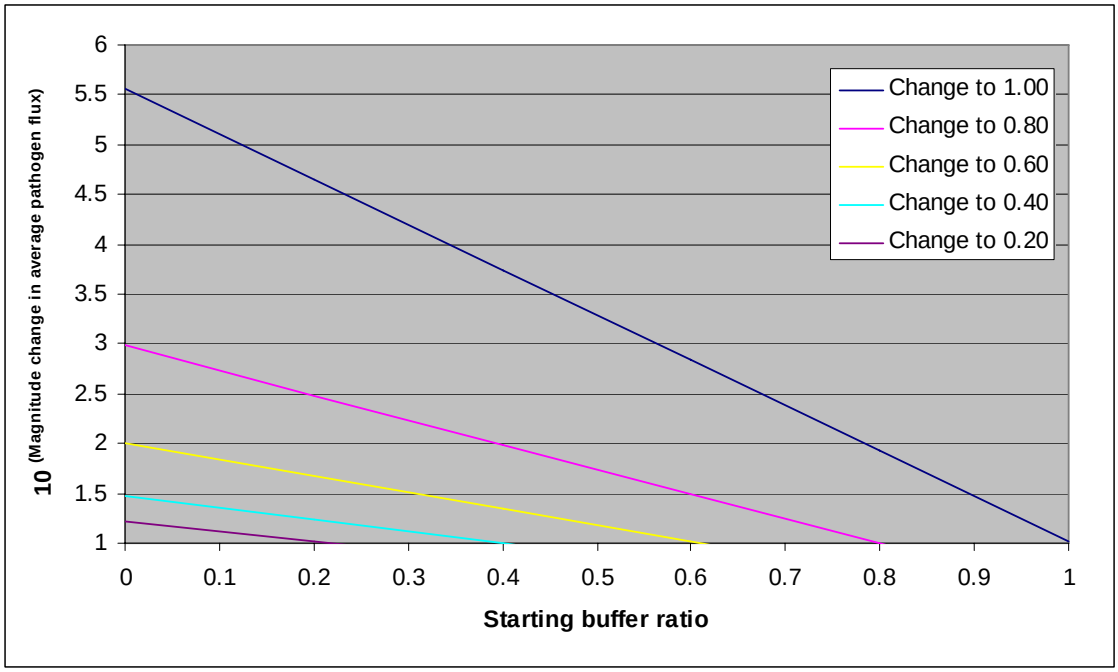

Figure H.3 - Starting buffer ratio against change in <u>average pathogen flux</u> for different final buffer ratios

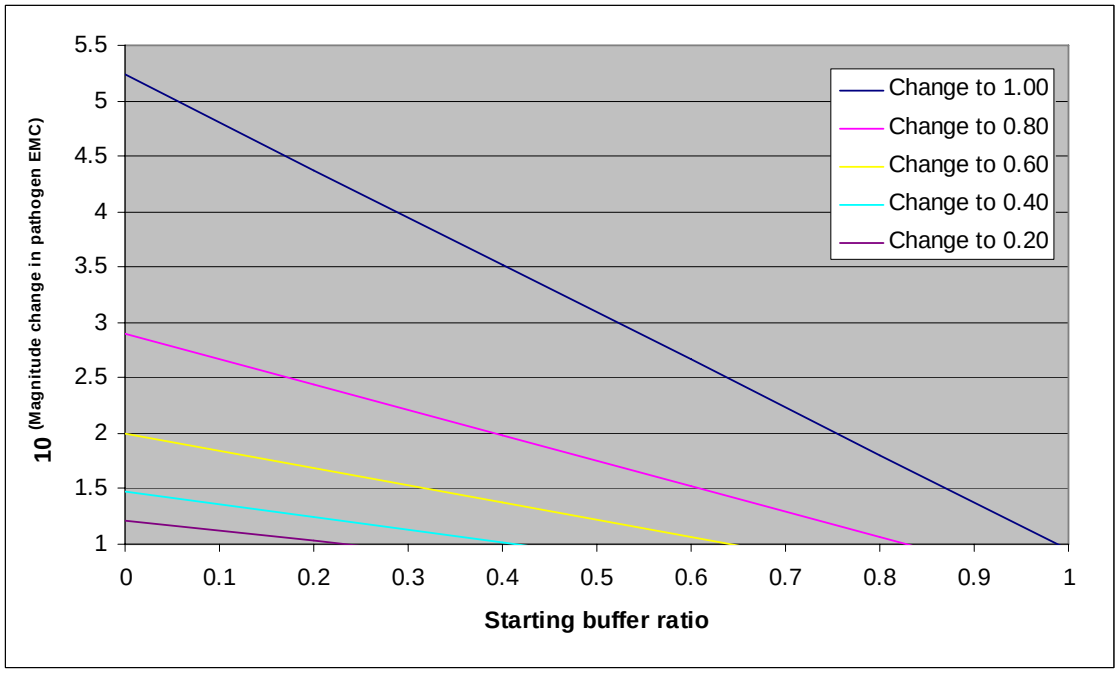

Figure H.4 – Starting buffer ratio against change in <u>EMC</u> for different final buffer ratios

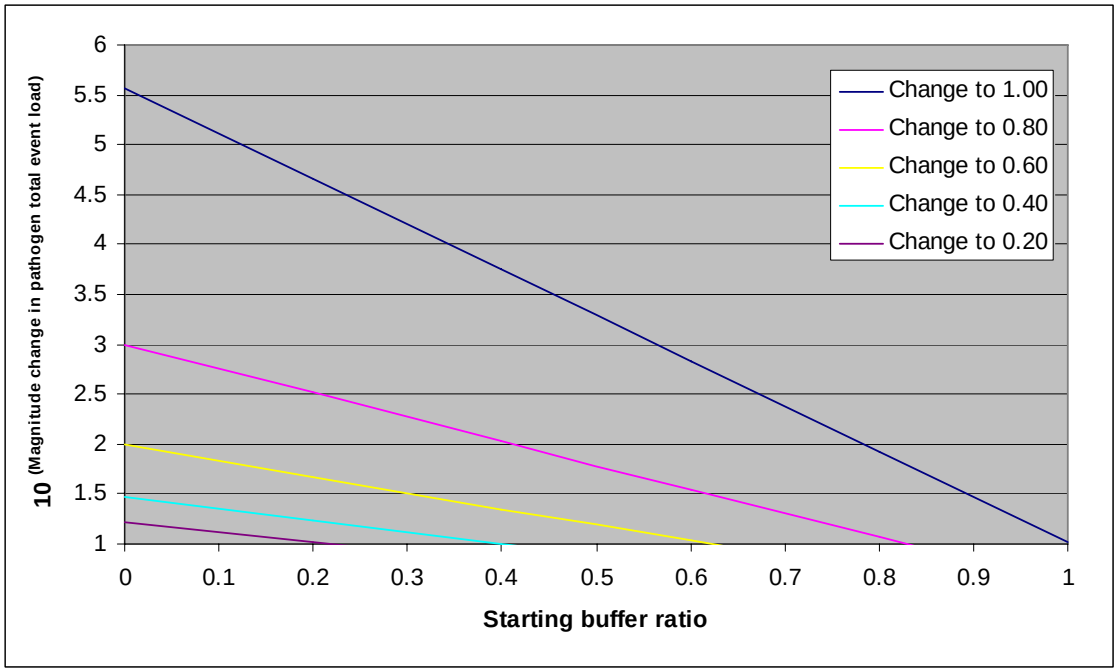

Figure H.5 - Starting buffer ratio against change in pathogen event load for different final buffer ratios

Appendix I – Uncertainty analysis results

Table I.1 – Actual R^2 values and % changes for uncertainty testing of the buffer ratio

% change in buffer ratio	Overall		Event 1		Event 2		Event 3		Event 4		Event 5	
	R^2	% change	R^2	% change	R^2	% change	R^2	% change	R^2	% change	R^2	% change
15	0.64	27.14	1.00	1.02	0.10	-4.30	0.01	-98.29	0.04	401.32	0.79	-0.16
14	0.63	26.68	0.99	0.92	0.10	-4.01	0.27	-61.81	0.03	327.63	0.79	-0.15
12	0.62	24.44	0.99	0.74	0.10	-3.24	0.61	-14.56	0.02	218.42	0.79	-0.13
10	0.60	20.98	0.99	0.58	0.10	-2.58	0.67	-5.85	0.02	144.74	0.79	-0.10
5	0.55	10.24	0.99	0.24	0.10	-1.15	0.71	-1.13	0.01	46.05	0.79	-0.05
0	0.50	0	0.99	0	0.10	0	0.71	0	0.01	0	0.79	0
-5	0.45	-9.34	0.98	-0.18	0.11	1.05	0.72	0.46	0.01	-23.68	0.79	0.04
-10	0.42	-16.74	0.98	-0.32	0.11	2.00	0.72	0.73	0.00	-39.47	0.79	0.09
-15	0.39	-22.76	0.98	-0.44	0.11	2.77	0.72	0.88	0.00	-48.68	0.79	0.14

Table I.2 – Actual *E* values and % changes for uncertainty testing of the buffer ratio

% change in buffer ratio	Overall		Event 1		Event 2		Event 3		Event 4		Event 5	
	E	% change	*E*	% change	*E*	% change	*E*	% change	*E*	% change	*E*	% change
15	0.53	75.30	0.84	104.67	-0.15	-63.43	-0.72	-468.77	-9.31	-39.71	0.06	-26.90
14	0.55	79.54	0.86	110.74	-0.15	-58.76	-0.64	-429.63	-9.12	-36.83	0.06	-25.09
12	0.56	84.09	0.89	117.27	-0.14	-49.53	-0.49	-354.65	-8.74	-31.17	0.06	-21.47
10	0.56	83.33	0.89	116.37	-0.13	-40.62	-0.36	-284.26	-8.37	-25.64	0.06	-17.85
5	0.48	58.25	0.74	81.48	-0.11	-19.45	-0.05	-128.01	-7.49	-12.41	0.07	-8.92
0	0.30	0	0.41	0	-0.09	0	0.19	0	-6.67	0	0.08	0
-5	0.03	-91.38	-0.12	-128.04	-0.08	17.80	0.39	99.71	-5.89	11.58	0.08	8.81
-10	-0.35	-215.92	-0.83	-302.67	-0.06	33.87	0.53	171.18	-5.18	22.30	0.09	17.73
-15	-0.83	-373.58	-1.74	-523.84	-0.05	48.31	0.61	214.39	-4.52	32.25	0.10	26.40

Table I.3 – Actual R^2 values and % changes for uncertainty testing of the pathogen reduction rate

Log change in reduction rate	Overall		Event 1		Event 2		Event 3		Event 4		Event 5	
	R^2	% change	R^2	% change	R^2	% change	R^2	% change	R^2	% change	R^2	% change
-1	0.42	-15.5	0.98	-0.30	0.11	1.81	0.72	0.69	0.005	-36.84	0.79	0.08
0	0.50	0	0.99	0	0.10	0	0.71	0	0.008	0	0.79	0
1	0.51	1.50	0.99	0.04	0.10	-0.19	0.71	-0.14	0.008	6.58	0.79	-0.01

Table I.4 – Actual *E* values and % changes for uncertainty testing of the pathogen reduction rate

Log change in reduction rate	Overall		Event 1		Event 2		Event 3		Event 4		Event 5	
	E	% change	*E*	% change	*E*	% change	*E*	% change	*E*	% change	*E*	% change
-1	-0.28	-190.81	-0.69	-267.43	-0.06	31.05	0.51	160.27	-5.30	20.44	0.09	16.05
0	0.30	0	0.41	0	-0.09	0	0.19	0	-6.67	0	0.08	0
1	0.34	13.06	0.49	18.28	-0.10	-3.38	0.15	-21.16	-6.81	-2.19	0.08	-1.67

Table I.5 – Loads and peaks and % changes for uncertainty testing of the buffer ratio

% change in buffer ratio	Load		Feb 05 Peak		Sep 06 Peak	
	Value	% change	Value	% change	Value	% change
15	4468	-9.21	6560	-64.39	3013	-8.86
14	4498	-8.60	7351	-60.10	3032	-8.29
12	4558	-7.38	8933	-51.51	3072	-7.09
10	4619	-6.14	10515	-42.93	3111	-5.91
5	4770	-3.07	14469	-21.47	3209	-2.95
0	4921	0	18424	0	3306	0
-5	5072	3.07	22378	21.46	3404	2.95
-10	5223	6.14	26332	42.92	3502	5.91
-15	5374	9.21	30285	64.38	3599	8.86

Table I.6 – Loads and peaks and % changes for uncertainty testing of the pathogen reduction rate

Log change in reduction rate	Load		Feb 05 Peak		Sep 06 Peak	
	Value	% change	Value	% change	Value	% change
-1	5196	5.59	25613	39.02	3288	5.37
0	4921	0	18424	0	3306	0
1	4893	-0.57	17705	-3.90	3483	-0.54