Integration of Farm-scale and Catchment-scale Models to Quantify the Effect of Mitigation Practices on Nitrogen Load in the Tararua Catchment

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Abstract

Leached nitrogen from pastoral lands has been identified as a key contaminant contributing to detrimental water quality in New Zealand agricultural landscapes. However, the effectiveness of various management and mitigation measures at reducing the overall catchment nitrogen load in rivers is poorly understood, especially at catchment scale. A robust evaluation of the impact of mitigation measures on water quality is constrained by the limitations of current modelling techniques, particularly their capability to model spatial and temporal variability in nitrogen transport, loads and the potential attenuation of nitrate in flow pathways between the root zone on farms and the receiving waters. This thesis aimed to develop a methodology to integrate a farm-scale nutrient budgeting model, Overseer, with a catchment-scale hydrology model, eWater SOURCE (SOURCE), to determine the effectiveness of farm- and catchment-scale mitigation practices at reducing the dissolved inorganic nitrogen (DIN) load in rivers.

A SOURCE model for the Tararua Catchment was set up and calibrated. This model defined and mapped 3,996 functional units (i.e., hydrologic response units) to model the spatial variability of relevant catchment characteristics including climate, land use, soils, and underlying geology. This informed the parameterisation of model inputs related to: rainfall runoff, water flow pathways, and nutrient generation and attenuation. The Overseer estimates of root zone nitrogen (predominantly nitrate) losses for different combinations of land use, soil, and climate (rainfall) were integrated using a look-up table approach with SOURCE to predict river DIN loads across different sub-catchments in the Tararua Catchment. A simple mixing model, which assumed that the average annual nitrate losses from the farm root zone (modelled by Overseer) were mixed into interflow and percolation to groundwater (modelled by SOURCE) from the soil profile, was used to calculate the DIN concentrations in slow flow (groundwater) and quick flow (surface runoff and interflow) components from different functional units. A comparison of the modelled annual average root zone nitrate losses with the measured average annual river DIN loads suggested that between 10 and 90 % of nitrate losses are attenuated, likely through subsurface denitrification, across different sub-catchments. The integrated SOURCE model was calibrated and validated by comparing the modelled and measured daily river flows and monthly DIN loads at six sites in the study catchment. The model was able to predict river average monthly DIN loads across different sub-catchments more accurately when spatially variable nitrogen attenuation factors,

based on soil and geological characteristics, were applied to both slow flow and quick flow pathways. The modelling efficiency (NSE) ranged from 0.6 to 0.8 while percent bias (PBIAS) ranged from -2 to 15, indicating an acceptable calibration of the model.

The model was then used to investigate the potential effects of various farm- and catchment-scale scenarios to reduce river DIN loads in the study catchment. The modelling results suggest that the catchment-scale scenarios of targeted drainage (quick flow) management, matching intensive land use (dairy farming) to potentially high nitrate attenuation capacity land, and 6 ha of wetlands resulted in a reduction of 11%, 13% and 8%, respectively, in the average annual river DIN load in the study catchment. In contrast, modelling a reduction of 10 to 30% reduction in the average annual root zone nitrate losses from both sheep/beef and dairy farming areas resulted in a 6 to 19% reduction in the overall average annual river DIN load. Interestingly, modelling a reduction of 30% reduction in the average annual root zone nitrate losses only from sheep/beef and dairy farming areas over low to medium nitrogen attenuation capacity lands also resulted into similar level of 15% reduction in the overall average annual river DIN load. This highlights that it is crucial to reduce root zone nitrate losses from headwater catchments and those with highly permeable soils and geology, high rainfall and low subsurface nitrate attenuation capacity.

The findings of this thesis clearly suggest that catchment-scale mitigation practices can reduce the river DIN load on a catchment-scale, without significantly impacting farm production, and should be targeted to specific areas. The innovative methodology to integrate farm-scale (such as Overseer) and catchment-scale models (such as SOURCE) described here can be further developed to help identify targeted and effective water quality management measures.

This thesis is dedicated in honour of the memory of my Pop, Bruce McMurray, whose wisdom and resilience inspires me to greater heights.

I wish I could have shared this journey with you.

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Mā te kimi ka kite, Mā te kite ka mōhio, Mā te mōhio ka mārama.

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List of Abbreviations

APSIM	Agricultural Production Systems Simulator
AF	Attenuation Factor
DCD	Dicyandiamide
DIN	Dissolved inorganic nitrogen. Measure of nitrate-nitrogen, nitrite-nitrogen, and ammoniacal-nitrogen.
DEM	Digital elevation model
FDC	Flow duration curve
FSL	Fundamental Soils Layer
LiDAR	Light detection and ranging
LINZ	Land Information New Zealand
LUC	Land use Capability
masl	Meters above sea level
MFE	Ministry for the Environment
N_2	Nitrogen
N_2O	Nitrous oxide
NH_3	Ammonia
NH_4^+	Ammonium
NIWA	National Institute of Water and Atmospheric Research
NO_2^-	Nitrite
NO_3^-	Nitrate
NPS-FM	National Policy Statement for Freshwater Management
NSD	National Soils Database
NSE	Nash–Sutcliffe model efficiency coefficient
PBIAS	Percent bias
pH	Scale used to specify the acidity or basicity of an aqueous solution
QGIS	Quantum Geographic Information Systems (GIS software used)
Q-Map	1:250 000 Geological Map of New Zealand
REC	River Environment Classification
RISC	Rainfall interception store capacity

RMSE	Root mean squared error
SC	Sub-catchment
SMSC	Soil moisture store capacity
SOURCE	eWater SOURCE framework
SWAT+	Soil & Water Assessment Tool
TN	Total nitrogen
TON	Total oxidised nitrogen (nitrite + nitrate)
VCSN	Virtual Climate Station Network

1 Introduction

1.1 Context

Agriculture and its associated industries play a key role in food-security, and economic and social welfare. However, the interaction between agriculture and the environment is becoming increasingly important. During the past 30 years, agriculture in New Zealand has become more intensive, resulting in increased nutrient inputs and subsequent losses of nutrients to waterways (Larned et al., 2018). Intensive pastoral systems are considered a major contributor of increased nitrate concentration in waterways due to highly concentrated urine patches that cannot all be taken up by the grass and are instead leached from the soil profile to receiving waters (Ball & Ryden, 1984; Quinn et al., 2009). This is of a critical concern due to eutrophication which has many subsequent effects on freshwater ecosystems and their aquatic life-supporting capacities (Cameron et al., 2013). In response, greater scrutiny and increasing regulations, as formulated in the National Policy Statement for Freshwater Management (NPS-FM), requires adaption from the farming industry to help reduce nitrate losses to receiving waters. However, agriculture is a key industry in New Zealand and contributes to 70% of export revenues so a holistic approach must be taken that does not impact agricultural productivity and profitability (Statistics New Zealand, 2019). Therefore, steps must be taken to develop targeted and effective water quality measures to reduce nitrogen load in rivers, while maintaining or improving farm productivity in New Zealand agricultural landscapes. This is particularly important for the Tararua Catchment due its susceptibility to nitrate leaching and the high proportion of agricultural land use within the catchment.

A sound understanding of the sources, transport, attenuation processes, and fate of nutrients lost from farms to waterways is crucial to manage and mitigate any adverse impacts of agricultural intensification on water quality. Mitigation strategies play a pivotal role in reducing nitrogen load in waterways and preserving farms' abilities to maximise production. The wide range of strategies currently available have varying degrees of effectiveness (Durand et al., 2015; Menneer et al., 2004; Monaghan & De Klein, 2014). This indicates a need to assess which mitigation strategies are most effective at reducing nitrogen loads in waterways. Recent research has determined that there are limited opportunities to reduce nitrogen leaching from on-farm practices, while maintaining farm productivity (Jacobsen & Hansen, 2016; McDowell et al., 2014). Instead, catchment-scale practices such as matching land use intensity with land nutrient attenuation capacity, controlled drainage, woodchip bioreactors, and/or wetlands, should be considered (Singh & Horne, 2020).

Modelling is a common strategy to compare scenarios related to water quality. Models provide a simplified representation of reality that allows the complex interplay of hydrology and biogeochemical processes, spatial variability of catchment characteristics and nutrient transport to be accounted for (Cichota & Snow, 2010). Previous research has used the approach of either farm-scale or catchment-scale modelling to assess nitrogen loss (McDowell et al., 2014). However, there are many inadequacies with using these methods of assessment independently. Farm scale models are unable to simulate the transport of nitrogen to rivers, in particular spatially variable nitrogen attenuation capacity as affected by different hydrogeological settings across the catchments. However, catchment models are limited in their ability to model farm-scale processes and up until now, the research on mitigation practice effectiveness has tended to focus on farm-scale rather than catchment models. Hence, integration of farm- to catchment-scale models is proposed, including spatially variable nitrogen attenuation capacity to help assess potential effects of both farm- and catchment-scale mitigation measures.

This research will contribute to a deeper understanding of nitrogen processes and contribute to the growing area of research in water quality by exploring the effects of mitigation practices on nitrogen load.

1.2 Objectives

The aims of this study are to develop an integrated model to investigate the effectiveness of various farm- and catchment-scale mitigation practices at reducing nitrogen loads in the Tararua Catchment. Specifically, the objectives are to:

- Review the processes pertaining to the nitrogen cycle, the range of mitigation practices available to reduce nitrogen losses, and the existing methods and models to assess the effectiveness of these practices;

- Develop an integrated farm-scale and catchment-scale model to simulate the hydrological regime, and nitrogen transport and attenuation processes in the Tararua Catchment; and
- Determine the effectiveness of selected farm-scale and catchment-scale mitigation practices on reduction of river DIN loads in the catchment.

1.3 Structure

This thesis comprises seven (7) chapters. Chapter 1 gives a brief background, highlights that further research is required to develop integrated farm- and catchment-scale models for assessment of water quality scenarios, and defines the research aims and objectives. Chapter 2 provides a review of existing research on nutrient flows and methodologies to evaluate effectiveness of mitigation practices from farm- to catchment-scale. It briefly describes the importance of agriculture and its potential environmental impacts in terms of nitrogen losses, and then reviews the concepts and processes of the nitrogen cycle and potential mitigation practices to reduce nitrogen losses from farm to receiving waters. In the latter part of the chapter, existing methodologies and techniques employed to measure the effectiveness of mitigation practices, as well as the available models, are examined. Chapter 3 provides background into the geographical and hydrogeological characteristics of the study area, the Tararua Catchment, which covers ~3200 km^2 upstream of the Manawatū Gorge. Chapter 4 describes the materials and methods used to integrate and parametrise the farm-scale nutrient budget model Overseer and the catchment-scale hydrology model SOURCE, to model nitrate losses and river DIN loads in the study area. It details the collation and processing of relevant geographical and hydrogeological data, and the model's setup and calibration using the measured stream flow and water quality records in the study area. Chapter 4 also defines and describes various in-field and catchment-scale mitigation scenarios that were evaluated to reduce nitrogen loads in the study sub-catchments. Chapter 5 presents the hydrology and water quality calibration results and the effect of different mitigation scenarios on nitrogen loads across the study sub-catchments. Chapter 6 provides a discussion of the results and their implications for policy and practice to reduce DIN loads in waterways. Finally, Chapter 7 summarises the findings and makes suggestions for future research to further develop integrated modelling tools to help evaluate targeted and effective water quality measures across agricultural landscapes.

2 Literature Review

This literature review is narrative in nature and is based on constructivist epistemology. Its purpose is to develop knowledge relevant to the objectives of this thesis, to find gaps in existing research and identify possible methodologies that have been used with success in the past. The search was carried out in various databases, including Google Scholar and the Massey University Library catalogue. Citation searching was used to find more recent research that cites key papers as well as looking for materials within a paper's research list.

The inclusion criteria for research to be incorporated into the literature review was that articles must be from a reputable source. For example, articles that are peer-reviewed, theses, or from industry or government. The articles must also have been published in the last 50 years and provide insight into the research questions. Where possible, data and research in a New Zealand context was used although due to the lack of research, findings from other countries with similar agricultural practices will also be used.

2.1 Environmental Impacts and Importance for Agriculture

Nitrogen is a naturally occurring macronutrient essential to support plant growth, ecosystems, and maintain agricultural productivity. While nitrogen is essential, in excess it can lead to the enrichment of surface water, which promotes protein synthesis and an increase in plant growth causing macrophyte, phytoplankton, and periphyton proliferation. Smith et al. (1999) defined this process as eutrophication, and they presented a significant analysis and discussion on this subject. Eutrophication occurs when the growth of organic matter (algae and vascular plants) is not limited by the supply of nutrients in the waterway, particularly inorganic nitrogen and phosphorus (McDowell & Hamilton, 2013; Smith et al., 1999). In plants, nitrogen is found in the chlorophyll molecule and nucleic acids and is a primary constituent of basic amino acids, which are the building blocks of proteins and enzymes. Nitrogen makes up 2-4% of plant dry weight, and between 200-800 kg N/ha/yr is taken up by plants (Hatch et al., 2002). Larned et al. (2018) estimated that between 2013 and 2017, 70% of New Zealand's rivers had at least one form of nitrogen whose median concentration was above the natural condition guideline value given in the NPS-FM, which raises significant concerns over eutrophication in New Zealand rivers.

Eutrophication is a major environmental problem and is the leading cause of water quality degradation and subsequent ecosystem degradation. The range of effects from eutrophication includes increased turbidity, impeded river flows, blockage of water supply intakes, oxygen deficiency, changes in pH levels, and increased toxicity (McDowell & Hamilton, 2013; Scarsbrook & Melland, 2015). Consequences of these changes can disrupt ecosystem functioning, as a loss of submerged vegetation and habitat causes changes in food webs and a loss of biodiversity (Scarsbrook & Melland, 2015; Smith et al., 1999). Water quality degradation not only has a detrimental effect on freshwater ecosystems but also poses risks to animal and human health; it can cause methaemoglobinaemia, cancer, and heart disease (Fan & Steinberg, 1996). Of added concern is that it also reduces waterways' aesthetic and recreational appeal, which is a key aspect of NPS-FM and New Zealand's tourism branding. Therefore, degradation of surface water quality by eutrophication is of significant societal, environmental, and economic importance.

Intensive agricultural systems are considered a major contributor to increased nitrogen concentrations in waterways due to the leaching of farm nutrients to ground and surface waters (Cameron et al., 2013). The Parliamentary Commissioner for the Environment (2015) estimated that approximately 29% more nitrogen was leached in 2012 than in 1990, and nitrogen levels in rivers have increased by 12%, placing increasing pressure on water quality. This can be explained by a change from sheep and beef systems to intensive dairy farming, which corresponds with a 17% increase in stocking rate and increased use of fertiliser and irrigation (Quinn et al., 2009). The typical nitrogen loss from dairy farming is approximately 65 kg N/ha/yr compared to 20 kg N/ha/yr from sheep and beef farms (Menneer et al., 2004). Table 1 presents the typical nitrogen leaching values from a range of land uses. The large variation in leaching for each land use is expected due to changes in management and location. Both arable cropping and vegetable cropping systems have higher leaching rates of 30-60 kg and 80 –292 kg, respectively (Hatch et al., 2002). For New Zealand, little information exists regarding the amount of nitrogen lost from horticultural systems. This study will focus on pastural grazed systems.

Table 1. Typical nitrogen leaching rates.

Land use	N leaching (kg N/ha/year)		References
	Range	Mean	
Dairy	15-115	65	(Di & Cameron, 2010; Ledgard et al., 1999; Ledgard et al., 2001; Monaghan & De Klein, 2014; Scarsbrook & Melland, 2015; Silva et al., 1999)
Sheep and Beef	6-66	21	(Cameron et al., 2013; Menneer et al., 2004; Quinn et al., 2009)
Forestry	1-28	5	(Davis, 2014; Dymond et al., 2013; Parfitt et al., 2006)

There has been increasing societal pressure to minimise the impact of agricultural intensification on the environment and prevent deterioration of water quality. This has led to consumers demanding agricultural products with a lower environmental footprint and has also led to market pressure to demonstrate sustainability credentials (Scarsbrook & Melland, 2015). In addition, improving water quality has been addressed by policy initiatives and regulations such as the NPS-FM which requires regional councils to develop and implement plans that mandate limiting nitrogen losses to water. The targets set by regional councils highlights the need to improve current farm management practices and that increased research needs to go into the effectiveness of various mitigation practices. This requires in-depth knowledge of the nitrogen cycle and its links to waterways.

2.2 Nitrogen Cycle

This section reviews literature on the complex processes that govern the nitrogen cycle, as effective water quality management requires an understanding of the transport and transformation processes of nitrogen from the farm to waterways.

2.2.1 Sources of Nitrogen

Nitrogen contaminates surface water from various sources and can be broadly classified as point and non-point sources. Pollution from a fixed point of discharge that is released into a waterway via pipes or drainage is referred to as point source pollution (McLaren & Cameron, 2002). In contrast, non-point source discharges are dispersed across paddocks and landscapes and are from a combination of different sources. This makes them more complex and difficult to control. In many agricultural catchments, non-point sources usually dominate nitrogen inputs to waterways (Parfitt et al., 2006).

Soils in New Zealand generally contain between 0.1% and 0.6% nitrogen in the top 15cm, with approximately 98% being present in the organic form (Cameron et al., 2013). Nearly all of the organic nitrogen is found in the soil organic matter and is made up of; plant residues, humus, microbial biomass, manure, urine, and nitrogen fixed via legume pastures. However, organic nitrogen in these forms is not available for plant uptake or leaching unless it is transformed into inorganic nitrogen (McLaren & Cameron, 2002). Soil inorganic nitrogen represents a small and transient pool that accounts for < 2% of the total soil nitrogen content (Hatch et al., 2002). Inorganic forms of nitrogen originate from fertilisers, animal excreta or the by-products of mineralisation of organic nitrogen. They include ammonium (NH_4^+), nitrite (NO_2^-), and nitrate (NO_3^-) - all of which are readily available for plant uptake in the soil-water system (McLaren & Cameron, 2002).

Numerous studies have shown that agricultural practices are responsible for most of the degradation in water quality and that the risk of NO_3^- leaching increases with increasing stocking rate and fertiliser application (David et al., 1997; Larned et al., 2018; Monaghan et al., 2005; Parfitt et al., 2006; Quinn et al., 2009). In particular, NO_3^- leaching from intensive grazing systems is well documented for New Zealand and research has identified that ruminant-grazed dairy systems have the highest contribution to NO_3^- leaching rates (Bristow et al., 1992; Cichota et al., 2012). Additional nitrogen application to the soil-water system can have a negative impact on water quality. As regulations in New Zealand are focused on maintaining and enhancing water quality, the ability to mitigate nitrogen input to waterways and minimising the effects of agriculture is essential.

Nitrogen is a key input into farming systems to increase productivity as the quantity of available nitrogen is often inadequate for optimum crop and pasture production. Historically in New Zealand, nitrogen was primarily supplied through the nodules of nitrogen-fixing clover (Parfitt et al., 2006).

However, the application of fertilisers has increased by over 800 % over the last 50 years as intensification has occurred and productivity has become more important (Foley et al., 2011). Between 1990 and 2015, total nitrogen applied through fertiliser application in New Zealand increased by 627% (9,000 tonnes in 1990 to 429,000 tonnes in 2015) (Statistics New Zealand, 2019). It is now well established from a variety of studies that direct leaching of nitrogen fertiliser only has a marginal effect on the quantity of NO_3^- leaching and only when applications are excessive (>400 kg N/ha/yr) or untimely (>50 kg N/ha in winter) (Menneer et al., 2004).

Another nitrogen input is the application of dairy effluent to the soil. There is concern that excessive application of effluent may cause nitrogen leaching as it has a high concentration of nitrogen in the inorganic form. However, research by Monaghan and De Klein (2014) determined this was unlikely if the effluent is diluted and evenly spread. Ultimately, the risk of nitrogen leaching from the application of effluent depends on several factors, such as the number of ponds in the catchment, the proportion of ponds that are adequately lined, stocking rate, and effluent application rate and area.

It is generally understood that NO_3^- leaching increases exponentially when nitrogen inputs to the soil are above 150-200 kg N/ha/yr, despite the type of nitrogen input, as when total nitrogen inputs to pasture increases, a greater amount of nitrogen is cycled through grazing animals (Menneer et al., 2004). Any remaining nitrogen that is not immobilised by microorganisms, or utilised by plants, is a potential source of leaching.

As noted previously, extensive research has found that the primary source of the nitrogen that leaches under pastural systems is urine patches from grazing dairy cows rather than from fertiliser (Ledgard et al., 1998; McLaren & Cameron, 2002; Monaghan et al., 2002; Silva et al., 1999). This suggests that opportunities to achieve a reduction in nitrogen leaching from fertiliser management are small. According to Dymond et al. (2013), livestock urine accounted for around 78% of the nitrogen leached from agricultural soils in New Zealand in 2012. Livestock ruminants are considered to be inefficient users of dietary nitrogen as a smaller amount of nitrogen ingested from pasture is used while the majority is excreted in the form of urea which is rapidly converted to NH_4^+ and then to NO_3^-. Bristow et al. (1992) suggested that 70% of nitrogen that cows ingest is excreted while Jarvis et al. (1996) proposed 60-90% and Oenema et al. (2005) proposed 95%. Some of this nitrogen is lost through volatilisation, but most of it gets nitrified by soil bacteria to NO_3^- (Silva et al., 1999). Cattle urine contains about 16 g urea/L, resulting in nitrogen concentrations of about 4 g/L, although daily variability ranges from 1-13 g N/L (Bristow et al., 1992). The most frequently cited study is by Haynes and Williams (1993) who stated that urinary nitrogen loading by dairy cows can be up to 1000 kg N/ha while Selbie et al. (2015) proposed 200-2000 kg N/ha and Cameron et al. (2013) proposed 400 – 1366 kg N/ha. Collectively, these studies outline a critical role for mitigating nitrogen leaching as the very high concentration of nitrogen under the small area of the urine patch exceeds what can be used by the plant; accordingly, there is a high potential for the nitrogen to leach. The leaching potential is particularly high during winter when the soil is wet and excess water drains from the root zone (Cameron et al., 2013; Menneer et al., 2004). Although cattle have a higher leaching rate than sheep due to larger urination volumes, sheep display strong camping behaviour which can result in similar leaching rates in specific areas (Menneer et al., 2004).

As a gas, nitrogen makes up approximately 78% of the atmosphere. In this form, it is inactive and plants and animals cannot metabolise it because of its strong triple bond (Jarvis et al., 1996). The triple bond must therefore be broken before the nitrogen can be used. This is mediated by nitrogenase enzyme, used by organisms in a process called biological N fixation. Atmospheric nitrogen enters the agricultural nitrogen system by biological fixation through a symbiotic relationship with rhizobium bacteria in the root nodules of leguminous crops (Pakrou & Dillon, 2000). These convert light energy to carbohydrates and the bacteria utilise the enzyme nitrogenase to reduce nitrogen (N_2) to ammonia (NH_3) (Di & Cameron, 2002). Previous research has established that common rates of fixation are between 10 and 200 kg N/ha/yr, with Ledgard et al. (1998) reporting that white clover fixes between 29 and 75 kg N/ha/yr. Nonetheless, this varies with environmental conditions and decreases with increasing fertiliser application (Parfitt et al., 2006). The fixed nitrogen acquired by legumes benefits subsequent crops since nitrogen excreted in root exudates and what remains in the roots decomposes to produce mineral nitrogen which other plants can then take up. However, it is possible for this decomposition to contribute to leaching, since decomposing plant residues can release as much as 200 kg N/ha/yr (Jarvis et al., 1996).

Other minor nitrogen inputs may include atmospheric deposition and the weathering of parent soil material. Non-biological nitrogen fixation combines nitrogen and oxygen to produce nitrogen oxides which are deposited from the atmosphere into the soil through dry and wet deposition (Di & Cameron, 2002). In New Zealand, inputs from nitrogen deposition are only 1-5 kg N/ha/yr, as there are low levels of industrial pollution and the prevailing wind patterns blows gaseous forms of nitrogen oxides out to sea (Parfitt et al., 2006).

2.2.2 Transformation Processes

The nitrogen cycle is made up of system inputs, changes in nitrogen storage within the soil system (variability in mineral nitrogen concentration), and system outputs. The system can also be formalised using the nitrogen mass balance equation proposed by Di and Cameron (2002) to describe the quantity of mineral nitrogen in the soil (Equation 1).

$$N = Np + Nb + Nf + Nu + Nm - Npl - Ng - Ni - Nl - Ne \quad (1)$$

where p, b, f, u, m, pl, g, i, l, and e correspond to precipitation and dry deposition, biological fixation, fertiliser, urine and dung, mineralisation, plant uptake, gaseous losses, immobilisation, leaching loss and erosion and surface runoff, respectively.

The processes governing the transformation of nitrogen in the soil are vital to understanding the partitioning of nitrogen in the soil-plant system and where it is lost from the system. The agricultural nitrogen cycle is described in detail by Di and Cameron (2002), McLaren and Cameron (2002), and Pakrou and Dillon (2000), among others and is summarised in Figure 1.

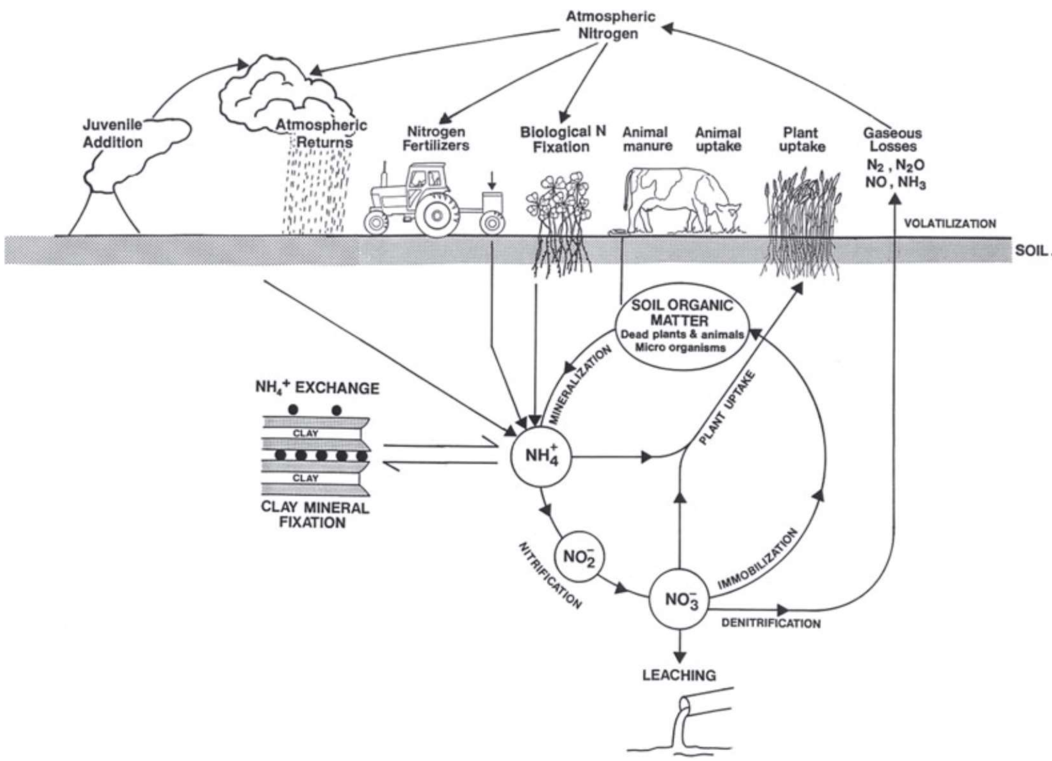

Figure 1. Nitrogen cycle (McLaren & Cameron, 2002).

2.2.2.1 Mineralisation

Soil organic nitrogen must be decomposed and converted to the inorganic compounds NO_3^- and NH_4^+ by soil bacteria and fungi in order to be available to plants (McLaren & Cameron, 2002). This biogeochemical process is called mineralisation and includes ammonification where organic nitrogen is broken down to NH_4^+ ions and nitrification where NH_4^+ is converted to NO_3^- (Jarvis et al., 1996). Data from several studies suggest that there are several factors affecting mineralisation rates of soil, including the quantity of organic nitrogen, soil temperature, soil moisture content and microbial biomass (Hopkins et al., 2011; Jarvis et al., 1996; McLaren & Cameron, 2002).

Soil microbes take up NH_4^+ and NO_3^- which immobilises the nitrogen. This regulates the net production of inorganic nitrogen and determines the amount of inorganic nitrogen available for plant uptake and leaching. Pasture extracts significant quantities of NO_3^- or NH_4^+: uptake rates are approximately 200 to 700 kg N/ha/yr (Hopkins et al., 2011). Once taken up by plants, NO_3^- can be translocated within the plant unaltered, or reduced to NH_3 within the root (Pakrou & Dillon, 2000). Once NH_3 has been produced, it is converted into amino acids, amides or amines before being returned to the soil as crop residues to undergo the mineralisation process again (Ford & Bormans, 2000).

2.2.2.2 Ammonification

Ammonification is the process where heterotrophic bacteria and fungi break down proteins of the organic matter and oxidise it into NH_3 which is then hydrolysed into NH_4^+ (McLaren & Cameron, 2002). NH_4^+ is rapidly nitrified to NO_3^- by soil microorganisms so its concentration in most soils is typically low. In addition to nitrification, NH_4^+ can also be retained by the soil as it is held tightly by the negative charges of clay minerals and soil organic matter through electrostatic attraction (Pakrou & Dillon, 2000). This means it is relatively immobile and does not leach through soils easily. However, occasionally it can be removed in overland flow, especially in poorly structured soils that are subject to erosion. NH_4^+ ions are exchangeable. This means that when other cations are added to the soil solution, the NH_4^+ ions on the cation exchange sites are released back into solution and can be readily used by vascular plants and algae for growth, utilised by microorganisms, or undergo volatilisation (Di & Cameron, 2002).

2.2.2.3 ***Nitrification***

Nitrification is the process where under aerobic conditions, autotrophic bacteria oxidise NH_4^+ to NO_3^- which mobilises nitrogen and increases losses to watercourses. The rate of nitrification is one of the principal factors determining the rate of nitrogen leaching. Nitrification rates are at a maximum when soil moisture content is at field capacity, pH is between 4.5 and 7.5, soil temperature is between 25 and 30 degrees Celsius, and there is a high initial quantity of NH_4^+ and biomass of bacteria (Di & Cameron, 2007).

The first reaction is where the ammonia monooxygenase enzyme associated with *Nitrosomonas* bacteria oxidises NH_4^+ to NO_2^- (Hatch et al., 2002). NO_2^- is very reactive and toxic to aquatic life. However, since it has a short half-life, there is negligible accumulation in the soil (Scarsbrook & Melland, 2015). However, if soils have a high NO_3^- concentration, pH greater than 7.5, high temperature, and poor aeration, NH_4^+ oxidation can exceed NO_2^- oxidation which allows it to accumulate and be leached (Di & Cameron, 2007).

The second reaction is where *Nitrobacter* oxidise NO_2^- to NO_3^- (McLaren & Cameron, 2002). NO_3^- is the most plant-available form of nitrogen as it is highly soluble, and its negative charge means it is poorly bound to soils (Di & Cameron, 2007). It is widely accepted that NO_3^- is the dominant form of nitrogen that is leached due to high mobility in the soil-water system (Cichota et al., 2012; Hopkins et al., 2011; Monaghan & De Klein, 2014; Parfitt et al., 2006). NO_3^- formed through nitrification can also undergo immobilisation or denitrification.

2.2.2.4 Denitrification

Denitrification is one of the mechanisms by which nitrogen is lost from the soil water system (Barton et al., 1999). Denitrification is the process where NO_3^- is reduced to the gaseous nitrogen forms, nitrous oxide, and dinitrogen in the absence of oxygen. Denitrification consists of a sequence of enzymatic reactions and occurs when microbes use NO_3^- as an electron acceptor in their respiratory process (Cameron et al., 2013). It requires the availability of electron donors such as dissolved organic carbon or Mn^{2+} and Fe^{2+} (Pakrou & Dillon, 2000). If the electron donor is organic, the microbes must be heterotrophic, while if the electron donor is inorganic, the microbes must be autotrophic. Denitrification also requires anaerobic conditions as found in waterlogged soil or anaerobic micro-sites within the soil so that NO_3^- is used instead of oxygen for respiration (Eckard et al., 2004).

Denitrification rates are hard to determine and can be extremely variable, both spatially and temporally, and may have been overestimated in many soil studies (Keeney & Hatfield, 2008). They have been cited to range from 0–239 kg N/ha/yr and are typically around 5-20 kg N/ha/yr under agricultural systems (Barton et al., 1999). Denitrification is the main nitrogen attenuation process in the shallow soil system, particularly in wetlands and riparian planting where carbon to nitrogen ratios are high. The carbon to nitrogen ratio regulates the NO_3^- production due to a metabolic balance between carbon and nitrogen, with soils with a high ratio soils promoting decomposition and low denitrification (Jahangir et al., 2012). However, the key problem with this explanation is that the ratio alone is a poor predictor of nitrogen leaching or retention.

Denitrification can be considered as either a beneficial or a detrimental soil process. On the positive side, denitrification removes NO_3^- before water percolates into ground or surface water (Jahangir et al., 2012). However, it is now understood that the denitrification process plays an essential role in potentially increasing the emission of N_2O, effectively swapping one pollutant for another. N_2O is a potent greenhouse gas that makes up 17% of New Zealand's greenhouse gas inventory, 96% of which can be traced to agriculture (Quinn et al., 2009).

2.2.2.5 Volatilisation

Volatilisation is a chemical reaction that results in the production of NO_3 gas which is emitted to the atmosphere. Most of the NO_3 that is volatilised is returned to the earth's surface through wet or dry deposition (Pakrou & Dillon, 2000). In a study investigating the quantity of annual NH_4^+ losses, Bishop and Manning (2011) reported that losses are relatively small and range from 10 to 50 kg N/ha/yr. Volatilisation only occurs when the soil pH is >7 and there are free NH_4^+ ions in the soil (McLaren & Cameron, 2002). This commonly occurs following the application of urea fertiliser or animal urine. In Cameron et al. (2013) review of nitrogen losses, five characteristics leading to an increased rate of volatilisation were identified. These are: increasing soil pH, temperature, NH_4^+ concentration, and a low cation exchange capacity.

2.2.3 Nitrogen Transport Pathways

NO_3^- is water-soluble and is primarily transported in water from agricultural land to receiving waterways (Follett, 2008). Nitrogen leaching arises when the capacity of the plants to uptake nitrogen is less than the amount of nitrate in the soil or when the soil's ability to store added water from rainfall or irrigation is exceeded. The critical flow pathways for the transport of nitrogen in water can be divided into either surface or subsurface pathways. Subsurface transport mechanisms can be further defined as leaching, deep percolation to groundwater or artificial drainage (Follett, 2008; Monaghan et al., 2016). The transport of nitrogen is primarily driven by the amount of water that infiltrates or runs off the soil profile. After infiltration, water movement is partitioned into lateral or vertical flow (Capel et al., 2008). Based on the soil-water partitioning coefficient for NO_3^-, sub-surface transport mechanisms are considered the main transport process (Logan, 1993; McKergow et al., 2007).

Surface flow also provides a pathway for the transport of nitrogen to waterways. It is an intermittent process that can cause temporarily large increases in nitrogen load when the pathway operates (Monaghan et al., 2016). This occurs when ammoniacal nitrogen attaches to soil particles and accumulates in the soil profile during prolonged dry periods (McLaren & Cameron, 2002). It is then transported when runoff occurs in response to significant rainfall events where the rainfall intensity exceeds the soil's infiltration rate (Drewry et al., 2006). There can be delays in nitrogen transport as nitrogen is able to build up in soil and it is the water movement that determines when it is transported. This raises an interesting point that the effects of some management practices, such as high fertiliser use, may not be reflected in waterway nitrogen concentrations immediately as when drainage volumes are low, pastoral systems can utilise nitrogen fertiliser without any impact on waterways. The accumulation of NO_3^- in the soil in low drainage years will be displaced in subsequently higher drainage years (Eckard et al., 2004; Follett, 2008). The amount of dissolved nitrogen transported in surface flow is a function of rainfall intensity and the physical characteristics that influence infiltration rate (Drewry et al., 2006). Impermeable and poorly drained soils typically have greater surface flow. Losses of particulate nitrogen, which is bound to soil eroded by surface flow can also contribute to eutrophication if the organic nitrogen decomposes during or after the erosion processes (McDowell et al., 2009; Monaghan et al., 2016).

Nitrogen is primarily transported to waterways through the continuous process of groundwater transport, including vertical percolation to groundwater and horizontal saturated groundwater flow (Eckard et al., 2004; Monaghan et al., 2005). Since NO_3^- is a negatively charged ion, it is repelled by the cation exchange sites in the soil and moves freely in soil water. Leaching can be either via matrix flow or through preferential flow (McLaren & Cameron, 2002). Matrix flow occurs by convection, diffusion, and dispersion (Cameron et al., 2013; Monaghan et al., 2016). Convective transport occurs due to the mass of water flowing through the soil during drainage events. Diffusive transport occurs as a diffusive flux is created due to the concentration gradient between the mobilised NO_3^- and the NO_3^- in the surrounding soil (Cameron et al., 2013). Hydrodynamic dispersion occurs due to, among other factors, the range of flow path lengths resulting from the differences in flow velocities and tortuosity of soil pores (McLaren & Cameron, 2002). Preferential flow is the rapid movement of water through macropores in the soil (Follett, 2008). Macropores are formed within the soil by plant roots, earthworms, and freezing and thawing or wetting and drying cycles. Preferential flow is not subject to denitrification and therefore results in higher NO_3^- concentrations in groundwater (Monaghan et al., 2016). It also causes faster flow velocities, which means leaching will occur at a quicker rate (Sigunga et al., 2008). While macropores typically only represent up to 5%, or less, of total soil porosity they can significantly affect nitrogen transport (Sigunga et al., 2008). However, the size and number of the largest pores is often difficult to predict as they may be transient and have large spatial and temporal variability.

Artificial drainage, such as mole-tile drains, are commonly installed in the subsurface of agricultural land to remove excess soil water from land that would otherwise be prone to waterlogging (Monaghan et al., 2002). This improves plant growth and enables year-round productive land use. However, mole drainage decreases the denitrification potential of soil by increasing aeration and allows nitrogen to bypass the soil retention and plant utilisation zone quickly (Cameron et al., 2013; Srinivasan et al., 2020). This results in more nitrogen remaining in the form of NO_3^- as it can be transported to waterways without being attenuated in the subsurface. Rozemeijer et al. (2010) concluded that in some areas, artificial drainage can make up to 90% of the NO_3^- load to surface water. This is particularly common in New Zealand as approximately 2.5 million ha of land is artificially drained, and the tile drains are generally shallow (0.5 – 0.7m below the ground surface) (Monaghan et al., 2016).

2.2.4 Factors Affecting Nitrogen Leaching and Attenuation.

Many of the processes within the nitrogen cycle are governed by soil and hydrological characteristics. Every pastoral system has a specific capacity to store and utilise mineral nitrogen in the soil profile. Nitrogen that is not stored or utilised is likely to be leached when hydraulic conditions permit.

Many studies have found correlations between anthropogenic, physical, and hydrological factors, catchment characteristics, and nitrogen quantity in waters. This explains why estimates of the quantity of NO_3^- leached from grazed pastures vary significantly. Spatial variation in nitrogen attenuation mostly arises from heterogeneous physical characteristics, while temporal variations arise from climatic conditions (Drewry et al., 2006). Transport pathways also influence the different quantities of nitrogen in the sub-surface, groundwater, and surface water systems (Eckard et al., 2004). Research by Selbie et al. (2015) showed that most areas within a catchment have an equal chance of contributing to long-term NO_3^- loss and source factors tend to govern the magnitude of nitrogen loss, while transport factors dictate the delay caused by percolation through various soil horizons (Monaghan et al., 2016). In contrast, Elwan et al. (2015) concluded that water flowing through areas with high nitrogen attenuation potential delivers less nitrogen to receiving waters than water moving through areas with low attenuation potential, despite the source. Given the wide range of physical factors that influence nitrogen river loads, it is more likely that the conclusion drawn by Elwan et al. (2015) is correct.

Factors that influence or increase the magnitude of nitrogen losses include; soil permeability, soil structure, steep slopes, underlying geology, soil saturation, cultivation, land erosion, presence of plantings, infiltration of water and the timing of the infiltration event, land use, soil management, soil nitrogen transformation rates, stocking type and rate, pasture composition, and growth rate (Cameron et al., 2013; McDowell et al., 2014; McKergow et al., 2007). Biogeochemical (denitrification) processes in the subsurface pathways between farms and surface water bodies are also influenced by catchment characteristics that affect the leaching rate, flow rate, flow pathway length, and residence time of nitrogen-enriched water (Jahangir et al., 2012). The vulnerability of a stream's water quality to excess nitrogen depends on several factors including its size, water level and the surrounding topography, as well as the form of nitrogen and the timing of its supply. However, much of the research on this topic has been descriptive in nature. Climate is a major driver for the biological, chemical, and physical processes which determine nitrogen cycling and losses. This is due to soil temperature and moisture content being primary drivers of the rate of mineralisation which determines inorganic nitrogen availability (Di & Cameron, 2002). Climate also plays a key role in the hydrological processes that govern water and nitrogen movement through soils because of the solubility of NO_3^-.

In general terms, more rainfall results in more drainage which increases the rate at which NO_3^- is leached through the soil profile (Silva et al., 1999). The leaching potential is particularly high in winter when rainfall inputs exceed evapotranspiration demand and excess water drains from the root zone (McDowell & Hamilton, 2013). Pasture also has a lower ability to utilise nitrogen in cooler conditions. Di and Cameron (2010) demonstrated that nitrogen leaching losses from nitrogen fertiliser applied in the autumn resulted in 15%-19% being leached compared to 8–11% when applied in the spring. Nitrogen losses are also high in autumn as NO_3^- tends to accumulate on the soil surface during summer when the plant growth is low and nitrogen uptake is limited. In addition, rewetting of the soil after a long period of drought can increase the mineralisation rate, generating further $NO_3^-$to be leached (Cameron et al., 2013). This indicates that mitigation practices that can reduce nitrogen inputs to pasture during autumn are likely to be more effective at reducing its losses to waterways than those implemented at other times of the year (Monaghan & De Klein, 2014).

In addition to the hydrological cycle, nitrogen that is present in the soil zone is affected by the chemical and physical properties of soil (Follett, 2008). The permeability of the soil has a large effect on nitrogen leaching as it determines the rate that water and soluble NO_3^- moves through saturated soil material (McDowell et al., 2009). Soil permeability is primarily controlled by the texture, structure, and density of the soil materials. In general, soils that are more frequently saturated (associated with shallow water table conditions, lower infiltration rates, poor drainage, or higher rainfall), have fine textures, a high carbon content, a greater propensity for surface runoff and lower nitrogen leaching rates. Evidence of Hopkins et al. (2011) suggests that NO_3^- leaching is less in clay soils (poorly drained) than in poorly structured sandy soils (well-drained) because of the slower water movement. A longer residence time means there is a greater potential for geochemical reactions and denitrification to occur. There is also greater retention of NH_4^+ ions in clay soils due to greater electrostatic attraction, lower soil permeability, and lower hydraulic connectivity to the underlying groundwater table. The distinction between soil types is further exemplified by McLaren and Cameron (2002) who noted that silt loam soils have far greater leaching loss of clay loam soils. Soils with a higher percentage of clay are poorly drained and have a low infiltration rate, and therefore are more likely to lose nitrogen through surface runoff (Follett, 2008). Low hydraulic conductivity and highly chemically reactive rocks (glauconite, pyrite and organic matter) are associated with lower potential for denitrification and greater leaching rates (Elwan, 2018). This was demonstrated by a number of studies (Jahangir et al., 2012; Krantz & Powars, 2000).

In summary, it can be seen that the literature identifies multiple factors responsible for the variability in nitrogen leaching and attenuation across landscapes.

2.3 Mitigation Practices for Reducing Nitrogen River Loads

Prevention rather than remediation is the most effective method for reducing water quality degradation. Therefore, it is important that mitigation practices are employed to limit the nitrogen transported to waterways. This section describes mitigation practices that have the potential to reduce nitrogen leaching from New Zealand dairy and sheep and beef farms. A change of land use and a deintensification of agriculture has been cited as the strategy that reduces nitrogen leaching the most (Menneer et al., 2004). However, productive farms are important to food security and the New Zealand economy. Agriculture contributes 70% of export revenues and 12% of gross domestic product earnings

(Ministry for Primary Industries, 2017). Dairy farming, in particular, is being challenged to navigate the competing interests of increasing production and minimising the consequential environmental impacts. Therefore, a dialectical approach to choosing mitigation practices, that balances productivity with environmental benefit, is needed.

There are numerous management practices that increase productivity while reducing nitrogen losses by enhancing the overall nutrient-use efficiency by plants and animals such as diet manipulation, use of different pasture species, or animal breeding practices (Menneer et al., 2004; Selbie et al., 2015). However, this study focusses on mitigation practices that decrease nitrogen river loads while the inputs to the farm remain the same. It is important to note that when scale, connectivity, and variation in natural attenuation are taken into consideration, a large leaching source may not necessarily equate to a large nitrogen load to rivers (Jarvis et al., 1996; Singh & Horne, 2020). Together, these studies indicate that it is vital that the scientific basis of mitigation techniques and their impacts on nitrogen loads downstream are explained through a holistic perspective.

This section reviews in-field, edge-of-field and catchment-scale mitigation practices. The use of in-field practices has been well documented, with most studies concluding that in-field practices impact productivity and do not always achieve the nitrogen loss mitigation needed (Hashemi et al., 2018). Scarsbrook and Melland (2015) argued that current mitigation strategies have significantly improved the loss of sediment and phosphorus to waterways but are not effective at decreasing nitrogen losses. McDowell et al. (2009) and Jacobsen and Hansen (2016) also suggest that there are limited cost-effective options to substantially reduce nitrogen leaching from dairy farms despite considerable research efforts. However, edge-of-field techniques have potential to significantly lower nitrogen river loads at relatively small cost. To date, there have been few studies that quantify the effect of catchment-scale practices. A combination of these practices may be most effective approach in the future. In other words, it is concluded that achieving greater nitrogen reductions with little effect on agricultural production will require combining in-field measures with enhanced attenuation of nitrogen before it reaches water bodies (Eckard et al., 2004; Monaghan, Wilcock, et al., 2007). Hashemi et al. (2018) concluded that this strategy could reduce the expected nitrogen load in a Danish catchment by 38%. If these results proved to also hold in a New Zealand catchment, they would provide strong evidence for the need to implement catchment-scale measures in combination with in-field and edge-of field measures.

2.3.1 In-field Mitigation Practices

2.3.1.1 Strategic Grazing

Strategic grazing is where the duration of grazing is controlled, and animals spend periods of time in herd homes or stand-off facilities and receive supplementary feed. This reduces urine nitrogen inputs to pasture and consequently reduces NO_3^- leaching – especially during periods of high risk when drainage occurs (McDowell et al., 2018). It has been conclusively shown that reducing urine inputs to the soil decreases nitrogen leaching (McDowell et al., 2018). Temporal patterns of loss suggest that the management of urinary nitrogen deposited in the months preceding winter drainage events is key to reducing potential nitrogen losses. In several recent studies on Taranaki and Southland dairy farms, the use of off-paddock systems during winter reduced nitrogen leaching by up to 60% (Monaghan & De Klein, 2014; Silva et al., 1999). The importance of the timing of mitigation practices is also evident in the case of Monaghan et al. (2016), who found that a restricted autumn grazing strategy reduced nitrogen losses by 43% on average. Stand-off facilities also allow effluent from cows to be collected, diluted, and returned to the soil more evenly at times of soil moisture deficit, reducing the risk of nitrogen leaching (de Klein & Ledgard, 2005). However, there is a risk of increasing NH_3 or N_2O emissions from the collected effluent as well as increases in capital costs, animal health costs, and labour requirements.

2.3.1.2 Nitrification Inhibitor

Nitrification inhibitors are chemical compounds that reduce the conversion rate of NH_4^+ to NO_3^-, which in turn, reduces nitrogen leaching and N_2O emissions (Di & Cameron, 2007; Monaghan et al., 2013). Nitrogen in the form of NH_4^+ is less likely to contribute to leaching as it is a positively charged ion and is bound by soil's negatively charged cation exchange sites and is more likely to be taken up by plants or immobilised into soil organic matter (McLaren & Cameron, 2002). However, nitrification inhibitors' effectiveness appears to be influenced strongly by rainfall, temperature, and the frequency and timing of application (Di & Cameron, 2007). In addition, Monaghan et al. (2013) clearly highlighted that there is a range of adverse side effects from using nitrification inhibitors such as decreasing the pH of soil.

Dicyandiamide (DCD) is a common nitrification inhibitor that works by inhibiting the oxidation of NH_4^+ to NO_3^- by interfering with cytochrome oxidase in the respiratory electron transport system of bacteria (Monaghan et al., 2013). Cameron et al. (2014) identified that DCD reduced nitrogen leaching from urine by 48%–69%. Similarly, Monaghan et al. (2013) ascertained that the application of DCD reduced the amount of nitrogen lost in drainage by between 20–40 kg/N/ha. In contrast, Kim et al. (2014) used a different methodology to Monaghan et al. (2013) and Cameron et al. (2014) and did not find a consistent reduction of nitrogen leaching from the application of DCD but measured a 54-78% reduction in N_2O emissions. While there is evidence that DCD may be a beneficial tool in reducing nitrogen leaching, it is currently not available for use in New Zealand due to the risk of DCD traces being measured in milk (Monaghan et al., 2013).

2.3.1.3 Fertiliser Timing

The timing of nitrogen fertiliser application is critical to reducing losses. Applying nitrogen fertilisers during periods of minimal or no drainage in summer reduces the risk of leaching (Eckard et al., 2004). If irrigation is required, it should be applied using a scheduling system that takes into account the weather, as research has shown that leaching losses are directly related to rainfall in the month following fertiliser application (Pakrou & Dillon, 2000). Fertiliser should also be applied at rates and times that match plant demand for nitrogen, increasing fertiliser efficiency and reducing leaching (Silva et al., 1999). Fertilisers and manures should be applied evenly and away from watercourses, using a properly calibrated spreader (McDowell et al., 2018). A study by Ledgard et al. (1999) looked at the effect of fertiliser application on nitrogen losses. They concluded that if application rates are less than 200 kg/N/ha/yr and are timed correctly, losses from fertiliser are negligible. Furthermore, this suggests that the opportunities to achieve reductions in nitrogen leaching from fertiliser management are small and research should be focussed on strategies to mitigate the effects of urinary nitrogen application.

2.3.2 Edge-of-field and Catchment-scale Mitigation Measures

Edge-of-field mitigation and catchment-scale practices reduce nitrogen by attenuating nitrogen through biogeochemical processes such as denitrification in the subsurface environment (Schipper et al., 2005). They have the potential to be at least as beneficial as farm-scale practises as they increase the efficiency of pollutant reduction, are economically attractive, and minimise the extent of areas affected by restrictive land use practices (Hashemi et al., 2018). Catchment-scale practices refer to those that aim to reduce nitrogen load over the whole catchment.

2.3.2.1 Riparian Planting

Riparian buffer zones are often considered an efficient way to reduce NO_3^- delivery to waterways as they enhance plant uptake and have high denitrification activity. The effectiveness of attenuation at removing nitrogen largely depends on the buffer zone's ability to intercept and modify flow pathways and is thus strongly site-specific (Monaghan & De Klein, 2014). The high effectiveness of riparian buffers at reducing NO_3^- pollution is widely documented (Bouraoui & Grizzetti, 2014; Parkyn et al., 2003; Silva et al., 1999) but there are disadvantages. Buffer systems increase gaseous nitrogen emissions (Wilcock et al., 2009). Riparian planting may not be sufficient to minimise very low NO_3^- concentrations in an intensive agriculture catchment if the hydrological settings do not allow optimal retention (Haag & Kaupenjohann, 2001). Further, riparian buffers may only effectively remove nutrients for a period, and then nutrient accumulation may mean they become a nutrient source (Drewry et al., 2006). In sum, Durand et al. (2015) concluded that riparian buffers are successful complementary measures but have limited impact when implemented alone.

2.3.2.2 Matching Land use Intensity with Nitrogen Attenuation Capacity

Nitrogen river loads can be reduced by matching the land use intensity (type of farm system, stocking rate and nitrogen fertiliser) with the nitrogen attenuation capacity of the landscape. For example, landscapes where the nitrogen-attenuation capacity is small should have less intensive land use (i.e. less nitrogen leaching) while inputs could be higher on areas with higher attenuation potential, allowing productivity to be kept high while reducing nitrogen river loads (Collins et al., 2016). Elwan et al. (2015) and Rivas et al. (2020) both identified that nitrogen attenuation is spatially variable and local hydrogeological settings, significantly influence transport and transformation of nitrogen. Following on from this, Singh and Horne (2020) highlighted that with better understanding and mapping of nitrogen attenuation, there is potential to utilise existing natural and new built-in nitrate-attenuation capacity to significantly reduce water-quality impacts from dairy farming across environmentally sensitive agricultural catchments. Their modelling suggested that by relocating intensive dairy to high nitrogen attenuation areas the dairy farming nitrogen losses (to the river) could be reduced by 16 to 19% in the Tararua and Rangitikei catchments. Sarris et al. (2019) also demonstrated that focusing mitigation practices to areas where nitrate residence time is short, such as riparian zones or areas with low natural nitrogen attenuation, results in greater reduction of nitrogen discharges through groundwater. The authors concluded that when target areas were identified based on their nitrate reduction potential, smaller decreases in total nitrate inputs and greater nitrate discharge reduction could be achieved compared to a spatially uniform application of mitigation measures. Hashemi et al. (2018) suggested that setting aside land with low attenuation capacity would be an effective measure when farm mitigation measures have already substantially reduced leaching but there is a need for further reductions. In Denmark, spatially varying or linking agricultural nitrogen mitigations with geological heterogeneity has been found to be a cost-effective approach to reducing nitrogen (Jacobsen & Hansen, 2016). In summary, there may be potential to reduce river nitrogen loads by targeting landuse and potential nitrogen attenuation. However, careful landuse planning in relation to potential nitrogen attenuation measurements, mapping and modelling will be needed to spatially align intensive land use activities with high nitrogen attenuation capacity land units. It is also prudent to note that waterways have different water quality targets and when the current farming system's nitrogen losses are redistributed across the different nitrogen attenuation potential land units, the limits may or may not be met due to the current water quality state.

2.3.2.3 Controlled Drainage

In some situations, artificial drainage may be a key source of nitrogen losses due to the bypassing of natural attenuation in the subsurface. Controlled drainage manages the drainage rate from the soil profile by operating a series of control structures in drains that allow the outlet level to be adjusted (Woli et al., 2010). This can reduce nitrogen losses by restricting drain flows during drier periods and managing the soil water content to promote increased denitrification (Bonaiti & Borin, 2010). However, Ballantine and Tanner (2013) concluded that the contribution of denitrification to the total reduction in nitrogen load is small compared to the contribution of flow reduction.

There are many methods of implementing controlled drainage. The simplest approach is to manually place weirs in the drains during summer and remove them during wet periods in winter (Woli et al., 2010). However, this may increase surface runoff from rainfall events during summer. Alternatively, permanent outlet controls can slow subsurface drainage rates by raising the water level which reduces the hydraulic gradient to the drain (Bonaiti & Borin, 2010). The disadvantage of this method is that it is unlikely to enable sufficient contact time to stimulate microbial processes such as denitrification. Another method is automated management of weirs, which could enable dynamic adjustment in response to soil water content and rainfall. Bonaiti and Borin (2010) determined that controlled drainage using dynamic adjustment reduced nitrogen losses by 63% compared to 46% using a constant depth.

There is limited research evaluating the effectiveness of controlled drainage as a way of reducing nitrogen river loads in New Zealand, although there is some evidence to suggest that it may be beneficial (Ballantine & Tanner, 2013). Overseas studies have reported that NO_3^- can be reduced by 36-85% by controlled drainage (Ballantine & Tanner, 2013). Controlled drainage appears to be most effective on flat land with an impermeable layer about 1–3 m below the surface (Bonaiti & Borin, 2010).

2.3.2.4 Recycling Drainage Water

Nitrogen river loads can also be reduced by harvesting, diverting, and storing drainage water with a high nitrogen concentration in a reservoir. The stored water is then used to supplement irrigation during the drier periods (Wesström & Joel, 2010). This enables the nitrogen to be diluted and spread evenly. It also has the effect of allowing the water to be attenuated through the soil. Singh and Horne (2020) suggested that it may be possible to construct larger, shared drainage-water storage dams at suitable locations, ultimately protecting the larger areas of the catchment. This would negate the prohibitive cost of constructing dams on every farm. Recycling drainage water also has the added benefit of enabling irrigation in times of low rainfall.

2.3.2.5 Woodchip Bioreactors

Woodchip bioreactors are trenches filled with woodchips that provide a carbon source for denitrification. They are positioned to receive and treat drainage waters from surface and subsurface drains (Christianson et al., 2012). Hudson et al. (2018) observed that a woodchip bioreactor in the Waituna Lagoon catchment in Southland, New Zealand, resulted in a 94% reduction in median daily NO_3^-

load. Similarly, Rivas et al. (2020) found that a $78m^3$ woodchip bioreactor reduced NO_3^- by between 48% and 99%. The capacity of woodchip bioreactors to reduce nitrogen river loads is dependent on the bioreactor, the drainage system, and weather. Woodchip bioreactors are most effective where the rate of nitrogen leaching is large. They are less effective in landscapes where agricultural land use is homogenous and non-point sources are dominant. In addition, more research is needed to ascertain any potential pollution swapping and bioreactor efficiency during high flow events (Rivas et al., 2020).

2.3.2.6 Wetlands

Wetlands promote significant nutrient conversion and retention. They reduce nitrogen river loads by increasing nitrogen attenuation through plant uptake and microbial denitrification (Uuemaa et al., 2018). The nitrogen attenuation rate depends on; the residence time of the water, the upstream catchment area, temperature, pH, carbon availability, plant growth, plant species, and nitrogen input (Hashemi et al., 2018). Zaman et al. (2008) challenged the widely held view that denitrification is the dominant nitrogen removal mechanism in wetlands, suggesting that plant uptake is the main process as denitrification only accounts for 6–7% of nitrogen removal. However, this theory does not fully explain why nitrogen attenuation is still high during periods of low plant growth. It is more plausible that the ratio of nitrogen attenuation to plant uptake is variable and changes of the lifetime and seasonal cycle of the wetland.

Nutrient removal of constructed wetlands has been well-studied. In an investigation into constructed wetlands, Tanner and Sukias (2011) showed that over small areas (less than 1.6% of the drained area), wetlands can significantly reduce nitrogen losses from intensively-grazed dairy pastures by up to 63%. In contrast, there have been few attempts to quantify the effectiveness of natural seepage wetlands. This is because diffuse, spatially, and temporally variable inflows and outflows are difficult to measure, leading to significant uncertainty in the attenuation capacity of natural wetlands (Ramesh et al., 2020). However, Peterson et al. (2001) found that headwater streams can retain and transform over 50% of inorganic nitrogen inputs. Uuemaa et al. (2018) also concluded that for a small natural headwater catchment, wetlands could reduce total nitrogen load by 57%. However, such studies remain narrow in focus and only include headwater wetlands. Nonetheless, indications are that headwater wetlands are often more effective than downstream wetlands at reducing nitrogen river loads due to their topography, high storage capacity, and gradual discharge (Ramesh et al., 2020). It is also important to note that if a wetland's capacity for storage or transformation is exceeded, it can also become a source of nitrogen because of its direct connection to the stream network (Uuemaa et al., 2018).

The evidence reviewed in this section suggests a pertinent role for investigating the effect of a combination of mitigation practices to reduce nitrogen river loads.

2.4 Methods of Assessing the Effectiveness of Mitigation Strategies

The next chapter describes the evaluation of potential methods for assessing the effectiveness of mitigation strategies.

Effective management of water quality requires the ability to assess and quantify the impact of management techniques on nitrogen loads to waterways. As described in previous sections, the response of water quality to mitigation measures depends on many factors that have high heterogeneity within a catchment including climate, catchment physical characteristics, land use practices, and the timing and location of mitigation measures (McDowell et al., 2018). Modelling typifies the conventional scientific method for assessing nutrient exports as models can represent the complexity of agricultural and nitrogen systems, and the outputs are quantifiable (Anastasiadis et al., 2013). A model integrates a range of existing knowledge to provide a simplified representation of reality that focuses on the processes, inputs, and outputs of a system (Cichota & Snow, 2010). This allows the complex interplay of hydrology and biogeochemical processes, spatial variability of soil, topography, land use, temporal variability of climate, land management practices, and nutrient transport to be accounted for. Models provide an effective way to comprehensively understand and investigate mitigation practices by quantifying the magnitude of their effect and variability of response in space and time (Anastasiadis et al., 2013; Cherry et al., 2008). It also allows the future response of a system and the extent of intervention necessary to meet goals to be determined (McDowell et al., 2014).

An alternative method to assess the effectiveness of mitigations is by experimentation and measurement, i.e., monitoring phenomena such as nitrogen load in waterways. However, measurements alone only provide values for a specific context in terms of the source, receiving waterway, and land physical characteristics. Taking measurements is also time-consuming and has a high cost (Bouraoui & Grizzetti, 2014; Cichota & Snow, 2010). In addition, measurements do not allow future effects to be predicted as trials are not feasible to implement on a catchment-wide basis and identification of what management practice is having the greatest effect is difficult (Anastasiadis et al., 2013). Variations in weather also make it difficult to distinguish the effect of the mitigation method from the environmental effect or how the response to a mitigation measure might vary with climate (Cherry et al., 2008). In addition, the temporal and spatial lag between management actions and environmental response means evaluating management via measurement often takes a long time (many years) or is often inaccurate and requires many assumptions (Bouraoui & Grizzetti, 2014). Measurement also has limitations for correctly interpreting water quality trends as a small number of measurements are usually taken and there is high temporal variability in river concentrations (Parliamentary Commissioner for the Environment, 2015). Therefore, measurement is more suited to paddock and farm-scale analysis where the effect of the range of environmental processes is more easily accounted for or interpreted.

Modelling overcomes many of the challenges presented by measurement approaches, although the disadvantage of modelling is that there is always a degree of inaccuracy or uncertainty as models provide an imperfect representation of reality (Anastasiadis et al., 2013). This is due to the many complex processes that do not easily translate into models such as preferential flows in structured soils or the redistribution of rainfall intensities by the vegetation canopy (Pechlivanidis et al., 2011). Model inaccuracy is also due to limitations of the measurement techniques needed to inform and validate modelling and the concept of equifinality (Bouraoui & Grizzetti, 2014). The result of these difficulties means it is not possible to model the heterogeneity within the catchment in detail, which introduces inherent structural uncertainty. Uncertainty also arises from model input data including: parameters and datasets, model assumptions and simplifications, stochastic uncertainty, and code uncertainty such as software bugs and numerical approximations (Vaze et al., 2012). Vaze et al. (2012) described the analysis of uncertainty in hydrologic river system models and noted that errors stemming from epistemic uncertainty can be minimised by additional study and investigation. However, even with moderate levels of uncertainty, models can generate informative insights (Anastasiadis et al., 2013). There are limits to how far the concepts developed from modelling can be taken. Difficulties arise when an attempt is made to implement policy based on modelling, as critics have argued that models provide inaccurate values for key processes related to nitrogen dynamics in the farm system, leaching from the soil profile and transport to the receiving environment. That said, the use of modelling is recognised in

New Zealand for research, environmental analysis and policy development (Cichota & Snow, 2010). Models have been used successfully in numerous studies to understand and estimate the nutrient losses from catchments and to ascertain the effect that soil, geology, climate, land use, and management factors have on nitrogen leaching (Cherry et al., 2008). They have also been used to help quantify and predict the efficacy of wetlands for removing excess nutrients (Uuemaa et al., 2018).

Models can be classified as either farm-scale or catchment-scale models. Farm-scale models provide estimates of nutrient loss on a farm, paddock, or plot scale and are often used to assess the effectiveness of management decisions (Anastasiadis et al., 2013). These models generally calculate the amount of nutrients that are lost from the topsoil layers (Drewry et al., 2006). In contrast, catchment-scale models consider nutrient loss from the entire catchment and are typically used to model nutrient transport including spatial and temporal variability of this movement (Bouraoui & Grizzetti, 2014). Most catchment-scale models take into consideration groundwater attenuation and can model both non-point and point sources. Many studies have evaluated the influence of catchment characteristics on nitrogen concentration in waterways at a catchment scale. However, catchment models are limited in their ability to model farm-scale processes and up until now, the research on mitigation practice effectiveness has tended to focus on farm-scale rather than catchment models. Therefore, in order to determine the effect of mitigation practices on nutrient export on a catchment scale, both farm-scale and catchment-scale models must be used.

McDowell et al. (2014) and Drewry et al. (2006) also highlighted the importance of moving research from site-specific farm-scale models to more generalised catchment-scale models. This is due to farm-scale models considering different hydrological pathways to catchment-scale models (Quinn et al., 2009). Farm-scale models simulate losses from farms but not how much ends up in waterways which must be done by catchment modelling to account for the effects of attenuation (Durand et al., 2015). In addition, it is the cumulative nitrogen load in a waterway that is important and depends on the upstream characteristics and management (Cichota & Snow, 2010; Drewry et al., 2006).

Changing from modelling an area at a small scale to large scale is a common problem in hydrology that has not been adequately addressed. The extrapolation of a model to a larger scale makes the inherent assumption that the hydrological and physical relationships are independent of scale, essentially ignoring natural heterogeneity (Cherry et al., 2008). This increases uncertainty about the applicability of parameters at catchment-scale as several factors influence nitrogen retention (Bouraoui & Grizzetti, 2014). Scaling-up techniques have been noted as an important area for further research, although these are also often associated with considerable uncertainty (Drewry et al., 2006).

The benefits of both farm-scale and catchment-scale models, and the difficulties of using scaling-up techniques, highlight the need for an integrative approach and to identify appropriate farm-scale models to use in conjunction with catchment models. While integrating a 3D groundwater model would be beneficial in terms of physical representation, it is not strictly necessary for this study as it is likely to have negligible impacts on mitigation effectiveness (Bouraoui & Grizzetti, 2014). The effect of groundwater takes (such as bore abstraction), flow losses and gains (such as spring inflows, groundwater recharge or the loss to underlying aquifer systems), and changes in groundwater storage as a result of changes in groundwater levels or pressures, will be essentially accounted for in the calibration of the groundwater component of a catchment surface water model.

2.4.1 Model Classification

It is important to consider the conditions a model is developed for when selecting a model. Young et al. (1996) suggested that the many Northern Hemisphere nutrient export studies are inappropriate for use under Australian conditions, as Australia has lower atmospheric deposition, fertiliser input, and cattle densities than in the Northern Hemisphere. These same conditions found in Australia would also apply, to some degree, to New Zealand.

There is a wide range of models that have been developed to evaluate nutrient losses from farm systems. This section reviews the strengths and weaknesses of commonly used models with the aim of informing the selection of a catchment model that can be integrated with a farm-scale model. When choosing a model, its complexity should be balanced against its purpose and uncertainty (Anastasiadis et al., 2013). Vaze et al. (2012) highlighted that data paucity should limit the complexity of the model chosen as more complex models need more data for calibration and validation. The results from a simple model, while less detailed, are often more meaningful than a complex model. Complex models with too many parameters can lead to noise, diminished predictive power, and the obscuring of significant behaviour. However, a model that is too simple may mean it fails to adequately explain the observations (Perrin et al., 2001). The inter-relationship between data, model complexity and model performance is visually presented in Figure 2. Quinn et al. (2009) described the best approach to model selection as the Minimum Information Requirement, where the simplest model structure that satisfies the modelling needs and ensures that the model parameters retain physical significance, should be chosen. A classification system was proposed by Wheater et al. (1993) which groups models by their structure, spatial distribution, stochasticity, and spatial-temporal application. The following sections review models using this categorisation, with an emphasis on the models' advantages and disadvantages.

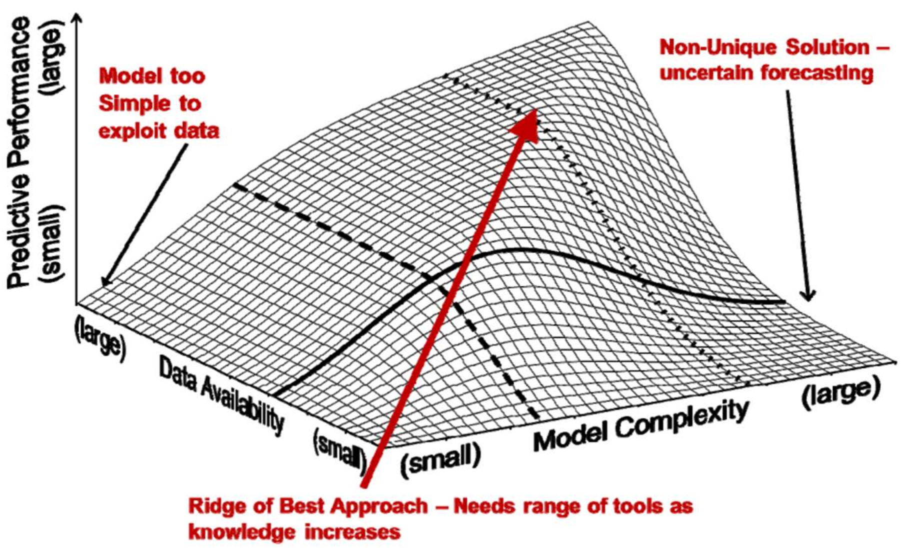

Figure 2. Balancing model complexity and data availability (eWater, 2018).

Process-based models are mechanistic in the simulation of systems and quantify complex processes, including the physical processes of nitrogen transport and transformation in both unsaturated and saturated zones (Pechlivanidis et al., 2011). These models aim to represent nitrogen processes both spatially and temporally. This allows dominant sources and loss pathways to be identified which informs the placement of mitigation practices (Collins et al., 2016; Sarris et al., 2019). However, spatial models are often validated using catchment outlet data which provides no information on how the model performs spatially. Hydrological components are defined by fully measurable parameters and are modelled using the governing equations of motion, based on continuum mechanics, so do not require calibration (Wheater et al., 1993). However, this means process models have large data requirements, are time-intensive to run, and are not ideal to use to model large catchments. Process models are also susceptible to scaling errors where the results from small scale laboratory or field experiments are extrapolated to the catchment scale to determine parameters (Vaze et al., 2012).

Empirical models are the simplest type of model and use statistical relationships based on observed data to identify sources of nitrogen generation (Vaze et al., 2012). They do not simulate the physical processes. Instead, they are based on quantitative relationships of nitrogen mass balance data collected from local farms, or on the probability density function of solute travel times (Pechlivanidis et al., 2011). This is advantageous as it increases the ease and time efficiency of model development as there is no need to understand the underlying physical characteristics and processes of the hydrologic system. However, the disadvantage of the lack of theoretical explanation for derived empirical relationships means the results may not be accurate and instead are approximations. In addition, an empirical model is only considered valid for the range of the underlying data (Cichota & Snow, 2010). Empirical models are generally catchment-specific and do not directly account for spatial distribution, temporal variances, or lags in transport processes. Therefore, they are more suitable for farm-scale analysis.

Conceptual models are a practical compromise between process and empirical models and are suited to long-term prediction in large catchments (Pechlivanidis et al., 2011). Conceptual rainfall-runoff models are informed by the main processes but rather than simulating each individual process, they often comprise of several conceptual stores that represent water held within the soil, vegetation, or stream. Fluxes of water between these stores and in and out of the model are controlled by mathematical equations (Vaze et al., 2012). Conceptual models are more data-intensive and complex than empirical models. However, they represent some of the mathematical-physics based processes in a conceptual manner, particularly in cases where physical parameters are difficult to measure, which simplifies the model (Fua et al., 2017). Most of the parameters require empirical evidence, but not all the model parameters have a direct physical interpretation and are measurable. These parameters are typically estimated through calibration against observed data (Moriasi et al., 2007). The disadvantage of this is that the model may have several optimal parameter sets (Pechlivanidis et al., 2011). The spatial distribution of physical characteristics is accounted for by dividing the catchment into sub-catchments that have unique combinations of catchment characteristics (Fua et al., 2017). This preserves spatial variation while reducing data requirements. Most researchers modelling nitrogen on a catchment scale have utilised conceptual models, although there is a range of complexity and accuracy between individual models (Cichota & Snow, 2010). A complex model would increase the sensitivity to mitigation practices, although, without sufficient empirical evidence, the adjustment of coefficients is arbitrary. An advantage of conceptual models is that they take less time to run while also considering non-linear processes. However, the main disadvantage is that a high level of modeller skill is required to conceptualise the model and correctly define hydrological phenomena.

In order to accurately model the effectiveness of mitigation measures, nitrogen sources must be correctly identified and quantified. Therefore, the key requirements of the model are the ability to model both overland flow and leaching pathways, event-based loads, land use, and management practices. Many different models can be used to assess this, each with its own unique characteristics and deficiencies. Conceptual based models are considered the optimum model type for this study due to the smaller data requirements compared to process-based models while maintaining physical representation. In the following sections, two farm-scale models and two catchment-scale models are described and evaluated to determine which models are most suitable for use in this study. This study does not consider modelling to achieve a particular water quality target in which case a process-based model would be preferred, rather it focusses on relative reductions in river nitrogen loads by different in-field and catchment-scale measures in a catchment.

2.4.2 Potential Models

This section reviews two common farm-scale models and two common catchment-scale models that when integrated would have the capability to simulate the proposed mitigation strategies. The models reviewed all have varying levels of complexity and uncertainty, capability to simulate mitigations, and have been designed for different purposes and scales (Cherry et al., 2008). They also vary in their mechanisms (Pechlivanidis et al., 2011).

2.4.2.1 Agricultural Production Systems Simulator

The Agricultural Production Systems Simulator (APSIM) is a highly advanced process-based model, configured from component modules, that simulates the biophysical processes of farming systems (Keating et al., 2003; McCown et al., 1996). APSIM was designed to be used as a research tool to evaluate alternative management strategies and changes in climate on agricultural production, soil nutrient content, and the environment (McCown et al., 1996). It produces farm level estimates of production, drainage, and nutrient leaching from the soil on a daily time-step.

APSIM is structured around plant, soil, and management modules and a large number of parameters are necessary (Vibart et al., 2015). These include a full range of management controls that allow the user to specify rules to characterise and control the simulation. It also includes water balance modules that model water transport through the soil profile either by using a tipping bucket method or a numerical solution of the Richard's infiltration equation (McCown et al., 1996). Plant modules are available for a wide range of crops and simulate the critical physiological processes, including phenology, organ development, water and nutrient uptake, carbon assimilation, biomass and nitrogen partitioning between organs, and responses to abiotic stresses (McCown et al., 1996). A soil carbon/nitrogen model simulates nitrification and denitrification, including emissions of N_2O. The model inputs include fine resolution spatial data on climate, slope, soil properties, irrigation, and crop and stock management (Vibart et al., 2015). The inputs required for soil are detailed and in order to produce accurate results, laboratory testing of *in situ* soil is required.

APSIM models the movement of nitrogen on a farm scale and estimates the quantity of most forms of nitrogen lost in the system (Vibart et al., 2015). A range of pasture species and root zone depths can be modelled. However, it lacks the ability to model multiple blocks on a farm. This requires manual adjustment of inputs to account for imports and exports from the modelled paddock to other parts of the farm.

APSIM's application in New Zealand is very limited but is increasing. It was used by the Pastoral 21 group to inform the development of Overseer and the DairyNZ Whole Farm Model, by Snow et al. (2007), to simulate drainage and runoff in tile-drained soils and by Asseng et al. (2004) to assess the impact of climate change on plant growth.

2.4.2.2 Overseer

Overseer is a steady-state, empirical farm system model. It produces estimates of long-term average nutrient outputs via drainage and runoff at a farm scale (Wheeler, 2016). Initially, Overseer was developed for fertiliser management but has recently been used to evaluate the nutrient budget of different farm systems, land uses, and management practices (Wheeler et al., 2007). The nutrient budget is the primary output of the model and summarises the various movements of nutrients through the farm system during the year. Overseer has also been used to inform the development and application of environmental policies (Wheeler et al., 2011).

The inputs to Overseer are limited and comprise information that is easily obtained, including land use, stock numbers and production, soil characteristics, climate, and stock management practices (Ledgard et al., 2001). Overseer models the movement of nitrogen through the farm and estimates the nitrogen lost below the root zone for both individual blocks and the farm as a whole (Wheeler, 2016). However, it assumes all pasture species have a root zone of 60cm when species such as red clover can extract water from up to 1.5m. Overseer has settings to represent nitrogen immobilisation, although these are categorised from high to low and cannot be changed over time without running separate models (Wheeler et al., 2007). Overseer models farms in the steady-state condition. This means the model does not simulate soil processes explicitly, and particularly, the important processes of decomposition of crop residues and nitrogen mineralisation that occur during land use transitions (Moot, 2019). Overseer comprises a wide range of farm types and management systems, including the ability to model mitigation options.

Overseer is widely used in New Zealand including on countless farms. It was developed for a New Zealand context, which means the management practices and environmental characteristics are suited to New Zealand conditions (Selbie et al., 2013). Hawkes Bay, Waikato, and Horizons regional councils adopted Overseer to inform their regional environmental plan changes, and every dairy farm must have had Overseer run as part of the Clean Streams Accord (Upton, 2018). Overseer has also been used in multiple research projects focusing on nitrogen leaching, and simplified versions have been incorporated into catchment level models such as CLUES (Ledgard et al., 2001; McDowell et al., 2014; Selbie et al., 2013).

2.4.2.3 Soil and Water Assessment Tool

The Soil and Water Assessment Tool (SWAT+) is a semi-distributed catchment-scale model that simulates stream and groundwater flow, soil moisture, nutrient transport, and management practices (Neitsch et al., 2011). It represents processes in several ways which allows the most appropriate method to be selected.

SWAT+ can be considered a flexible, process informed, conceptual model, which makes it computationally efficient with a high degree of precision (Douglas-Mankin et al., 2010). SWAT+ takes into account spatial variability by disaggregating the catchment by topography, land use, and soil type to form Hydrologic Response Units (Ullrich & Volk, 2009). SWAT+ has a high level of detail and therefore has extensive data input requirements, including topography, soil, land use, climate, fertiliser application, livestock densities, grazing periods, and crop rotations. SWAT+'s key advantage is that it has built-in processes to simulate management practices.

SWAT+ represents the hydrological processes of infiltration, evapotranspiration, percolation into a deeper aquifer, water losses by runoff, and lateral and groundwater flow. It also simulates the nitrogen transformation processes of mineralisation, denitrification, volatilisation, and plant uptake (Hoang, 2019). Nitrogen sources in SWAT+ include fertiliser, manure or residue application, fixation by legumes, and atmospheric deposition. SWAT+ simulates the dynamics of five forms or pools of nitrogen: NH_4^+, NO_3^-, active organic nitrogen, stable organic nitrogen associated with humic substances, and fresh organic nitrogen associated with the crop residues (Ullrich & Volk, 2009). However, it does not account for nitrogen movement through groundwater and instead calculates leaching as a surface process by accounting for nitrogen in surface runoff and lateral flow (Davie, 2004). A study by Ekanayake and Davis (2005) found that as surface processes are dominated by storm events, the model underestimates baseflow. This could explain why there are mixed results of the model's ability to simulate nitrogen. Cao et al. (2006) assert that SWAT+'s performance is adequate for the whole catchment but not for sub-catchments.

SWAT+ has been used extensively worldwide to evaluate the effect of management practices and physical characteristics on hydrological and nutrient environments at catchment scales (Jung & Kim, 2017). In New Zealand, the model has been applied to the Motueka catchment and Lake Rotorua (Ekanayake & Davis, 2005; Me et al., 2015).

2.4.2.4 eWater SOURCE

eWater SOURCE (SOURCE) is an integrated catchment model and operations tool designed to support the planning and management of freshwater resources. It was developed as the Australian national hydrological modelling platform (Vaze et al., 2012). SOURCE is a physically representative catchment hydrological model that simulates the most important processes and pools of water resource systems, including changes in biophysical properties. It can be used to investigate the relative and absolute differences in water flow and water quality outcomes between different landscapes, land uses, and land management practices (Fua et al., 2017). SOURCE has an in-built ability to simulate management practices of land use, riparian buffers, and wetlands.

The fundamental architecture of a SOURCE model comprises a series of connected sub-catchments and drainage networks. SOURCE uses nodes with connecting links that enable the flow and constituent processes that occur along the flow path to be controlled (Fua et al., 2017). SOURCE models simulate nutrient load on a daily time-step at a range of spatial scales. The platform comprises a range of models and tools, including rainfall-runoff models (i.e., SIMHYD), water demand models, and constituent generation, retention, transport, and decay models. While SOURCE has basic in-built models that can model constituent generation, its key advantage is that its flexible modular architecture allows customised plug-ins, models, and data import tools to be used (Black et al., 2011). This means it can be modified to address specific local problems.

SOURCE models a wide range of hydrological processes, including interception storage, evaporation losses, soil moisture storage, surface runoff, soil infiltration, sub-soil drainage, flow in the unsaturated zone, stream base flows, and the attenuation of ground and surface water flow components (Black et al., 2011). The exact calculation and method to model the hydrological processes are dependent on the rainfall-runoff model selected. Three flow routing methods are available to model travel time and attenuation, pure lag, translation, and a generalised streamflow storage routing method, which can represent linear, non-linear, and variable parameter Muskingum routing (Vaze et al., 2012). However, biogeochemical and biological processes are not inherently considered during the simulation of nitrogen by SOURCE, and hence, must be manually applied using a catchment attenuation factor (Fua et al., 2017). An implication of this is that spatial and temporal variations in attenuation are likely to not be adequately simulated.

SOURCE has been used in New Zealand to model various catchments, including those in Hawkes Bay, Bay of Plenty, and Northland, to inform Regional Plan changes. However, it lacks application in a research context.

2.5 Model Selection

APSIM and Overseer are both farm-scale models that can estimate nitrogen loss from farms. However, they are different in several ways. Overseer is a steady-state (static or time-invariant), semi-empirical (data-driven), and deterministic (each set of input data will always produce the same output data) model. In contrast, APSIM is a transient (temporal), mechanistic (process-driven), stochastic (statistical) model (Vibart et al., 2015).

Overseer is the favoured tool for modelling within New Zealand as it has been calibrated for New Zealand's farming systems, uses inputs that are easily accessible, and is user friendly (Ledgard et al., 2001). New Zealand's pastoral farming systems are unique, with the majority of nitrogen losses resulting from urine patches. Overseer better simulates New Zealand's leaching conditions as it models individual urine patches while APSIM uniformly spreads urine over a paddock. However, APSIM has been shown to provide comparable long-term results whilst also providing additional capability to simulate agricultural processes (Vibart et al., 2015). APSIM has a high information input which is beneficial as it makes the model more representative of environmental conditions and characteristics (Holzworth et al., 2014). However, a possible negative implication of this is that if the data required is not available, the uncertainty resulting from the model's parameterisation will be propagated through to the final model output. While Overseer also has uncertainty, with one of the main problems associated with its use being the lack of physical resource data mapped at farm scale, particularly soil and LUC data, its simple structure allows error in inputs to be transferred to the model output in more a transparent manner (Vibart et al., 2015). However, Overseer has been subjected to considerable criticism from Upton (2018) and Moot (2019) due to its simplicity and lack of transparency and validation.

APSIM is advantageous over Overseer for modelling the future impact of management strategies. This is because it operates on a daily time-step, so has the ability to incorporate time-sensitive and transient farming scenarios such as variable fertiliser applications (Vibart et al., 2015). Operating on a daily time-step also allows APSIM to consider temporal patterns of loss, which is beneficial to assess how measures can be implemented more strategically and effectively than those applied irrespective of timing. In contrast, Overseer produces annual averages over relatively large areas, with drainage and leaching calculations on a monthly time-step. An implicit assumption by Overseer is that the farming practice is assumed to be in steady-state, with no changes from year to year as inputs are annual averages and remain constant throughout the model timeframe (Upton, 2018). This means that Overseer fails to acknowledge the significance of evaluating pasture development status or day-to-day management and there is no distinction between developed, developing, and conversion scenarios (Vibart et al., 2015). It also means that Overseer is not suitable for estimating nitrogen loss from particular years nor for examination of episodic events such as storms, individual nutrient applications, or systems in transition.

Despite the disadvantages of Overseer, its ability to model urine patches and its suitability to New Zealand is considered of the greatest importance for this project. In addition, using the Minimum Information Requirement approach, Overseer is the simplest model that satisfies the needs of the project (Wheeler, 2016). This increases confidence in the model as each parameter has a physical justification and more complex models have increased uncertainty. Therefore, Overseer will be used as the farm-scale model for this project.

SOURCE and SWAT+ share similarities. They are both process-based, conceptual models that can model water quality transport and generation over a catchment scale. Both use a semi-distributed approach by separating sub-catchments into spatially separate areas based on land use, soil, and topographic properties by using Hydrologic Response Units (SWAT+) or Functional Units (SOURCE) (Black et al., 2011; Douglas-Mankin et al., 2010).

However, only SWAT+ allows the simulation of in-field management practices such as crop rotations, fertiliser and manure application rates and timing, tillage, sowing, and harvesting time (Douglas-Mankin et al., 2010). SOURCE has the ability to model catchment-scale management practices but it requires the integration of other models to simulate in-field practices (Black et al., 2011). The integration of other models into SOURCE is easy due to its flexible architecture. This allows any other model to be used to simulate farm-scale constituent load and then be transferred to the catchment-scale model (Vaze et al., 2012). SWAT+'s approach of simulating in-field management strategies within the model is considered better as it decreases the uncertainty that is introduced when integrating models and is more time-efficient. However, it does have limitations compared to modelling management practices in a farm-scale model. For example, SWAT+ assumes vegetation growth does not change between seasons, and tile drains and land use are set up as a single management input. SWAT+ also has limitations for modelling nitrogen, including the scale effects of aggregation and its inability to simulate nitrogen in groundwater and individual urine patches (Hoang, 2019). SWAT+ assumes losses are evenly distributed across a paddock which is not the case in a pastural system. This highlights that integrating SWAT+ with a farm system model, such as Overseer, would improve its applicability to New Zealand catchments.

SWAT+ requires large quantities of input data and has multiple parameters. Obtaining the necessary data has been cited as a key disadvantage (Jung & Kim, 2017). Developed primarily for the United States, SWAT+'s climate and soil databases would need extending or adapting for use elsewhere. In contrast, SOURCE can utilise simpler rainfall-runoff models with lower complexity. A downside of using a simple model is that it may also lead to uncertainty in the model results and evaluations, the upside is that the inputs are easily available to better reflect the local conditions.

For the purpose of this research, the ability to integrate Overseer and simulate catchment-scale mitigation practices is considered most important. Initially, a SWAT+ model was set up with the goal of integrating Overseer due to the benefit of SWAT+ having the inbuilt capability to simulate mitigation practices. However, after consultation with the developers of SWAT+, it became clear that the complexity of SWAT+'s processes meant it was not feasible to replace the topsoil layer with Overseer.

Instead, it was concluded that adjustments needed to be made to SWAT+ to improve its ability to simulate New Zealand conditions, in particular urine patches. However, this was not feasible given the time constraints of the project, so the decision was made to use SOURCE as it allowed for easier integration of the models.

2.6 Conclusion

The literature review has highlighted the importance of reducing nitrogen river loads to improve water quality. The nitrogen cycle is clearly complex and includes a wide variety of transport and transformation processes. As agriculture is the dominant source of nitrogen, it is important that strategies are developed to reduce nitrogen losses from farms. A range of in-field, edge-of-field and catchment-scale practices have been developed to help reduce nitrogen losses. However, the effectiveness of various management and mitigation measures at reducing overall nitrogen load in rivers is poorly understood, especially at catchment scale. Modelling is the preferred method to assess the effects of mitigation practices and the literature review has identified that a combination of farm-scale and catchment-scale models should be used. Overseer was selected as the farm-scale model due to its suitability for modelling New Zealand farms, while the conceptual model SOURCE was chosen as the catchment-scale model because of its ability to integrate with Overseer. Together, these models have the ability to simulate the effectiveness of both farm-scale and catchment-scale mitigation measures at reducing river nitrogen loads.

3 Study Area – The Tararua Catchment

The Tararua Catchment is located in the south of New Zealand's North Island. The most prominent features within the catchment are the Puketoi, Ruahine, Tararua Ranges, and the Manawatū River. The catchment's area is approximately 3200 km^2, and the outlet is located upstream of the Manawatū Gorge. The Manawatū River is one of New Zealand's fastest flowing rivers, with discharges of up to 102 m^3/s and a total stream length in its catchment of 9,648 km. Its headwaters are on the East Coast, and it flows west through the Manawatū Gorge (Horizons Regional Council, 2011).

Water quality in the Tararua Catchment has degraded over the last 200 years as a consequence of increasing agricultural development. NO_3-N concentrations often exceed the recommended limit (0.444 ppm for dissolved inorganic nitrogen at some flow rates) and are among the highest in the country, which contributes to the growth of periphyton, especially during low flows (Horizons Regional Council, 2011).

Within the Tararua Catchment, there is extensive spatial variation in topography, soil, geology, and climate. These physical characteristics have a significant hydrological influence. Therefore, a sound understanding is needed to manage nutrient transport effectively. The conclusions made in the following sections regarding the likely hydrological and nutrient transport pathways from different physical characteristics examines each characteristic separately and assumes all other factors remain the same, whereas, in reality, there is an interplay between them, and it is a balance of all characteristics that governs the pathways. For example, the ranges have a steep slope and low permeability geology, which indicates surface runoff would be dominant, but the soil is high permeability which indicates that baseflow dominates (Clark et al., 2016).

3.1 Topography

There is considerable variability in slope and elevation across the Tararua River Catchment which affects the hydrological response. Within the Tararua Catchment, elevation ranges from 60 m to 1497 m with an average of 316 m (NZVD2016) (Figure 3). NZVD2016 can be converted to metres above sea level by using the NZGeoid2016 model and the appropriate vertical datum relationship grid, which uses precise levelling and applies an orthometric correction. Along the middle axial Ruahine and Tararua Ranges, there is a high elevation of above 800m and a slope of between 20-30 degrees (Horizons Regional Council, 2011). In the area surrounding Woodville, slopes are typically less than 5 degrees (classified as flat). In the middle reaches of the catchment, the land is generally more rolling with slopes varying between 10 and 25 degrees, increasing up to 30 degrees on the sides of river valleys. The ranges have very steep slopes commonly exceeding 30 degrees, with slopes of up to 40 degrees in the incised gorge.

Runoff generated in catchments with steeper slopes will transport nitrogen more readily via surface flow due to the erosivity across the surface compared to flat land (Quinn et al., 2009). Rapid change in topographical elevation or steep slopes can have a significant bearing on the rainfall-runoff generation process and hence the characteristics of flow. The slope can also influence the volume and timing of runoff. These characteristics will be important to consider when checking the accuracy of the model water balance.

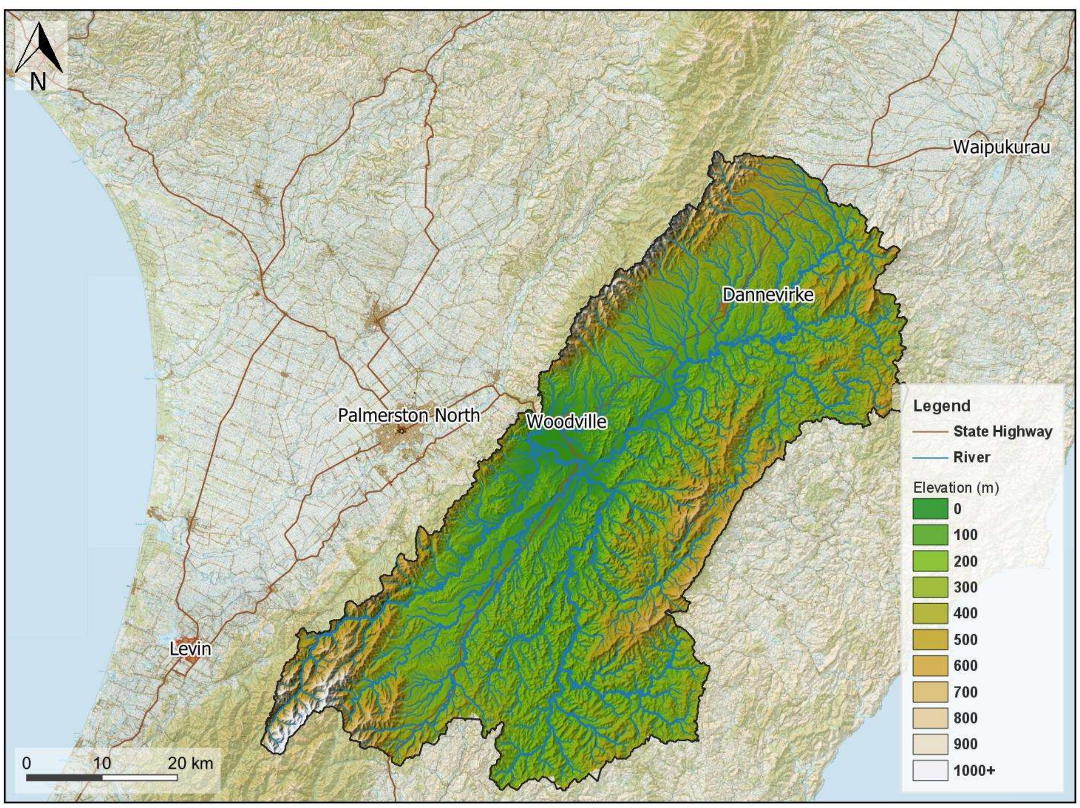

Figure 3. Tararua Catchment elevation (Land Information New Zealand (LINZ), 2020).

3.2 Climate

Rainfall and evaporation have a significant influence on flow and nutrient transport. The climate of the Manawatū region is influenced by the topography and reflects the disturbed westerly airflow interspersed by anticyclones (Pearce et al., 2016).

The rainfall gradient generally follows the topography, with higher mean annual rainfall correlated with areas of higher elevation as presented in Figure 4. The mean annual precipitation varies from 945 mm in the middle catchment to 6265 mm in the ranges (Chappell, 2015). Rainfall in the ranges is high due to the orographic influence from the prevailing westerly winds. A rain shadow effect is evident across the central portion of the catchment. Rainfall also exhibits a seasonal pattern, with either January or February being the driest months due to more frequent anticyclonic behaviour. The river catchment has a temperate climate favourable for pastoral farming (Pearce et al., 2016). The temperature has a relatively small range across the catchment with the median annual temperature ranging from 11-14 degrees. There is significant year-to-year variability in the climate. This is mainly a result of random year-to-year fluctuations such as the Southern Annular Mode, Interdecadal Pacific Oscillation, El Niño and La Niña.

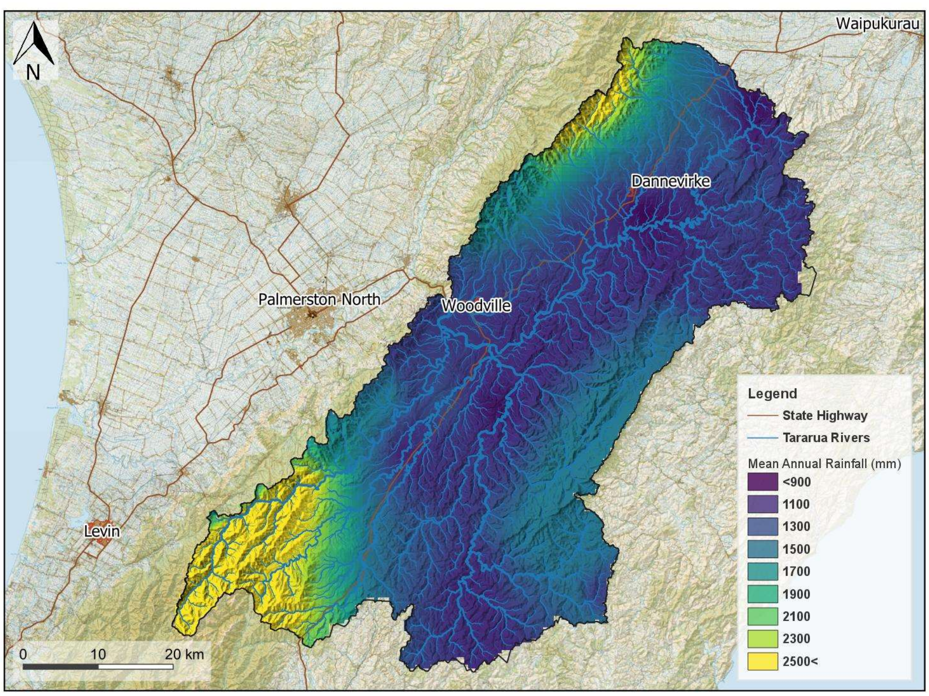

Figure 4. Tararua Catchment mean annual rainfall (Ministry for the Environment (MFE), 2016).

3.3 Geology

An overview of the underlying geology in the Tararua Catchment is presented in Figure 5. The major rock types are mudstone (42%) and gravel (31%) (Qmap, 2014). The Tararua Catchment is constrained in the west by the axial Tararua and Ruahine Ranges and in the east by the Waewaepa and Puketoi ranges.

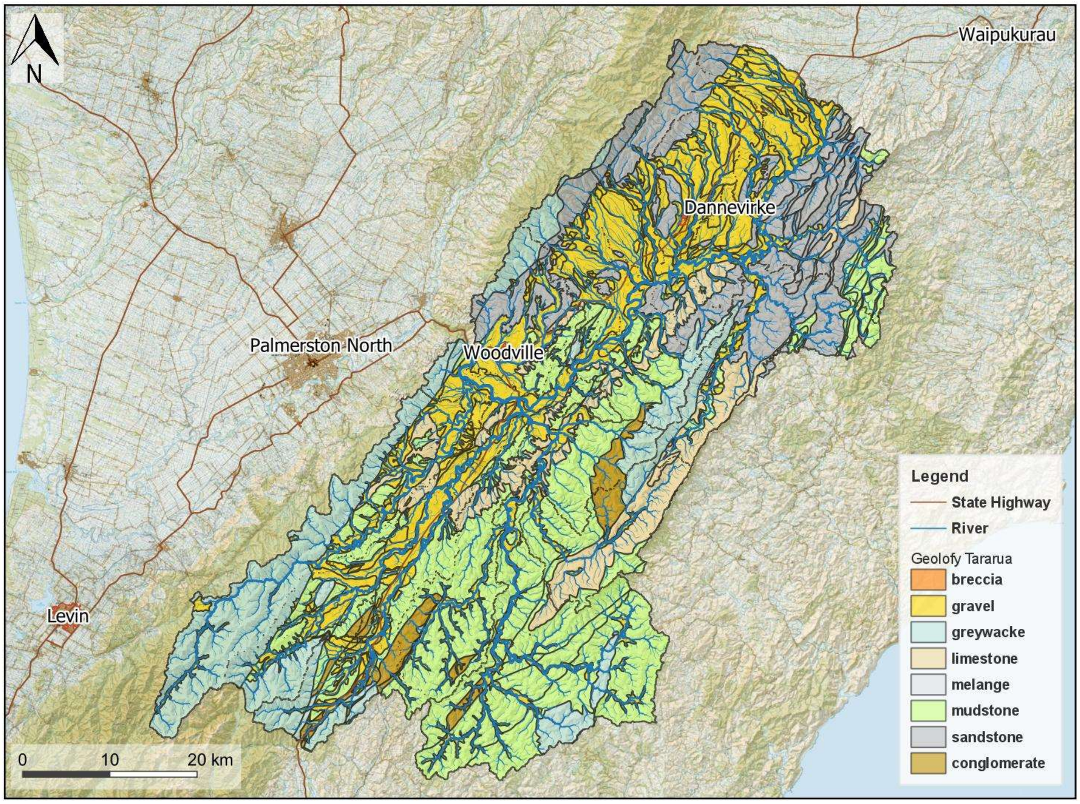

Figure 5. Tararua River Catchment main rock group derived from Q-Map (1:250 000) (GNS, 2014).

The uplift of the Tararua and Ruahine Ranges occurred approximately 1.5-3 million years ago during a period of long-term dip-slip on the Wellington and Mohaka Faults (Lee & Begg, 2002). The elongated depression between these ranges is named the Pahiatua Basin, which has been subject to alluvial aggradation and degradation for at least a million years (Lee & Begg, 2002). Coinciding with this was the downcutting of the Manawatū Gorge from the antecedent river. The Manawatū River north-east of the gorge is entrenched in terraces formed during the Pleistocene glaciation (Rawlinson & Begg, 2014). The river catchment is dissected by several active and inactive faults. These are dominantly strike-slip and dip westward and are associated with folds in Neogene and Quaternary deposits (Lee & Begg, 2002).

The Tararua and Ruahine axial ranges are characterised by non-porous and poorly permeable, highly fractured greywacke (northwest-tilted blocks of indurated siltstone and sandstone). The elevated terraces between the Manawatū River and the Tararua Range are formed from the last interglacial marine sediments (Rawlinson & Begg, 2014). Tertiary marine sediments of mainly mudstone and sandstone overlain by Early Pleistocene sedimentary rocks extend to the east to form the Waewaepa and Puketoi Ranges. The Pahiatua Basin is composed of Quaternary alluvial gravel with a mean depth of 49.5 m and a maximum depth of 227.7 m (Lee & Begg, 2002).

The primary rock types provide substantial control over the subsoil drainage rate and the rate of movement of water through the unsaturated zone between the soil and the groundwater table (McLaren & Cameron, 2002). The younger, more unconsolidated sands are likely to provide higher rainfall infiltration rates, and surface water runoff from these geological units would typically be lower than the older more consolidated sands. Greywacke typically has a much lower permeability than gravel. This indicates that the rates of sub-soil drainage, percolation to groundwater, and groundwater recharge are expected to be lower in the southern ranges compared with the northern hill country (Bekesi & McConchie, 1999).

3.4 Soil

The soil within the Tararua Catchment is variable. The soil in the ranges is characterised by steepland soils and yellow-brown earths with shallow and stony profiles (Cowie & Rijkse, 1977). These soils are prone to leaching and erosion as they are well-drained, and friable. On the lower slopes, upper hill country, and terraces, the soils are predominately loams formed from wind-blown silts with volcanic ash, and also unconsolidated sands (Cowie & Rijkse, 1977). They are classed as intergrades between yellow-brown loams and yellow-brown earths. These soils have imperfect drainage (Cowie & Rijkse, 1977). As described in Section 2.2.4, the soil's chemical and physical properties influence the quantity of nitrogen likely to be leached from the soil profile. Of greatest importance to this study are the hydraulic characteristics that influence infiltration and soil drainage rates, as these have a large bearing on the quantity of nitrogen that can be transported from the soil profile (McLaren & Cameron, 2002). For example, the permeability of the soil affects the partitioning of heavy rainfall into surface runoff or soil infiltration and ultimately percolation to groundwater (McDowell et al., 2009). Soil hydraulic characteristics typically reflect soil texture. The dominant soil textures within the Tararua Catchment are silt loam (52%) and sandy loam (16%), as shown in Figure 6.

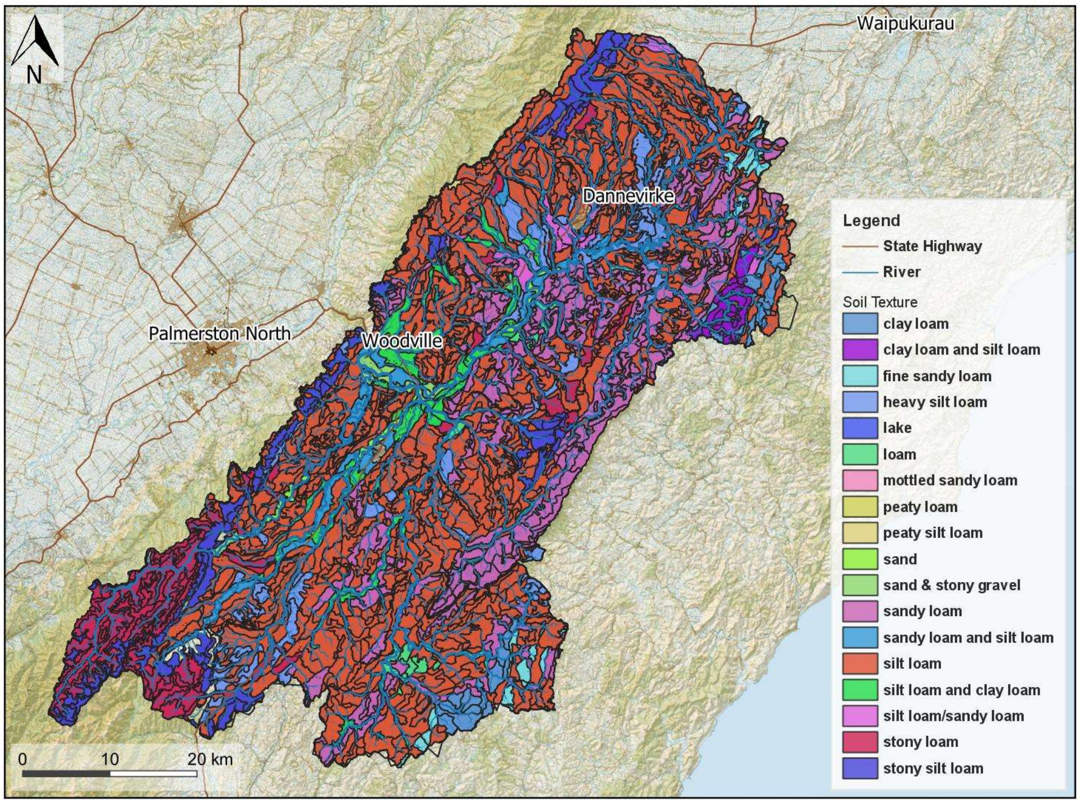

Figure 6. Tararua Catchment soil textures derived from the Fundamental Soils Layer (1:50 000) (Landcare Research LRIS Portal, 2020).

Across the Tararua Catchment, the soil permeability is medium, with small areas of high and low permeability (Horizons Regional Council, 2011). The unconsolidated, stony soils in the ranges exhibit high permeability, enabling rapid vertical drainage through the soil profile and subsequent percolation to groundwater, as opposed to direct surface runoff during high-intensity rainfall events (McLaren & Cameron, 2002). This indicates that the catchments in the ranges are controlled by baseflow properties and are vulnerable to nitrogen leaching. Coarse-textured, well drained soils such as sand and sandy loams are found in the basin and along the rivers. Similar to stony soils, coarse-textured soils are also highly susceptible to nitrogen leaching. In contrast, the fine-textured and consolidated soils (e.g., clay and peaty loams) by Woodville exhibit low permeability, increasing the potential for ponding and runoff in response to rainfall events (McLaren & Cameron, 2002). These soils have a shallow groundwater depth which will also result in a propensity for ponding. This means that they are less susceptible to nitrogen leaching than other soil types and nitrogen transport will occur dominantly through surface pathways. However, in order for these soil types to be suitable for land uses such as dairy, artificial drainage is commonly installed, which increases nitrogen losses.

3.5 Land use

Land cover in the Tararua Catchment is dominated by pastoral farming, with sheep and beef comprising of the largest proportion (Table 2). Sheep and beef, dairy and forest are the dominant land uses across the whole catchment consisting of 1917 km^2, 510 km^2, and 659 km^2, respectively (Horizons Regional Council, 2011). Table 2 and Figure 7 shows how these land uses vary across the catchment. Dairy commonly occurs on areas with flat topography, and free draining and fertile soils. Sheep and beef farms commonly occur on less fertile soils and rolling to steep hill country. Forest generally occurs in the ranges and other areas unsuitable for any other land use either as a result of slope or fertility.

Table 2. Land use distribution (Horizons Regional Council, 2011).

Catchment	Dairy (%)	Sheep and Beef (%)	Forest (%)	Urban (%)
Upper Manawatū	17	69	13	<1%
Tiraumea	3	79	17	0
Mangatainoka	30	47	22	<1%
Upper Gorge	21	37	41	<1%

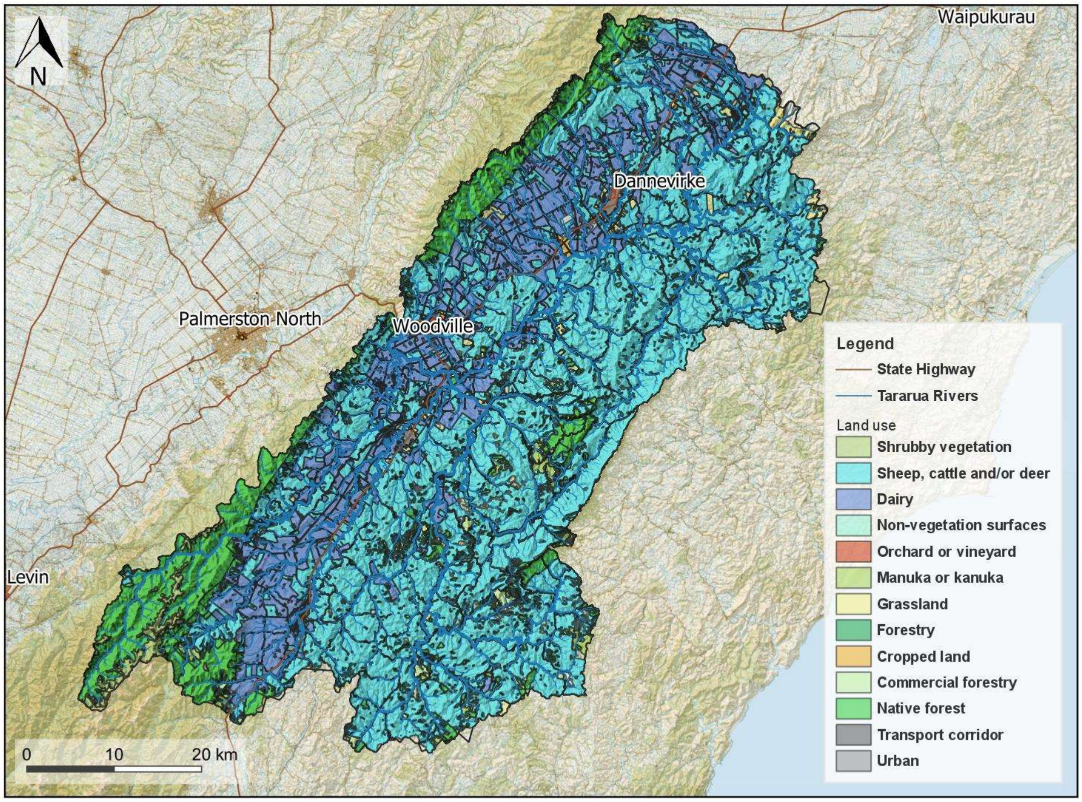

Figure 7. Land use in the Tararua Catchment (1:63360) (Sourced (data requested) from Horizons Regional Council, 2020).

Land cover and land use within a catchment exerts a significant influence on the load of nitrogen transported to waterways. Increased vegetation density produces a buffer and acts to limit the surface transport of nitrogen (Follett, 2008). Higher stocking rates generally occur in flatter areas and dairy farms. Stocking rate is correlated with the quantity of diffuse nitrogen available to be mobilised and leached from fertiliser application and urine patches (Drewry et al., 2006). The land use and vegetation cover of an area are also some of the controlling drivers of hydrological responses. The density of vegetation, level of anthropogenic or natural disturbance, and the type of vegetation cover contribute to the movement of water through a catchment on both a temporal and spatial scale (Rowe et al., 2002). These are important factors to consider in the development of the river flow and nitrogen models.

4 Methods and Materials

The literature review in Section 2.4 highlighted the advantages of using an integrated farm-scale and catchment-scale model to simulate water quality scenarios. Based on the review, SOURCE was selected as the catchment-scale model and was integrated with the farm-scale model, Overseer, to simulate nitrogen transport from farms to rivers. Figure 8 presents a schematic overview of the methodological framework to integrate the Overseer and SOURCE models for the Tararua Catchment. Note that calibration of the model only occurred for the baseline scenario and not for subsequent mitigation scenario runs.

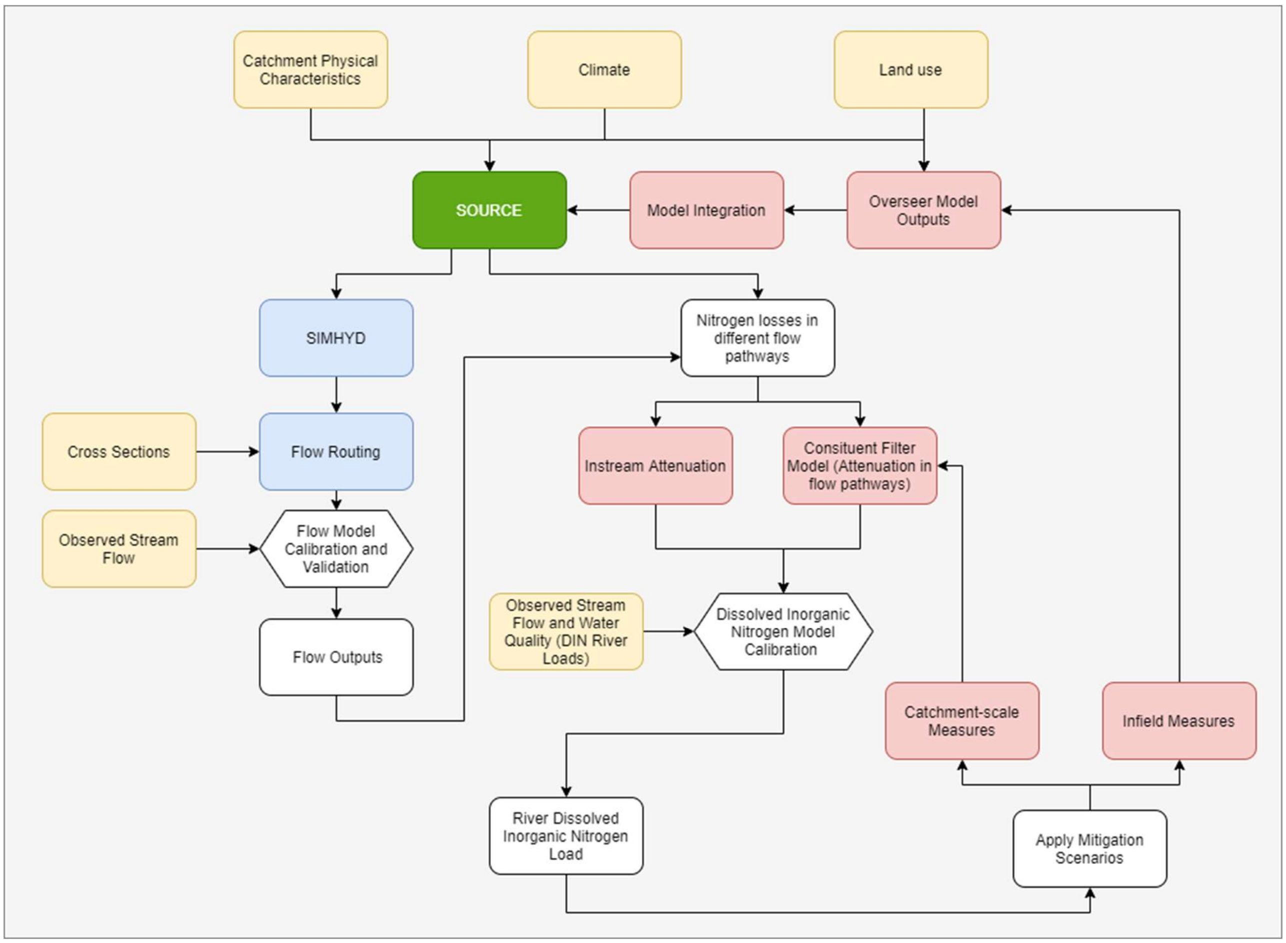

Figure 8. A schematic overview of integration of farm-scale Overseer and catchment-scale SOURCE models for the Tararua Catchment.

This chapter describes the methods and materials used to integrate and parameterise the Overseer and SOURCE models, and their calibration and validation in the Tararua Catchment. It also defines and describes the various in-field and catchment-scale mitigation scenarios that were evaluated for their ability to reduce DIN loads in the study sub-catchments.

4.1 Available Data and Data Preparation

A wide range of data layers based on the Tararua Catchment's physical characteristics were required to develop and parameterise the integrated Overseer and SOURCE model, such as soil, climate, geological, elevation, and measured flow and water quality data. Table 3 lists the geographical and hydrogeological datasets used to construct and calibrate the integrated Overseer and SOURCE models for the study catchment. The data was either provided by Horizons Regional Council or publicly available from external providers.

Table 3. Summary of the geographical and hydrogeological datasets used to construct and calibrate the integration of Overseer and SOURCE models.

Data	Description	Data Origin
Digital Elevation Model (DEM) – 8m resolution	8 m resolution DEM raster of the Tararua Catchment. The DEM was used to determine the catchment elevation and slope for flow model parameterisation and sub-catchment delineation. Note that this DEM was created by the interpolation of 20m contours with post-processing and filtering (LINZ, 2012).	LINZ, 2020
River Environment Classification (REC2) River Network Shapefile	The river network was used to assist in sub-catchment delineation and to develop nodes and links in the SOURCE model.	MFE, 2010
Water Management Sub-zones	These sub-zones were determined by several factors, including (but not limited to) geology, pressure and presence of monitoring sites. They were used to initiate the sub-catchment delineation process.	Horizons Regional Council, 2010
Land use Capability Class (LUC)	Shapefile specifying the capacity of the land to support long-term sustained production after taking into account the physical	LINZ, 2020

Data	Description	Data Origin
	limitations of the land. Used to determine which land would be suitable for dairy farming.	
Fundamental Soils Layer (FSL) Shapefile	A spatial layer of the key soil attributes derived from the National Soils Database (NSD) and the New Zealand Land Resource Inventory. The FSL was used to inform functional unit (FU) delineation and model parameterisation.	(Landcare Research LRIS Portal, 2020)
Soil Information	Soil attributes including soil hydrological group, soil depth, soil texture, available water capacity, bulk density, organic carbon content, saturated hydraulic conductivity, soil albedo, soil erodibility factors and rock fragments were provided for the Manawatū Region.	Sourced (data requested) from A. Parshotam (2020)
Geological Map (Q-Map)	1:250,000 geological shapefile describing surface geology, geomorphology, stratigraphy, structural geology, tectonic history, and engineering geology. Q-Map was used to inform functional unit delineation and model parameterisation.	(GNS, 2014)
Land use Shapefile	A spatial layer of primary and secondary land uses for the Manawatū River Catchment. This was used to define the functional units and assign the root zone nitrate losses estimated by the Overseer model.	Sourced (data requested) from Horizons Regional Council (2020)
Rainfall Distribution Raster	Distribution of mean annual rainfall across New Zealand based on interpolation of Virtual Climate Station Network (VCSN) data (5 km resolution). Used to inform sub-catchment delineation.	(MFE, 2016)
Observed Flow Data	Continuous daily flow record (with data gaps) from 1975 to 2020 over 10 sites across the Tararua catchment. Used to calibrate and validate SOURCE model.	Sourced (data requested) from Horizons Regional Council (2020)
Observed Water Quality Data	Monthly spot measurement samples of water quality from 1989 to 2020 over 9 sites across the Tararua Catchment. Used to calibrate and validate the SOURCE model.	Sourced (data requested) from Horizons Regional Council (2020)
Observed Point Source Discharge Data	Monthly measurement samples from 2007 to 2020 over ten sites across the Tararua Catchment. Used to model nitrogen input from point sources.	Sourced (data requested) from Horizons Regional Council (2020)
Climate Data	VCSN data for rainfall, relative humidity, solar radiation, potential evapotranspiration, wind	(National Institute of Water and

Data	Description	Data Origin
	speed, minimum and maximum temperatures from 1997-2016. Used as inputs to SOURCE.	Atmospheric Research (NIWA), 2016)

4.1.1 Measured River Flow and Water Quality

Measured river flow and water quality data was used to analyse spatial and temporal variations in the river flow and nitrogen loads in the study catchment. More importantly, this data was required to calibrate and validate the integrated models for their accuracy in simulation of river flow and nitrogen loads across the sub-catchments.

Horizons Regional Council provided observed daily river flow data for a range of locations within the Tararua Catchment (Appendix A). Six sites were selected as primary flow sites and were given the greatest weighting during model calibration (Table 4). Their locations are displayed in Figure 9. These sites were selected as they were on main river branches, had a long flow record, minimal periods of missing data, a corresponding water quality gauge, and were downstream of more than one sub-catchment. The four remaining sites were also used as an additional calibration check and their locations are presented in Appendix A.

Horizons Regional Council also provided monthly water quality data for the same river monitoring locations. Of particular interest to this study were recordings of total nitrogen (TN), NO_3^-, NH_4^+, and TON. The dissolved inorganic nitrogen (DIN) was used for nitrogen model calibration it has the greatest impact on stream health (Quinn et al., 2009). DIN was calculated as the sum of measured NO_3^--N, NO_2^--N, and NH_4^+-N concentrations. For gauges where there were no measurements for NO_3^--N or NO_2^--N, DIN was calculated as total oxidised nitrogen (TON) plus NH_4^+-N.

Table 4. Summary of the primary measured flow and water quality sites.

Site Name	Sub-catchment	Flow		Water Quality	
		Date Range	Notes	Date Range	Notes
Manawatū at Hopelands	16	4/09/1988-31/07/2020	28 days of missing data. No data from 24/07/1992 to 11/11/1992.	8/01/1989-12/12/2018	No measurements between 1993 and 2008
Manawatū at Upper Gorge	37	18/07/1979-31/07/2020	13 days of missing data.	1/01/2007-12/12/2018	
Manawatū at Weber Road	7	2/01/1975-31/07/2020	35 days of missing data from 2017. No data from 14/04 2020 to 6/05/2020.	19/07/1993-12/12/2018	
Mangahao at Ballance	35	2/01/1975-31/07/2020	9 days of missing data.	21/07/1989-12/12/2018	No measurements between 1993 and 2008
Mangatainoka at Pahiatua Town Bridge	30	1/01/1975-31/07/2020	11 days of missing data.	13/10/1989-11/12/2018	No measurements between 1993 and 2008
Tiraumea at Ngaturi	27	1/01/1980-31/07/2020	20 days of missing data as well as between 25/06/2018-6/07/2018.	2/07/2008-11/12/2018	

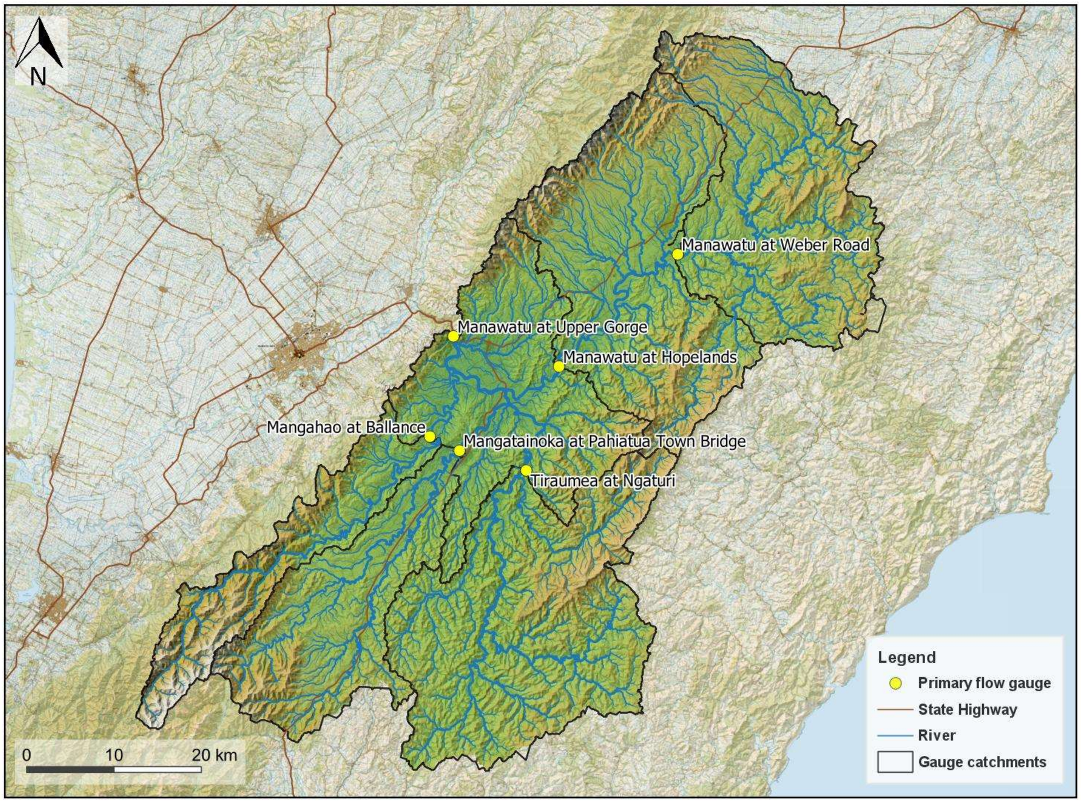

Figure 9. Tararua Catchment primary flow gauge locations and their catchments.

4.1.1.1 Nitrogen Load Calculation

Estimates of nitrogen loads are needed to assess the state of water quality spatially and temporally, and for calibration and validation of the integrated model. Comparison of load rather than concentration allows the actual quantity of nitrogen in a stream to be determined and compared across the catchment.

River loads cannot be directly measured and must be calculated from concentration data. Calculation methods have been developed to estimate the actual load and account for the bias created by the infrequent sampling of water quality. There are multiple methods as Elwan et al. (2018) described, to calculate river nitrogen loads using the measured river nitrogen concentrations and river flow. Each method has its own limitations and uncertainties because the concentration is a function of flow at the particular moment the sample is taken (Elwan et al., 2018). In addition, the measured concentration is most likely a point sample which implies that the constituent is fully mixed, and this concentration exists across the entire cross-section of the river.

In this study, the flow-weighted method was used to calculate the river DIN load as a product of the total flow and flow-weighted average DIN concentration (Elwan et al., 2018), described as follows (Equation 2).

$$L = mQ_t\left(\frac{\sum_{i=1}^{n} C_i Q_i}{\sum_{i=1}^{n} Q_i}\right) \tag{2}$$

where:

L = Annual river load (t/yr);

m = Unit conversion factor;

C_i = Dissolved Inorganic Nitrogen (DIN) concentration (mg/L);

Q_i = Mean daily flow measured at the *i*th day (L/day); and

Q_t = Total annual flow (L/year).

Elwan et al. (2018) found that for the monthly water quality sampling of DIN at the Manawatū River at Teachers College monitoring site, the flow weighted method of load calculation performed best in terms of bias and root mean squared error (RMSE) when compared with the river DIN load, termed as 'actual load' calculated as a product of the daily measurements of DIN and river flow over a year (1/05/2010 to 30/04/2011). However, this flow-weighted method still has the potential to deviate from the actual load by up to 11% (Elwan et al., 2018).

4.1.1.2 Nitrogen Load and Catchment River Flow Analysis

This section explains the methods for spatial and temporal analysis of calculated DIN loads and measured river flows. Spatial analysis was conducted by comparing the DIN load at each of the monitoring locations across the Tararua Catchment to highlight high load generation areas. The load was calculated both as an absolute value and as an area-weighted average value (load generated per unit of area (kg/ha/yr), as the area upstream of the monitoring site is likely to impact the quantity of load.

The measured flows were assessed spatially by comparing the catchment discharge coefficient across the monitoring sites. The catchment discharge coefficient was found by calculating the mean annual flow, mean annual rainfall and the ratio of flow to rainfall on an annual average basis. The rainfall was taken as an area-weighted average of all sub-catchment interpolated rainfall above each gauge.

Temporal analysis (monthly and annual variations) aimed to highlight in which months and years high loads occurred. A regression analysis was conducted between annual average rainfall and annual average DIN load for each site to assess the impact of climatic variation on DIN loads. It also enabled the spatial and temporal coherence of water quality data against rainfall to be checked. The regression analysis indicated a weak positive correlation between rainfall and DIN load, meaning rainfall is a significant variable and needs to be accounted for in Overseer modelling.

4.1.2 Climate

Climate data was required as an input to both the farm-scale model, Overseer, and the catchment-scale model, SOURCE. Climate inputs for the period 1997-2016 were sourced from the Virtual Climate Station Network (VCSN) database. The VCSN data provides daily estimates of climate variables including rainfall, solar radiation, wind speed, temperature, potential evapotranspiration (PET), relative humidity, vapour pressure and soil moisture on a 5 km regular grid covering New Zealand (Macara et al., 2020). The VCSN derives the daily rainfall using trivariate (latitude, longitude, and elevation) thin-plate smoothing spline interpolation of observation data in the National Climate Database (Tait et al., 2012). PET data was calculated by the Penman-Monteith method using inputs of net radiation, relative humidity, air temperature, and wind before it was interpolated using the trivariate thin-plate smoothing spline method (Tait & Woods, 2007).

The advantage of using VCSN data is that it provides a temporally and spatially continuous dataset. This means the dataset does not require processing to fill in periods of missing data, which can occur due to a rain gauge malfunction or different record durations. Another advantage is that the data is processed in a consistent way across the whole of New Zealand, which is important if similar studies are to be developed in other regions. There is a lack of observation stations within the Tararua Catchment with up-to-date data, which also highlights VCSN data's usefulness. A potential disadvantage of using VCSN data is that its accuracy is dependent on the observation datasets, and if these are sparse or unreliable, the VCSN data is hindered to a similar level of accuracy (Macara et al., 2020). In addition, as the data is synthetic and not observed, there will be some degree of error in the data. Tait et al. (2012) concluded that the VCSN data produces an acceptable estimate of observed rainfall in elevations less than 500m with a mean absolute error of 2 – 4 mm in bias corrected daily rainfall. However, it is not as reliable in complex mountainous terrain with the mean absolute error in daily rainfall ranging from 10 to 120 mm. This can be partially attributed to insufficient observation data on which to base the VCSN estimates. There is a low-density network of weather stations installed at high altitude, which means the interpolations used in the VCSN estimates may be based on storms that occurred outside a particular catchment, or some storms may be missed entirely (Tait et al., 2012).

To check the accuracy of the VCSN interpolation within the Tararua Catchment, VCSN data was compared to the observation based CliFlo data at three sites within the catchment. Time series plots at different levels of temporal aggregation suggested that VCSN rainfall within the Tararua Catchment was within approximately 110% of gauged rainfall and exhibits close agreement in monthly and seasonal variation. The percentage difference between CliFlo station 2390 and VCSN station 30977, located approximately 3 km apart, showed that the percentage difference of actual rainfall for each month in 2010 ranged from 98 to 109% of the VCSN estimated rainfall.

The rainfall peaks in the VCSN dataset were visually checked against the flow peaks observed in the measured flow data to see if the size of peaks approximately correlates with the amount of rainfall and that the peaks occur at about the same time, taking into account expected changes in this relationship with antecedent flow conditions. Given the advantages of utilising the VCSN rainfall, and the relatively close agreement to gauged rainfall, for the purposes of this study, VCSN data is considered to have sufficient accuracy to use in the model.

A total of 318 VCSN data points within the Tararua Catchment were provided as a series of DAT files for each day. These points were processed using Python to provide a time series for each point before kriging interpolation was used to interpolate the data to the centroid of each sub-catchment. Up to 10

VCSN points can fall within each sub-catchment, and as SOURCE only requires one time series per sub-catchment, an inverse-distance-squared interpolation to the sub-catchment centroid was used to better represent each sub-catchment's climate. The data was then processed into the required format for input into SOURCE. The script used to perform these tasks is provided in Appendix B. The mean elevation of each sub-catchment was found by calculating the area-weighted average from the 8 m DEM and was assigned to each climate input in SOURCE.

For Overseer modelling, the sub-catchments were grouped into high, medium, and low rainfall regimes based on the mean annual average rainfall received. Figure 10 presents a comparison of mean monthly rainfall and PET data in different sub-catchments across the Tararua Catchment. The darkest blue colour represents high rainfall (> 1655 mm per year), which is typical of the ranges. The lightest blue colour represents low rainfall (< 1157 mm per year), which is characteristic of the lower areas, while the blue colour represents medium rainfall (1157 - 1655 mm per year), which is characteristic of the hill country areas. The classification of each sub-catchment's rainfall regime is presented in Appendix C.

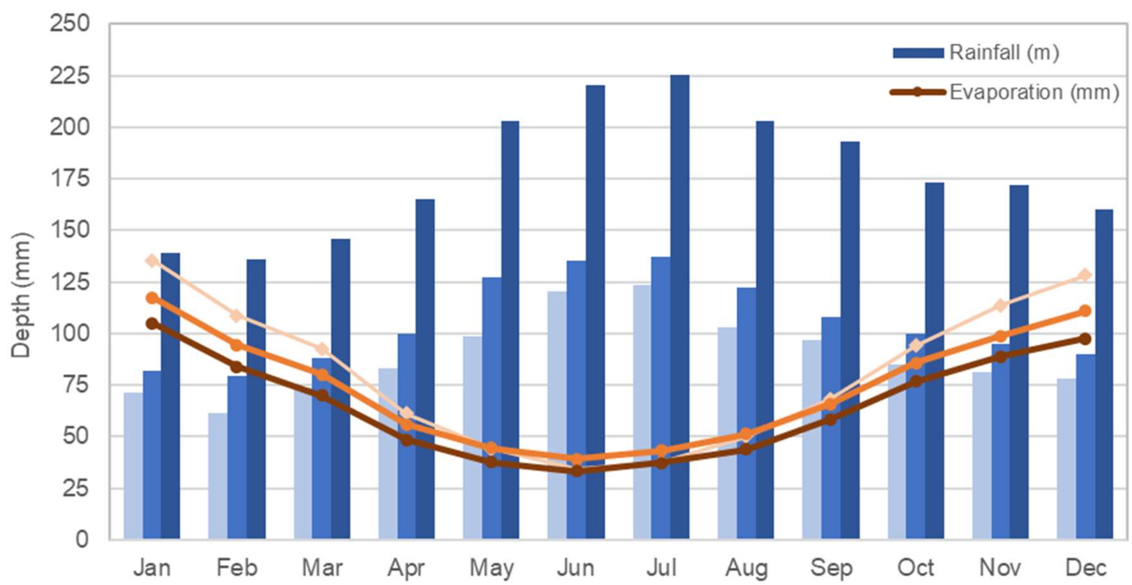

Figure 10. Mean monthly rainfall and potential evapotranspiration variations in Tararua sub-catchments.

Section 4.1.1 noted the influence of annual rainfall on variations in nitrogen loads measured in the rivers. However, the development of Overseer models for different years is time-consuming, as wet and dry years have different management strategies. Therefore, Overseer and the integrated SOURCE model were run for an 'average' climatic year to simulate the average annual DIN loads in the river. Figure 11 displays the total annual rainfall for each year for the three representative sub-catchments in low, medium and high rainfall areas. From this analysis, it was concluded that the annual rainfall received in 2010 fell around the average annual rainfall between 1999 and 2016 (Table 5), and this would be used for average annual nitrogen modelling.

Table 5. Comparison of annual rainfall in 2010 and annual average rainfall between 1999 and 2016.

Rainfall Regime	Annual Rainfall in 2010 (mm)	Annual Average Rainfall Between 1999 and 2016 (mm)
Low	1,068	1,103
Medium	1,358	1,465
High	2,275	2,302

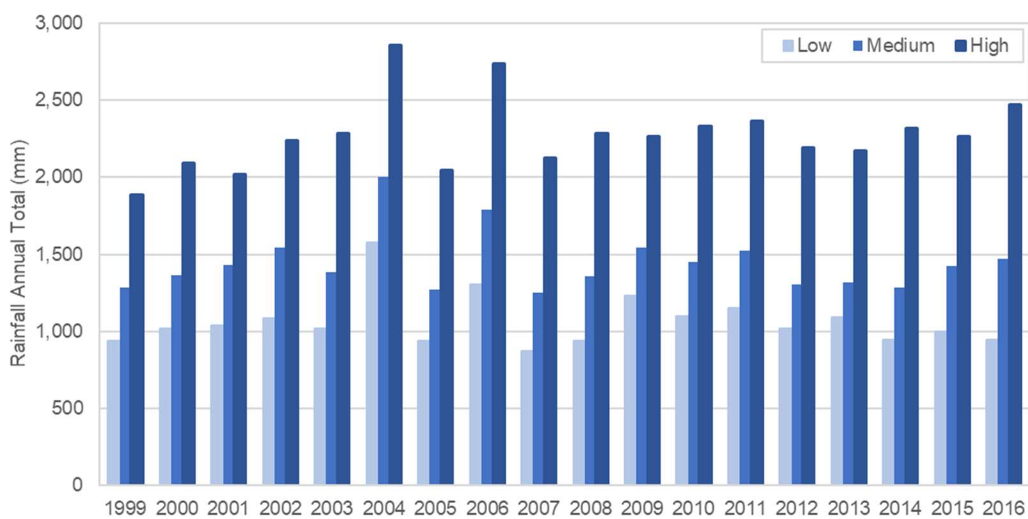

Figure 11. Annual rainfall variations in Tararua sub-catchments.

4.1.3 Elevation and Slope

The catchment elevation and slope maps were used to help identify, delineate, and characterise the hydrological response throughout the catchment. A DEM for the Tararua Catchment was extracted from the New Zealand wide 8 m DEM. This was downloaded from the LINZ website in tiles which were merged using the mosaic tool in Quantum Geographic Information Systems (QGIS) to create a single DEM and then clipped to the shape polygon of the Tararua Catchment. The Wang and Liu (2006) method in QGIS was used to identify and fill sinks in the DEM. Using a filled-DEM is important to create a hydrologically accurate flow–direction raster and to preserve the downward slope along the flow path when delineating sub-catchments (Wang & Liu, 2006). A slope raster was developed from the original 8 m DEM using the terrain analysis tool in QGIS.

4.1.4 Sub-catchment Delineation

A SOURCE catchment model comprises a series of interconnected sub-catchments that are discretised to reflect the localised physical characteristics of each sub-catchment. Sub-catchment delineation was undertaken to allow parameters to be applied in the model that reflect the spatial variation. The influence of physical characteristics on the catchment's overall hydrological response and behaviour was considered during the sub-catchments' delineation.

The sub-catchment boundaries were based on the Water Management Sub-zones delineated by Horizons Regional Council. Where the sub-zone boundary extended beyond a river monitoring gauge, it was adjusted, as the positioning of the sub-catchment drainage point at a monitoring site significantly enhances the ability to accurately calibrate the model. The sub-catchments were also further delineated based on areas of similar geology, soil, topography, and climate to enable the application of homogenous catchment parameters in the rainfall-runoff model. This was done by creating a shapefile of each potential sub-catchment outlet and using the tools available in QGIS to calculate the upstream catchment as outlined in Appendix D. In areas where a suitable sub-catchment was not delineated, likely as a result of the coarseness of the DEM, the delineation was achieved by following the LINZ Topo50 contours along the areas of highest elevation and splitting channels on main branches.

Analysis of slope was undertaken to identify sub-catchments that demonstrated a large slope range and therefore needed to be delineated further. This resulted in 37 sub-catchments, as shown in Figure 12. Table 6 shows the slope statistics for three representative sub-catchments.

Table 6. Elevation and slope and elevation statistics.

Site	Elevation Mean (masl)	Elevation Minimum (masl)	Elevation Maximum (masl)	Slope Mean (degrees)	Slope Minimum (degrees)	Slope Maximum (degrees)
Ranges (SC 33)	844.19	419.18	1489.70	25.98	0.63	44.45
Hill Country (SC 2)	280.00	77.35	777.65	11.95	0.00	37.21
Basin (SC 11)	64.65	26.90	90.44	0.20	0.00	1.13

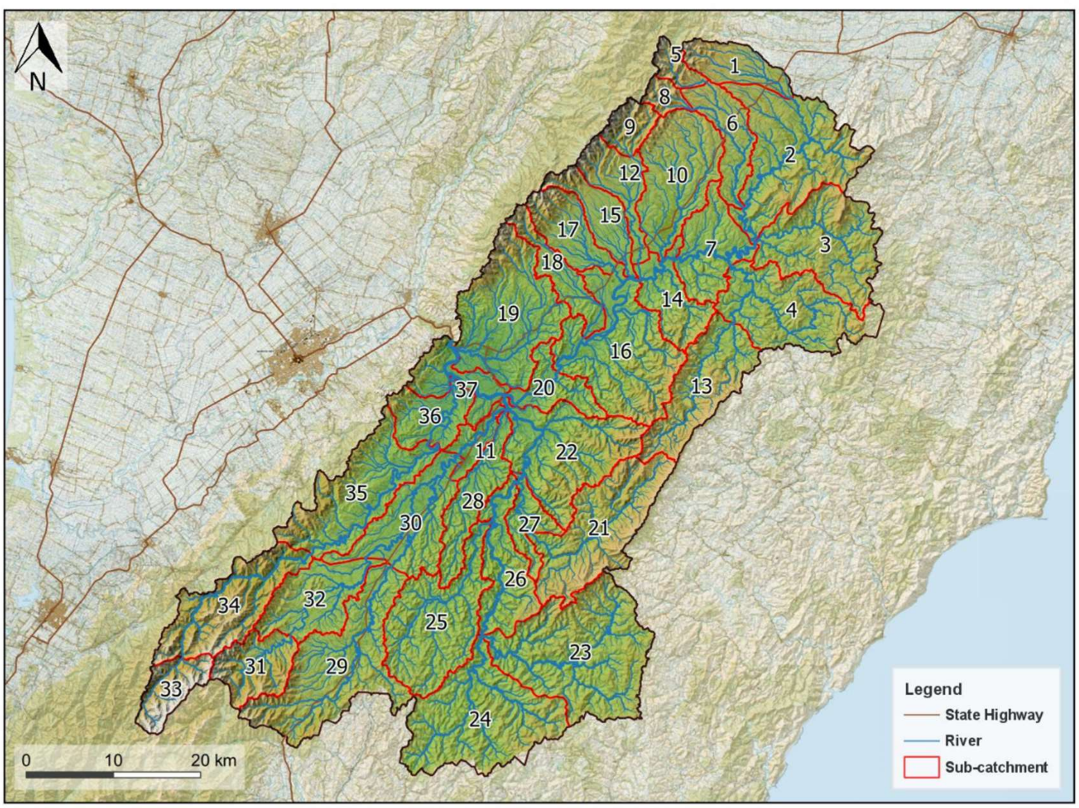

Figure 12. Sub-catchments delineated for SOURCE modelling of the Tararua Catchment.

A balance between sub-catchment size and modelling accuracy was sought. As catchment size increases, catchment parameters are smoothed out due to averaging, eliminating most of the spatial variation and thus the responsiveness of the model, whereas when catchment resolution decreases, the parameters applied better reflect the local-scale variation but more input data and computational time to run and analyse the results is required. In this model (Figure 12), there is still a moderate level of hydrogeological variation within each sub-catchment but increasing the number of sub-catchments would have significantly increased the model complexity. Additionally, a greater proportion of the hydrogeological variation is covered by the introduction of functional units, defined as unique combinations of soil, geology, attenuation and land use (Section 4.2).

4.1.5 Land use

Horizons Regional Council provided a shapefile of recent land use in the catchment (Figure 7). To enable this to be converted to a raster ready for import into SOURCE, a unique value was assigned to each different land use that would be represented as a functional unit in the model. Dissolve and rasterise tools in QGIS were then used to produce a land use raster with a pixel size of 10 m. Dairy, sheep and beef, and forest land uses were selected to be developed into functional units as these land uses had the largest area. Additionally, a functional unit was developed for urban areas, as the characteristics of urban land use are significantly different to any other land use. A more accurate model could have been developed by increasing the number of land uses, such as low and high intensity dairy and sheep and beef categories, and cropping areas, that were incorporated into functional units. However, this would have significantly increased the number of simulations that needed to be developed in Overseer for estimates of farm-scale nutrient losses (Section 4.4.1). It was not clear whether the benefit of increasing complexity would justify the additional work. Further work is needed to develop more efficient ways to account for such variations and to establish how important it is to use them.

Appendix D presents the secondary land uses (obtained from Horizons Regional Council) and their corresponding functional unit.

4.1.6 Soil

The NZ Fundamental Soils Layer (FSL) and the National Soil Database (NSD) (Table 3) were used to parameterise the hydrologic characteristics of each soil group in the catchment. Parshotam (2018) detailed the method to process New Zealand soil data for catchment-scale models. This involved joining the NSD to the FSL polygons by the New Zealand Soil Classification codes and using database queries of the NSD to find the relevant soil hydrologic information needed to parameterise the top soil horizon.

Of greatest importance was soil drainage which was used to inform the infiltration coefficient parameter in the rainfall-runoff model. The potential rooting depth was also used as a guide of the relative depths of soil when setting the soil moisture store parameter.

Soils were grouped into classes of fine texture (poor natural drainage), intermediate texture (imperfect drainage), coarse textures (well-drained) and stony soils (excessive drainage). Each soil group was used in the development of the functional units for modelling of the rainfall-runoff and spatially variable nitrogen attenuation capacity across the catchment (Section 4.2.1). The grouping of soil textures into these categories is presented in Appendix D.

4.1.7 Geology

Geological data from Qmap (Table 3) was used to group the catchment geology into the model functional units that correspond to the different geological permeability and nitrogen attenuation capacity classification of the rock types. Geological permeability was assessed using both the main rock and sub rock attributes. As described in Section 2.2.4, rock permeability is positively related to well-drained soils and gravels and negatively related to imperfectly drained soils and mudstone. Permeable rocks have a high saturated hydraulic conductivity value. Using the hydraulic conductivity values given by Freeze and Cherry (1979) and Zarour (2008), a classification of 'Low' was assigned to mudstone and peat, 'Medium' was assigned to sandstone and limestone, and a classification of 'High' was assigned to gravels. The grouping of geological units into these categories is presented in Appendix D. This data was used to develop functional units, parameterise the rainfall-runoff model, and to create spatially variable nitrogen attenuation classes.

4.1.8 Nitrogen Attenuation

Singh et al. (2017) and Elwan (2018) developed a simple hydrogeologic-based nitrogen attenuation capacity classification of different land units defined as combinations of soil types and their underlying geology. This nitrogen attenuation capacity classification was built into each functional unit to allow modelling of spatially variable nitrogen attenuation capacity in the sub-catchments. Both rock types and soil textures were assigned nitrogen attenuation classifications based on their potential for denitrification as determined by their chemical reactivity and hydraulic conductivity. Section 2.2.4 describes the impact the physical characteristics have on denitrification in the subsurface environment. Low permeability rocks such as mudstone were assigned a high nitrogen attenuation classification, and vice versa. The exception to this was greywacke which was assigned a low attenuation classification although it has low permeability. This was due to the high likelihood of it being inert (Zarour, 2008). Fine-textured soils were given a high nitrogen attenuation classification while stony soils were given a low classification, as per their soil drainage characteristics and relative soil water residence times. Poor drainage and higher soil water residence time means there is more time for subsurface denitrification to occur. The attenuation classifications for soil and geology are detailed in Appendix D. The attenuation classification for geology and soil texture were then averaged to give an overall nitrogen attenuation classification to each functional unit in the model. This is displayed in Table 7, noting that greywacke differs from this classification.

Table 7. Grouping of soil and geology spatially variable nitrogen attenuation capacity of different land units in the catchment.

Soil Texture / Drainage	**Geological Permeability**	**Overall Attenuation Class**
Fine textured / poor drainage	Low	Medium
Fine textured / poor drainage	Medium	High
Fine textured / poor drainage	High	High
Intermediate textured / fair drainage	Low	Medium
Intermediate textured / fair drainage	Medium	Medium
Intermediate textured / fair drainage	High	High
Coarse textured / good drainage	Low	Low
Coarse textured / good drainage	Medium	Medium

Soil Texture / Drainage	Geological Permeability	Overall Attenuation Class
Coarse textured / good drainage	High	Medium
Stony soils / well drained	Low	Low
Stony soils / well drained	Medium	Medium
Stony soils / well drained	High	Medium

4.2 SOURCE Model Setup

eWater SOURCE was used in conjunction with the embedded rainfall-runoff model, SIMHYD, and the nutrient generation model, Overseer. This section focusses on the setup of the catchment-scale model. The key SOURCE packages used in this study were the geographic editor, SIMHYD rainfall-runoff model, routing model, constituent generation model and the constituent filter model. The documentation for SOURCE produced by eWater (2018), outlines the many equations used in the model.

4.2.1 SOURCE Model Construction

The geographic wizard in SOURCE was used to import files that were developed externally. This included the sub-catchment raster, filled 8 m DEM, and the River Environment Classification (REC) stream network. Climate data was imported in a format described in Section 4.1.2. Following this, a shapefile with nodes and links representing drainage between sub-catchments was developed. Table 8 outlines the key model features.

Table 8. SOURCE model features.

Model Feature	Approach	Rationale	Limitations
Flow timestep	Daily	Measured flow data was available on a daily scale and a daily time-step allowed temporal variation to be identified.	
Constituent time-step	Annual	Overseer is designed to produce annual average nutrient losses, although it can output monthly nutrient	Limits the use of the model for examining the effects of temporal variability.

Model Feature	Approach	Rationale	Limitations
		losses. No process has been developed for disaggregation to daily. Annual average loads were used due to greater confidence in this data.	
Flow model period	1997-2016 Calibrated for 1999-2007 Validated for 2008 - 2015	The length that the model was run for was governed by the length of input climate data. 1997 to 1999 was specified as a warmup period to equilibrate the initial storage states (pervious area and groundwater) in the model.	
Nitrogen model period	1/1/2010 - 31/12/2010	2010 was typical of average climatic conditions (Section 4.1.2). Running the model over a single year minimised the number of Overseer models needed. A two-year warm-up period was included.	Running the model over a longer period would have given a better representation of the long-term variability in loads. It would have also allowed the effect of climate on nitrogen leaching and mitigation effectiveness to be analysed.
Rainfall-runoff model	SIMHYD with routing	SIMHYD is embedded within SOURCE and has been used successfully in a range of Australian catchments with similar physical characteristics as the Tararua Catchment (Freebairn et al., 2015).	
Flow routing	Storage routing	Commonly-used model which accounts for flow attenuation as flow moves through the vadose zone.	Relies on the use of default parameters and increases model uncertainty.
Constituent routing	Lumped routing	Simplest approach, where constituents are routed within a link based on kinematic wave theory. The	Assumes fully mixed conditions within a link.

Model Feature	Approach	Rationale	Limitations
		constituent flux and concentration move from the top of a link to the downstream end of a link within a time-step, preserving the mass balance (eWater, 2018).	

The functional units divided each sub-catchment into areas of similar hydrological behaviour. Functional units were established as a combination of the different soil, geology, attenuation, and land use categories detailed in sections 4.1.4 to 4.1.6. While the categories defined in these sections do not fully represent the variability within each sub-catchment, they ensure that the effect of physical characteristics on flow and nutrient output is specified to an informative level. An area was assigned to each functional unit by loading a raster into SOURCE. Functional units of less than 100 ha were excluded and merged with the neighbouring functional unit with the largest common boundary using the elimination tool in QGIS. The total area that was merged only represented 0.1% of the total catchment and in most cases the neighbouring functional unit shared at least one common variable (soil, geology or land use) with the merged functional unit. A different approach was used for urban functional units due to the significantly different characteristics of urban land use. Any land use classified as urban was set as a singular urban functional unit, regardless of underlying soils or geology. In addition, no area was excluded. The nitrogen attenuation category in each functional unit was only used to develop the constituent filter model and was ignored in the parameterisation of the rainfall-runoff model. This resulted in 3,996 functional units across the catchment.

4.2.2 Flow Model Parameterisation

A lumped conceptual rainfall-runoff model, SIMHYD available in SOURCE, was used to model different water flow components (surface runoff, interflow, and percolation to groundwater) from the soil profile. SIMHYD is a mass balance model that is based on conceptual relationships between different hydrological processes and estimates daily stream flow from daily rainfall and potential evapotranspiration data (Singh et al., 2009). The model contains three water stores, for interception loss, soil moisture, and groundwater, and estimates runoff generation from three processes - infiltration excess runoff, interflow (and saturation excess runoff), and baseflow (Figure 13).

SIMHYD operates by rainfall first filling the interception store, which is emptied by evaporation. An infiltration function then determines the infiltration capacity. The rainfall that exceeds the infiltration capacity becomes infiltration excess runoff. Next, a soil moisture function diverts the infiltrated water to the river (as saturation excess runoff/interflow), groundwater store (as recharge), and soil moisture store. Interflow and groundwater recharge are estimated as a linear function of the soil wetness (soil moisture level divided by soil moisture capacity). In this process, interflow also represents saturation excess runoff processes. The remaining moisture flows into the soil moisture store. Evapotranspiration from the soil moisture store is estimated as a linear function of the soil wetness but cannot exceed the atmospherically controlled rate of potential evapotranspiration. The soil moisture store has a finite capacity and overflows into the groundwater store. Baseflow is simulated as a linear regression from the groundwater store. The equations governing these processes are explained by eWater (2018) and a schematic diagram of the structure of SIMHYD showing the interaction between parameters is presented in Figure 13.

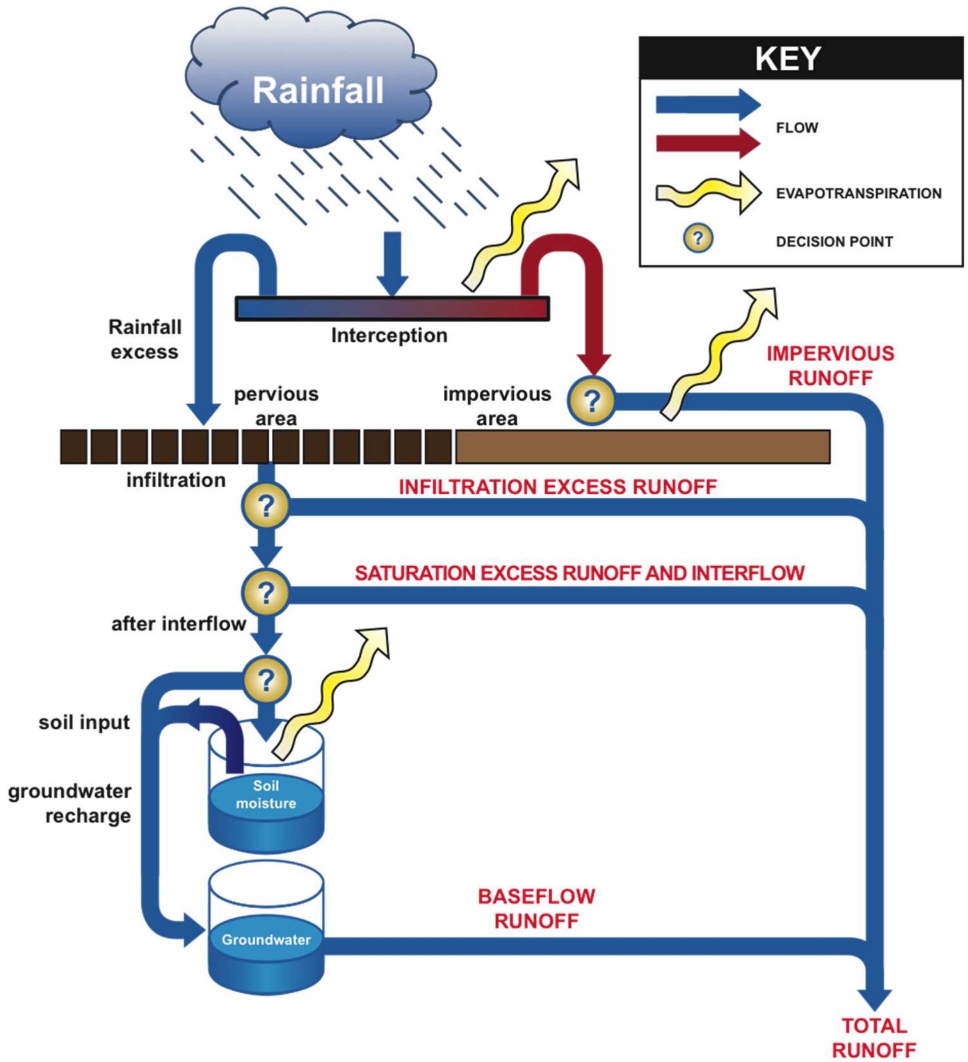

Figure 13. SIMHYD structure (eWater, 2018).

Table 9 details the definition of each SIMHYD input parameter and its relationship with the catchment physical characteristics. As explained in Section 4.1, the catchment's physical characteristics were used to make informed decisions regarding the initial parameterisation of flow. Different parameter values were assigned for each functional unit and sub-catchment. A range was defined for each parameter in each sub-catchment which set boundaries for the parameter's calibration based on the associated catchment characteristics (Appendix E). During the calibration process, the parameters were adjusted within this range, which allowed a consistent relationship between the model parameters and the physical characteristics of the functional unit to be maintained. Understanding the operation of SIMHYD and the hydrological cycle was important to be able to combine it with Overseer.

Table 9. SIMHYD parameter description and determination.

<table>
<tr><th>Parameter</th><th>Description</th></tr>
<tr><td>Baseflow coefficient</td><td>An increase in baseflow is derivative of the baseflow coefficient with respect to precipitation (Vaze et al., 2012). The baseflow coefficient was parameterised based on geological units’ permeability, where low permeability rock was assigned a lower baseflow coefficient.</td></tr>
<tr><td>Perv. Fraction</td><td>Refers to the portion of catchment that is pervious and is not directly linked to drainage systems (Chiew & Siriwardena, 2005). Values were selected with regard to land use. Urban areas were given low values of between 60 and 70%, and agricultural and forest areas were given high values of 98-100% (Freebairn et al., 2015).</td></tr>
<tr><td>Impervious Threshold</td><td>This is the surface water depth of the impervious fraction. It influences the amount of pervious surface ponding. Urban was assigned higher values than agricultural and forestry land uses.</td></tr>
<tr><td>Infiltration coefficient</td><td rowspan="2">The model uses the infiltration coefficient in combination with the infiltration shape and soil moisture storage capacity (SMSC) to calculate the actual infiltration rate, which regulates the volume of water entering the soil and the resulting surface runoff (Singh et al., 2009). D. Horne (personal communication, 2021) provided values for the infiltration rate for each soil group. While land use does have an impact on infiltration, with dairy generally having a lower infiltration rate than sheep and beef due to pugging, the effect of land use was excluded to simplify the model. The coefficient and shape values were derived from the infiltration rates using the equation:
Infiltration rate = Perv. Fraction * Infiltration coeff. * exp (-Infiltration Shape * SMSC)</td></tr>
<tr><td>Infiltration shape</td></tr>
<tr><td>Interflow coefficient</td><td>Interflow is the lateral movement of infiltrated water in the vadose zone. In the SIMHYD model, interflow is estimated as a linear function of soil moisture level divided by soil moisture capacity (Singh et al., 2009). This captures the effects of both interflow and saturation excess runoff processes. Interflow was predominately based on underlying geology with low permeability rock given a high interflow coefficient. High interflow coefficients were also given for fine-textured soils on dairy land use, regardless of the underlying geology. This was to account for the likelihood of artificial drainage in fine textured soils under dairy land use, which reduces flow to groundwater.</td></tr>
</table>

Parameter	Description
Rainfall interception store capacity (RISC)	Defines the storage capacity of rainfall intercepted by the overhead canopy or vegetation which does not reach the soil zone. It is related to the canopy area. RISC was parameterised with regard to land use, with forest receiving higher values than dairy and sheep and beef. Literature states that typical values for forest are 2mm and grasses 1mm (Rowe, 2002).
Recharge coefficient	Proportion of effective rainfall that can potentially become recharge to groundwater (eWater, 2018). High recharge coefficients were assigned to highly permeable rocks, while low permeability rocks and fine-textured soils were assigned low recharge coefficients.
Soil moisture store capacity (SMSC)	The size of the soil moisture store in terms of depth of water. SMSC was parameterised by estimates provided by D. Horne (personal communication, 2021). D. Horne derived these values using the relationship between plant available water and rooting depth for different soil groups.

4.2.3 Flow Model Routing

SOURCE has three types of streamflow routing available. Straight through and lagged flow routing both do not consider flow attenuation, while storage routing does (eWater, 2018). Flow attenuation is important as the change in response in sub-soil drainage as water moves through the vadose zone affects the temporal pattern of nitrogen delivery to the groundwater. Therefore, storage routing was used in the model.

Storage routing uses the Muskingum method to transpose the flow temporally (eWater, 2018). This is a lumped kinematic approach based on mass conservation and the assumption of monotonic relationships between storage and discharge in a link (United States Department of Agriculture, 2014). It is a simplification of the full momentum equation and assumes that diffusion and dynamic effects are negligible. The method uses index flow in flux, and storage and mass balance equations. A weighting factor is used to adjust the bias between inflow and outflow rate, allowing for attenuation of flow (eWater, 2018).

Inputs to parameterise the routing include depth to groundwater, vertical hydraulic conductivity, and extinction depth. Larger depth to groundwater and lower vertical hydraulic conductivity increases vadose zone travel times (Elwan, 2018). In this study, the default values specified by SOURCE were used, which required supplying the DEM and selecting the most appropriate soil texture, ground cover, and geological unit for each sub-catchment.

In order to generate a rating curve for the river stage, the cross-section editor in SOURCE was used to specify the physical cross-section of each river section. The cross-section, in conjunction with Manning's equation, was used to calculate the relationship between discharge and water level. A Manning's n of between 0.03 and 0.05 for each cross-section was used, based on typical New Zealand river conditions and analysis of aerial imagery (Hicks & Mason, 1991).

Using QGIS, river cross-sections were extracted from the DEM at regularly spaced intervals, ensuring that each reach's geometry was represented by several points. This process involved generating a polyline perpendicular to the river channel and interpolating points along the line using the geoprocessing tool. The elevation at the point locations and the lowest elevation along the profile was then extracted to form the cross-section profile. To calculate the channel slope at each cross-section, a k-nearest neighbour search was performed on each polyline's centre point, and then the average slope was taken. The code used to process the data is presented in Appendix F. The accuracy of this process could have been improved using LiDAR or a higher resolution and hydrologically corrected DEM.

4.2.4 Model Assumptions

A number of assumptions were made during the model development where insufficient data was available or where simplifications were required to streamline model development.

The effect of consented and permitted water takes, permitted wastewater discharge activities, and irrigation on river flow are not considered. However, the calibration to the measured river flow data means the model parameters are adjusted to represent these water takes and discharges in the river flow simulations across the sub-catchments. The majority of water takes are small (less than the cumulative allocation limit of 2.34 m^3/s at Manawatū at Upper Gorge). While in some sub-catchments the abstraction consents and permitted takes may have a large impact during low flows, the overall significance of their exclusion is considered low, and likely has less impact than the assumptions that would be required to include the actual use of the consented and permitted takes without requisite information available.

Due to averaging, discrete features of soil, land use, and geology are not modelled explicitly. However, they are encapsulated by averaging and a small area change will not impact the results given the overall scale of the model.

In terms of the routing applied to streamflow, it is assumed that the friction slope is approximately equal to the bed slope, the flow velocity is uniform, the water surface is horizontal across any section perpendicular to the longitudinal flow axis, and flows are gradually varying (eWater, 2018).

4.2.5 Flow Model Calibration and Validation

The SOURCE model was calibrated and validated by comparing the simulated daily flows with the measured daily flow records at 10 sites in the Tararua Catchment (Figure 9). The available measured flow records were divided into two datasets; (1) from 1999 to 2007 used for the model calibration, and (2) from 2008 to 2015 used for the model validation. All sub-catchments were calibrated and validated due to the Manawatū at Upper Gorge flow recording site being downstream of all sub-catchments.

The model was calibrated to the measured flow data via a two-stage process. A combination of automatic calibration via the inbuilt calibration wizard and manual calibration was used. All catchments were calibrated due to the Manawatū at Upper Gorge gauge being downstream of all catchments.

The calibration wizard allows meta-parameters (multiple model parameters grouped together) to be defined. This reduces the number of independent model parameters that need to be calibrated. Each unique functional unit across the sub-catchments was set as a meta-parameter group, and maximum and minimum values were defined for each group. All parameters were calibrated between their given range (Appendix E). Nash-Sutcliffe efficiency (NSE) log daily and absolute bias (Section 4.4.1) were chosen as the objective functions, which the calibration seeks to maximise or minimise. These functions were chosen as the combination of these statistical measures ensure that the model is calibrated for timing of streamflow events (NSE) while achieving a low bias in the total streamflow (absolute bias). Both objective functions were assigned a weighting of one, meaning the calibration aims to improve them both equally. The Shuffled Complex Evolution (SCE), a global optimiser that learns the parameter set for calibration from previous runs, was used to calibrate the model (Duan et al., 1992). The SCE algorithm selects a number of sets of metaparameter values at random and groups these into complexes, which are shuffled and randomly redistributed. The evolution is competitive because although there is a random selection, the metaparameter sets that return better values of the objective function receive higher weighting in the selection process and are therefore more likely to be selected. The default values for Q (the number of metaparameter sets that are selected at random from within each complex to form the parents for the evolution process), P (the number of complexes to be run), M (the number of sets of metaparameters in each complex), α (the number of times that mutation of parameter sets should be attempted), and β (the number of new offspring that should be generated within each complex) were used.

Once an acceptable level of automatic calibration was reached, manual calibration was performed to further improve model performance. The manual calibration allowed slight adjustments of parameters within a meta-parameter group to account for variation in physical characteristics only defined by sub-catchment delineation, such as topography and slope. The manual calibration for each gauge occurred individually, moving from upstream to downstream gauges, and involved iteratively adjusting and fixing the parameters until the highest level of flow calibration that could practically be achieved was produced. Using manual calibration allowed the model's performance to be considered against a broader range of model performance evaluation criteria than the calibration wizard allowed. For example, after analysis of the water balance, changes to the interception parameter were made to ensure the absolute losses through interception were in line with literature values. As the purpose of the integrated modelling development is to model nitrogen transport to waterways, which is dominated by sub-surface flow, a higher weighting was placed on statistics that emphasise low flows rather than runoff events. Values were only adjusted within the initially defined range to ensure the physical representation and validity of parameters (Vaze et al., 2012). This is important due to model parsimony, and the related problems of model equifinality, which means that more than one combination of parameter values will result in a good calibration, but not all combinations will necessarily be realistic or valid (Vaze et al., 2012).

The model validation was undertaken to confirm that the model calibration was acceptable for the intended purpose and that it produces reliable results (Refsgaard & Henriksen, 2004). The split sample test was used where the available flow records were split into two parts. The model was calibrated using the flow records from 1999-2007 and the model was validated against the flow records from 2008-2015. The model's calibration and validation performance were quantified using the statistical performance measures defined and described in Section 4.4. The final input parameters used in the model are presented in Appendix E.

4.3 Models Integration – Nitrogen Model Set-up

This section details how the root zone nitrate losses estimated from Overseer were integrated with the SIMHYD simulated quick flow (surface runoff and interflow) and slow flow (groundwater) pathways in SOURCE. The model integration aimed to simulate average monthly and average annual river DIN loads in the study sub-catchments.

The farm-scale Overseer model was integrated into the SOURCE model to provide the root zone nitrate loads. While SOURCE has inbuilt nutrient generation models, these are primarily simple empirical models and are not directly linked to farm management processes (eWater, 2018). In contrast, Overseer models farm management and physical characteristics, making it more beneficial to use. There are various options to integrate Overseer within SOURCE. One method is to develop a custom plugin to the SOURCE framework to represent Overseer processes. However, this is technically difficult and requires access to the Overseer source code. Another method uses the constituent configuration model in SOURCE, which applies either EMC/DWC values, a known concentration, function or rating curve to model nitrogen (eWater, 2018).

In this study, the known concentration component available in SOURCE was used, in which a monthly average nitrate concentration time series was applied to the quick flow (surface runoff and interflow) and slow flow (baseflow) components of each functional unit in the model.

The smallest time-step Overseer can be run on is monthly. Therefore, the SOURCE model was run on a monthly time-step for the representative climate year 2010. When reading in the concentration time series from Overseer, SOURCE assumes that the measurements were made at the first instant of the month and that each measurement stands for the whole month (eWater, 2018). SOURCE does not interpolate between adjacent observations or otherwise attempt to calculate mean data or moving averages. Regarding moving the flow time-step from daily to monthly, SOURCE averages the smaller time-step for the month (eWater, 2018).

4.3.1 Overseer and Nutrient generation

The Overseer estimates of rootzone nitrogen (predominantly nitrate) losses were integrated using a look-up table approach with SOURCE to predict river DIN loads across the sub-catchments. To identify nitrate leaching from the rootzone, Overseer models were constructed by D. Horne (Personal communication, 2021) for a 'typical' farm, for each combination of climate (rainfall regimes), land use (dairy and sheep and beef), and soil types (fine textured, intermediate textured, coarse textured and stony soils) across the sub-catchments. Numerous sources of information were consulted to glean data and information to help identify the most appropriate stocking rate and performance level for each of these farms. Other inputs to Overseer were selected to reflect a typical farm. The features of farm performance, farm management and predictions of nitrate leaching were 'sense checked' by comparison with a large set of Overseer files for actual dairy farms in the study area. While the notion of a typical farm has some obvious limitations in simulations of nitrate leaching from farms at the sub-catchment level, the inputs listed above are the key drivers of nitrate leaching from farms, including the magnitude of Overseer's values, and so in setting these for each of the combinations, a degree of confidence can be attached to the relative ranking of nitrate losses from the different functional units.

To limit the number of models that need to be constructed, only high, medium, and low rainfall regimes were modelled, which required each sub-catchment to be assigned a classification. The method for this was detailed in Section 4.1.2. Overseer models were constructed for the average climatic conditions using the climatic data for year 2010 (Section 4.1.2).

The variability of DIN concentrations from month to month was examined (Appendix A). This was used to determine whether the SOURCE model should be run on an annual or monthly time-step. This analysis also enabled the variation of DIN across each month and year to be assessed and any significant anomalies identified. Given the considerable variation between summer and winter DIN concentrations over most of the sites, it was clear that a monthly time-step was needed.

Models were created by D. Horne (Personal communication, 2021) for all dairy combinations and sheep and beef combinations that made up greater than 5% of the total agricultural (dairy, and sheep and beef) area. For the sheep and beef Overseer models, the coarse textured and stony soil categories were combined, and the intermediate textured and fine textured soil categories were combined to limit the number of models that needed to be developed.

Forest loads were assumed an average load of 2 kg N/ha/yr, split evenly throughout the months. While it is expected there would be temporal variation, the negligible leaching from forest means it will have minimal impact on the model.

Nitrogen (DIN) loads for urban land use were applied by using the measured data. Horizons Regional Council provided monthly flow volumes and DIN concentrations for municipal and wastewater discharges throughout the Tararua Catchment. Using the flow weighted method described in Section 4.1.1.2, a monthly average DIN load was calculated for the wastewater discharges from the urban area. The calculated annual average DIN loads for the point sources are presented in Appendix G. These measured DIN loads were applied to the model using a constituent inflow node in the corresponding sub-catchment. It is assumed that the DIN produced in urban areas, not accounted for by point sources, is minimal. Consequently, any diffuse DIN losses from urban areas were not modelled in Overseer and point source discharges were applied to SOURCE separately.

4.3.2 Water Balance Comparison

The first step in the integration of Overseer and SOURCE was to evaluate the different water balance components simulated by the models. It was essential to determine which flow outputs were comparable. Firstly, it needed to be understood what flow components of SIMHYD, are referred to by SOURCE as quick flow and slow flow (when added together quick flow and slow flow equal total flow). After extensive analysis, it was determined that quick flow simulated in SOURCE was equivalent to the output of attenuated surface runoff or interflow, infiltration excess run-off, and impervious runoff combined from the SIMHYD model. Therefore, quick flow represents surface runoff, lateral movement, and artificial drainage flow pathways. The slow flow simulated in SOURCE was equivalent to baseflow discharges from the SIMHYD model and represents groundwater (base) flow pathway. Drainage from

Overseer is comparable to percolation to groundwater in SIMHYD, while runoff and artificial drainage in Overseer are considered comparable to infiltration excess runoff and interflow, respectively in SIMHYD. An important distinction to note is that saturation excess runoff (overflow of the soil moisture store) is modelled in conjunction with interflow in SIMHYD. This effectively means that interflow in SIMHYD includes a component of what is generally considered part of overland flow along with infiltration excess run-off. However, this distinction is mainly conceptual and is expected to have limited bearing on the results of the model.

The water balance from Overseer and SIMHYD was compared on an annual average basis, with a focus on the drainage component. This was to determine whether the Overseer estimated nitrate losses could be exported as concentrations and directly imported into SOURCE or whether post-processing of the results would be required. It was observed that in many sub-catchments, there was no runoff modelled in Overseer. This appeared to be an artefact of the model that was unable to be overcome and has the effect of poorly representing overland nitrate losses (D. Horne, personal communication 2021). Both Overseer and SIMHYD produced higher groundwater percolation annually in stony and coarse-textured soils than in intermediate and fine-textured soils. However, upon analysis of the monthly water balance, it became clear that Overseer estimated no drainage or nitrate losses occurred between October and May. In contrast, SIMHYD simulated percolation to groundwater as occurring year-round, albeit less in summer Figure 14 14). One explanation for this is that percolation to groundwater from SIMHYD and drainage from Overseer are not directly comparable, as they occur at different depths. SIMHYD represents the movement of water arriving at groundwater which the model assumes is at depth. Since the SMSC represents a 1m soil profile in the model, there is continued arrival of soil water at the interface to groundwater due to the long residence time (Section 4.1.1.2). In contrast, Overseer simulates the drainage from the soil root zone (~ 60 cm), but not deeper groundwater percolation. Another explanation is that SIMHYD potentially simulates percolation to groundwater as two components, direct groundwater recharge and saturation excess groundwater recharge (Singh et al., 2009). In contrast, Overseer only simulates saturation excess drainage, which should be the case in soils without cracks (Wheeler, 2016). To test this theory, the direct groundwater recharge was turned off in SIMHYD by setting the recharge coefficient parameter to zero. This impacted the water balance outputs by slightly reducing annual groundwater percolation and increasing soil evaporation. It also caused groundwater percolation to reach zero in eight out of nine years. However, the model was recalibrated using a small recharge coefficient in the range of 0 to 0.20 to allow groundwater percolation to occur each day but with smaller flows in summer as expected in the field conditions.

Overseer simulates the leaching of nitrate to the bottom of the root zone (~ 60 cm soil profile) (Wheeler, 2016). However, before nitrate leaches from the soil zone and enters groundwater, it travels through the vadose zone where the mass is temporally transposed (Bouraoui & Grizzetti, 2014). SIMHYD simulates groundwater transport of flow, including travel through the vadose zone, horizontal saturated groundwater flow, and vertical percolation to groundwater (eWater, 2018). As SOURCE simulates nitrogen and flow independently and attaches nitrogen to the model flow after it has been simulated, the nitrogen does not follow through the same routing process. This means it needs to be routed and mixed with groundwater before being applied to SOURCE. This distinction is made clear in Figure 14, which shows SIMHYD simulated percolation to groundwater (closely matched to Overseer drainage and flow in which nutrient loads is exported) and slow flow (the model baseflow which discharge nutrient loads to receiving waters).

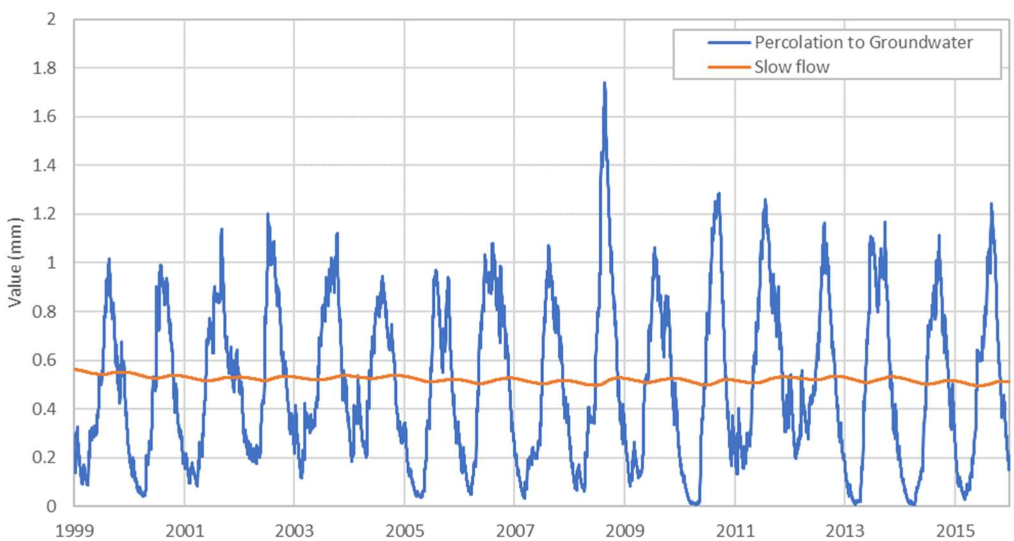

Figure 14. A comparison of percolation to groundwater and slow flow simulated by SIMHYD model in SOURCE.

4.3.3 Application of Overseer Outputs to Quick flow and Slow flow

The Overseer outputs were applied as nitrogen concentrations to the quick flow and slow flow components in SOURCE. However, Overseer does not distinguish between surface runoff and groundwater leaching transport pathways and instead estimates nitrogen losses from the soil profile. Therefore, in order to integrate the Overseer results into SOURCE, a nitrogen concentration calculation models was developed, described as follows.

Annual average nitrate loads from Overseer were used to integrate with the SOURCE model. It is assumed that the nitrate loads are perfectly mixed in all flow pathways (except for surface runoff) throughout the year. Percolation to groundwater was used rather than slow flow to generate slow flow nitrate concentrations to better represent the seasonal nature of soil drainage and baseflow to the river. While this method compromises the monthly variation in the Overseer estimates, this variation is potentially less important than the water flow pathways given the scale of analysis.

Firstly, the annual mean nitrate concentration of soil drainage (interflow + groundwater percolation) was calculated by dividing the average annual nitrate load with the annual drainage (interflow + groundwater percolation) from the soil profile. Then, for quick flow, the calculated mean annual drainage nitrate concentration was multiplied by the interflow for each month to give the interflow load, which was subsequently divided by the quick flow for the month to give the quick flow nitrate concentration for each month (Equation 5). For slow flow, the calculated annual mean drainage concentration was multiplied by the percolation to groundwater and then divided by the slow flow for each month to give the slow flow concentration (Equation 6). This method meant both quick flow and slow flow nitrate concentrations were generated for each month.

$$QF_{ci} = m\frac{\frac{N}{(P+IF)} * IF_i}{QF_i} \tag{5}$$

$$SF_{ci} = m\frac{\frac{N}{(P+IF)} * P_i}{SF_i} \tag{6}$$

where:

m = Unit conversion factor;

N = Annual average nitrate load from Overseer (kg/ha/yr);

Q_i = Flow at ith month (mm);

SF_i = Slow flow at ith month (mm);

QF_{ci} = Monthly quick flow concentration (g/m^3);

SF_{ci} = Monthly slow flow concentration (g/m^3);

IF = Annual interflow (mm);

IF_i = Interflow at the ith month;

P = Annual percolation to groundwater (mm);

P_i = Percolation to groundwater at ith month (mm); and

QF_i = Quick flow at ith month (mm).

4.3.3.1 Nitrogen Inputs into SOURCE

Overseer estimates of root zone nitrate losses for different combinations of climate, land use and soil types, as described in Section 4.4.1, were assigned to each functional unit in the SOURCE model. The nutrient generation model as described above in Section 4.3.1 was used to calculate the input nitrate concentrations for both quick flow and slow flow from each functional unit and sub-catchment - a total of 3,996 combinations. The python script that was used to calculate this is presented in Appendix H.

This process ensured that the interflow, percolation to groundwater, quick flow and slow flow used in the calculation of nitrate concentration were specific to each functional unit and sub-catchment. It also ensured that the effect of topography and geology, which was not accounted for in the Overseer outputs was incorporated into the model. Finally, the calculated mean nitrate concentration values were applied to the known concentration component in SOURCE by using a function. The pattern variable specified the monthly quick flow and slow flow nitrate concentration for each functional unit, while the function specified a lookup of the month of the model simulation and applied the corresponding value in the pattern variable.

4.3.4 Nitrogen Attenuation Factor

Nitrate can be attenuated in the subsurface environment between leaving the root zone and entering surface water by biogeochemical transformations and various biological growth-related uptakes. These processes include dissimilatory NO_3^- reduction to NH_4^+, assimilation of NO_3^- into microbial biomass, NO_3^- uptake through phreatophytes, and denitrification (Cameron et al., 2013). As explained in Section 2.2.4, many factors influence spatially variable nitrogen attenuation, including the hydrogeochemical settings of the subsurface environment (Elwan et al., 2015; Follett, 2008; Jahangir et al., 2012).

A common approach in catchment nutrient accounting is to apply an attenuation factor to reduce the nitrogen load simulated at the sub-soil interface to match the nitrogen load measured at the catchment outlet (Elwan et al., 2015; Parliamentary Commissioner for the Environment, 2018; Snelder et al., 2020). This represents a simplification of the total biogeochemical transformations of nitrogen which occurs in flow pathways but is a practical solution to account for nitrogen attenuation in catchment-scale modelling while managing complexity.

The in-built constituent filtering model in SOURCE was used to capture the effect of nitrogen attenuation on simulation of in-stream nitrogen concentrations and loads. Filtering models represent the transformation of constituents between generation of the nutrient and arrival at the sub-catchment link (river). These processes and practices are not represented explicitly but are combined and empirically represented by the filter model. The model removes a specified percentage of nitrogen loads in slow flow and/or quick flow for each functional unit, defined as the nitrogen attenuation factor. The attenuation factor can be defined as the quantification of the total attenuation capacity, the percentage of nitrogen leached from the root zone that is reduced, or the difference between the root zone nitrate losses and measured DIN loads in the river (Elwan et al., 2015). The attenuation factor varies from 0 (i.e., no attenuation) to 1 (i.e., 100% attenuation). It is important that nitrogen leaching from the farm root zone and the nitrogen loads measured in the river are quantified on an average annual basis to remove any effects of time lags and changes in nitrogen storage in the system, when calculating the attenuation factor (Elwan et al., 2015).

The measured annual average river DIN loads that the integrated model was calibrated to, were calculated using the long-term daily river flow (from 1975 to 2020) and monthly DIN concentration (from 1989 to 2020). Morgenstern et al. (2017) established that the mean residence time of surface water during low flows ranges from less than 12 months through to 11 years in the Tararua Catchment, depending on the geology. Water in the Mangatainoka River can be less than a year old as it moves quickly through shallow gravel strata. In contrast, to the east of the Ruahine Range, the mean residence time can be more than 11 years as mudstone and siltstone slow the passage of water (Morgenstern et al., 2017). As the annual average river DIN load used in the model was calculated for a period 20 years longer than the estimate of mean residence time, the system is considered in a state of equilibrium, which justifies the calculation and application of the nitrogen attenuation factor, described as follows:

In this study, three approaches were used to apply an attenuation factor to the simulated nitrogen loads. Firstly, a uniform factor of 0.55 was applied to the filter model. This was determined by calculating the nitrogen attenuation needed at the catchment outlet (Manawatū at Upper Gorge) and applying it uniformly to all functional units. The attenuation factor was applied to both slow flow and quick flow. The method for this is detailed in Equation 7.

$$AF = \frac{Rootzone\ N\ losses - River\ DIN\ load}{Rootzone\ N\ load} \tag{7}$$

This approach was used by (Snelder et al., 2020). However, research by Elwan (2018) determined that nitrogen attenuation is spatially variable and is related to soil and geological characteristics.

Building upon the research from Elwan (2018), who assessed the spatial variability of subsurface nitrogen attenuation on an annual average basis using an empirical model, a second approach was used where the attenuation factor was applied on a functional unit basis rather than the common approach of applying a uniform factor or a factor to each sub-catchment. The use of the percentage filter model in SOURCE allowed a variable attenuation factor based on the functional unit to be set using equations. The attenuation classification of high, medium, and low capacity was included in each functional unit as described in Section 4.1.8. In this approach, the attenuation factor was only applied to slow flow, with the reasoning being that the majority of nitrogen attenuation occurs in the sub-soil environment.

The nitrogen attenuation factors for each attenuation categories were calibrated using the measured river nitrogen loads (Section 4.1.1). Estimates of the initial ranges given for the nitrogen attenuation factor are provided in Table 10, and the final calibration values are given in Section 5.4. The nitrogen attenuation factor was calibrated within the range with the aim of achieving the best possible match between the modelled and measured average monthly DIN loads in the river as evaluated by the criteria in Section 4.4.

Table 10. Initial nitrogen attenuation factor range applied only to slow flow.

Attenuation Class	Attenuation Factor Range
Low	0.1 – 0.30
Medium	0.35 – 0.70
High	0.70 – 0.95

The third approach was to apply different attenuation factors for each flow pathway, where a spatially variable attenuation factor (as in the second approach) was applied to both quick flow and slow flow pathways. The basis for this was that interflow, which is included in quick flow, could be attenuated to a degree. As interflow is only one component of quick flow and is expected to be attenuated less than slow (groundwater) flow, a lower range was provided for the quick flow attenuation factor than for slow flow (Table 11). No attenuation factor was applied to quick flow for dairy fine-textured functional units, as artificial drainage is assumed to occur, meaning that nitrogen attenuation in the interflow will be bypassed. Additionally, no nitrogen attenuation factor was applied to point source nitrogen inputs.

Table 11. Initial nitrogen attenuation factor range when applied to both quick flow and slow flow.

Attenuation Class	Slow Flow Attenuation Factor Range	Quick Flow Attenuation Factor Range
Low	0.1 – 0.30	0.0 – 0.20
Medium	0.35 – 0.70	0.20 – 0.40
High	0.70 – 0.95	0.40 – 0.60

4.3.4.1 In-stream Attenuation

Attenuation of DIN also occurs via in-stream processes, including various biological growth-related uptakes as inorganic forms of nitrogen are converted to organic forms. This can occur through various processes, including nutrient spiralling, uptake of DIN by riparian plants, submerged macrophytes, bacteria and fungi, and the conversion of solutes to particulate organic nutrients (Dodds et al., 2002). The nitrogen assimilation in-stream was modelled using the in-built first-order decay stream processing model in SOURCE (Equation 8). This exponential decay model means that the instream nutrient assimilation rate was directly proportional to the nutrient concentration, and the model could calculate an attenuation rate based on the travel time along each reach and the first-order rate constant. This type of reaction is common in the uptake of nitrogen in the water column as a result of chemical adsorption or biological nutrient uptake (Dodds et al., 2002). The model was parameterised by using the wetted area of the cross-sections for each stream calculated in Section 4.3.2, and default values of 0.6 and 0.5 were used for periphyton cover and nitrogen uptake proportion required to calculate the attenuation co-efficient *k* in the model.

$$C_z = C_0 \left(\frac{d}{t}\right)^{-k} \tag{8}$$

where:

C_z = Final nutrient concentration;

C_0 = Source nutrient concentration;

k = Attenuation coefficient (calculated from input parameters of periphyton cover and nitrogen uptake rate);

d = Reach depth; and

t = Travel time of the reach.

4.3.5 Nitrogen Model Calibration and Validation

The calibration process for nitrogen model involved using the calibrated hydrology model in SOURCE to iteratively adjust the attenuation factor for each functional unit to minimise the objective function between the modelled and measured average monthly DIN loads in the river. No calibration occurred for the model run with no attenuation factor, or a uniform attenuation factor application.

The spatially variable attenuation factor was calibrated within the initial ranges for high, medium, and low attenuation capacity categories (Table 10). At first, the objective function was set to reduce the absolute bias between the average monthly modelled and measured river DIN loads. However, it became clear that achieving a calibration to summer DIN loads would be difficult as the objective function potentially biased the model to match the winter DIN months due to their higher magnitudes. Therefore, the objective function was set to equally weight the measured DIN loads for each month in the calibration process.

The spatially variable attenuation factor applied to both quick flow and slow flow was calibrated within the initial ranges provided in Table 11, using the same equal weighting method at first. However, to reach an optimal calibration, the attenuation of slow flow was calibrated with a weighting of 70% applied to summer/low flow months (between September and March) river DIN loads. The calibrated values of the nitrogen attenuation factor for slow flow were then fixed and the calibration was rerun for quick flow attenuation using an equal weighting for all months. The reasoning for this was that the slow flow nitrate load dominates during spring and summer months (September to March) so ensuring a good calibration for these months helped to separate the potential correlation effects of both quick flow and slow flow attenuation calibration during the autumn and winter months (April to August).

The calibration of in-stream uptake was minimal. Singh et al. (2017) developed a simple model to estimate the potential DIN uptake by periphyton in streams and rivers. Using the Singh et al. (2017) model, Elwan (2018) estimated that potential in-stream nitrogen uptake accounted for a maximum of

3.1% of the estimates of root zone nitrate losses in the Tararua Catchment, suggesting in-stream attenuation is insignificant compared to river DIN load. This is in contrast to Dodds et al. (2002) who considered in-stream attenuation to be important to account for during baseflow periods. Given the high level of uncertainty in the parameterisation of the in-stream model and lack of input data, once the outputs were checked for sensibility and that they were within a similar range of instream attenuation as estimated by Elwan (2018), no further calibration occurred for in-stream uptake. Rather, the nitrogen model calibration focussed on calibration of the attenuation factor for different functional units. This was considered acceptable as the nitrogen attenuation losses resulting from the in-stream attenuation only represented a minor proportion of the total river DIN loads. In addition, referring to Figure 2, this approach is likely to have the best predictive power, given the balance between complexity and data availability.

4.4 Model Evaluation Criteria

This section describes the range of approaches used to assess how well the simulated flow and river DIN loads match the observed measurements.

Flow hydrographs, constituent time series, and flow duration curves (FDC) were used to provide a visual means of assessing the model's calibration and validation. Hydrographs and nitrogen load time series were used to subjectively evaluate the magnitude, systematic deviations (over or under-prediction), and dynamic behaviour (temporal variations, timing, shape, rising limb, falling limb, and baseflow) of the model on a daily or monthly basis (Vaze et al., 2012). FDCs show the percentage of time that flow of a certain magnitude is likely to be exceeded on a long-term basis; this allows any differences in the frequency distribution of modelled and measured flows to be readily identified (Moriasi et al., 2015). Statistical performance measures allow the model performance to be quantified numerically and provide an objective measure to assess the ability of a model to predict nominated variables accurately. The methods presented below were utilised during the model calibration phase, with the aim of producing a good agreement to each of them, recognising that different model performance measures can have different ranges of conditions for which they are best suited.

4.4.1 Statistical Performance Measures

An extensive range of statistical measures are described in the literature (Krause et al., 2005; Moriasi et al., 2007; Moriasi et al., 2015), with the Nash-Sutcliffe efficiency (NSE), coefficient of determination (R^2), root mean square error (RMSE) and percent bias (PBIAS) most frequently used in hydrologic modelling. Each method's suitability depends on a range of factors including, but not limited to, the spatial resolution and the temporal scale of the dataset, the physical characteristics of the variable being simulated, and the statistical distribution of the data (Moriasi et al., 2015). In this study, NSE and PBIAS were selected to assess the model's performance as they can be applied to both flow and water quality and both daily and monthly time-steps.

The quality of observation data was assessed by visual analysis of time-series data looking for systematic or step changes within the data and calculating the number of missing data points in the dataset. The gauges with high-quality observation datasets (all primary monitoring sites, see Section 4.1.1) were given more weight when carrying out model performance evaluations as statistical measures assume that the dataset is error-free and all error variance is contained in the simulation results (Moriasi et al., 2007). For the gauges with lower quality datasets (all secondary monitoring sites), percentile statistics were used as these are a more appropriate measure of model performance when errors or missing data exist (Moriasi et al., 2007).

4.4.1.1 The Nash-Sutcliffe Efficiency Coefficient (NSE) / Model Efficiency (EF)

The Nash-Sutcliffe efficiency (NSE) and Model efficiency (EF) are both normalised statistics that determine the relative magnitude of the residual variance compared to the measured data variance and estimate the error relative to the natural variability of the measured values (Nash & Sutcliffe, 1970). NSE and EF are single index values that can range from $-\infty$ to 1, with a value of 1 indicating a perfect match between the modelled and measured data (McCuen et al., 2006). A value of zero represents a prediction no better than the random variation in the observed data, and increasingly negative values indicate increasingly poorer predictions. NSE is a robust performance measure that is suitable to use for both flow and nitrogen to assess the match between measured and modelled data (Moriasi et al., 2007). However, it cannot be used to help identify model bias.

The model efficiency is calculated using Equation 10, while NSE is calculated in Equation 11.

$$EF = \frac{\sum_{i=1}^{n}(O_i - \overline{O})^2 - \sum_{i=1}^{n}(S_i - O_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \tag{10}$$

$$NSE = 1 - \frac{\sum_{i=1}^{\mathrm{n}}(O_i - S_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \tag{11}$$

where:

N = Number of observations;

S_i = Simulated (modelled) variable (daily flow or average monthly DIN loads) at the *i*th site;

O_i = Observed (measured) variable (daily flow or average monthly DIN loads) at the *i*th site; and

$\bar{O}$ = Mean of the measured variable (daily flow or average monthly DIN loads) at the *i*th site.

The NSE is affected by many factors, including sample size, outliers, and bias (McCuen et al., 2006). The largest disadvantage of the NSE is the calculation of the difference between modelled and measured values as square values, which places emphasis on large errors. Large errors tend to be associated with high streamflow values, which can lead to neglection of the baseflow calibration. To overcome NSE sensitivity to extreme values, a logarithmic transformation can be used (Krause et al., 2005) (Equation 12). Based on the recommendations in Moriasi et al. (2007), the log-transformed NSE was selected as the most appropriate and NSE from here on in refers to the log-transformed equation. Table 12 presents the classification of NSE for flow and nitrogen model performance. Different performance criteria are used for flow and nitrogen with the criteria for flow being stricter due to less uncertainty in the observation data measurements and that more observed data is available (Moriasi et al. 2015).

$$NSE = 1 - \frac{\sum_{i=1}^{\mathrm{n}}(\ln O_i - \ln S_i)^2}{\sum_{i=1}^{n}(\ln O_i - \ln \bar{O})^2} \tag{12}$$

Table 12. Performance evaluation criteria for Nash-Sutcliffe efficiency (Moriasi et al. 2015).

Measured	**Temporal Scale**	**Very good**	**Good**	**Satisfactory**	**Not Satisfactory**
Flow	Daily/ Monthly/ Annual	NSE>0.80	0.70< NSE ≤ 0.80	0.5 < NSE ≤ 0.70	NSE ≤ 0.50
Nitrogen	Monthly	NSE>0.65	0.50< NSE ≤ 0.65	0.35 < NSE ≤ 0.50	NSE ≤ 0.35

However, the log-transformed version of NSE does not remove the influence of sample size (McCuen et al., 2006). The impact of sample size is well-recorded across the literature, but very limited research identified a suitable sample size (Krause et al., 2005; Moriasi et al., 2015). Therefore, an analysis using a stochastic approach was undertaken to test the impact of sample size on NSE. This involved randomly selecting 500 sample populations of the same number of unique data points. The NSE was calculated for each sample realisation. This procedure was repeated for incrementally increasing sample sizes, and the mean and standard deviation of the 500 NSE outputs were assessed. This found that with increasing sample size, the standard deviation of the NSE outputs decreases, as shown in Figure 15 (i.e., the randomness of the dates selected is overcome by population size). At samples with approximately 200 data points, there was no significant change in statistical measures, indicating that increasing the population size will not necessarily improve the statistical results, ceteris paribus. Therefore, caution is advised when using NSE with flow gauge sites with less than 200 data points. This also indicates the disadvantage of only running integrated Overseer and SOURCE models for an average climatic year, as it means there is a lack of sufficient data points to calibrate and validate the model for its simulations of average monthly river DIN loads. In this study, a total of 9 water quality monitoring sites were used, providing 96 data points for calibration of the average monthly river DIN loads.

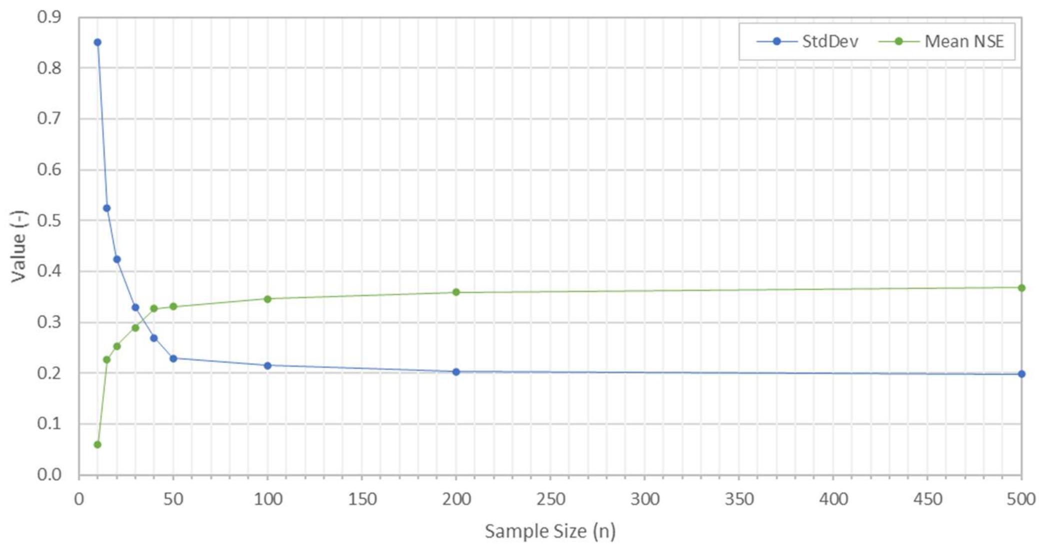

Figure 15. Impact of sample size on Nash-Sutcliffe efficiency.

4.4.1.2 Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is a measure of the deviations of a model. Residuals are a measure of how far from the regression line data points are. This means RMSE can measure of how spread out these residuals are using Euclidean distance or how concentrated the data is around the line of best fit (Krause et al., 2005).

The RMSE (Equation 15) is a measure of error of the squared differences between modelled and measured values, and lower values suggest a better model performance (Moriasi et al., 2015). However, RMSE does not account for the relative size and nature of the error.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(S_i - O_i)^2} \tag{15}$$

4.4.1.3 Percent Bias (PBIAS) / Coefficient of Mass Residual (CRM)

PBIAS measures the tendency of a model to predict larger or smaller values compared to corresponding measured data points and evaluates the relative size and nature of the error (Moriasi et al., 2015). It evaluates whether the deviations are systemically positive or negative. PBIAS is reported as a percentage, and values can range from -∞ to ∞, with the optimal value being zero. A positive PBIAS value indicates the model has a bias towards under-estimating the modelled variable, while a negative value indicates the model is biased towards over-estimating the modelled variable. PBIAS is calculated using the formula outlined in Equation 13. The removal of outliers is required for sample populations where the relative standard error (RSE) is greater than 10% (Moriasi et al., 2015). This is equivalent to the coefficient of mass residual (CRM)*100. PBIAS can give a deceiving rating of model performance if the model overpredicts as much as it underpredicts, in which case PBIAS will be close to zero even though the model simulation is poor. Therefore, it is recommended that PBIAS be used with other statistical measures to evaluate model performance. Table 13 presents the classification of PBIAS for flow and nitrogen model performance. Similar to NSE, the criteria for flow is stricter than for nitrogen.

$$PBIAS = \frac{\sum_{i=1}^{n}(O_i - S_i) * 100}{\sum_{i=1}^{n} O_i} \tag{13}$$

Table 13. Performance evaluation criteria for Percent Bias [%] (Moriasi et al. 2015).

Measured	**Temporal Scale**	**Very good**	**Good**	**Satisfactory**	**Not Satisfactory**
Flow	Daily/ Monthly/ Annual	PBIAS < ±5	±5 ≤ PBIAS < ±10	±10 ≤ PBIAS < ±15	PBIAS ≥ ±15
Nitrogen	Monthly	PBIAS < ±25	±25 ≤ PBIAS < ±40	±40 ≤ PBIAS < ±70	PBIAS ≥ ±70

4.4.1.4 Coefficient of Determination (R^2) / Pearson's Correlation Coefficient (r)

Pearson's correlation coefficient (r) and the coefficient of determination (R^2) describe the degree of collinearity between simulated and measured data. The correlation coefficient, which ranges from −1 to 1, is an index of the degree of linearity of the relationship between observed and simulated data. If r equals 0, no linear relationship exists. If r = 1 or −1, a perfect positive or negative linear relationship exists (Krause et al., 2005). The coefficient of determination or R-squared is a statistical measure of how well the regression predictions approximate the real data points. It represents the proportion of the variance for a dependent variable explained by an independent variable in a regression model (Moriasi et al., 2015). An R^2 of 1 indicates that the model explains all the variability of the response data around its mean, indicating less error variance. Although r and R^2 have been widely used for model evaluation, these statistics are oversensitive to high outliers and insensitive to additive and proportional differences between model predictions and measured data (Krause et al., 2005). The formula is presented in Equation 14. This equation also equates to 1 minus the residual sum of squares divided by the total sum of squares.

$$R^2 = \left[\frac{\sum_{i=1}^{n}(O_i - \bar{O})(S_i - \bar{S})}{\sqrt{\sum_{i=1}^{n}(O_i - \bar{O})^2}\sqrt{\sum_{i=1}^{n}(S_i - \bar{S})^2}} \right]^2 \quad (14)$$

4.4.1.5 Slope and Intercept

The slope and y-intercept of the best-fit regression line can also indicate how well modelled data matches measured data. The slope represents the relationship between modelled and measured values, while the y-intercept indicates a lag or lead between model predictions and measured data (Krause et al., 2005). A slope of 1 and y-intercept of 0 indicates a perfect match between measured and modelled data. The slope and y-intercept are commonly examined under the assumption that measured and modelled values are linearly related, which implies that all of the error variance is contained in simulated values and that measured data is error-free (Moriasi et al., 2007).

4.5 Scenario Development

The integrated farm-scale Overseer and catchment-scale SOURCE models were applied to quantify the effect of mitigation practices on DIN loads in the Tararua Catchment. A range of scenarios were developed to evaluate the mitigation practices (Section 2.3). Only a small selection of mitigation practices were modelled due to the difficulty of implementation in SOURCE, and some mitigation practices were simplified to be modelled. The following describes each scenario:

4.5.1 Baseline Scenario

The baseline scenario represents current conditions that were modelled to calibrate the integrated models for predictions of current average monthly river DIN loads in Tararua sub-catchments. This provides a reference to quantify the relative reductions in river DIN loads as effected by different in-field and catchment-scale measures.

4.5.2 In-field Mitigation Practises

There is a wide range of in-field strategies that have the potential to reduce nitrate leaching from the farm root zone. Instead of quantifying effects of various in-field measures on reduction in nitrate leaching from the farm root zone, this analysis grouped the measures to answer the question: If root zone nitrate leaching was reduced by a certain percent, what would be the effect on the overall DIN river loads, accounting for spatially variable potential nitrogen attenuation in different flow pathways? To model this scenario, the root zone nitrate losses from Overseer dairy farms were reduced by 5 – 30% for all nitrogen attenuation categories, 30% for only those farms on low nitrogen attenuation areas and 30% for those on low and medium nitrogen attenuation areas. The model nitrogen calculation was then repeated, and the model run using the calibrated (same as in the baseline scenario) attenuation factor for both quick flow and slow flow pathways. This method with the same reductions was repeated for sheep and beef land use.

4.5.3 Catchment-scale Mitigation Practises

Catchment-scale mitigation practises refers to those that aims to reduce river DIN loads over the whole catchment or a large part of the catchment, rather than on a specific farm.

4.5.3.1 Matching Land use to Nitrogen Attenuation Capacity

This scenario aimed to match intensive land uses with a high potential for nitrogen leaching (dairy) with areas that have a high capacity for nitrogen attenuation in subsurface environment. 5,313 ha of dairy on low attenuation capacity land was switched with 4,968 ha of sheep and beef on high attenuation land in LUC classes 1 – 4, as shown in Table 14. LUC classes 1 – 4 are considered suitable for dairy farming, so switching land use should not result in a considerable loss of production. Previous studies (Menneer et al., 2004; Monaghan, Hedley, et al., 2007) have identified that land use change can significantly reduce nitrogen river loads. Therefore, the area of each land use type within the catchment was kept constant to ensure the change in the amount of nitrogen attenuated rather than land use change was assessed.

Table 14. Area of dairy and sheep and beef land use on high, medium, and low attenuated land.

LUC	Sheep and Beef (ha)			Dairy (ha)		
	Low	Medium	High	Low	Medium	High
1	0	107	1	-	417	-
2	0	10,615	443	0	17,463	835
3	3,460	15,667	972	1,623	12,816	197
4	1,854	6,865	3,545	1,610	4,348	560
5	669	529	7			
6	15,478	58,528	41,407	714	6,870	3,724
7	5,322	12,043	19,982	1,364	418	297
8	9	330	53	2	76	-
Total	26,792	104,684	66,410	5,313	42,408	5,613

4.5.3.2 Drainage Management

As explained in Section 2.3.2.2, there are various methods to manage drainage, from controlled drainage to woodchip reactors and drainage water recycling (Singh & Horne, 2020). This scenario assumed that all area on dairy fine-textured soils (modelled as having artificial drainage) were attenuated by 75% to represent drainage management measures (Singh & Horne, 2020). This was applied to the quick flow component as artificial drainage was modelled as interflow (in the baseline scenario, quick flow attenuation was set to 0% for dairy fine-textured soils), while the slow flow attenuation remained the same as the baseline scenario.

4.5.3.3 Wetlands

Natural or constructed wetlands have been identified as a major catchment-scale mitigation practices to reduce nitrogen loads to the receiving waters (Tanner et al., 2018; Wilcock et al., 2011). SOURCE can model wetlands using the 1st Order Kinetic Model k-C* filter model. This model has been successfully used to describe the reduction in concentration within grass filter strips, swales, ponds, wetlands, or sedimentation basins (eWater, 2018).

The concentration of nitrogen in a parcel of water moves towards an equilibrium value by an exponential decay process as it enters a wetland (Wong et al., 2006). This behaviour can be described by the first-order kinetic (or *k-C**) model, in which *C** is the equilibrium value or background nitrogen concentration, and *k* is the exponential rate constant (Equation 9). The effectiveness of this model is a function of the inflow concentration, the ability of the wetland to reduce nitrogen concentration, the inflow, and the wetland area. The *k* parameter lumps the influence of the biogeophysical factors that act to remove nitrogen. The model process can be expressed as:

$$e^{\frac{-k}{q}} = \frac{C_{out} - C^*}{C_{in} - C^*} \tag{9}$$

where:

C^* = the background concentration (mg/L);

C_{in} = the input concentration (mg/L);

C_{out} = the output concentration (mg/L);

k = the rate constant (m/s); and

q = the hydraulic loading (flow rate per surface area) of the wetland.

A higher k means a faster approach to equilibrium, and hence a higher treatment capacity (provided C^* is less than C_{in}) (Wong et al., 2006). In the long term, the model performance is sensitive to the value of C^*, as this is the value that the outflow nitrogen concentration tends towards.

In this study, typical parameter values, given by eWater (2018) for the wetland model in SOURCE (Appendix I), were used to quantify effects of three wetland nodes placed downstream of sub-catchment (SC) 16, 22, and 30 (Figure 12). These locations were selected due to their higher concentrations of nitrate leaching upstream. However, this wetland scenario is hypothetical as further analysis is needed to identify which locations would be suitable based on the topography and flow regime of the area.

5 Results

This chapter describes and analyses the results of the spatial and temporal dynamics of river flow and nitrogen loads as well as the calibration and validations of the integrated farm nitrate loss (Overseer) and catchment hydrology (SOURCE) models. Finally, this chapter presents the results of the simulations of in-farm and catchment-scale mitigation measures as compared to the current (baseline) conditions.

5.1 Spatial and Temporal Dynamics of Flow and Nitrogen Load

This section analyses the measured river flow and nitrogen concentration data in the Tararua Catchment and how they vary spatially and temporally. Further, it investigated the integrity of the measured data used in the flow calibration process to gain a conceptual understanding of the catchment's flow regime.

5.1.1 Catchment Discharge

Table 15 presents the calculated mean annual rainfall, mean annual flow, and the ratio of flow to rainfall on an annual average basis (catchment discharge coefficient) for the primary flow gauging sites (Figure 9). The rainfall was taken as an area-weighted average of all sub-catchment interpolated rainfall above each gauging site.

Table 15. Rainfall and flow characteristics of the Tararua Catchment, based on the measured rainfall and river flows from 1989 to 2016.

Monitoring Site	Area (km^2)	Mean Annual Flow (m^3/s)	Mean Annual Precipitation (m)	Catchment Discharge Coefficient (%)	Mean Specific Discharge ($m^3/s/km^2$)
Manawatū at Weber Road	718	14.0	1.31	47%	0.020
Manawatū at Hopelands	1,267	25.1	1.39	45%	0.020
Mangahao at Ballance	277	14.8	2.70	62%	0.053
Mangatainoka at Pahiatua Town Bridge	401	18.1	1.89	76%	0.045
Tiraumea at Ngaturi	747	15.8	1.38	48%	0.021

Monitoring Site	Area (km^2)	Mean Annual Flow (m^3/s)	Mean Annual Precipitatio n (m)	Catchment Discharge Coefficient (%)	Mean Specific Discharge ($m^3/s/km^2$)
Manawatū at Upper Gorge	3,200	84.9	1.54	55%	0.027

Depending on the climate and the catchment characteristics, the general expectation is that the catchment evaporative process in most typical New Zealand catchments will account for approximately 35 – 45% of total rainfall (Rowe et al., 2002; Spronken-Smith & Sturman, 2001). Thus, catchment discharge (surface water and groundwater flows collectively) should account for approximately 55 – 65% of rainfall.

In the Tararua Catchment, the measured mean annual flow as a percentage of the mean annual rainfall ranged from 45% (Manawatū at Hopelands) to 76% (Manawatū at Pahiatua) with a mean of 56% (Table 15). This is similar to expected, where the catchment discharge is within the expected range.

Figure 16 presents the measured specific discharge plotted against the mean annual precipitation at each primary and secondary monitoring site. This provides an indication of the average flow variability between sub-catchments due to either climatic or catchment characteristics and readily highlights any outliers. The high R^2 value between the specific discharge and rainfall received, suggests that rainfall has a major influence on streamflow discharges compared to the variation in sub-catchment characteristics. The deviation of the data points from the trend line is likely to be attributed to the different soil and subsoil hydraulic properties within each gauged catchment.

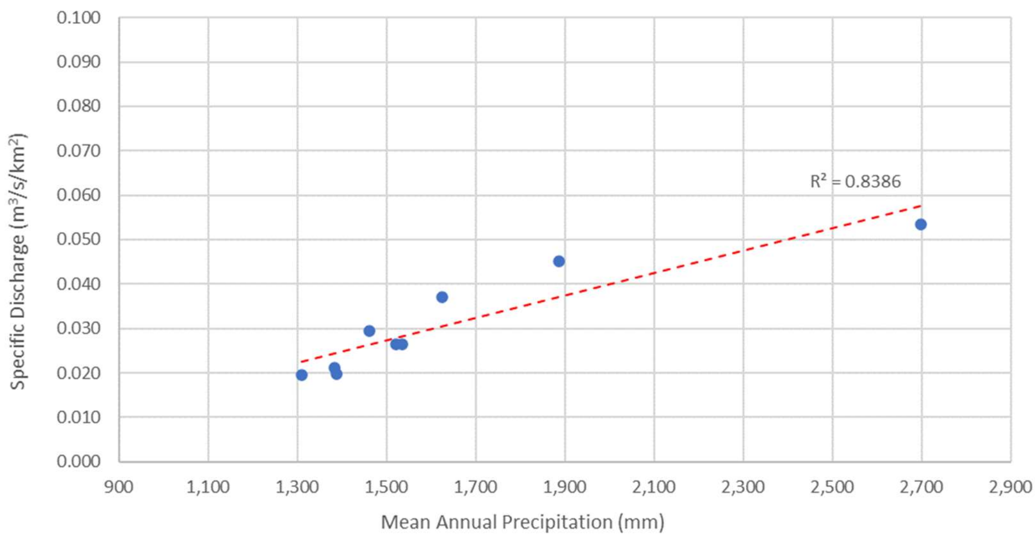

Figure 16. Mean annual precipitation versus specific discharge measured in the Tararua Catchment between 1989 and 2016 for all primary and secondary monitoring sites.

5.1.2 Water Quality

A comparison of TN, NO_3^--N, and DIN was undertaken to visualise how the different nitrogen measurements differed between the measurement sites, and the differences between DIN (which the integrated model was calibrated to predict) and total nitrogen load in the river. This was only calculated for a period of 10 years (2006 – 2016) as these were the only years where data was available for all sites.

The DIN loads accounted for 46-76% of TN load, while NO_3^--N accounted for 89-98% of the DIN load (Figure 17). This was expected as most leached nitrogen is in the form of NO_3^--N (Quinn et al., 2009). The percentage of NO_3^--N load was greater than Elwan et al. (2018) found in the Rangitikei Catchment. This could possibly be attributed to the larger contribution of agriculture in the Tararua Catchment as there are more natural forested areas in Rangitikei catchment, which have lower leaching rates (Davis, 2014).

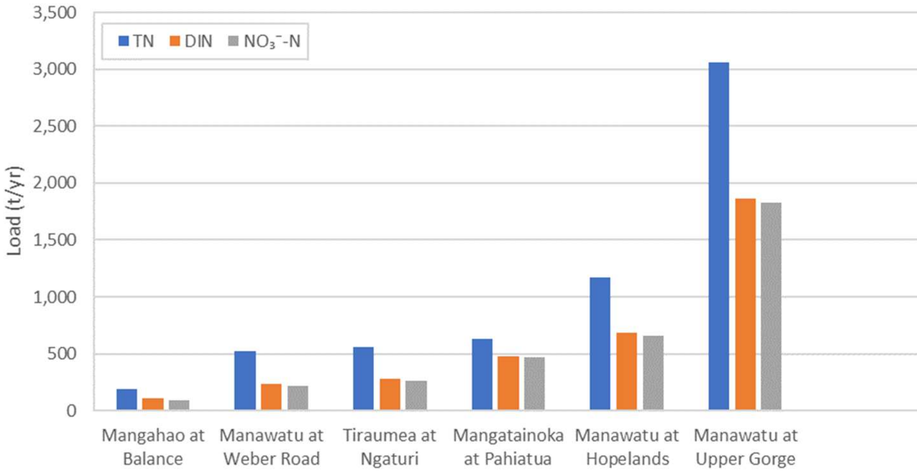

Figure 17. Estimates of mean annual TN, NO_3-N and DIN loads across the primary calibration sites as calculated between 2006 and 2016

The year-to-year variation in DIN load was analysed for each monitoring site. On average, there was a variation of 53% between the minimum and maximum annual DIN load for the period 2006 to 2016. It was hypothesised that a large proportion of this variation was related to variation in the annual rainfall received. A regression analysis between annual average rainfall and annual DIN load indicated a weak positive correlation between rainfall and DIN load, which is displayed for the Manawatū at Upper Gorge gauge in Figure 18. Similar results were produced for the other gauges. It appears that rainfall accounts for approximately 40% of the variation in the DIN loads as determined by a statistic analysis of rainfall variation compared to DIN load variation. The rest of the year-to-year variation is likely a result of land use change, variation in farm management practices, and/or instream processes in the rivers.

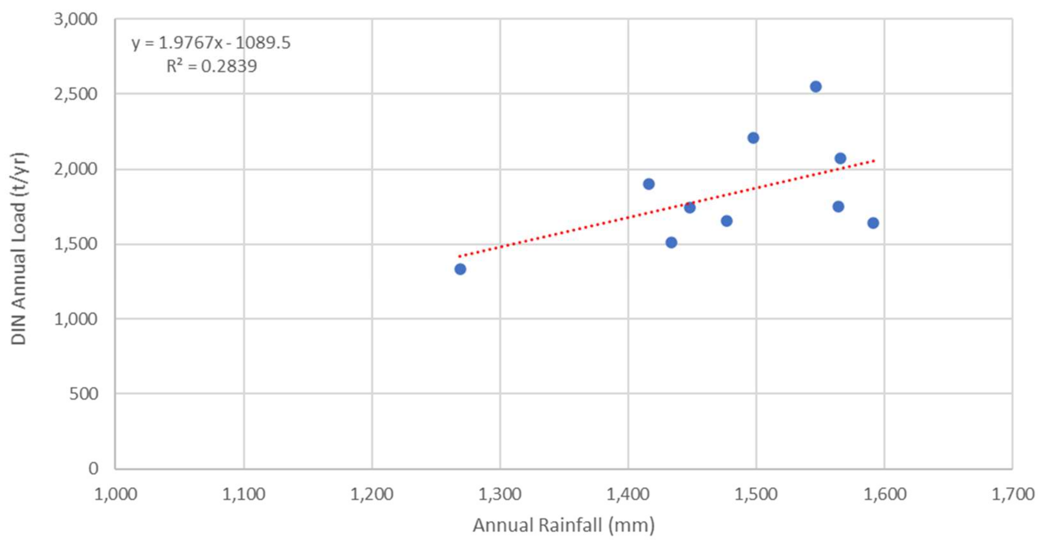

Figure 18. Regression of annual rainfall and annual DIN load for Manawatū at Upper Gorge, from 2006 to 2016.

The monthly variability in DIN concentrations was also examined. Mean monthly DIN concentrations at the Manawatū at Upper Gorge site ranged from 0.21 in January to 0.97 mg/L in July. Higher DIN concentrations and river flows were measured between June and October, with 69- 75% of the annual DIN load occurring between these months. This is likely due to the winter months experiencing the most rainfall (Section 4.1.2) and that the rainfall is correlated to nitrogen leaching from the farm root zones. However, the increase in load must be greater than the dilution caused by greater flow as typically concentration decreases as flow increases. This indicates that a significant portion of the DIN load is associated with quick flow, which is plausible due to the large amount of artificial drainage which facilitates high nitrogen loads from agricultural land. Analysis of the measured data showed high DIN loads in winter months (June to October) while the research from Di and Cameron (2010) and Monaghan and De Klein (2014) found that losses of nitrogen in the soil are greatest in autumn months (March to June). However, this could suggest a lag in the transport of nitrogen from the soils to the waterways, which is entirely feasible depending on the distance between the farm and stream.

It is also apparent from this analysis that there is significant spatial variability in river DIN concentrations, with an average annual DIN concentration of 0.20 mg/L calculated at Mangahao at

Ballance and an average annual DIN concentration of 0.93 mg/L calculated at Mangatainoka at Pahiatua, as presented in Appendix A. This is likely to result from the different land uses, soil, geology, topography, and climate regimes between the sub-catchments. The temporal pattern in river DIN concentration also varies spatially, with Tiraumea at Ngaturi displaying similar DIN concentrations across each month, as compared to Manawatū at Hopelands which has high variability in monthly DIN concentration (Appendix A).

5.2 Flow Calibration and Validation Results

This section describes the results of the calibration and validation of the catchment-scale hydrology model, SOURCE, to simulate river flow, and an analysis of the modelled water balance and hydrological regime of the study sub-catchments.

5.2.1 Sensitivity Analysis

The aim of the sensitivity analysis was to determine the effect of changes or errors in the model input parameters on model outputs and the relative importance of various parameters in the flow model.

Sensitivity analysis was undertaken by varying each parameter individually, by +10% and -10% and evaluating the influence on mean annual average flow. However, this method does not consider the interaction between parameters nor that a change in one parameter may be compensated for by a change in another parameter (Vaze et al., 2012). It also does not consider the range that parameters are defined within and that those defined within a narrow range may appear more sensitive.

The sensitivity analysis results for the Manawatū at Upper Gorge site indicates that the model is most sensitive to changes in soil moisture storage capacity, pervious fraction, and baseflow index. This finding corresponds to the results from eWater (2018). The mean annual average flow varied between –25% and +10% with the parameter changes. While some of the parameters may not have affected the annual average flow, they may have influenced the shape, recession, timing and baseflow, and quick flow partition.

5.2.2 Model Performance

The measured river flow records were divided into two parts, where SOURCE-SIMHYD was calibrated using the flow records from 1999 to 2007 and the model was validated using the flow records from 2008 to 2016. The final parameters used for each functional unit in the SOURCE-SIMHYD model are presented in Appendix F. Appendix J presents the model performance metrics (NSE, PBIAS, RMSE and R^2) for the flow calibration and validation periods for the primary gauging sites in the study catchment. It is clear that across every performance metric the calibration period (1999 to 2007) performs slightly better than the validation period (2008 to 2016), but both periods perform well.

Overall, there is a high level of confidence in the model's ability to predict flow. Table 16 presents the flow statistics and the measures of the model's performance (NSE and PBIAS) for each of the primary gauges. These indicate a close agreement between the modelled and measured median and maximum flows, with a slight underprediction of the minimum flow across all gauges.

The obtained NSE values range from 0.6 to 0.8 and the PBIAS values range from -9.39 to 15.35 (Table 16) evaluated the model's ability to predict river flows to range between Satisfactory to Very Good. This evaluation of NSE indicates that the timing of flow and seasonal trends are successfully simulated. Apart from at Mangatainoka at Pahiatua, PBIAS is negative at all gauges, which indicates the tendency of the model to slightly overpredict flows. Most gauges have a similar evaluation classification for both NSE and PBIAS. The exception to this is Mangahao at Ballance, which performs satisfactorily for NSE (0.6) but very good for PBIAS (-2) (Table 16), indicating that while the flows are in the correct range, the timing is slightly out. This is likely to be a result of the parameters used to model flow attenuation.

Table 16. Flow calibration statistics for calibration and validation periods (1999 to 2016).

Monitoring Location	Minimum (L/s)		Median (L/s)		Maximum (L/s)		NSE	PBIAS
	Measured	Modelled	Measured	Modelled	Measured	Modelled		
Manawatū at Hopelands	2,130	790	15,100	15,161	1,270,000	1,210,989	0.7	-4.82
Manawatū at Upper Gorge	6,040	2,262	52,700	46,638	2,280,000	3,021,835	0.7	-5.28

Monitoring Location	Minimum (L/s)		Median (L/s)		Maximum (L/s)		NSE	PBIAS
	Measured	Modelled	Measured	Modelled	Measured	Modelled		
Manawatū at Weber Road	1,130	527	6,750	7,087	930,000	730,433	0.8	-8.11
Mangahao at Ballance	792	536	6,200	6,164	434,000	328,483	0.6	-2
Mangatainoka at Pahiatua	606	601	9,730	8,647	480,000	373,569	0.6	15.35
Tiraumea at Ngaturi	2,010	835	7,440	6,439	608,000	629,784	0.7	-9.36

Manawatū at Upper Gorge is at the outlet of the Tararua Catchment so presents an aggregation of all upstream sites. The calibration (1999-2007) and validation (2007-2016) of the measured and modelled flow are presented in the hydrograph and FDC in Figure 19 and Figure 20, respectively. The magnitude of flow is successfully simulated with some over and some underprediction which signifies that the model appears to be suitable for use to simulate river flows. The NSE, PBIAS, RMSE and R^2 values were 0.7, -5.28, 57,821, and 0.9, respectively. While RMSE is high, in relation to the flow magnitude it is not unreasonable, and the rest of the statistics indicate a ‘Very Good’ calibration.

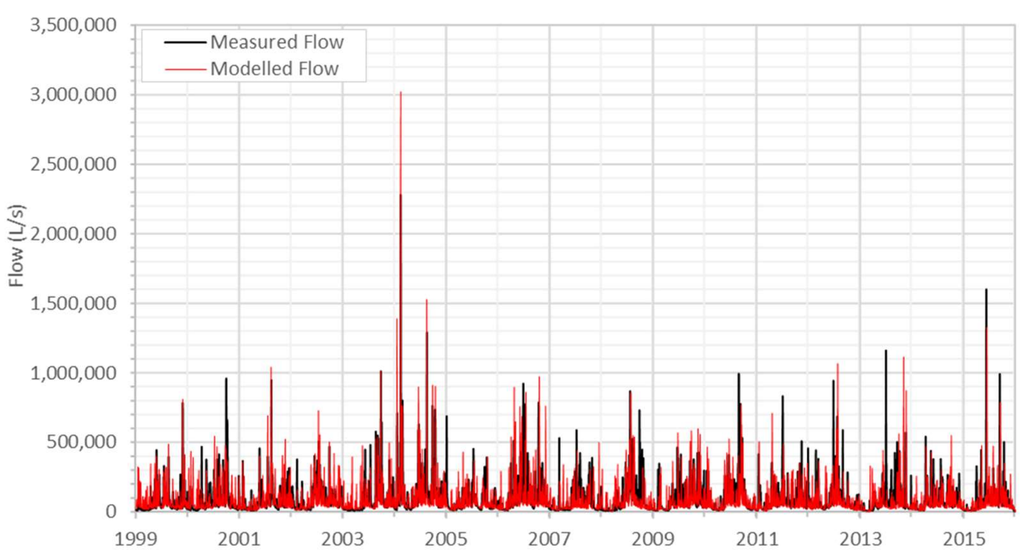

Figure 19. Hydrograph of the measured and modelled flow at Manawatū at Upper Gorge.

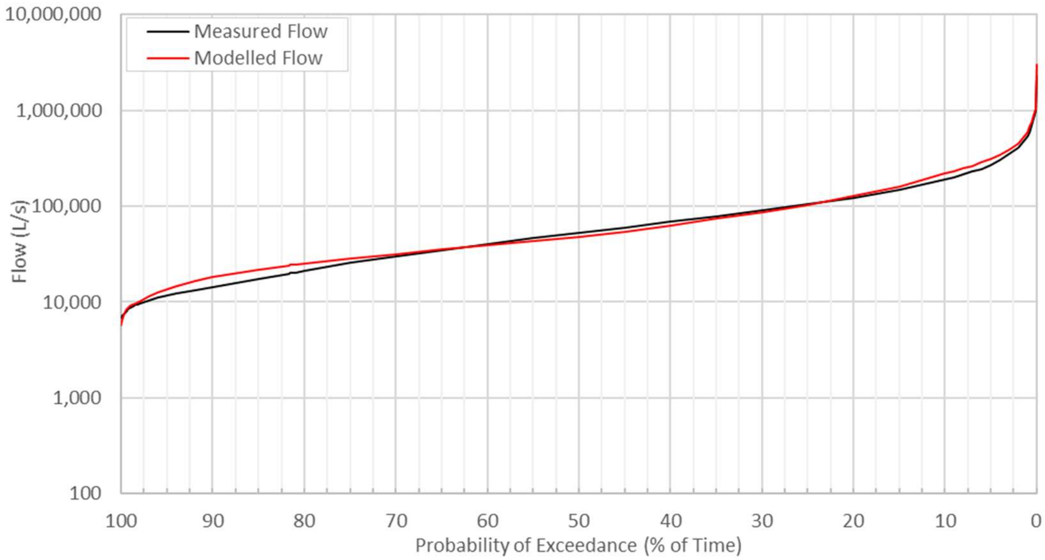

Figure 20. Flow duration curve of the measured and modelled flow at Manawatū at Upper Gorge.

The model performed the relatively poor to describe the gauge at Mangatainoka at Pahiatua, which performs satisfactorily achieving a NSE value of 0.6 and a PBIAS value of 15.35 (Table 16). A comparison of the measured and modelled flow for Mangatainoka at Pahiatua is presented in the hydrograph and FDC in Figure 21 and Figure 22, respectively. It is the only gauge where the model underpredicts the flow according to PBIAS. This is also apparent in the FDC (Figure 22), where peak flows, and flows that are exceeded more than 92% of the time are underestimated. Potential explanations for the underestimation are high estimates of interception and evapotranspiration in hills, not accounting for groundwater recharge and/or uncertainties in rainfall inputs and streamflow gauging itself. Given that a large part of this gauge's catchment is located in the hill country, it is unlikely this underestimation can be attributed to not accounting for lateral groundwater recharge. Rather, the most likely explanation is that the parameters governing evaporation need to be adjusted in order to increase baseflow and surface flow. However, adjustment of these parameters would deviate from the relationships developed with the physical characteristics. As there is a good calibration at Manawatū at Upper Gorge which is downstream of this gauge, the parameters were not adjusted, but this means caution is needed when drawing conclusions at this gauge. This calibration is presented for flow on a daily time-step, although the water quality model uses a monthly time-step. The monthly flow calibration is significantly better than the daily calibration due to smoothing of flow (results not shown).

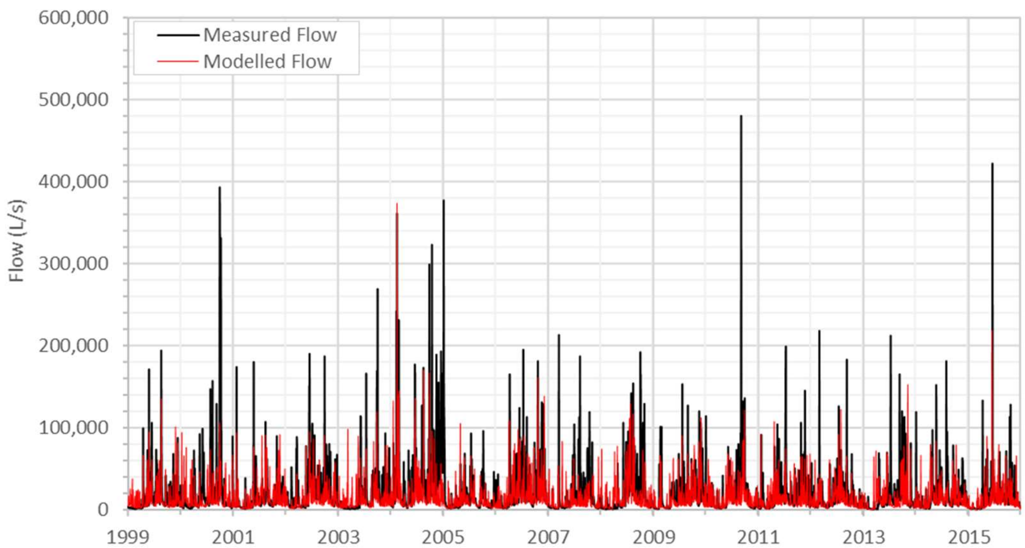

Figure 21. Hydrograph of measured and modelled flow at Mangatainoka at Pahiatua.

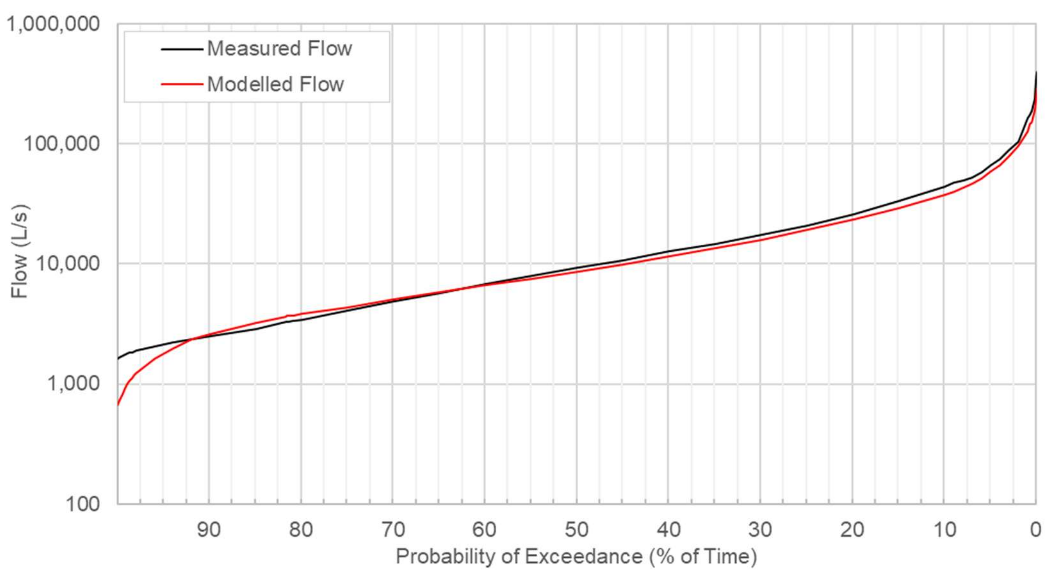

Figure 22. Flow duration curve of measured and modelled flow at Mangatainoka at Pahiatua.

The hydrographs and flow duration curves for rest of the flow gauging sites in the catchment are presented in Appendix J. The flow duration curves indicate that the model slightly underestimated low flows across all gauges. Similar to at Mangatainoka at Pahiatua, a possible explanation for the underestimation is the lack of spatial scale in the information available on soil types and geology used to parameterise the model. This hindered the level of detail available to describe specific physical properties potentially contributing to slightly weakened model performance especially at low flows. Other possible explanations are that a higher weight is given to the high flows in the calibration objective function and that the measurement procedures to obtain the observed data are a source of uncertainty.

Overall, the hydrographs, FDC and the measures of model performance indices (Appendix J) indicate that the model did successfully simulate the timing, shape, and recession of flows at all gauging sites. They also highlight that both the calibration and validation periods have similar performance levels, which places a high level of confidence in the model.

5.2.3 Catchment Water Balance

The catchment water balance uses the principle of conservation of mass, in which the rainfall is partitioned into soil evaporation, plant transpiration, canopy interception evaporation, surface runoff, interflow, and groundwater flow, with the remainder equating to the change in soil moisture content. The number of components presented in this analysis are limited by the outputs that can be modelled in SOURCE. For example, plant transpiration and lateral interflow cannot be recorded separately for each monitoring site in SOURCE. Instead, the SOURCE model records the rainfall partitioning into evapotranspiration (accounting for soil evaporation, plant transpiration and canopy interception evaporation), quick flow (i.e. surface runoff including overland flow, infiltration and saturation excess runoff and interflow) and sub-soil drainage (contributing to groundwater flows) (Table 17). However, this simplified water balance still provides insight into the dominant flow processes and spatial variability of the flow regime and into which locations certain mitigation measures might be most effective. The modelled water balance is ‘closed’, meaning it does not factor in losses and gains to groundwater, instead a simplified model is used to simulate the baseflow (slow flow) contribution to the streamflow.

Table 17 provides a simplified overview of the water balance for each gauge in the Tararua Catchment. As the magnitude of the water balance changes with the climate regime, these flow portioning values are presented as percentages of the average annual rainfall received. However, the actual values in mm were compared against the literature as a check on the operation of the model. The outputs for each functional unit in mm simulated for an average rainfall year (2010) in the medium climate regime, which were compared to the Overseer water balance, are presented in Appendix K.

Table 17. Modelled rainfall partitioning in Tararua sub-catchments.

Monitoring Site	Quick flow (%)	Evapotranspiration (%)	Sub-soil Drainage (%)
Manawatū at Hopelands	18	47	35
Manawatū at Upper Gorge	27	48	25
Manawatū at Weber Road	27	47	26
Mangahao at Ballance	26	52	22
Mangatainoka at Pahiatua	35	48	17
Tiraumea at Ngaturi	31	48	21

The water balance of each functional unit (Appendix K) suggested that higher permeability soils and geology such as sand and gravel produced more soil percolation and baseflow, while lower permeability soils such as clay loams produced more runoff. Forest had more interception loss than pasture, and fine-textured soils had the greatest soil evaporation. Of particular importance was the split between infiltration excess runoff, interflow, and groundwater recharge (Appendix K). Fine-textured soils have the greatest infiltration excess runoff as they have the lowest infiltration rates. Of the water that is infiltrated, higher permeability geology had the most groundwater recharge while lower permeability geology had more interflow. The percolation to groundwater also varied between soil types with stony and coarse-textured soils displaying a larger range between minimum and maximum flows, while fine-textured soils displayed a more constant profile. In winter, stony soils produce much higher soil drainage but in summer, the percolation between the soil types is similar.

The evapotranspiration losses (interception and soil evaporation collectively) in the SOURCE model accounted for between 41% and 52%, which agrees with the literature (Rowe et al., 2002; Spronken-

Smith & Sturman, 2001). Given the significant areas of forest within each sub-catchment, there will be substantial losses associated with interception. Additionally, the modelled runoff coefficient (runoff and sub-soil drainage) is similar to the measured runoff coefficient calculated in Section 5.1.1. For Manawatū at Upper Gorge: the modelled runoff coefficient was 0.52 (Table 17) as compared to the measured runoff coefficient of 0.55 (Table 15).

The largest component of the catchment discharge was quick flow (runoff) followed by percolation to groundwater representing the slow (baseflow) flow component. This is reflective of large portions of the sub-catchment area with relatively impermeable soils and geological profiles. Surface runoff accounts for 35% of the water balance in the Mangatainoka at Pahiatua catchment, which is a function of the steeper slopes and lower permeability soils in the sub-catchment. In contrast, Manawatū at Hopelands has more permeable soils and geological profiles, which results in greater percolation to groundwater.

5.3 Model Integration Results

5.3.1 Overseer Nitrate Losses

Appendix L presents the Overseer estimated average annual nitrate losses (kg/ha/yr) from the farm root zone for combinations of land uses (dairy and sheep and beef), soils (stony soils, and coarse, intermediate and fine textured), and rainfall regimes (low, medium and high). The nitrate losses modelled from Overseer were within the range of the typical nitrate losses found in the literature, as presented in Table 1 in Section 2.1. The estimates of dairy nitrate losses varied from 36 to 84 kg N/ha/yr depending on the rainfall regime and soil type, which falls within the range of 15 to 115 kg N/ha/yr derived from the review of the literature in Section 2.1. The highest nitrate losses were modelled in the high rainfall regime and stony soils, while fine-textured soil in the low rainfall regime had the least. The estimates of sheep and beef nitrate losses ranged from 14 to 24 kg N/ha/yr, which also falls within the range of 6 to 66 kg N/ha/yr suggested in the literature in Section 2.1. The monthly trend of nitrate losses was similar across all soil types and rainfall regimes, with no losses occurring between November and March and the highest losses occurring in April and May, before steadily decreasing each month to until October. The exception to this is the fine-textured soils, where the highest nitrate losses occurred in July and August. This is likely due to high water holding capacity of fine-textured soils reaching saturation and soil percolation later in the winter months increasing the lag in water and nitrogen movement. Forest nitrate losses were assumed an average of 2 kg N/ha/yr (Davis, 2014), split evenly throughout the months, while urban loads were modelled using the measured loads from each point source as presented in Appendix G.

5.3.2 Input of Overseer Nitrate Losses into SOURCE

As described in Section 4.3.3, a Nutrient Generation models was developed to integrate Overseer nitrate losses into SOURCE for catchment-scale simulations. The model translated the estimates of average annual loss (kg/ha/yr) into the resultant monthly nitrate concentrations for quick flow and slow flow from the soil profile as nitrogen inputs into SOURCE.

The DIN concentrations applied to SOURCE are presented in Appendix M for a select example functional units as it is not practical to display them for all. Overall, the average monthly nitrate concentrations in slow flow ranged from 0.1 - 7.1 mg/L for sheep and beef, dependant on each functional unit's rainfall-runoff model parameters, the rainfall regime, and Overseer nitrate losses. The average monthly nitrate concentrations in quick flow ranged from 0.6 - 11 mg/L for sheep and beef and were dependant on the same variables. In contrast, under dairy land use, the average monthly nitrate concentrations ranged from 0.3 - 15.7 mg/L for slow flow and 0.7 - 41 mg/L for quick flow.

5.4 Nitrogen Calibration Results

This section presents the calibration of the modelled river DIN loads using four different methods of applying a nitrogen attenuation factor. These different scenarios were compared with measured loads. The river DIN loads rather than concentration was primarily assessed for the calibration. The discrete load refers only to the load generated in that sub-catchment (not including the influence of upstream catchments, stream routing or point sources) and the cumulative load refers to the total load in the river.

5.4.1 No Nitrogen Attenuation Factor

The first model run assumed no attenuation of nitrate losses in its flow pathways from the land to river. This simply compared the modelled nitrate leaching from the soil profile with the measured loads of DIN in the river. The discrete root zone annual average nitrate losses were between 7.05 and 304.95 N t/yr across the sub-catchments, and the average annual cumulative DIN loads ranged from 7.05 to 4,278 N t/yr (Figure 24 and Figure 25). Unsurprisingly, assuming 'no attenuation' resulted in poor agreement between modelled and measured river DIN loads with a significant over estimation of the modelled DIN loads at every monitoring location (Figure 23 and Figure 27). For example, the cumulative river DIN at the catchment outlet (Manawatū at Upper Gorge) was overestimated by 230%. There are two possible explanations for this overestimation: either the modelled losses from farms in the sub-catchments were too large or there is significant nitrogen attenuation between farm root zones and the river. It was concluded that the overestimation of river DIN loads resulted from the lack of accounting for nitrogen attenuation (no nitrogen attenuation factor application) in its flow pathways from the land to rivers. This conclusion is supported by the reasonable nature of the estimates as root zone nitrate losses, as supported by the literature. For example, sub-catchment (SC) 33 comprised of 100% forest land use and the area-weighted average DIN losses from the catchment were 1.99 N kg/ha/yr (Figure 26). SC 32 comprised of 65% dairy and had area-weighted average DIN losses of 27.73 N kg/ha/yr (Figure 26). These DIN losses fall within the typical nitrate leaching rates discussed in Section 2.1. SC 11 is the only sub-catchment that appears to have losses different to what would be expected from the land use as it predominately sheep and beef yet has a relatively high area-weighted average leaching loss of 23.9 N kg/ha/yr. However, this can be explained by its highly permeable geology and soils. The cumulative DIN loads increased from upstream to downstream, with SC 37 (Manawatū at Upper Gorge site) having the largest annual average cumulative DIN load of 4,278 N t/yr (Figure 24), while the discrete DIN loads were influenced by sub-catchment area.

Figure 27 shows a scatter plot comparison of the measured and modelled mean annual DIN loads in the rivers. The high R-squared value indicates the model's ability to simulate the spatial variation in the observed loads between the sub-catchments. However, the gradient of the best-fit line is far greater than one (2.3), indicating that the modelled river DIN loads were significantly over-predicted. The modelled river DIN loads were approximately between 1.5 and 3 times greater than the measured river DIN loads (Figure 27), which indicated that there is large attenuation of nitrogen in its flow pathways from land to rivers. Also, the nitrogen attenuation needed to achieve a good calibration varied spatially, with higher attenuation needed in the northern catchments (68% at Manawatū at Weber Rd) than in the southern catchment (32% at Mangatainoka at Pahiatua).

The monthly river DIN load calibration results are presented for Manawatū at Upper Gorge in Figure 23 and the rest of the gauges in Appendix N. Upon analysis of the monthly river DIN load results, the temporal trend of both the measured and modelled river DIN loads appeared to be similar across each gauge, with each month's river DIN loads being significantly overestimated by the model (Figure 23). In general, the river DIN loads were over estimated by a greater degree in the summer months (November to April) compared to the winter months (May to October). For example, at the catchment outlet (Manawatū at Upper Gorge), the river DIN load in January was over simulated by 261% as compared to 180% in August. However, the peaks occurred at the same time between the measured and modelled river DIN loads, but as expected there was a time lag compared to the Overseer inputs (Appendix L).

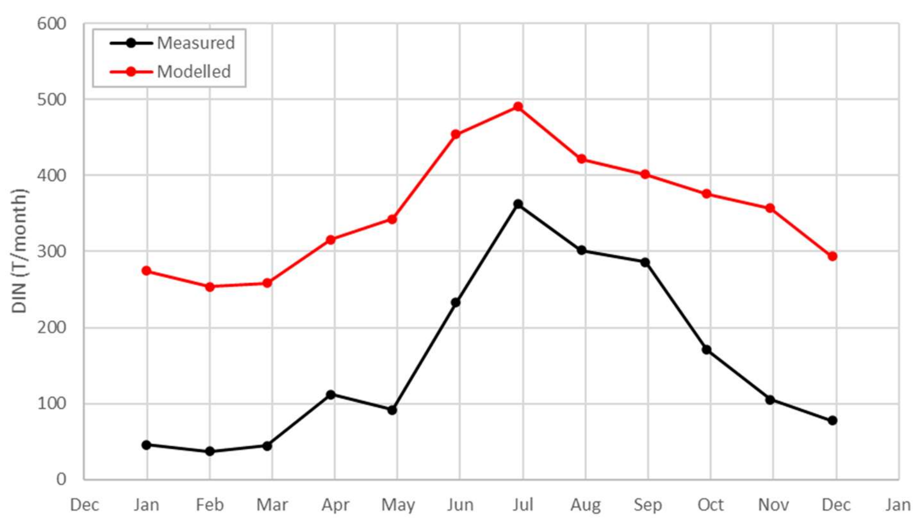

Figure 23. A comparison of measured and modelled monthly average DIN loads (t/month) at Manawatū at Upper Gorge, modelled with no nitrogen attenuation.

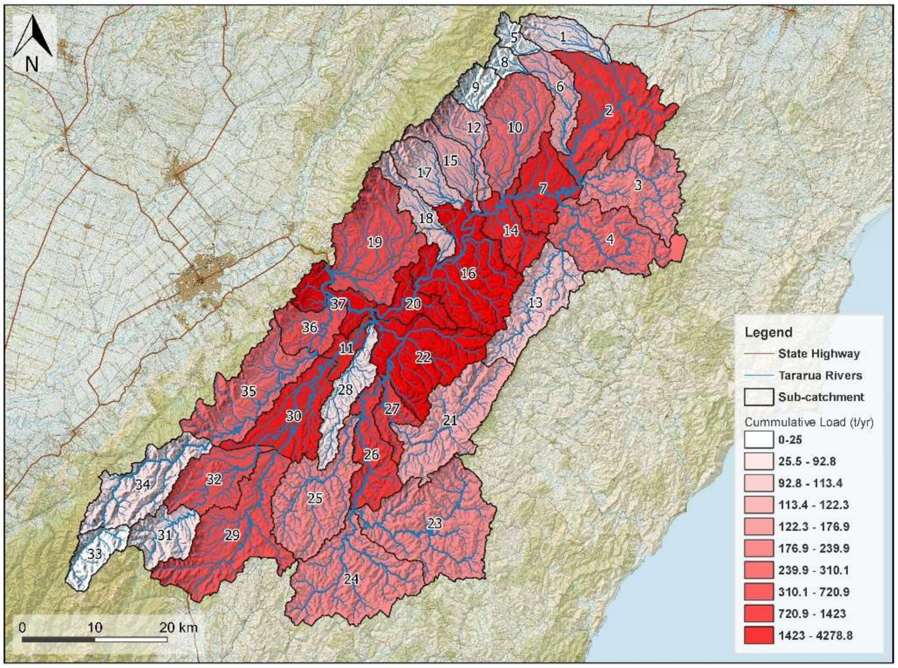

Figure 24. Cumulative river DIN load (t/yr) in Tararua sub-catchments with no nitrogen attenuation factor.

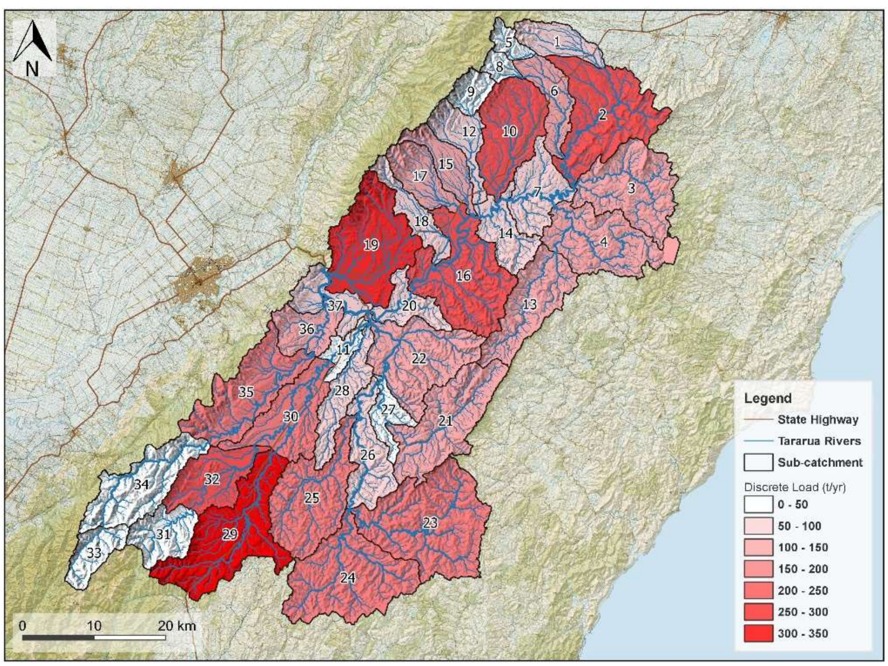

Figure 25. Discrete DIN load (t/yr) in Tararua sub-catchments with no nitrogen attenuation factor.

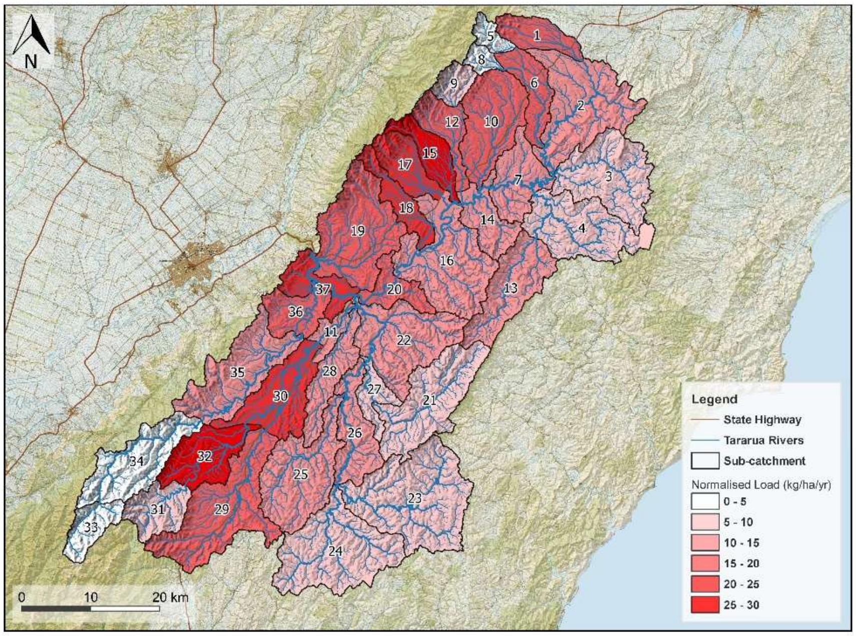

Figure 26. Area-weighted average discrete DIN load (kg/ha/yr) in Tararua sub-catchments with no nitrogen attenuation factor.

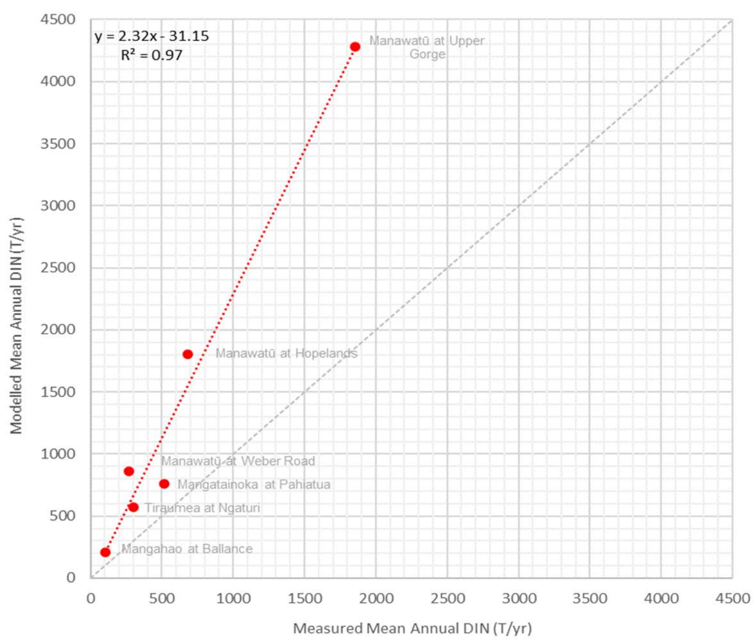

Figure 27. Measured vs modelled cumulative river DIN load (t/yr) in the Tararua sub-catchments, modelled with no nitrogen attenuation factor applied.

5.4.2 In-stream Attenuation Results

As explained in Section 4.5.2.1, the in-stream attenuation was simulated using the default model input parameters due to the lack of information around specific input parameters, measured data to calibrate the model to, and its overall small proportion of overall DIN load in the rivers.

The model simulated in-stream attenuation ranged from 0.1 - 11.4 t/yr for each sub-catchment, which equates to 1 – 6% of the nitrogen losses in the respective sub-catchment. In-stream attenuation was lower in the sub-catchments with lower DIN concentration, vice versa. Overall, the instream attenuation was simulated at 131.18 t/yr or 3% of the total catchment nitrogen losses. Elwan (2018) also estimated that potential in-stream nitrogen uptake accounted for a maximum of 3.1% of the estimates of root zone nitrate losses in the Tararua Catchment using the simple model developed by Singh et al. (2017) model.

The results presented in the following sections include the in-stream attenuation factor.

5.4.3 Uniform Nitrogen Attenuation Factor

A uniform nitrogen attenuation factor was applied for all combinations of soils and geology across the sub-catchments. Using a uniform nitrogen attenuation factor of 0.55 (Section 4.3.4) improved the calibration between the modelled and measured river DIN loads (Figure 28 and Figure 29). The calibration of average monthly river DIN load at Manawatū at Upper Gorge was Very Good with a PBIAS and NSE of 4.93 and 0.68, respectively. The measured river DIN load was 1866 t/yr, while the modelled load was 1821 t/yr. This close agreement was expected as the uniform nitrogen attenuation factor was calculated as difference between the average annual root zone nitrate losses and the measured cumulative river DIN load at Manawatū at Upper Gorge. Figure 28 presents a comparison of the modelled and measured average monthly river DIN loads at Manawatū at Upper Gorge. While the timing of average monthly river DIN load delivery matched, the magnitude between summer and winter differed. The average monthly river DIN loads were overestimated during the summer months (November to May) and underestimated during the winter months (June to September). As the attenuation factor was applied equally, the spatial variation in the river DIN loads across the sub-catchments was modelled the same as with no nitrogen attenuation factor, albeit reduced.

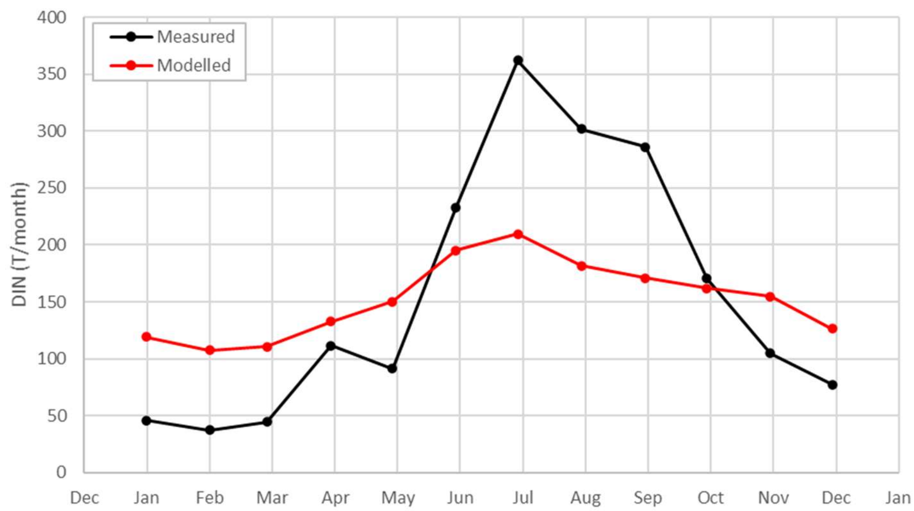

Figure 28. A comparison of measured and modelled monthly average DIN loads (t/month) at Manawatū at Upper Gorge, modelled with a uniform attenuation factor.

While the calibration of average monthly river DIN load at Manawatū at Upper Gorge was evaluated 'Very Good', the calibration of average annual river DIN loads varied at the rest of the monitoring sites with both over- and under-estimation (Figure 29). The difference between the modelled and measured average annual river DIN loads varied from -195 to +105.2 t/yr across the monitoring sites. For the calibration of monthly average river DIN loads, PBIAS was classified as 'Satisfactory' and ranged from -59 to +57, while NSE was classified as either 'Good' or 'Satisfactory' across the monitoring sites. Figure 29 shows that the calibration of average annual river DIN loads significantly improved by a uniform attenuation factor, with a trendline slope close to 1. However, this figure also highlights the overestimation and underestimation of average annual river DIN loads at some gauges, such as Manawatū at Weber Road and Tiraumea at Ngaturi.

The average annual river DIN load at Manawatū at Weber Road is underestimated by a uniform nitrogen attenuation factor, potentially due to the high proportion of low attenuation capacity soils and geology within the sub-catchment, meaning a nitrogen attenuation factor of less than 0.55 is required. In contrast, the geology upstream of Tiraumea at Ngaturi is predominantly mudstone and peat, so is likely to need a greater attenuation factor than 0.55. Overall, the sub-catchments upstream of the gauges that are overestimated have a high proportion of potentially high nitrogen attenuation capacity geology and soils such as mudstone and fine-textured soil. In contrast, the sub-catchments upstream of the gauges that are underestimated have a high proportion of geology and soils that potentially have a low capacity for nitrogen attenuation, such as gravel and stony soils. This aids to confirm that the nitrogen attenuation factor is related to physical characteristics and should vary spatially.

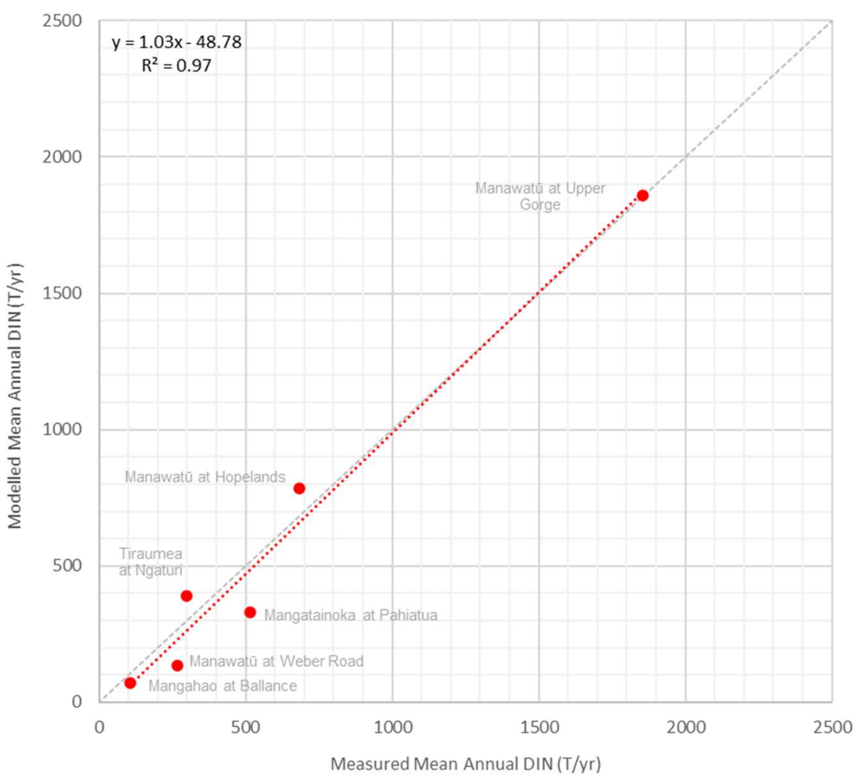

Figure 29. Measured vs modelled river DIN load (t/yr) in Tararua sub-catchments, modelled with a uniform nitrogen attenuation factor applied.

5.4.4 Spatially Variable Nitrogen Attenuation Factor

A spatially variable nitrogen attenuation factor applied to slow flow was calibrated for each combination of low, medium and high nitrogen attenuation capacity soils and geology across the sub-catchments. The use of a variable nitrogen attenuation factor significantly improved both the annual average and monthly average calibration of the river DIN loads (Figure 30 and Figure 31). The spatial variable nitrogen attenuation factor was calibrated at 0.23 for low, 0.58 for medium, and 0.94 for high nitrogen attenuation capacity soils and geology combinations. Across all the sites, the calibration was considered 'Very Good', with PBIAS ranging from -5.12 - 6.98. The modelled and measured average annual river DIN loads differed by only -4.8 - 2.9 t/yr. It is evident from these results that the model successfully simulated the annual average load at all sites. The gradient and R^2 values in Figure 30 were significantly improved from the previous methods and confirmed the good calibration of average annual DIN loads. The poor NSE value (while improved from using a uniform attenuation factor) can likely be attributed to the lack of data points (Section 4.4.1.1), although it could also indicate differences in the timing or estimation of each particular data point.

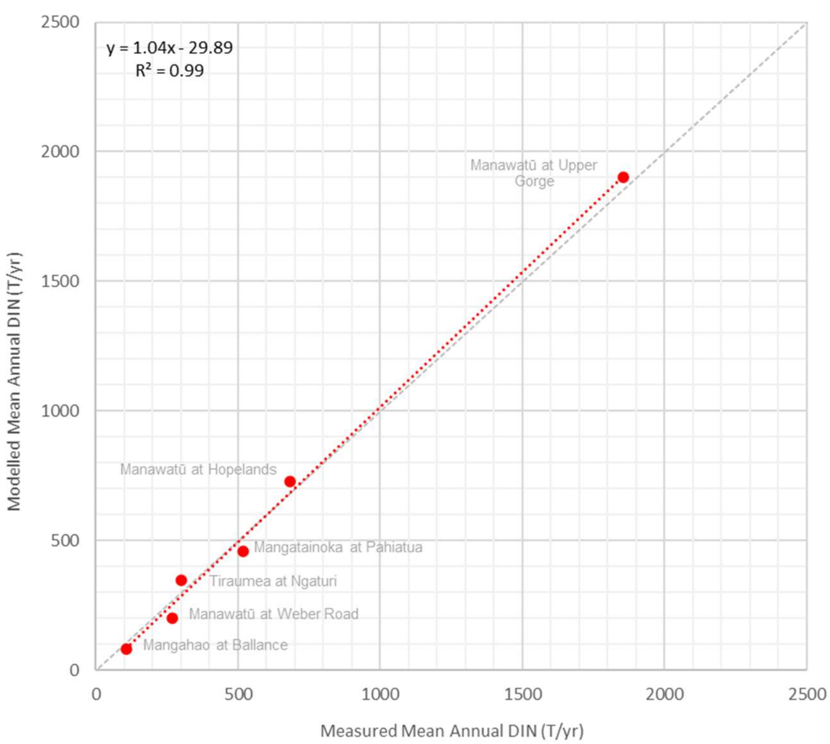

Figure 30. Measured vs modelled river DIN load (t/yr) in the Tararua sub-catchments, modelled with A spatially variable nitrogen attenuation factor applied.

However, the monthly distribution of river DIN loads did not reach a good calibration between the measured and modelled data using the spatially variable nitrogen attenuation factor applied to only the slow flow. Figure 31 presents a comparison of the measured and modelled monthly average river DIN loads at Manawatū at Upper Gorge, and the rest of the monitoring sites, presented in Appendix N, display a similar pattern. The monthly average river DIN loads were overestimated at most of the gauges in the summer months (December to May) but was underestimated in the winter months (June to November). The problem that this represents is compounded by the flow calibration underestimating baseflow at several sites. If the flow underestimation was corrected, it would likely increase the DIN load over the summer months as summer months are baseflow dominated, making the overestimation worse. The poor performance of river DIN simulation on a monthly time-step could be attributed to many factors, including inadequate temporal simulation of landscape or stream processes, temporal dynamics of nutrient generation, or a variable nitrogen attenuation in different flow pathways. The overestimation of monthly average river DIN loads in the summer months suggested a potentially higher nitrogen attenuation in slow (base) flow that dominates the summer flows. Similarly, the underestimation of monthly average river DIN loads in the winter months suggested a potentially lower nitrogen attenuation in quick (surface runoff and interflow) flow that dominates the winter flows.

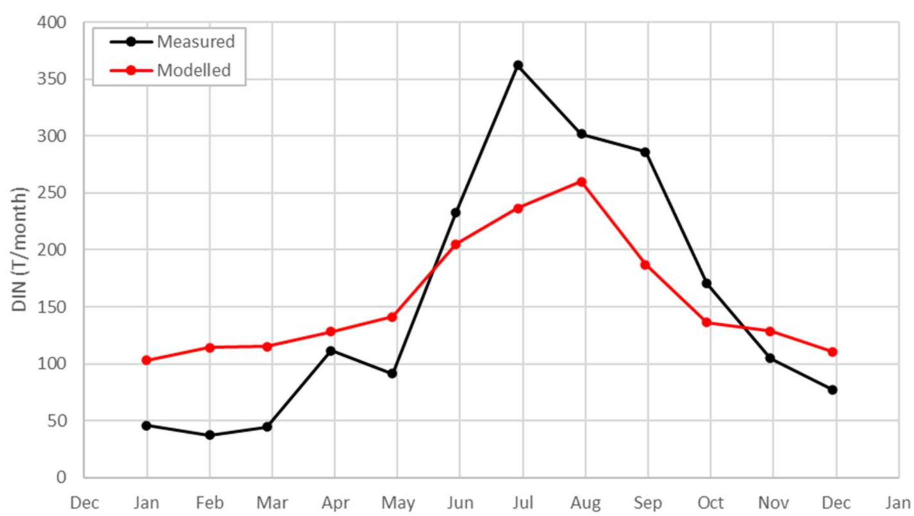

Figure 31. A comparison of measured and modelled monthly average DIN loads (t/month) at Manawatū at Upper Gorge, modelled with a spatially variable attenuation factor.

5.4.5 Spatially Variable Attenuation Factors Applied to Different Flow Pathways

The spatially variable nitrogen attenuation factors were calibrated separately for different flow pathways (quick flow and slow flow components), for each combination of low, medium, and high nitrogen attenuation capacity soils and geology across the sub-catchments. The application of spatially variable nitrogen attenuation factors to different flow pathways significantly improved the fit of the modelled and measured average monthly and average annual river DIN loads (Figure 32 and Figure 37). The calibrated values of spatially variable nitrogen attenuation factors are provided in Table 18.

Table 18. Spatially variable nitrogen attenuation factors to different flow pathways for each combination of low, medium, and high nitrogen attenuation capacity soils and geology in Tararua sub-catchments.

	Attenuation Factor		
	Low	**Medium**	**High**
Quick flow	0.06	0.19	0.46
Slow flow	0.15	0.49	0.81

The monthly model performance is considered 'Very Good', with NSE values of between 0.69 and 0.93 at each gauge. The time series plots, presented in Figure 32 and Appendix N, illustrate the model's ability to successfully simulate the seasonal variation in the river DIN loads across all six gauging sites. This is significantly improved from applying attenuation only to slow flow. In addition to seasonal variation, the time series plots (Appendix N) demonstrate the model's ability to simulate response in both baseflow and quick-flow DIN concentrations under different land uses, soils, and geology.

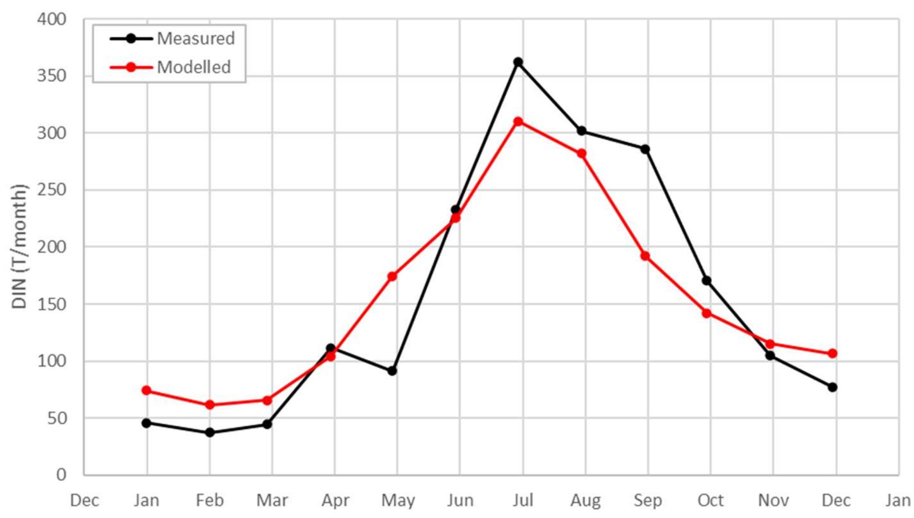

Figure 32. A comparison of measured and modelled monthly average DIN loads (t/month) at Manawatū at Upper Gorge, modelled with a spatially variable attenuation factor applied to different flow pathways.

Table 19 summarises the monthly river DIN statistics at each monitoring site, which demonstrates that the mean monthly river DIN loads are very similar between the measured and modelled data, but the monthly river DIN minimum and maximum loads were either slightly over- or under-estimated. Overall, the PBIAS values were classed as 'Very Good' at each site.

Table 19. A comparison of the measured and modelled monthly river DIN statistics at each monitoring site in Tararua sub-catchments.

Monitoring Site	Minimum (kg/month)		Mean (kg/month)		Maximum (kg/month)		PBIAS
	Measured	Modelled	Measured	Modelled	Measured	Modelled	
Manawatū at Hopelands	10.5	12.9	57.0	57.5	123.6	125.4	-0.78
Manawatū at Upper Gorge	37.1	47.4	155.5	155.7	362.3	325.1	-0.10
Manawatū at Weber Road	3.7	7.7	22.4	22.5	66.3	48.2	-0.44

Monitoring Site	Minimum (kg/month)		Mean (kg/month)		Maximum (kg/month)		PBIAS
	Measured	Modelled	Measured	Modelled	Measured	Modelled	
Mangahao at Ballance	1.9	1.0	8.9	9.0	16.2	17.6	-1.80
Mangatainoka at Pahiatua	12.9	7.3	43.1	42.9	75.7	71.8	0.39
Tiraumea at Ngaturi	8.6	6.5	25.0	24.5	58.1	64.3	1.86

A comparison of Figure 25 (Section 5.4.1) and Figure 33 which present the discrete river DIN loads with and without attenuation show that applying a spatially variable attenuation factor, significantly changes the spatial distribution of river DIN loads. This highlights that catchments with a high root zone load do not necessarily need to be the focus for implementation of mitigation measures. The river DIN loads increased significantly in SC 29 to 32, which comprised of mainly low nitrogen attenuation capacity functional units. In contrast, the river DIN load in SC 23 to 27 significantly decreased and these sub-catchments mainly comprised of high nitrogen attenuation capacity functional units. The area-weighted average DIN loads in each sub-catchment ranged from 0.87 kg/ha/yr in SC 33 to 17.8 kg/ha/yr in SC 32 with an average of 6.03 kg/ha/yr over the whole catchment.

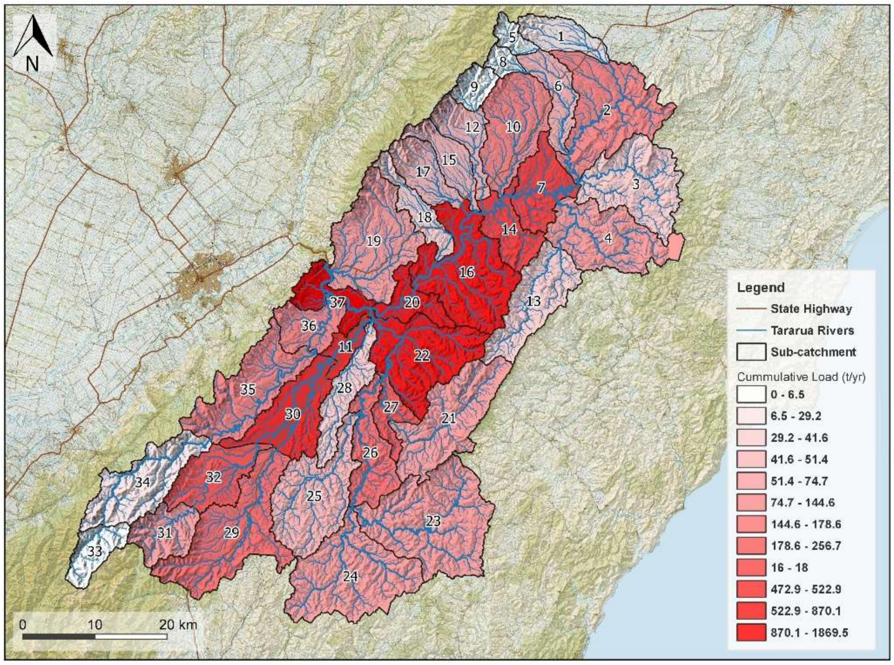

Figure 33. Cumulative DIN load (t/yr) in Tararua sub-catchments with spatially nitrogen variable attenuation factors applied.

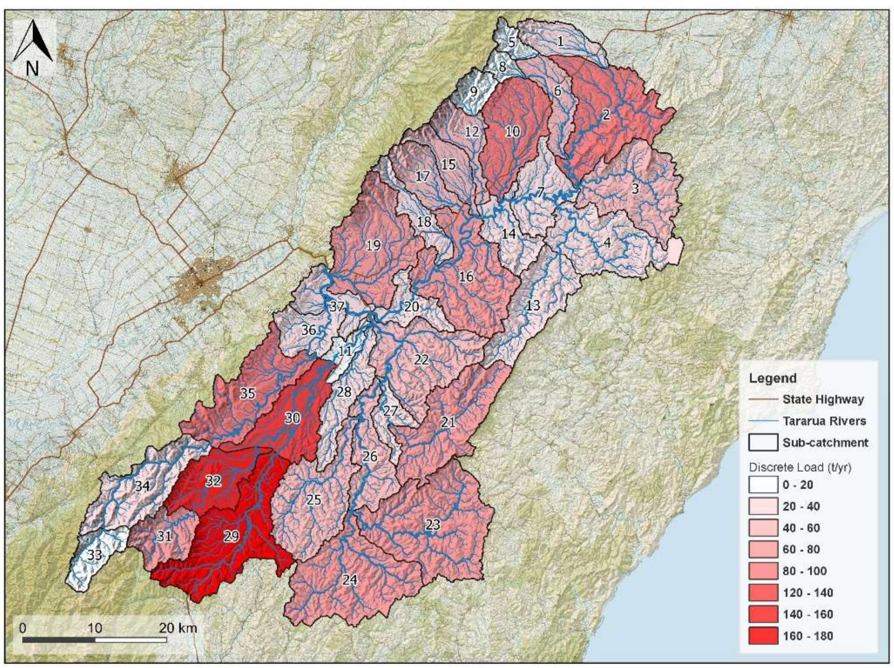

Figure 34. Discrete DIN Load (t/yr) in Tararua sub-catchments with spatially variable nitrogen attenuation factors applied.

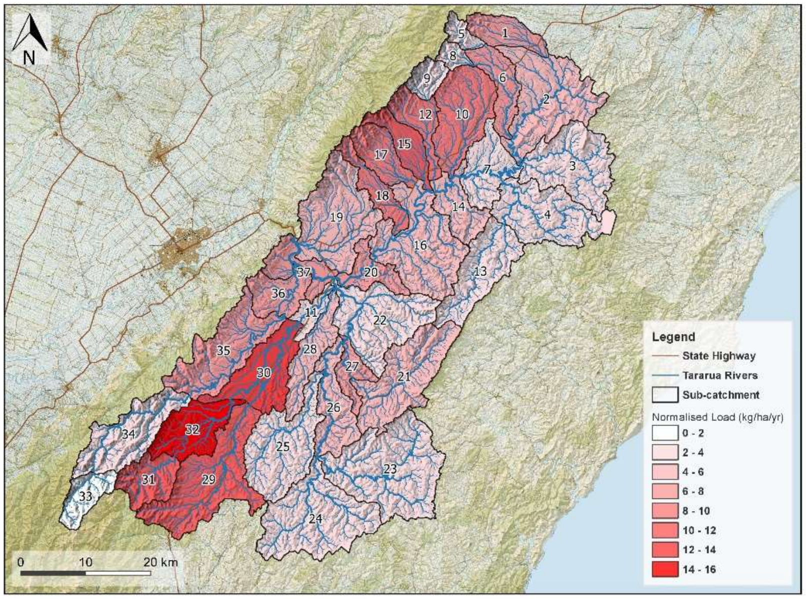

Figure 35. Area-weighted average discrete DIN load (kg/ha/yr) in Tararua sub-catchments spatially variable nitrogen attenuation factors applied.

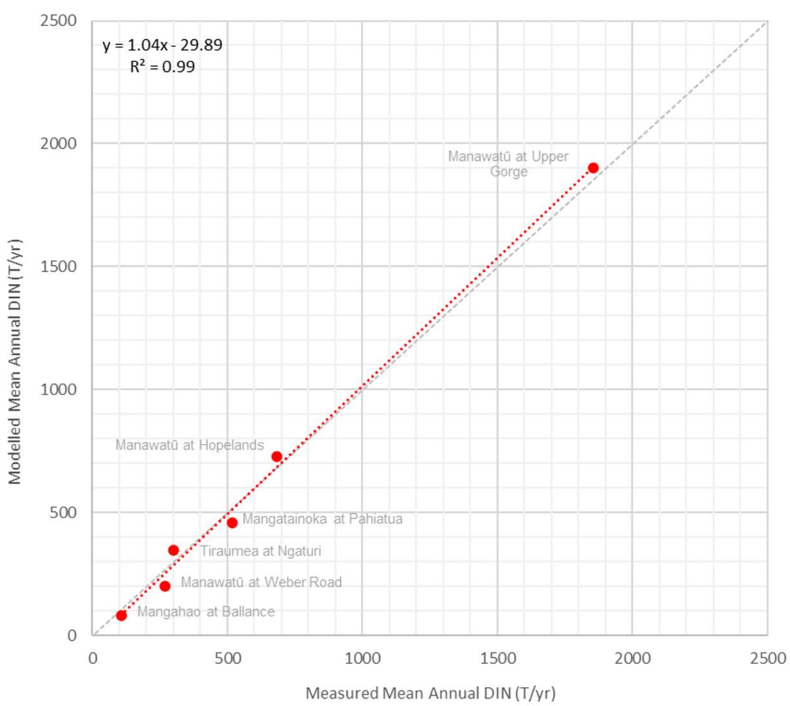

Figure 36. Measured vs modelled cumulative river DIN load (t/yr) in the Tararua sub-catchments, modelled with spatially variable nitrogen attenuation factors applied.

Figure 37 reproduces the calibration of the average monthly river DIN concentrations between the measured and modelled data. This figure demonstrates that the mean river DIN concentrations were simulated very similar to the measured data, although the upper and lower quartiles varied.

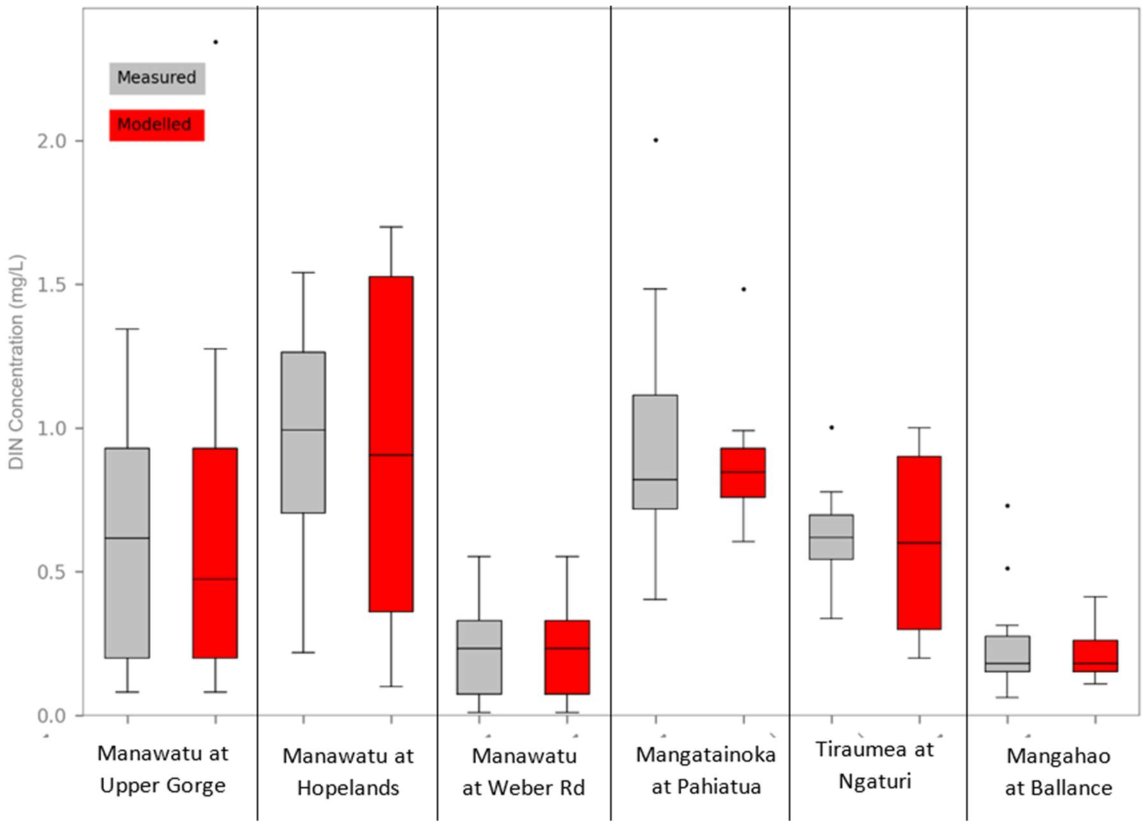

Figure 37. Comparison of the modelled and measured average monthly river DIN concentrations at different monitoring sites in Tararua sub-catchments, over an annual average year (2010).

5.4.6 Nitrogen Loads Calibration Summary

Overall, the model's performance with spatially variable nitrogen attenuation factors applied to quick flow and slow flow, was considered suitable to apply the model outside the calibration conditions and use it for scenario simulation. However, the exact nitrogen attenuation factors calculated will be influenced by the slight underestimation of flow in some sub-catchments (Appendix J). The ability of the model to simulate river DIN loads improved significantly by applying spatially variable nitrogen attenuation factors to different flow pathways. Table 20 presents the model performance statistics for each method of nitrogen attenuation factor application, while Figure 38 presents the actual error between the simulated and measured average annual river DIN loads. From these results, no nitrogen attenuation simulated significantly higher river DIN loads. A uniform attenuation factor achieved a good calibration of average annual river DIN load at Manawatū at Upper Gorge, but not at other gauges or for monthly values, while a spatially variable nitrogen attenuation factors applied to different flow paths achieved a better calibration of both average monthly and average annual DIN loads at all sites.

Table 20. Comparison of different nitrogen attenuation models performance measures in simulating average monthly river DIN loads at different monitoring sites in Tararua sub-catchments, over a period over an annual average year (2010).

Statistic	Nitrogen Attenuation Factor (AF)	Overall	Manawatū at Hopelands	Manawatū at Upper Gorge	Manawatū at Weber Road	Mangahao at Ballance	Mangatainoka at Pahiatua	Tiraumea at Ngaturi
RMSE	No nitrogen AF	74.7	95.7	199.5	50.4	8.8	24.1	23.3
	Uniform nitrogen AF	28.0	23.6	79.6	15.4	2.8	23.1	9.2
	Spatially variable nitrogen AF	19.8	21.0	38.3	11.0	4.4	12.3	5.5
	Spatially variable nitrogen AFs applied to different flow pathways	13.3	19.5	23.0	9.1	4.5	10.9	4.1
PBIAS	No nitrogen AF	-130.9	-164.4	-124.5	-221.4	-97.3	-50.5	-90.3
	Uniform nitrogen AF	24.9	-44.5	4.9	-59.2	57.8	37.1	36.5
	Spatially variable nitrogen AF	3.4	-4.2	1.3	-5.1	4.3	7.0	5.0
	Spatially variable nitrogen Afs	-0.1	-0.1	-0.1	1.8	-2.7	0.4	0.5

Statistic	Nitrogen Attenuation Factor (AF)	Overall	Manawatū at Hopelands	Manawatū at Upper Gorge	Manawatū at Weber Road	Mangahao at Ballance	Mangatainoka at Pahiatua	Tiraumea at Ngaturi
	applied to different flow pathways							
NSE	No nitrogen AF	-0.6	-5.0	-2.4	-6.2	-3.4	0.1	-1.0
	Uniform nitrogen AF	0.8	0.3	0.7	0.3	0.5	0.1	0.5
	Spatially variable nitrogen AF	0.9	0.7	0.5	0.7	0.7	0.7	0.9
	Spatially variable nitrogen AFs applied to different flow pathways	0.9	0.9	0.6	0.8	0.7	0.8	0.9

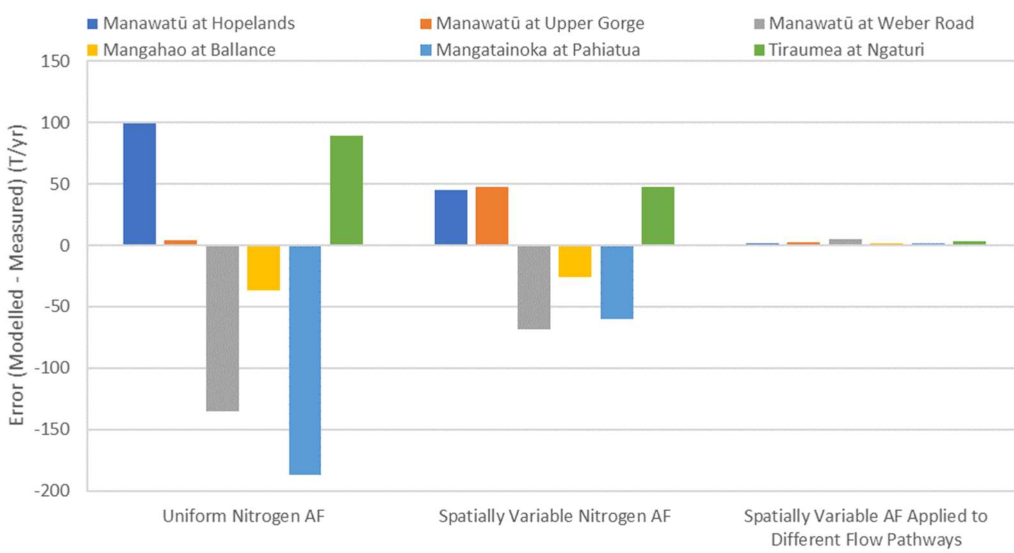

Figure 38. Comparison of error between the measured and modelled average annual river DIN loads (t/yr) using different nitrogen AF methods.

5.5 Scenario Results

This section presents the simulated effect of each water quality mitigation scenario had on nitrogen river loads within the Tararua sub-catchments. The root zone nitrogen loss refers to nitrogen losses from the soil profile (based on the Overseer estimates), while the river loads refer to the load of DIN that would be found in the river and includes nitrogen attenuation in its flow pathways from land to rivers (modelled by the integrated Overseer and SOURCE model). Models are often better at describing relative differences, such as the percentage increase or reduction of river DIN loads after a management change, rather than providing the absolute values of the changes in river DIN loads. It is important to take this into account when analysing the model outputs.

5.5.1 Baseline

The baseline scenario is the scenario that was modelled in Section 5.3.3 and represents the current conditions as a baseline to assess the effect of each mitigation scenario on the average annual root zone nitrate losses and river DIN loads. This scenario resulted into the cumulative average annual river DIN load of 1,897 t/yr, as compared to the cumulative average annual root zone nitrate loss of 4,279 t/yr in the sub-catchments. Discrete loads in each sub-catchment ranged from 3.06 - 178.59 N t/yr (Figure 34), while the cumulative loads ranged from 3.06 - 1869.54 N t/yr (Figure 33). A summary of the discrete annual average root zone nitrate losses and river DIN loads produced in each sub-catchment for each scenario is presented in Appendix O.

SC 29 and 32 have high discrete river DIN loads. As they are located in the catchment headlands (Figure 33), the high river DIN loads in the headwaters filter down and produce high cumulative river DIN loads in lower sub-catchments. Therefore, it is crucial to reduce river DIN loads in upstream sub-catchments as the nutrient losses from these sub-catchments have the greatest impact on the largest stretches of river. Of particular concern is the high cumulative load in SC 11. Given that there are only four sub-catchments upstream, the flow is small, so the predicted river DIN concentration is particularly high. From this analysis, mitigating nitrate losses in sub-catchments such as 29, 30 and 32 would significantly improve the overall river water quality of the catchment.

In this scenario, it is apparent that the root zone nitrate losses are translated more strongly to the river DIN loads in low nitrogen attenuation capacity areas such as in SC 13 and 14, while in high nitrogen attenuation capacity areas such as SC 19 and 22, there is a significant reduction between the average annual root zone nitrate losses and the average annual river DIN loads (Appendix O).

5.5.2 In-field Measures

In-field measures assumed a reduction in the root zone nitrate losses. Table 21 presents the area of sheep and beef and dairy under each nitrogen attenuation capacity functional unit, which is relevant to assess where in the catchment in-field mitigation practices would be best applied.

Table 21. Area of dairy and sheep and beef land use under different nitrogen attenuation capacity functional units in the Tararua Catchment.

Land use	Nitrogen Attenuation Capacity		
	Low	Medium	High
Sheep and Beef (ha)	26,792	104,684	66,410
Dairy (ha)	5,313	42,408	5,613

5.5.2.1 Dairy Root Zone Nitrate Losses Reduction

This scenario assumed a reduction of 5 to 30% in the root zone nitrate losses from dairy farming areas achieved by adoption of appropriate in-field measures such as fertilizer and stock management, pasture species and feeding strategies, duration-controlled grazing. Obviously, the assumed reduction in the root zone nitrate losses from dairy areas (due to the in-field measures) reduced both the root zone and river DIN load (Figure 39). However, the reduction in root zone nitrate losses transferred to relatively less reduction in the river DIN loads as some of the root zone nitrate losses from dairy farming on high nitrogen attenuation capacity areas are significantly attenuated. For example, a 10 % reduction in Overseer estimates of baseline dairy root zone nitrate losses resulted in an overall catchment root zone nitrate reduction of 4% (as sheep and beef losses were not reduced), which only equated to a 1.2% reduction in the overall river DIN load (Figure 39). Similarly, a 30% reduction in Overseer dairy root zone nitrate losses resulted in a 12% reduction in the sub-catchment cumulative root zone nitrate load and a 7.0 % reduction the sub-catchments cumulative river DIN load.

Applying the 30% reduction in Overseer dairy root zone nitrate losses to dairy farms only over low nitrogen attenuation capacity areas (30_L) resulted in a 0.8% reduction in the sub-catchments cumulative river DIN load (Figure 39). The small reduction was expected due to only 4% of the total catchment area falling under dairy, low attenuation land use (Table 21). Interestingly, applying the 30% reduction in Overseer dairy root zone nitrate losses to dairy farms over low and medium '30_L_M' nitrogen attenuation capacity areas resulted in a 6.8 % reduction in the sub-catchments cumulative river DIN load, which is similar to applying the 30% reduction in Overseer dairy root zone nitrate losses to all dairy farms (7% reduction).

These results clearly highlight that if the methodology with the variable attenuation factor proposed in this research is appropriate, there is little gain to be made by reducing root zone nitrate losses in dairy farms over high attenuation areas as the reduction is already taken care of by the system and by applying reductions to the root zone nitrate losses in dairy areas over only low and medium nitrogen attenuation capacity areas, similar reductions in the overall river DIN loads can be achieved (Figure 39).

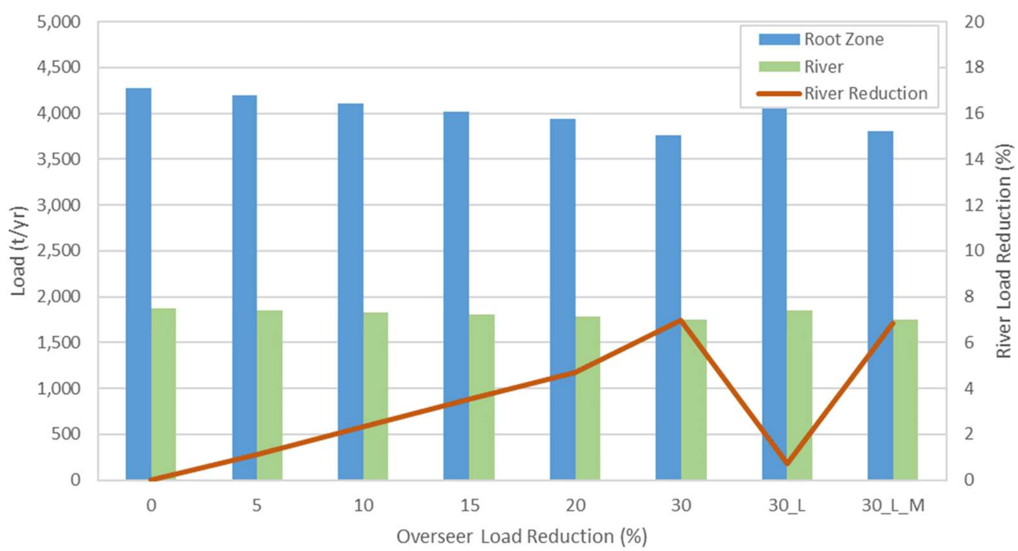

Figure 39. Influence of reduction in dairy root zone nitrate losses on the overall reduction in the Tararua sub-catchment's root zone nitrate losses and river DIN loads.

5.5.2.2 Sheep and Beef Root Zone Nitrate Losses Reduction

Similar to dairy, an assumed reduction in Overseer loads from in-field mitigation measures on sheep and beef farms, led to both root zone nitrate loss and river DIN load, reductions. Interestingly, the reduction in root zone nitrate losses resulted in a greater overall reduction in the cumulative river DIN load than in dairy farms. For example, a 15% reduction in dairy root zone nitrate loss resulted in a 3.5% reduction in overall cumulative river DIN load, but a 15% reduction in sheep and beef root zone nitrate loss resulted in a 5.4% reduction in overall cumulative river DIN load (Figure 40). This can be attributed to sheep and beef comprising of 62% of the total catchment area compared to dairy comprising of 16%. It is clear that the reduction from sheep and beef is strongly influenced by the area.

As expected, applying the 30% reduction in Overseer sheep and beef root zone nitrate losses to sheep and beef farms over low and medium '30_L_M' nitrogen attenuation capacity areas resulted in a 7% reduction in the sub-catchments cumulative river DIN load, which is similar to applying the 30% reduction in Overseer sheep and beef root zone nitrate losses to all dairy farms (10.5% reduction) (Figure 40).

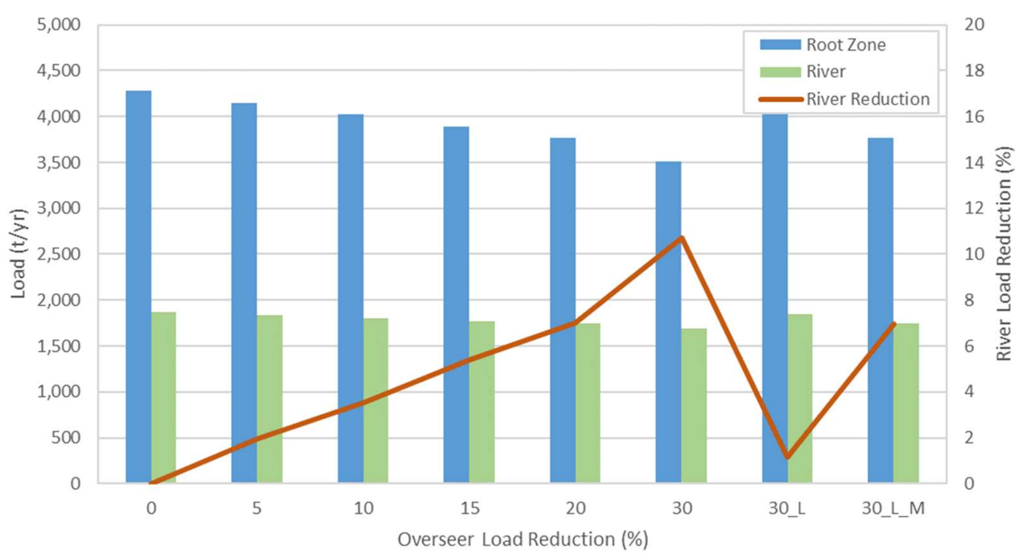

Figure 40. Influence of reduction in sheep and beef root zone nitrate losses on the overall reduction in the Tararua sub-catchment's root zone nitrate losses and river DIN loads.

5.5.2.3 Dairy and Sheep and Beef Root Zone Nitrate Losses Reduction

By applying the assumed reduction in Overseer root zone nitrate losses to both dairy and sheep and beef farms as a result of in-field measures, a greater reduction in overall cumulative river DIN load was made. A 10% reduction in Overseer root zone nitrate losses over both dairy and sheep and beef farms resulted in a 9.8% reduction in the overall average root zone nitrate losses in the catchment. This resulted into a reduction of 6% in the average annual river DIN loads. Similarly, a 30% reduction in Overseer root zone nitrate losses over both dairy and sheep and beef farms equates to a 29.6% reduction in the overall average root zone nitrate losses and a 19% reduction in the average annual river DIN load (Figure 41).

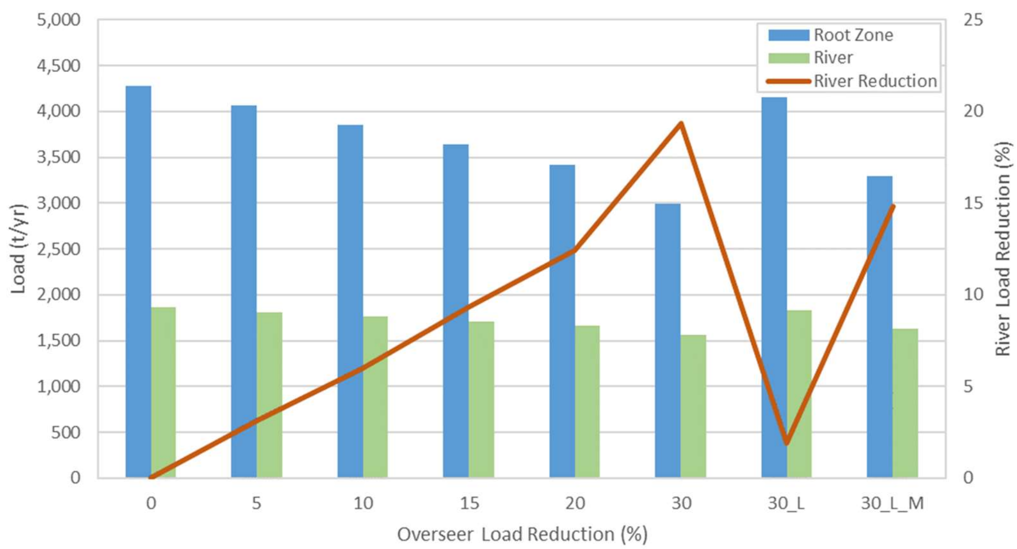

Figure 41. Influence of reduction in dairy and sheep and beef root zone nitrate losses on the overall reduction in the Tararua sub-catchment's root zone nitrate losses and river DIN loads.

It is important to note that a 30% reduction in root zone nitrate losses is unlikely to be feasible to achieve without loss of production. This scenario had no influence on the spatial or temporal distribution of load as the same inputs were just scaled down. However, in reality, farms in certain areas will have a greater capacity to achieve the necessary reductions than other farms. Additionally, the in-field mitigation measures applied will likely affect the temporal distribution of losses.

It should also be noted that the in-stream attenuation decreased from 3.0% in the baseline scenario to 2.5% when root zone nitrate losses were decreased by 30%. While this result is minor and expected based on the decay model applied to model in-stream attenuation, if in-stream attenuation remained constant, greater reductions in river loads would be observed.

5.5.3 Catchment-scale Measures

5.5.3.1 Matching Attenuation Capacity

Matching the potential nitrogen attenuation capacity of the soils and underlying geology to intensive land use could significantly reduce river DIN loads across the whole catchment. In this scenario, 5,313 ha of dairy land use on low nitrogen attenuation capacity areas was swapped with 4,968 ha of sheep and beef on high nitrogen attenuation capacity areas under LUC class 1 – 4 lands. This resulted in a reduction of 236 t/yr tonnes or 13% in the mean annual river DIN load at the catchment outlet (Figure 42).

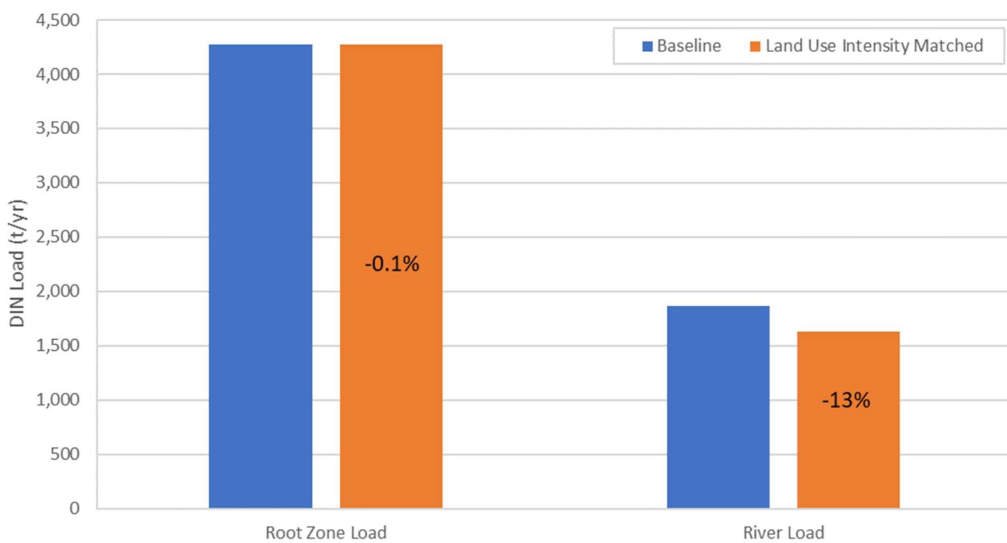

Figure 42. Impact of matching land use intensity with nitrogen attenuation capacity, on the cumulative average annual root zone nitrate losses and river DIN loads in the Tararua Catchment.

The cumulative root zone nitrate losses were very similar between the scenarios (Figure 42) because the decrease in the root zone nitrate losses caused by the shift of dairy off higher permeability soils and geology was offset by a similar increase in root zone nitrate losses generated from sheep and beef shifted to higher permeability soils and geology in these areas. For example, under a medium rainfall regime, the average annual Overseer estimated root zone nitrate loss under dairy coarse-textured soil was 57 N kg/ha/yr, whereas, under fine-textured soil, it was 51 N kg/ha/yr - a decrease of 6 N/kg/ha/yr. Similarly, the difference between Overseer estimated root zone N loss for sheep and beef on fine-textured soil and coarse-textured soil was an increase of 6 N kg/ha/yr. The rainfall regimes that dairy and sheep and beef are switched from are very similar, so this is unlikely to impact the difference between the estimates of the root zone nitrate loss.

Matching land use intensity to nitrogen attenuation capacity created significant differences in the spatial distribution of river DIN loads compared to the baseline scenario. The load generated in the southern catchment was significantly decreased, but the load in the north-eastern catchment slightly increased. Utilising the sub-catchment's variable nitrogen attenuation capacity in the functional units made a significant difference and allowed dairy production to occur without a large effect on the river DIN load. For example, the root zone nitrate loss for SC 23 increased by 22 t/yr, but the river load only increased by 3.7 t/yr due to the high attenuation capacity of the catchment. Similarly, in SC 20 the root zone nitrate loss increased by 19 t/yr but the river DIN load only increased 1.6 t/yr. No significant differences were found in the temporal variability of monthly loads between the baseline scenario and this scenario.

This scenario reduced the cumulative average annual river DIN loads by 13% and as the root zone nitrate losses remained the same, it is expected that the farm productivity was maintained. This indicates that there is scope within the Tararua sub-catchments to reduce river DIN loads by further matching intensive land use with high nitrogen attenuation capacity areas. However, there could be practical barriers to implementing this scenario. For example, dairy is easier to farm on free draining soils, although upon analysis of the functional units, it is clear that dairy is already farmed on intermediate and fine-textured soils in the sub-catchments.

5.5.3.2 Drainage Management

In the baseline scenario, nitrogen loads in quick flow from dairy on fine-textured soils were not attenuated as they represented potential artificial drainage facilitating the quick transfer of nitrate loss from the soil profile. In the drainage management scenario, it was assumed that drainage nitrogen loads (in quick flow from dairy on fine-textured soils) could be attenuated by 75% by utilising suitable conservation drainage management practices such as controlled drainage, drainage water recycling, woodchip bioreactors, and/or constructed wetlands (Singh & Horne, 2020). This drainage management scenario decreased the river DIN load at the catchment outlet by 11% but had no impact on the root zone nitrate losses as compared to the baseline scenario (Figure 43). The root zone losses were not affected as the same inputs were applied in this scenario.

The greatest reduction in river load occurred in sub-catchments 15, 20, and 29, due to the high proportion of dairy and fine-textured soils in these sub-catchments. The implementation of drainage management also improved the cumulative river DIN load downstream of these sub-catchments. The temporal profile of river DIN arrival at the river also changed in this scenario, with river DIN loads similar to the baseline occurring during the summer months but significantly less during winter months. This can be explained by less interflow (representing artificial drainage) being simulated during summer months in comparison to winter months (Appendix K).

This drainage management scenario shows a significant reduction in the overall river DIN the overall load in the Tararua Catchment, while maintaining farm productivity. However, the amount of reduction in the river DIN loads generated by this scenario simulation is directly related to the percentage of reduction applied to the drainage (quick flow) nitrogen attenuation which requires further investigation.

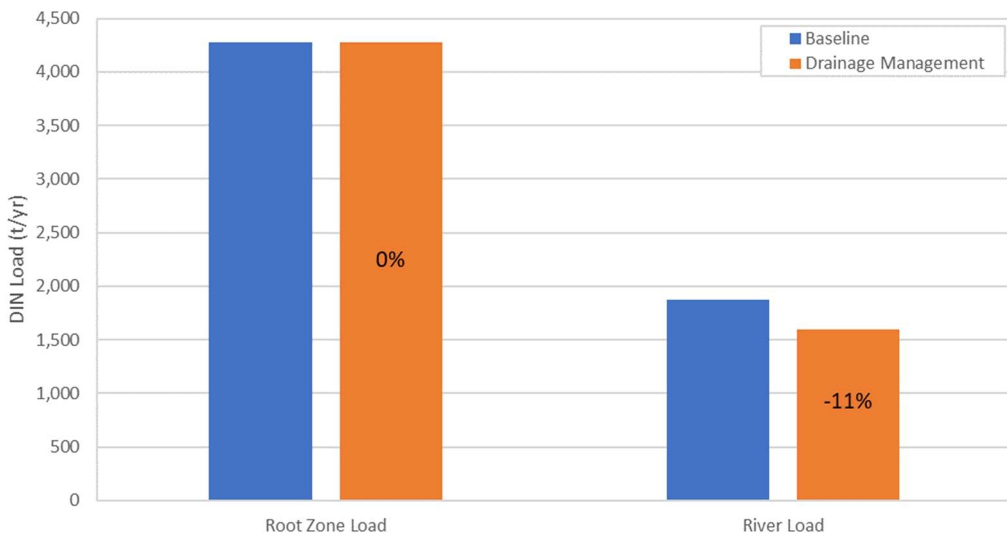

Figure 43. Impact of drainage management, on the cumulative average annual root zone nitrate losses and river DIN loads in the Tararua Catchment.

5.5.3.3 Wetlands

Similar to the drainage management scenario, the implementation of wetlands to treat not only drainage but small streams could reduce river DIN loads. Wetlands at key locations could be very effective at reducing nitrate river DIN loads in the catchment directly upstream of them. In this scenario, three wetland nodes were simulated downstream of the sub-catchments SC 16, 22 and 30 to treat the high concentrations of nitrogen leaching upstream.

The wetlands scenario reduced the overall catchment load by 9% (Figure 44), although the disadvantage was that some sub-catchment loads were not reduced. There was a predicted decrease in the cumulative annual average river DIN loads by 17%, 31% and 29% between the baseline and wetland scenarios in SC 16, 22, and 30, respectively. However, the parameterisation of the wetland model and number of wetlands placed, directly impacts the extent of reduction achieved. The wetlands had a larger effect on baseflow loads and a limited effect on quick flow loads.

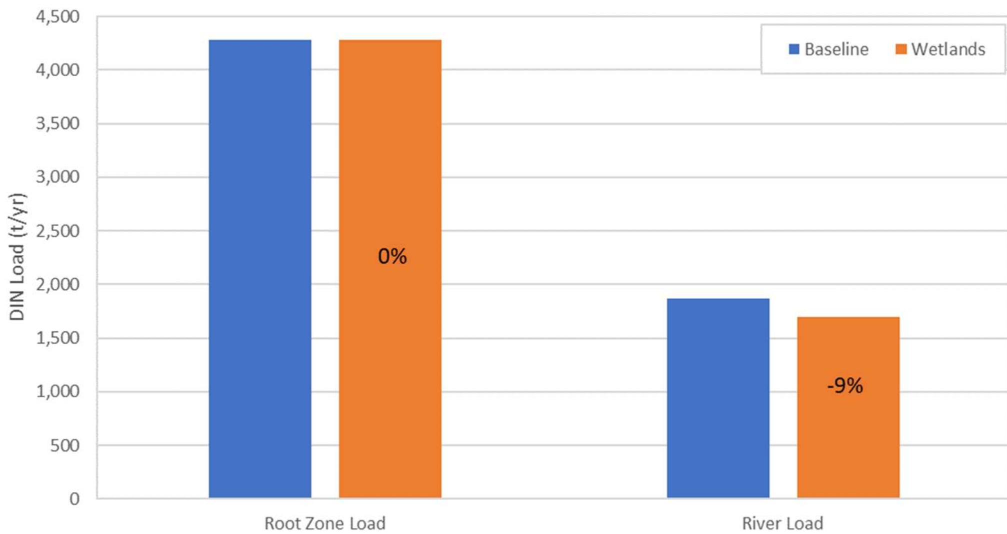

Figure 44. Impact of wetlands, on the cumulative average annual root zone nitrate losses and river DIN loads in the Tararua Catchment.

5.5.4 Summary

A comparison of reduction in estimate of average annual root zone nitrate losses and average annual river DIN loads across the scenarios are presented in Table 22. The reductions in average annual river DIN loads ranged from 7 % to 19 %.

Table 22. Estimates of reduction in average annual root zone nitrate losses and river DIN load in the Tararua Catchment, modelled under various in-field and catchment-scale mitigation strategies.

Strategy	Reduction in Average Annual Root Zone Nitrate Loss (N t/yr)	Reduction in Average Annual River DIN Load (N t/yr)	Percentage Reduction in Average Annual River DIN Load (%)
In-field Dairy ‘30_all’	513	130	7
In-field Sheep and Beef ‘30_all’	770	205	11
In-field Dairy and Sheep and Beef ‘30_all’	1283	355	19

Strategy	Reduction in Average Annual Root Zone Nitrate Loss (N t/yr)	Reduction in Average Annual River DIN Load (N t/yr)	Percentage Reduction in Average Annual River DIN Load (%)
Matching Attenuation Capacity	0	243	13
Drainage Management	0	205	11
Wetlands	0	168	9

6 Discussion

This chapter discusses the major findings of this research. It also discusses the assumptions made, uncertainties involved and modelling limitations, followed by suggestions for further research.

6.1 Integration of Farm-scale and Catchment-scale Models

A key objective of this study was to assess whether it is possible to integrate farm-scale and catchment-scale models to predict river DIN loads. The calibration of river flow and DIN loads from the integrated Overseer and SOURCE model to the measured data had evaluation classifications that ranged from 'Satisfactory' to 'Very Good', which indicates that a successful integration of farm-scale nutrient budget and catchment-scale hydrology models was reached (Section 5.4.6). In addition, the model outputs are comparable to those found in the literature, with sub-catchments that consisted of dairy land use, highly permeable soils and geology, and high rainfall regimes, producing higher river DIN loads (Cameron et al., 2013; McLaren & Cameron, 2002; Quinn et al., 2009). The integrated model also achieved a better prediction of river DIN loads than the empirical model developed and used by Elwan (2018). Elwan's (2018) model underpredicted the overall DIN load in the Tararua catchment by 87.4 t/yr (-5%), while the use of this integrated model overpredicted overall average annual river DIN load by 2.3 t/yr (<1%) as compared to the measured data. Also, the integrated model achieved a satisfactory prediction of average monthly river DIN loads, which was not possible by Elwan (2018) empirical model. In addition, by applying parameters on a functional unit basis, the integrated model was able to account for the heterogeneity within the sub-catchments, which aids to substantiate its accurate physical representation and prediction of river DIN loads.

Central to the success of the model integration was the flexible architecture of the SOURCE model. SOURCE provided the framework to integrate the models by setting up the sub-catchment structure and modelling the transport and transformation of flow and nutrients between sub-catchments (Figure 8). External outputs from SIMHYD and Overseer were attached to each sub-catchment which enabled each model to work on its own, in parallel, and meant that no modification to the operation of the models was needed. While this was beneficial, as it reduced the complexity of the model, it created limitations. One limitation was that Overseer used its own soil water balance simulation to generate nutrient losses from the soil profile. To ensure the models could be combined and physical representation maintained, the water balance between the SIMHYD and Overseer models was compared. While each model produced a water balance with components in a similar range, there was uncertainty in the comparison due to the different scales the water balance was simulated on. Additionally, uncertainty exists due to the questionable simulation of surface runoff and negligible soil drainage during summer months from Overseer. Another limitation of simulating water flow independently was that the Overseer outputs were not subject to routing of water flow in the subsurface profile. Also, Overseer does not account for the transformations of nitrogen in the subsurface environment (below the root zone) as it only simulates leaching to the bottom of the soil zone (Wheeler, 2016). After the soil zone, nitrogen mass travels through the vadose zone and groundwater, where the nitrogen mass could be attenuated (the signal is smoothed, and the total mass is conserved) before reaching the surface waters (Follett, 2008). SOURCE modelled spatially variable nitrogen attenuation using an attenuation factor, but the time lag in nitrogen flows was not fully modelled. Given this, it is interesting to note how well the seasonal variation in monthly average river DIN loads matched between the model prediction and the measured data. This suggests that to a degree, the time lag in nitrogen flows were accounted for using SIMHYD simulated water balance in the integration of OVERSEER nutrient generation to predict river DIN loads. Any discrepancy in the simulation of nitrogen flow lags would become more prominent should the models be run on a daily time-step. A possible improvement to the model would be to disaggregate the root zone nitrate losses from Overseer to a daily time-step and then apply a routing model such as the Muskingum equation. Ideally, the flow component of Overseer would be generated by SIMHYD allowing the water flow to be modelled with regard to the differences in physical characteristics, and nitrogen to be routed alongside the flow throughout the catchment. The development of an Overseer plugin for SOURCE would allow this to occur. However, the methods used in this initial research are sufficient to overcome many of the challenges identified in the literature review by using either farm-scale models or catchment-scale models independently.

One unanticipated finding was that baseflow in the model was underestimated at Mangatainoka at Pahiatua and overestimated at Makakahi at Hamua compared to measured flows (Figure 22 and Figure 57). While this discrepancy could be attributed to the model parameterisation, it is possible there may be gaining and losing reaches within the catchment, given the position of the Mangatainoka at Pahiatua and Makakahi at Hamua sites (Appendix J). It is possible that at Makakahi at Hamua, groundwater discharges from the hills are not captured at the gauging site and rather a portion of the groundwater in the upper catchments flows into a neighbouring stream (e.g. to north or south), or re-emerges further downstream below the monitoring point. A losing condition occurs when the river is perched above the local water table and a gaining condition is where the groundwater level resides above the river stage (Freeze & Cherry, 1979). Previous studies suggested the Tararua Catchment is an enclosed basin (Morgenstern et al., 2017), which means lateral groundwater flows into or out of the basin are considered negligible or non-existent. Therefore, discharge of groundwater out of the basin is most likely via groundwater seepage into the surface water systems and exits the basin along with surface waters in the west through the Manawatū Gorge. To assess this, a 3D numerical groundwater model would need to be developed. While in this model groundwater was simulated using the baseflow recharge and vadose zone processes, in the future, an alternative and more sophisticated approach that could be investigated in the future would be to a groundwater flow and transport model that could the losses and gains to groundwater. SOURCE has two integrated groundwater models, Groundwater Numerical Model for 1-Dimensional Flow (GN1D) and Groundwater Analytical Tool (GAT) saturated connection model that could be investigated to use in the future (Vaze et al., 2012). Additionally, use of a 3D groundwater model would allow simulation of attenuation within different geological layers. However, the disadvantage would be increased model complexity and greater data requirements for accurate parameterisation.

The other integral part of achieving integration of farm-scale and catchment-scale models was the development of the nutrient generation model. This model allowed the Overseer estimates of average annual root zone nitrate loss (kg/ha/yr) to be processed so they could be applied as resultant nitrate concentrations to the quick flow and slow flow components in SOURCE. The main assumption made in this process was that root zone nitrate losses are perfectly mixed in all flow pathways (Section 4.3.3). In reality, it is likely that nitrate concentrations vary seasonally. While the integrated models accounted for the seasonal nature of nitrate loss due to the variations in flow, it did not account for the seasonal nature of nitrate losses from the soil profile.

There were three key factors that determined the temporal variability of river DIN loads in the model: the water flow, nitrogen attenuation factor, and the Overseer estimates of root zone nitrate loss from the soil profile. From the comparison of the different integration models, it was clear that flow and the nitrogen attenuation factor had a greater influence than the timing of Overseer estimates of root zone nitrate loss, given that both tested nutrient generation models with different timing, i.e., monthly average versus annual average of Overseer root zone nitrate loss, produced similar quick flow and slow flow concentration results (Section 5.3.2). The integration of average annual Overseer root zone nitrate loss using the perfect mixing in the soil profile based of the SIMHYD water balance resulted in better profile of monthly distribution of nitrogen loads in different flow pathways. This supported the decision to use the model that utilised the annual average Overseer root zone nitrate loss.

However, in the future, a model should be developed where the monthly variation in the root zone nitrate losses is transferred to the catchment-scale model in a more informed manner. Achieving this would become more important with catchments of a smaller area. Another challenge faced in this research was the lack of ability in SOURCE or SIMHYD to model artificial drainage from the soil profile. While artificial drainage was accounted for through the adjustment of the interflow parameter, developing a plugin to model artificial drainage in specific areas should provide more accurate river flow and water quality results.

The integration of Overseer with SOURCE was beneficial as it enabled the transfer of on-farm losses to waterways to be simulated. It also allowed the spatial variability of root-zone nutrient losses to be assessed, as well as the impact of catchment-scale mitigation measures and attenuation on the wider catchment (Section 5.5). This was important as farm-scale models have different hydrological pathways to catchment-scale models, and there is a large amount of natural heterogeneity within the Tararua catchment. Additionally, it was important to focus on nitrogen entering receiving water bodies, so spatially variable nitrogen attenuation was accounted for enabling both in-field and catchment-scale mitigation measures to be assessed in detail. It should be acceptable to apply the methods used in this thesis to a wide range of farm systems in different geographical settings, as long as adequate input data is available. Using SOURCE is beneficial as the model can easily be adapted to suit different contexts as different rainfall-runoff and nutrient generations models can be used.

6.2 Nitrogen and Hydrological Regime in Tararua Catchment

Analysis of the Tararua Catchment's characteristics and model outputs, such as the water balance, root zone nitrate loss and river DIN loads determined that the transport processes within the Tararua

Catchment are highly variable both spatially and temporally. The model produced results that were in line with what was expected and results from previous studies. This section outlines points of interest.

Dairy land use contributes significantly more nitrate to overall catchment root zone losses than sheep and beef. This was evident from the analyses presented in Section 5.4.1 when no nitrogen attenuation was applied and catchments such as SC 33 which comprised of dominantly dairy land use, had high area-weighted average DIN loads. In the Tararua Catchment, dairy predominantly occurs in the western lowlands, which explains the high root zone nitrate losses in this area. Consistent with the literature, this research found that in the ranges of the southwestern sub-catchments, greywacke is the dominant geological unit so greater amounts of rainfall were partitioned into surface runoff, and therefore, nitrogen transport to waterways is dominated by quick flow (Table 17). In contrast, through the middle of the catchment in areas with more permeable soils and underlying gravel geology, the model estimated higher soil infiltration and subsoil drainage rates, and nitrogen was transported predominantly through slow flow. This gives insight into the types of water quality mitigation measures that would be most effective in each sub-catchment. Uuemaa et al. (2018) indicated that groundwater-dominated catchments would respond better to the implementation of wetlands compared to quick flow-dominated catchments, for which drainage management measures are more effective. The sub-catchment characteristics that lead to faster groundwater recharge and flow, such as well-drained soils and gravels, not only have greater root zone nitrate losses but have significantly more river DIN loads due to the unconducive environment for nitrogen attenuation in flow pathways. This means that these areas within the Tararua sub-catchments should be the focus for targeted in-field water quality mitigations, especially as they are also likely to be more responsive to catchment-scale mitigation measures for river DIN loads.

The year-to-year variation in river DIN loads suggested that a large proportion of the river DIN variation is related to variation in the rainfall received (Figure 18). The rest of the year-to-year variation is likely a result of land use changes and variation in farm management practices. The relationship between river DIN loads and rainfall varied between the monitoring sites, as higher rainfall areas do not necessarily produce higher leaching if the land use is less intensive. In the future, a range of further relationships could be investigated, such as the effect of temporal changes in land use on the nitrogen attenuation factor and river DIN concentrations and loads, if the nitrogen model was run for multiple years. However, dynamic land use layers would need to be developed.

This would also allow the calibration to focus on longer periods and a wider range of data. There was considerable variation between summer and winter river DIN concentrations. This suggests that nitrogen occurs in significant volumes in quick flow as it dominates flow over winter when losses are greater, while slow (groundwater) flows are more prominent in the summer months (Freeze & Cherry, 1979). Using the river DIN loads may not truly represent the nitrogen loads in the river as it does not include organic nitrogen (Quinn et al., 2009). While the analysis in Section 4.1.1 determined that, on average at annual scale, the majority of TN is DIN, this may change between sub-catchments and seasons, as over winter there is more surface runoff and therefore, organic nitrogen may have increased importance.

6.3 Nitrate Attenuation

Nitrogen attenuation in a catchment is known to occur in the groundwater system and riparian margin due to a combination of factors such as biogeochemical transformations (e.g., denitrification) and biological processes such as plant uptake. However, the biogeochemical and biological processes were not explicitly accounted for in the modelling process utilised for this study. Instead, the nitrogen attenuation factor was developed to capture the cumulative effect of various nitrogen attenuation processes on the reduction of nitrogen flows to surface waters (Section 4.3.4). This investigation followed on from Elwan's (2018) research which identified the link between soil, geology, and spatially variable nitrogen attenuation. The thesis aimed to build upon the previous findings and further examine the spatial variability of nitrate attenuation and the impact of applying nitrogen attenuation factors on river DIN loads simulated on a monthly time-step rather than an annual average. This study found that using a spatially variable attenuation factor applied to different flow pathways significantly improved the model performance, corroborating the association between physical catchment characteristics and spatially variable nitrate attenuation capacity of different land units (a combination of soil and underlying geology) (Table 20).

The decision to use a constituent filter model in SOURCE, rather than applying an attenuation factor manually like Elwan (2018), was advantageous, as it allowed for simulation of spatially variable nitrogen reduction and attenuation to be applied separately to quick flow (interflow) and slow flow pathways. As expected, the calibrated attenuation factors for quick flow were less than the slow flow as the residence time of nitrogen in interflow pathways is less, so there is less time for denitrification to occur. Nitrogen attenuation in the soil profile and by plant's uptake was modelled in Overseer.

Based on the calculation of the root zone nitrate losses, this study found that the nitrate attenuation needed in each sub-catchment to calibrate the integrated model varied from 0.23 at Makuri at Tuscan Hills to 0.78 at Manawatū at Weber Road. Considering the hydrological premise that these catchments have reasonably different soil and sub-soil hydraulic properties, these results aid to confirm that spatial variability in nitrate attenuation occurs due to soil and geological characteristics. For example, when comparing SC 36 and 13 that both have very similar root zone nitrate losses of 104 and 103 t/yr, respectively, the river DIN loads were significantly different at 55 and 38 N t/yr, respectively (Appendix O). This is due to differences in nitrate attenuation applied. This outcome is contrary to the findings from Selbie et al. (2015), who suggested that most areas within a catchment have an equal chance of contributing to long-term NO_3^- loss and source factors tend to govern the magnitude of nitrogen loss. A significant result that supports the conclusion that nitrate attenuation is spatially variable was that applying a uniform nitrogen attenuation factor resulted in a worse calibration of river DIN loads (PBIAS of 24.92) than applying a spatially variable nitrogen attenuation factor (PBIAS of 3.39).

Using the calibration that best fitted the river DIN data in the Tararua Catchment, the model predicted that between 15% and 81% of nitrate leached from the root zone is attenuated in slow flow and between 6% and 46% in quick flow before it reaches surface water, depending on the attenuation classification for each functional unit (Table 18). This is similar to Elwan (2018), who found that between 14 - 94%, with an average of 58%, resulted in an optimal calibration. However, there are still many unanswered questions regarding the actual nitrate attenuation rate and how this differs between high, medium, and low classes. For example, the current nitrogen attenuation classifications could be overestimating nitrate attenuation in the high class but underestimating nitrate attenuation in the low class.

At every monitoring site, the modelled river DIN loads were slightly overestimated in summer months and underestimated in winter months. While applying spatially variable nitrogen attenuation factors to both quick flow and slow flow minimised this, the difference in seasonal variation was still apparent (Appendix N). One possible explanation for this is that nitrate attenuation varies temporally. Research around rates of denitrification also suggests that there could be temporal variation in nitrate attenuation as greater denitrification occurs during summer, where warmer climatic conditions increase biological activity (Jahangir et al., 2012). The rate at which chemical reactions occur also significantly increases with temperature. There is no current research that contradicts this assumption and while this assumption makes conceptual sense, further research and observational data are needed to confirm it and to determine how best to incorporate it into the model. Another possible explanation for the overestimation of modelled river DIN loads in summer is that the seasonal variation in root zone nitrate simulated based on the average annual Overseer estimates is inaccurate, or more in-stream nitrogen attenuation occurs in summer than winter.

Improving how nitrate attenuation is accounted for in the model is one of the critical steps to increase confidence on its capacity to estimate nitrogen transport through the catchment. The nitrate attenuation used in the model was calibrated so could be affected by uncertainties in the models input parameters and the measured data used. It should also be noted that applying the nitrogen attenuation factor has the ability to mask errors in flow simulation or nutrient inputs. This is likely is happening at Mangatainoka at Pahiatua where flow was under simulated (Figure 22) but the river DIN load calibration matched well (Figure 84). Further research is recommended to validate the parametrisation of spatially variable nitrogen attenuation for different land units across the study sub-catchments.

Also, further investigation is recommended around the parameterisation of the in-stream attenuation model. A potential challenge in accurately modelling in-stream attenuation is that the SOURCE user interface has limited ability to independently apply attenuation to different nitrogen species, ignoring the conservation of mass involved in the transformation of nitrogen into different forms (eWater, 2018). Drewry et al. (2006) also identified deficiencies in the simulation of in-stream nutrient processing in catchment models.

6.4 Mitigation Practice Effectiveness

The calibrated integrated model was finally applied to investigate the effectiveness of various mitigation practices at reducing DIN loads in rivers within the Tararua sub-catchments. Contrary to expectations, this study did not find large differences in DIN river load reduction between different mitigation measures, although the locations within the catchment where DIN load was reduced varied. The results of this study indicated that in-field measures resulted in a maximum reduction of 19% in overall average annual river DIN load, when an in-field reduction of 30% in root zone nitrate losses was applied to both sheep and beef and dairy farming areas (Figure 41). The catchment-scale scenarios of matching nitrogen attenuation to land use intensity resulted in a 13%, drainage management in a 11% and wetlands in a 9% reduction in average annual river DIN load (Table 22). It is important to note that a large amount of analysis could be undertaken for each scenario, and adjusting the parameters significantly impact each scenario's effectiveness. However, this study is still able to provide high-level conclusions on the effectiveness of mitigations.

Overall, these results indicate that a range of mitigation measures can effectively reduce river DIN loads. They also indicate that the mitigation scenario chosen influences the spatial distribution of high river loads. While effective at reducing river loads, in-field practices are less favourable due to their potential impact on farm production to achieve high reductions in farm root zone nitrate losses. The river DIN load reduction achieved by in-field measures is equivalent to the reduction achieved through catchment-scale measures with no loss of significant production. Similarly, matching the land use intensity to nitrogen attenuation is less favourable due to the practical challenges associated with its implementation. Drainage management and wetlands could be used in conjunction with each other, with drainage management reducing the DIN losses from artificially drained land and wetlands reducing the load in small streams from other catchments with a high propensity for river DIN loads due to their underlying soils and geology. However, it is likely that a collaborative approach between farmers and council will be needed to ensure wetlands are placed at strategic locations. The modelling suggests that collectively, these measures would have the ability to reduce overall average annual DIN river loads by 24%.

The area within the Tararua Catchment and flow component that each mitigation practice reduced the nitrogen load from varied. The drainage management scenario reduced nitrogen load from areas with dairy on fine-textured soils, predominantly located in the middle sub-catchments. This also means it reduces quick flow nitrogen load mainly during winter months. In contrast, the wetlands scenario reduced nitrogen load from sub-catchments with intensive land use and highly permeable soils and geology. Also, the wetlands reduction was concentrated in small areas upstream of the wetland placement. Wetlands primarily reduce slow flow load. Matching attenuation capacity to land use intensity reduced DIN load over large areas of the catchment. It decreased load in the middle and western catchment but increased load in the eastern catchment. In-field measures reduced load uniformly over the catchment. However, in reality, it is likely that some areas will have greater scope for infield reduction than others. This suggests that a combination of mitigation measures will be most effective as it will enable DIN load to be reduced across the whole catchment. This is important as even though this study modelled that the overall catchment load decreased under every mitigation practice, under some mitigations, many streams will still receive the same quantity of load and be susceptible to poor water quality.

Section 2.3 identified that a holistic approach to choosing mitigation practices is needed that balances farm productivity with environmental benefits. Utilising this approach and taking into consideration the potential effect on farm production, it is likely that catchment-scale practices are more effective than in-field practices, although further holistic analysis is ideally needed. To achieve a 30% reduction in root zone nitrate losses, as modelled in the in-field scenarios, it is highly likely that farm production will be compromised. Research by the Dairy NZ Economics Group (2014) found that on a Waikato dairy farm, a 10% reduction in root zone nitrate leaching per hectare can be achieved with a minimal impact on farm profit and production. However, reductions in root zone nitrate leaching of greater than 20% will generally have an impact on farm operating profit and production of more than 10%. In contrast, a similar reduction in river DIN loads can be achieved with no significant impact on farm production using catchment-scale practices, although the capital cost needs further analysis.

The true effectiveness of each mitigation strategy also depends on the likelihood of uptake by farmers. The modelling shows that matching attenuation capacity with land use intensity could be successful at reducing river DIN loads and does not significantly impact overall farm production in the catchment. However, it is unlikely to be the most effective strategy due to practical challenges around its uptake. To implement this strategy, a coordinated approach across the whole catchment would be needed, but dairy farmers may not be willing to switch to operating sheep and beef farms, and vice versa (Samarasinghe et al., 2012). There is also likely to be a significant cost involved with converting sheep and beef to dairy farming, vice versa. Implementing this strategy may also raise questions regarding land ownership. However, the strategy would probably be achievable on a small scale where a single farm operates both dairy and sheep and beef and only farms the dairy on the high nitrogen attenuation land. There would also be barriers to the development of wetlands as a mitigation strategy because to achieve the scale of wetlands modelled in this scenario, significant areas of productive agricultural land will need to be converted. Therefore, drainage management appears to be an effective mitigation practice when the quantity of nitrogen reduced, the impact on production and ease of implementation is considered. That said, an economic analysis is recommended to compare each strategy in terms of capital and ongoing costs.

The results produced in this study are consistent with the results obtained by Singh and Horne (2020), whose exploratory analysis suggested that by managing critical flow pathways, river NO_3^- loads could be reduced by 10% and spatially aligning dairy land use with high nitrogen attenuation capacity could reduce NO_3^- loads by 19%. A key difference between the two studies was that this study was more physically based, while Singh and Horne's (2020) analysis was conceptual and at a very coarse scale. The slight discrepancy in percentage reduction between the studies could also be attributed to different land use maps and area under dairy fine textured soils.

It is clear that mitigation practices significantly reduce nitrogen load, which is a key determinant of water quality. However, the relationship between nitrogen load and eutrophication is complex and remains under-researched (McDowell & Hamilton, 2013). The vulnerability of a stream's water quality to excess nitrogen depends on several factors, including stream size and water level, and the surrounding topography (Smith et al., 1999). A waterway may be able to handle a higher nitrogen load without any impact on water quality, while another with a similar nitrogen load may be significantly impacted.

The river DIN load was primarily used to assess the nitrogen reductions in this study as it allowed for easier comparison between the sub-catchments and mitigation practices. However, in the future, river DIN concentration should also be assessed as it is directly linked to eutrophication and has biological significance (McDowell & Hamilton, 2013). It is important to note that this study assumed that the mitigation practices are fully functioning and the system had reached a steady state. Additionally, this study did not take into account the time lag in a stream's response to the implementation of mitigation measures. Bouraoui and Grizzetti (2014) found that there are three components that contribute to lag: the time needed to produce the desired effect (e.g., for trees to grow or construction to occur), the time it takes for the effect to be delivered to the waterway, and the time it takes for a waterway to respond to the effect. This is another factor that needs to be considered when selecting the most effective mitigation method. For example, a strategy that has a lag in development, such as matching land use with high nitrogen attenuation capacity areas, but larger effectiveness, may be considered less effective overall than a strategy that has a more instantaneous effect such as drainage management. From this, it is clear, that a combination of mitigation practices will be most effective.

6.5 Uncertainty and Limitations

As discussed in Section 2.4, modelling is inherently uncertain. In this study, uncertainties encompass model inputs and parameters which may have been transferred into potential error in the calibration of the attenuation nitrogen factor and the conclusions made on the effectiveness of mitigation measures. Uncertainties also exist due to the model structure and calculations.

This model only represents average conditions. Rainfall is grouped into three categories, although a large range still occurs within each. This may cause discrepancies in the relative results as some mitigation practices may be more effective under certain climates. In addition, the model outputs are only as accurate as the inputs into the model. For example, the model outputs could have been influenced by the area of each land use type, which was only accurate to the scale and for the date Horizons Regional Council sampled the land. In this study, due to data limitations, temporal changes in land use were also not accounted for. However, it is likely that between 2000 and 2016, land use changes would have instigated changes in the flow regime and more importantly in root zone nitrate losses. The soil and geological parameters used in the model were also estimated or inferred from coarse datasets meaning that some variation would have been lost. The FSL used for soil is 1:50 000, while Qmap used for geology is 1:250 000. Using higher resolution QGIS layers, especially for soils, would have significantly improved the accuracy of this analysis. The interpolated climatic inputs may also vary from the actual data to a degree. In particular, error in rainfall volumes, spatial distribution, or temporal distribution can result in significant error in the model predictions. It can also negatively impact the ability to identify other sources of error and can hide errors from improper parameter selection and model calibration (Drewry et al., 2006). To improve the accuracy of the simulations in the future, it will be key to ensure there is overlapping time periods in the land use, rainfall and measured flow and water quality datasets. The effect of consented water takes, permitted activities, artificial drainage, irrigation and losses from groundwater, and gains from groundwater on flow should also be considered.

While the integrated model performance is considered good in terms of its prediction of river flows and DIN loads, error may exist as the calibration to the measured data implies that all of the error variance is contained in simulated values and that measured data are error-free. Anastasiadis et al. (2013) and Elwan et al. (2018) highlighted that there is substantial uncertainty in reported water quality data due to the instantaneous nature of sampling and error resulting from the collection methods, meaning that low or high values may skew the measurements used in the calibration. An important finding relevant to the model calibration was the impact of the flow and water quality observations sample size on NSE and the evaluation of model calibration. While this finding is not new, with Moriasi et al. (2015) and Krause et al. (2005) also highlighting the effect of sample size, no other research has quantified how large a sample needs to be to have confidence in the NSE value. This study found that a sample size of 200 is needed (Figure 15). However, before this conclusion is used in other studies, the statistical analysis should be repeated as it is likely that the sample size needed will vary with changes in flow regimes. Due to running the nitrogen simulation for a single year, there were not 200 data points to calibrate the model to so the NSE results should be treated with caution.

Further uncertainty analysis of the nitrogen calibration results is also needed to confirm the impact of the potential uncertainties on the parameterisation of the nitrogen attenuation factor. This will have impacted the quantification of the spatially variable attenuation factor needed to reach a good calibration and the spatial variation of river DIN load. The margin of error in Overseer estimated N-leachate from the root zone could be in the order of ± 20% (Cichota & Snow, 2010). It should also be noted that the Overseer estimates of root zone nitrate losses were analysed for typical combinations of land use type, soil texture, and climatic regimes. This represents a crude estimate of root zone nitrate losses, and the differences in nitrogen leaching from every farm were not modelled due to the limited availability of more farm-specific input information.

An independent review into Overseer was conducted in 2021, during the time that this thesis was being prepared, which highlighted the confidence in Overseer as a model. Key findings were that: Overseer does not balance nitrogen mass and focuses on leaching of nitrate-nitrogen; does not adequately capture overland flow which can be a significant pathway for losses of non-nitrate forms of nitrogen; treats the soil as a single homogenous layer, limiting its ability to model soil hydrological flows and drainage of the soil solution; and uses climate data averaged over 30 years rather than actual climate data (Ministry for the Environment and Ministry for Primary Industries, 2021). Many of these same limitations of Overseer were also recognised throughout this study. In particular, the measured river DIN loads were used to calibrate the model to, given the majority of root zone losses from Overseer were presumed to be in the form of nitrate-nitrogen from the soil profile. Additionally, the model integration (Section 4.3) used a technique which limited the impact of Overseer's poor ability to model overland flow and soil drainage and the model was run for an average climatic year.

The calculation of river DIN load is another source of uncertainty that has the potential to impact the model calibration of the nitrogen attenuation factor and therefore its effects on the model outputs. However, as the flow-weighted method was used, which has a low bias, it is not considered to be a major source of uncertainty (Elwan, 2018). In contrast, the collection of measured data remains a significant source of uncertainty due to potential changes in the measurement methods and post-processing of the data (Vaze et al., 2012). For example, measured flow data is often calculated by applying a rating curve to measured water level data which can increase the error. Additionally, samples may not be taken across a range of flow rates which limits the understanding of the different processes, and routine water quality monitoring often does not capture large runoff events that may carry a significant proportion of the load (Bouraoui & Grizzetti, 2014). Care should also be taken when comparing river DIN load in the nitrogen calibration, as the difference between the observed and simulated load may be overpowered by the correlation of flows causing spurious relationships, as the variation in daily flow is generally several orders of magnitude greater than that of concentration (Vaze et al., 2012). However, the effect of this should be limited as the river DIN loads are being assessed over a long period of time so it is likely the variance in the flows will be of a similar order of magnitude.

A key point to note in this study is that changing the parameters of each mitigation practice may make it more or less effective. Further research is needed to confirm the parameters of the wetland model and the nitrogen attenuation achieved by drainage management. In particular, the effectiveness of wetlands at reducing nitrogen is dependent on its attenuation capacity, size and location. The selection of wetland locations in this study was very much hypothetical and, in the future, analysis of the topography, slope, land use, upstream river branches and flow regime is needed to determine which location would be suitable. However, these results provide tentative initial evidence regarding wetlands effectiveness. Additionally, discrepancies between the modelled and actual attenuation of nitrogen between root zone and river may influence the results. Given these limitations, the results should be considered indicative rather than an estimation of absolute values and are more suitable to assess relative change. The results from this study cannot necessarily be applied to other locations as the ability of each mitigation practice to reduce nitrogen load will vary based on the underlying geology and soil in the area. Also, some of the mitigation practices may be inappropriate to apply in some areas due to variability in soil and climatic factors.

Overall, the uncertainty in this model is not particularly different to the uncertainties that exist in any other model of equivalent complexity and their input parameters. It can be concluded that this uncertainty is unlikely to change the main message regarding the relative differences of the various scenarios studied, although the absolute values of the predicted river DIN loads and concentrations should be treated with caution. Notwithstanding the limitations discussed in this section, modelling represents the best available tool for investigating the fundamental questions of this study, and the simulation of the relative changes in root zone nitrate losses and river DIN loads between different mitigation scenarios has potential to help assess their relative effectiveness to reduce river nitrogen loads in agricultural catchments.

7 Conclusion

The primary aims of this study were to demonstrate whether it was possible to integrate farm-scale and catchment-scale models to predict river DIN loads in the Tararua Catchment, to investigate the effectiveness of various in-field and catchment-scale mitigation strategies at reducing river DIN loads and to understand the effects of spatial heterogeneity on river DIN loads in the Tararua Catchment. This would allow the hydrological regime and nitrogen transformation and transport processes in the Tararua Catchment to be better understood and the effectiveness of mitigation practices on a catchment scale to be determined.

One significant finding to emerge from this study was that it is possible to integrate eWater SOURCE and Overseer on a monthly time-step to predict monthly average river DIN loads. Soil, geology, climate, land use, and spatially variable nitrogen attenuation capacity were all applied on a functional unit basis, which was vital to developing a physically-based model that considered the significant hydrogeological heterogeneity within the sub-catchments. Overseer was linked with SOURCE by developing a nutrient generation model that applied the theory of perfect mixing to the Overseer estimates of root zone nitrate losses with the SIMHYD flow outputs, to model monthly nitrogen loads in both the quick flow and slow flow pathways. The integration of these models provided a comprehensive understanding of baseline river DIN loads in the Tararua sub-catchments and allowed assessment of the impact of various in-field and catchment-scale mitigation measures on the overall catchment river DIN load.

The integrated model produced a 'Very Good' calibration to the measured monthly average river DIN loads as assessed by time series plots and the model performance measures such as NSE, RMSE and PBIAS statistics. The framework developed and applied in this thesis to integrate farm-scale Overseer and catchment-scale SOURCE models could be adopted to assess many other scenarios that cannot be assessed by farm-scale or catchment-scale models alone. A further area of study would be to adapt a physically-based model such as SWAT+ to New Zealand farming conditions or to generate a SOURCE plugin for Overseer to reduce the uncertainty created by integrating models. Furthermore, integrating the SOURCE model with a 3D groundwater model would offer additional insights into nitrogen transport and transformations in the subsurface throughout the Tararua Catchment.

Overall, this study supports the idea that nitrogen attenuation is spatially variable. As compared to when a uniform nitrogen attenuation was applied, applying a spatially variable nitrogen attenuation based on relevant geology and soil classifications to interflow and slow flow pathways resulted in a significantly better calibration of the model to measured data in the Tararua Catchment. However, further uncertainty analysis of the nitrogen calibration results is needed to confirm the impact of the nitrogen attenuation factor parameterisation, considering the potential uncertainties in the OVERSEER estimates of root zone nitrate losses and the measured river flows and DIN loads. Also, further research is needed around the parameterisation of in-stream nitrogen attenuation as it was simulated using the default input parameters. The use of constituent filter models in SOURCE proved to be a highly insightful way to model subsurface DIN attenuation capacity as it allowed attenuation to be applied to different flow pathways and illustrated the potential for use in a range of applications. Future modelling of nitrogen should use a spatially variable attenuation factor, noting that while nitrogen attenuation in quick flow is much smaller than in the slow flow (groundwater) pathway, it improved the model performance significantly so is important to include.

This study adds to the growing body of research that indicates catchment characteristics should be considered when managing water quality outcomes. The understanding gained here should help to identify where water quality management efforts should be focused. The spatial variability in nitrogen attenuation and differences between the root zone nitrate losses and the river DIN loads highlight the need to focus on sub-catchments with low nitrogen attenuation areas when applying mitigation measures. Additionally, mitigation measures should be applied to sub-catchments that have highly permeable geology and soils produce greater groundwater flow as do those with high rainfall, which contributes relatively to large river DIN loads. In the Tararua Catchment, it is particularly important to apply mitigation measures to the headwater sub-catchments along the southern and western catchment as these have low nitrogen attenuation capacity lands, intensive land use, high rainfall, and permeable soils.

This modelling analysis highlighted that catchment-scale mitigation strategies, if developed and utilised effectively, can deliver better environmental outcomes while maintaining intensive agricultural production systems. The modelling results suggest that targeted drainage (quick flow) management from fine-textured soils under intensive dairy land use is likely the most effective mitigation practice, especially when the quantity of river DIN load reduced, impact on farm production, and ease of its implementation is considered. The results of this study also indicate that matching land use to the natural nitrogen attenuation capacity of the land or placing wetlands in strategic locations can be effective at reducing nitrogen loads to rivers. The analysis of in-field practices highlights the need to not just confine mitigation measures to dairy farms as sheep and beef farms can also contribute to large reductions in river DIN in the whole Tararua Catchment due to their large area.

Overall, this study has shown that there is a wide scope to use modelling to improve water quality management across a range of catchments. The innovative methodology developed to integrate farm-scale (such as Overseer) and catchment-scale models (such as SOURCE) will be instrumental to expand the scope of water quality scenarios that can be simulated to help achieve targeted and effective water quality management measures. This research also highlighted that while agriculture is one of the primary sources of nitrate leaching, catchment-scale mitigation practices show promise at reducing nitrogen load to rivers, while preserving the ability to maximise farm production. The findings of this research contribute to the literature surrounding the topic, provides guidance to farm managers considering mitigation practices and also facilitate a more comprehensive understanding of the water resource to assist with decisions and policy surrounding future use and management options that could be prioritised to improve catchment health. A natural progression of this work is to analyse the economic costs of each mitigation practice as this also has a significant bearing on what mitigation method is optimal.

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Appendix A. Water Quality Analysis

Appendix A presents the location of each gauge site and the average monthly and yearly DIN concentrations and loads.

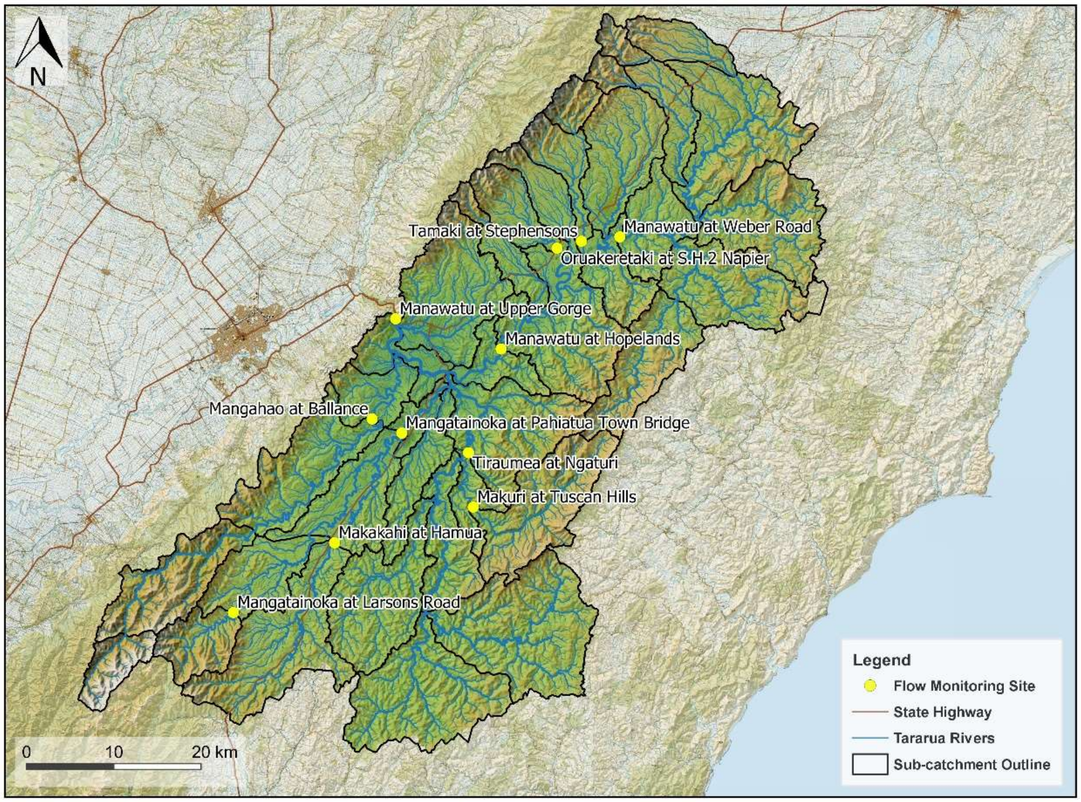

Figure 45. Location of both primary and secondary flow monitoring sites used in flow model

Table 23. Average monthly DIN concentration (mg/L) over the period from 2006 to 2016.

Month	Manawatū at Hopelands	Manawatū at Upper Gorge	Manawatū at Weber Rd	Mangahao at Ballance	Mangatainoka at Pahiatua	Tiraumea at Ngaturi
Jan	0.16	0.37	0.17	0.06	0.62	0.58
Feb	0.08	0.21	0.07	0.11	0.63	0.56

Month	Manawatū at Hopelands	Manawatū at Upper Gorge	Manawatū at Weber Rd	Mangahao at Ballance	Mangatainoka at Pahiatua	Tiraumea at Ngaturi
Mar	0.23	0.27	0.20	0.10	0.62	0.59
Apr	0.44	0.40	0.20	0.14	0.68	0.68
May	0.54	0.46	0.33	0.20	0.88	0.68
Jun	0.97	0.77	0.58	0.29	1.13	0.73
Jul	1.20	0.97	0.83	0.34	1.20	0.66
Aug	1.25	0.96	0.83	0.34	1.18	0.67
Sep	0.98	0.91	0.70	0.31	1.19	0.52
Oct	0.90	0.70	0.61	0.26	1.11	0.55
Nov	0.75	0.57	0.40	0.16	1.02	0.55
Dec	0.52	0.45	0.34	0.13	0.85	0.55
Average	**0.67**	**0.59**	**0.44**	**0.20**	**0.93**	**0.61**

Table 24. Average monthly DIN load (t/month) over the period from 2006 to 2016.

Month	Manawatū at Hopelands	Manawatū at Upper Gorge	Manawatū at Weber Rd	Mangahao at Ballance	Mangatainoka at Pahiatua	Tiraumea at Ngaturi
Jan	10.5	45.6	3.7	1.9	13.4	8.6
Feb	10.8	37.1	5.0	5.2	12.9	9.4
Mar	20.8	44.5	7.2	5.2	15.5	8.7
Apr	36.2	111.6	12.3	6.1	17.7	15.9
May	43.3	91.3	15.9	9.9	36.9	21.0
Jun	113.7	232.8	34.4	12.9	75.3	46.4
Jul	123.6	362.3	66.3	16.2	75.7	58.1
Aug	110.9	301.9	45.9	15.6	64.1	46.9

Month	Manawatū at Hopelands	Manawatū at Upper Gorge	Manawatū at Weber Rd	Mangahao at Ballance	Mangatainoka at Pahiatua	Tiraumea at Ngaturi
Sep	74.9	286.3	37.9	9.7	64.8	31.3
Oct	69.5	170.5	22.0	9.6	66.4	25.0
Nov	43.9	104.9	9.7	8.2	43.0	16.1
Dec	26.0	77.3	8.2	5.8	30.9	12.2
Average	57.0	155.5	22.4	8.9	43.1	25.0

Table 25. Annual DIN load (t/yr).

Year	Manawatū at Hopelands	Manawatū at Upper Gorge	Manawatū at Weber Rd	Mangahao at Ballance	Mangatainoka at Pahiatua	Tiraumea at Ngaturi
1989	398.6			53.4	279.1	
1990	867.6			160.0	706.1	
1991	866.3			174.4	652.7	
1992	390.7			168.7	681.3	
1993	239.4		102.1	151.3	288.3	
1994	644.8		138.2			
1995	1251.4		422.6			
1996	818.0		221.5			
1997	818.9					
1998	361.9					
1999	617.3		228.4			
2007	556.8	1338.6	142.4			
2008	893.8	2210.5	304.8	124.8	418.5	314.1
2009	791.9	2072.9	264.1	166.8	545.2	241.7
2010	672.4	2551.5	246.2	67.5	579.7	304.6

Year	Manawatū at Hopelands	Manawatū at Upper Gorge	Manawatū at Weber Rd	Mangahao at Ballance	Mangatainoka at Pahiatua	Tiraumea at Ngaturi
2011	703.3	1638.8	225.7	55.7	504.6	264.2
2012	667.1	1898.7	316.7	69.6	430.9	307.8
2013	679.5	1655.8	261.5	40.6	459.3	353.7
2014	510.1	1515.8	169.1	85.3	456.9	282.8
2015	849.8	1746.7	183.5	123.4	515.3	216.7
2016	717.1	1752.8	252.1	111.1	589.6	297.0
2017	708.5	1734.7	233.5	138.7	435.5	298.9
2018	947.5	2400.7	485.6	122.8	417.4	407.3
2019	513.2	1206.8	106.0	103.1	400.8	315.4
Average	686.9	1824.9	239.1	112.8	491.8	300.4

Appendix B. Python Script Used to Process VCSN Data

Appendix B presents the python script that was developed to process the VSCN data into a format suitable for import into eWater Source.

```
import pandas as pd
import os
import glob
import numpy as np
from scipy.interpolate import Rbf
#%%
#Import VCSN stations
VCSN=pd.read_csv(r"C:\Users\Elise Legarth\Documents\VCSN locations2.csv")
stationList = VCSN['EcoConnect'].tolist()
stationList=[str(c) for c in stationList]

#%% Create time series for each VCSN station
path=r'C:\Users\Elise Legarth\Documents\OneDrive_2_9-30-2020\OneDrive_2020-09-27 (1)\VCSN daily
data'

allfiles=glob.glob(os.path.join(path,'*.dat'))

for a, row in VCSN.iterrows():
 ID=(row["EcoConnect"])
 Rain=pd.DataFrame()
 Rad=pd.DataFrame()
 Wind=pd.DataFrame()
 RH=pd.DataFrame()
 TMax=pd.DataFrame()
 TMin=pd.DataFrame()

 for file in allfiles:
  df=pd.read_csv(file,sep=",")
  R=df[df['Agent']==ID][['Date','Rain']]
  Rain=pd.concat([R,Rain],axis=0)
  Rain.to_csv(r"C:\Users\Elise Legarth\Documents\VCSN\Rain @ %s.csv"%ID,index=False)
  Rad1=df[df['Agent']==ID][['Date','Rad']]
  Rad=pd.concat([Rad,Rad1],axis=0)
  Rad.to_csv(r"C:\Users\Elise Legarth\Documents\VCSN\Rad @ %s.csv"%ID,index=False)
  Wind1=df[df['Agent']==ID][['Date','Wind']]
  Wind=pd.concat([Wind,Wind1],axis=0)
  Wind.to_csv(r"C:\Users\Elise Legarth\Documents\VCSN\Wind @ %s.csv"%ID,index=False)
```

```
    RH1=df[df['Agent']==ID][['Date','RH']]
    RH=pd.concat([RH,RH1],axis=0)
    RH.to_csv(r"C:\Users\Elise Legarth\Documents\VCSN\RH @ %s.csv"%ID,index=False)
    TMax1=df[df['Agent']==ID][['Date','TMax']]
    TMax=pd.concat([TMax,TMax1],axis=0)
    TMax.to_csv(r"C:\Users\Elise Legarth\Documents\VCSN\TMax @ %s.csv"%ID,index=False)
    TMin1=df[df['Agent']==ID][['Date','Tmin']]
    TMin=pd.concat([TMin,TMin1],axis=0)
    TMin.to_csv(r"C:\Users\Elise Legarth\Documents\VCSN\TMin @ %s.csv"%ID,index=False)

#%% Interpolate timeseries to sub-catchment

climatedata = r'C:\Users\Elise Legarth\Documents\VCSN'

df = pd.read_csv(climatedata + r'\Rain @ ' + stationList[0][:5] + '.csv', usecols=[0], parse_dates= True,
index_col = 0 )

for station in stationList:
    dfTemp = pd.read_csv(climatedata + r'\Rain @ ' + station[:5] + '.csv', usecols=[0,1], parse_dates= True,
index_col = 0 )
    dfTemp.rename(columns=('Rain' : station[:5]), inplace=True)
    df = df.merge(dfTemp, left_index=True, right_index=True)

df = df.sort_index()

centroids=pd.read_csv(r"C:\Users\Elise Legarth\Documents\Catchment_Centroids.csv")
centroids.dropna(axis=0, how='all', inplace=True)

VCSN.dropna(axis = 0, how='all', inplace=True)
VCSN['EcoConnect']=VCSN['EcoConnect'].astype(int).astype(str)

interp = np.empty([64,1])

for i in range(len(df.index)):
  df2=df.iloc[i,:].astype(float).to_frame()

  df3=VCSN[['_X','_Y','EcoConnect']].merge(df2,right_index=True,left_on='EcoConnect',how='outer')
  rbf=Rbf(df3['_X'],df3['_Y'],df3.iloc[:,-1])

  #Interpolate on the point locations
  ptz=rbf(centroids.X,centroids.Y).reshape(64,1)
  interp=np.hstack((interp,ptz))

interp=interp[:,1:].T

interp=pd.DataFrame(interp)
```

```
interp[interp < 0] = 0

interp.columns=centroids.ID.tolist()

startdate=pd.read_csv(r'C:\Users\Elise Legarth\Documents\Date Start.csv')
startdate.columns=centroids.ID.tolist()
final = startdate.append(interp)

#save CSV file for each sub-catchment
outFolder = r'C:\Users\Elise Legarth\Documents\VCSN\SC'
subcatchments = final.columns.astype(str).tolist()

for SC in final.columns:
  final[SC].to_csv(outFolder + '\Rain_SC_' + str(int(SC)) + '.csv',index=False)
```

Appendix C. Functional Unit Groupings

Appendix C presents the grouping of soil, geology, land use and climate into categories that form the functional units in eWater SOURCE and their corresponding attenuation capacity classification where relevant (Section 4.1).

Table 26. Soil functional unit grouping.

Soil Type	Functional Unit	Attenuation Capacity
Sandy loam	Coarse textures (well-drained)	Low
Silt loam	Intermediate texture (imperfect drainage)	Medium
Loam	Intermediate texture (imperfect drainage)	Medium
Clay loam	Fine texture (poor natural drainage)	High
Sand	Coarse textures (well-drained)	Low
Strongly mottled silt loam	Fine texture (poor natural drainage)	High
Stony loam	Stony soils (excessive drainage)	Low
Sand & stony gravel	Stony soils (excessive drainage)	Low
Fine sandy loam	Intermediate texture (imperfect drainage)	Medium
Silt loam/sandy loam	Intermediate texture (imperfect drainage)	Medium
Stony silt loam	Stony soils (excessive drainage)	Low
Heavy silt loam	Fine texture (poor natural drainage)	High
Peaty silt loam	Fine texture (poor natural drainage)	High
Peaty loam	Fine texture (poor natural drainage)	High
Mottled silt loam	Fine texture (poor natural drainage)	High
Loamy sand	Coarse textures (well drained)	Low
Mottled sandy loam	Fine texture (poor natural drainage)	High

Soil Type	Functional Unit	Attenuation Capacity
Complex	Intermediate texture (imperfect drainage)	Medium
Black sand	Coarse textures (well-drained)	Low
Loamy peat	Fine texture (poor natural drainage)	High
Clay loam and silt loam	Fine texture (poor natural drainage)	High
Sandy loam and silt loam	Intermediate texture (imperfect drainage)	Medium
Mottled fine sandy loam	Intermediate texture (imperfect drainage)	Medium
Brown sandy loam	Coarse textures (well-drained)	Low
Black silt loam	Intermediate texture (imperfect drainage)	Medium
Black sandy loam	Coarse textures (well-drained)	Low
Silt loam and clay loam	Fine texture (poor natural drainage)	High
Silt loam on sand	Intermediate texture (imperfect drainage)	Medium
Weakly mottled sand	Intermediate texture (imperfect drainage)	Medium
Brown loamy sand	Coarse textures (well-drained)	Low
Black silt loam	Intermediate texture (imperfect drainage)	Medium
Black sandy loam	Coarse textures (well-drained)	Low
Silt loam and clay loam	Fine texture (poor natural drainage)	High
Silt loam on sand	Intermediate texture (imperfect drainage)	Medium
Weakly mottled sand	Intermediate texture (imperfect drainage)	Medium
Brown loamy sand	Coarse textures (well-drained)	Low
Loamy sand & sandy loam	Coarse textures (well-drained)	Low

Table 27. Land use functional unit groupings.

Land use	Functional Unit
Built-up area (urban) and settlements	Urban
Commercial forestry	Forest
Cropped land on livestock farms (incl. arable farms)	Forest
Cropped land within horticulture and lifestyle blocks	Forest
Cropped land within other land uses	Forest
Cropped land within vegetable cropping farms	Forest
Forestry on agricultural classed land	Forest
Forestry on lifestyle blocks	Forest
Forestry on non-agricultural land	Forest
Grassland within lifestyle blocks	Forest
Grassland within non-agricultural land uses	Forest
Grassland within vegetable cropping farms	Forest
Manuka or kanuka on agricultural land	Forest
Manuka or kanuka on lifestyle blocks	Forest
Manuka or kanuka on non-agricultural land	Forest
Native forest on agricultural classed land	Forest
Native forest on lifestyle blocks	Forest
Native forest on non-agricultural land	Forest
Non-vegetation surfaces (water, gravel or rock, ice, river, sand or gravel, quarry, bare surface) agriculture	Forest
Non-vegetation surfaces (water, gravel or rock, ice, river, sand or gravel, quarry, bare surface) lifestyle blocks	Forest
Non-vegetation surfaces (water, gravel or rock, ice, river, sand or gravel, quarry, bare surface) non-agriculture	Forest
Orchard or vineyard	Forest

Land use	Functional Unit
Pasture grazed as part of arable operations	Forest
Pasture grazed by dairy cows	Dairy
Pasture grazed by sheep, cattle, and/or deer	Sheep and Beef
Pasture grazed by specialist livestock (goats, emu, horses, etc.)	Sheep and Beef
Shrubby vegetation (excl. Manuka/kanuka) on agricultural land	Forest
Shrubby vegetation (excl. Manuka/kanuka) on lifestyle blocks	Forest
Shrubby vegetation (excl. Manuka/kanuka) on non-agricultural land	Forest
Transport corridor	Urban

Table 28. Geology and attenuation functional unit groupings.

MAIN_ROCK Attribute	Permeability Functional Unit	Attenuation Functional Unit
Mudstone	Low	High
Gravel	High	Low
Greywacke	Low	Low
Conglomerate	Medium	Low
Sandstone	Medium	Medium
Limestone	Medium	Medium
Debris	Medium	Medium
Claystone	Low	High
Coquina	High	Low

Table 29. Grouping of soil and geology spatially variable nitrogen attenuation capacity of different land units in the catchment.

Soil Texture / Drainage	Geological Permeability	Overall Attenuation Class
Fine textured / poor drainage	Low	Medium
Fine textured / poor drainage	Medium	High
Fine textured / poor drainage	High	High
Intermediate textured / fair drainage	Low	Medium
Intermediate textured / fair drainage	Medium	Medium
Intermediate textured / fair drainage	High	High
Coarse textured / good drainage	Low	Low
Coarse textured / good drainage	Medium	Medium
Coarse textured / good drainage	High	Medium
Stony soils / well drained	Low	Low
Stony soils / well drained	Medium	Medium
Stony soils / well drained	High	Medium

Table 30. Climate regime classifications for Overseer modelling.

Sub-catchment	Mean Annual Rainfall (mm)	Climate Regime
1	1,596	Medium
2	1,222	Medium
3	1,262	Medium
4	1,148	Low
5	2,167	High
6	1,573	Medium
7	1,068	Low
8	1,974	High
9	2,275	High
10	1,597	Medium

Sub-catchment	Mean Annual Rainfall (mm)	Climate Regime
11	967	Low
12	1,871	High
13	1,494	Medium
14	1,090	Low
15	1,655	High
16	1,077	Low
17	1,770	High
18	1,358	Medium
19	1,283	Medium
20	1,064	Low
21	1,655	High
22	1,157	Low
23	1,565	Medium
24	1,146	Low
25	1,301	Medium
26	1,229	Medium
27	1,219	Medium
28	1,290	Medium
29	1,709	High
30	1,258	Medium
31	3,312	High
32	1,983	High
33	3,957	High
34	2,920	High
35	1,746	High
36	1,200	Medium
37	1,216	Medium

Appendix D. Sub-catchment Delineation

Appendix D presents screenshots of the model set up in QGIS that was used to delineate the sub-catchments.

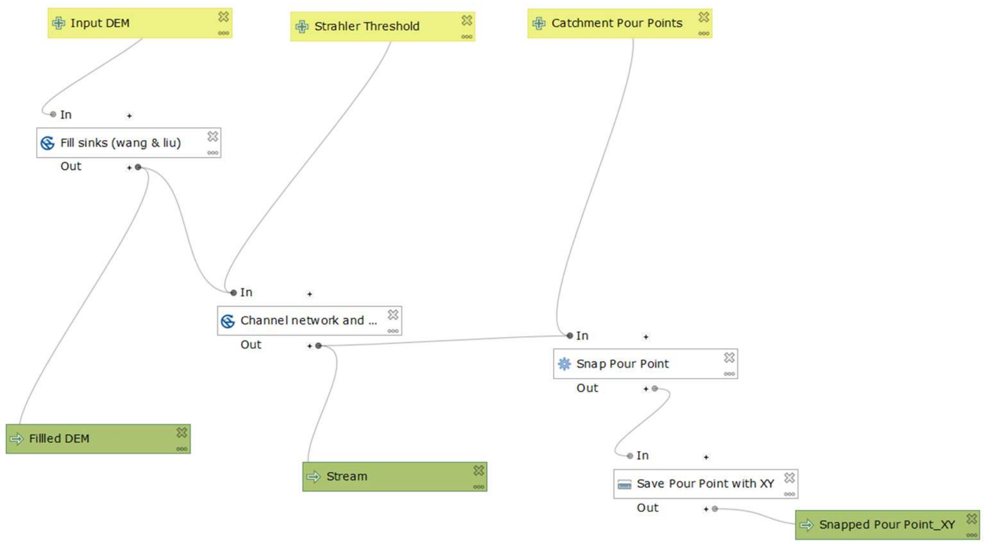

Figure 46. Step 1 to delineate sub-catchments.

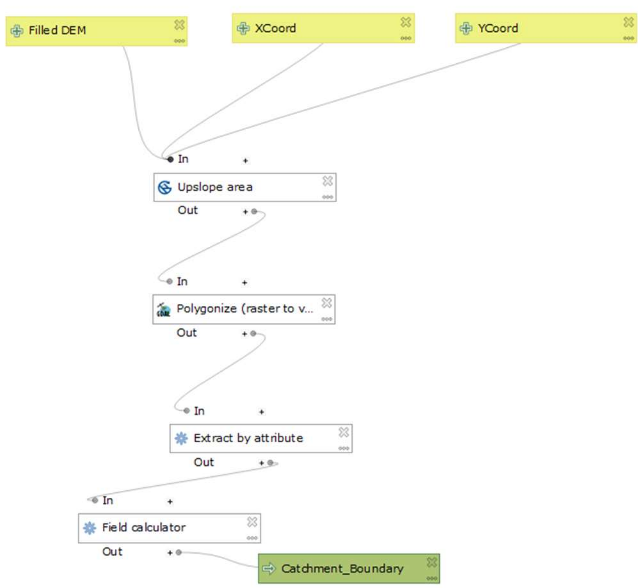

Figure 47. Step 2 to delineate sub-catchments.

Appendix E. SIMHYD Parameters

Appendix E presents the calibrated SIMHYD parameters. Note that functional unit notation is Landuse_Geological Permeability_Soil Texture. SS, IT, CT and FT refer to stony soils, intermediated textured soils, coarse textured soil, and fine textured soils, respectively. Descriptions of the variables can be found in Section 4.2.2.

Table 31. Calibrated SIMHYD parameters.

Functional Unit	Impervious Threshold (mm)	RISC (mm)	Perv. Fraction	SMSC (mm)	Infiltration shape	Infiltration Coeff.	Interflow Coeff.	Recharge coefficient	Baseflow coeff.
Dairy_Low_SS	0.5	1.0	1	45	0.01	400	0.7	0.2	0.03
Dairy_Low_IT	0.5	1.0	1	95	1	300	0.7	0.2	0.03
Dairy_Low_CT	0.5	1.0	1	65	0.05	400	0.7	0.2	0.03
Dairy_Low_FT	0.5	1.0	1	115	2	250	0.9	0.2	0.03
Dairy_Medium_SS	0.5	1.0	1	45	0.01	400	0.6	0.7	0.15
Dairy_Medium_IT	0.5	1.0	1	95	1	300	0.6	0.7	0.15
Dairy_Medium_CT	0.5	1.0	1	65	0.05	400	0.6	0.7	0.15
Dairy_Medium_FT	0.5	1.0	1	115	2	250	0.9	0.3	0.15
Dairy_High_SS	0.5	1.0	1	45	0.01	400	0.3	0.7	0.25
Dairy_High_IT	0.5	1.0	1	95	1	300	0.3	0.7	0.25
Dairy_High_CT	0.5	1.0	1	65	0.05	400	0.3	0.7	0.25
Dairy_High_FT	0.5	1.0	1	115	2	250	0.9	0.3	0.25
Forest_Low_SS	0.5	2	1	120	0.01	400	0.7	0.2	0.03

Forest_Low_IT	0.5	2	1	200	1	300	0.7	0.2	0.03
Forest_Low_CT	0.5	2	1	170	0.05	400	0.7	0.2	0.03
Forest_Low_FT	0.5	2	1	250	2	250	0.7	0.2	0.03
Forest_Medium_SS	0.5	2	1	120	0.01	400	0.6	0.7	0.15
Forest_Medium_IT	0.5	2	1	200	1	300	0.6	0.7	0.15
Forest_Medium_CT	0.5	2	1	170	0.05	400	0.6	0.7	0.15
Forest_Medium_FT	0.5	2	1	250	2	250	0.7	0.3	0.15
Forest_High_SS	0.5	2	1	120	0.01	400	0.3	0.7	0.25
Forest_High_IT	0.5	2	1	200	1	300	0.3	0.7	0.25
Forest_High_CT	0.5	2	1	170	0.05	400	0.3	0.7	0.25
Forest_High_FT	0.5	2	1	250	2	250	0.7	0.3	0.25
SheepBeef_Low_SS	0.5	1.0	1	45	0.01	400	0.7	0.2	0.03
SheepBeef_Low_IT	0.5	1.0	1	95	1	300	0.7	0.2	0.03
SheepBeef_Low_CT	0.5	1.0	1	65	0.05	400	0.7	0.2	0.03
SheepBeef_Low_FT	0.5	1.0	1	115	2	250	0.7	0.2	0.03
SheepBeef_Medium_SS	0.5	1.0	1	45	0.01	400	0.6	0.7	0.15
SheepBeef_Medium_IT	0.5	1.0	1	95	1	300	0.6	0.7	0.15
SheepBeef_Medium_CT	0.5	1.0	1	65	0.05	400	0.6	0.7	0.15
SheepBeef_Medium_FT	0.5	1.0	1	115	2	250	0.7	0.3	0.15
SheepBeef_High_SS	0.5	1.0	1	45	0.01	400	0.7	0.7	0.25
SheepBeef_High_IT	0.5	1.0	1	95	1	300	0.3	0.7	0.25
SheepBeef_High_CT	0.5	1.0	1	65	0.05	400	0.3	0.7	0.25
SheepBeef_High_FT	0.5	1.0	1	115	2	250	0.3	0.3	0.25
Urban	1	0.5	0.65	50	1	300	0.1	0.2	0.1

Appendix F. Python Script Used to Develop River Cross Sections

Appendix F presents the python script that was developed to produce cross sections of the rivers in the Tararua Catchment. These cross sections were used as an input to the flow routing model.

```
import geopandas as gpd
import pandas as pd
import numpy as np
import rasterio
import matplotlib.pyplot as plt
from scipy import spatial
import glob
import os
from scipy import stats

#%% This is used to extract the DEM value at points along the cross sections to make individual profile for open channel flow analysis

#Read in the points shapfile
pts=gpd.read_file(r"C:\Users\elise\OneDrive\Masters Thesis\GIS\Cross Sections\CS_pts.shp")
#Plotting the cross section points
pts.plot()

#Generate the x and y coordinates
pts['X']=pts.geometry.x
pts['Y']=pts.geometry.y
coords = [(x,y) for x, y in zip(pts.X, pts.Y)]

# Open the raster and store metadata
src = rasterio.open(r"C:\Users\elise\OneDrive\Masters Thesis\GIS\Cross Sections\DEM.tif")

# Sample the raster at every point location and store values in DataFrame
pts['Raster Value'] = [x for x in src.sample(coords)]
pts['Raster Value'] = pts.apply(lambda x: x['Raster Value'][0], axis=1)
del pts['geometry']

#Write the cross section csv files
xsections=pts.groupby(['ID'])

lowest=[]
for index, cs in xsections:
  print('Start generating Cross Sections %s'%index)
  cs['Distance']=((cs['X']-cs.iloc[0,:]['X'])**2+(cs['Y']-cs.iloc[0,:]['Y'])**2)**(0.5)
  profile=cs[['Distance','Raster Value']]
```

```
  minele=cs['Raster Value'].min()

  lowest.append(minele)
  #Write the cross section .csv file
  profile.to_csv(r'C:\Users\elise\OneDrive\Masters Thesis\GIS\Cross
Sections\Outputs\CS_profiles\CS%s.csv'%index,header=None,index=False)
  f,ax1=plt.subplots(1,figsize=(6.5,3.5))
  ax1.plot(cs['Distance'],cs['Raster Value'],lw=0.75)
  plt.close()
  ax1.set_title('%s'%index)
  f.savefig(r"C:\Users\elise\OneDrive\Masters Thesis\GIS\Cross
Sections\CS_figures\CS%s.png"%index,bbox_inches='tight')

xsections=pts.groupby(['ID']).size()
#Extract the lowest elevation along the profile
lowest=pd.DataFrame(lowest)
lowest.columns=['Lowest Elevation']

lowest['ID']=CroSections.index.tolist()
lowest.to_csv(r'C:\Users\elise\OneDrive\Masters Thesis\GIS\Cross
Sections\Outputs\LowestElevation.csv',index=False)


#%%This block is to estimate the average channel slope at cross section central point based on the neighbouting
stream points.

#Read in the cross section central point location
Cropts=gpd.read_file(r"C:\Users\elise\OneDrive\Masters Thesis\GIS\Cross Sections\Centerpts.shp")
Cropts['X']=Cropts.geometry.x
Cropts['Y']=Cropts.geometry.y
del Cropts['geometry']

#Read in the stream locations with slope as ratio
rivpts=gpd.read_file(r"C:\Users\elise\OneDrive\Masters Thesis\GIS\Cross Sections\Streampts.shp")
rivpts['X']=rivpts.geometry.x
rivpts['Y']=rivpts.geometry.y
del rivpts['geometry']

#Build the stream pts as a tree
tree=spatial.KDTree(rivpts[['X','Y']].values)
#Look for the nearest 10 for each river cross section central point
Neighbours=tree.query(Cropts[['X','Y']].values,k=10)[1]

Neighbours=pd.DataFrame(Neighbours)
Neighbours.index=Cropts['ID'].to_list()

#Perfomring the average calculation
Slopes=[]
for index, row in Neighbours.iterrows():
  Slopeavg=rivpts.iloc[row]['Sloperatio'].mean()
  Slopes.append(Slopeavg)
```

```
Cropts['Slope']=Slopes

Cropts.to_csv(r'C:\Users\elise\OneDrive\Masters Thesis\GIS\Cross Sections\Outputs\CrossSectionSlope.csv',index=False)

#Perform checks on k nearest neighbour search
check=rivpts.iloc[row]
check.to_csv(r'C:\Users\elise\OneDrive\Masters Thesis\GIS\Cross Sections\check2.csv')
```

Appendix G. Point Source Loads

Appendix G presents the annual average point source DIN loads that were used as an input t the SOURCE model.

Table 32. Annual average point source DIN loads in the Tararua Catchment, based on the observations between 2007 and 2020.

Site Name	Easting	Northing	Load (kg/year)
Dannevirke STP at microfiltered oxpond	2773500	6104200	61,671
DB Breweries at Industrial wastewater	2753300	6083100	1,151
Eketahuna STP at Secondary oxpond waste	2738000	6059000	545
Fonterra Pahiatua wastewater	2749600	6080100	251
Mangatera at u/s T.D.C. Ox Ponds	2773900	6104400	246
Norsewood STP at oxpond waste	2784800	6120100	803
Ormondville STP at 2nd oxpond waste	2788607	6116119	224
Pahiatua STP at Tertiary oxpond waste	2750900	6080900	2,686
PPCS Oringi STP at oxpond waste	2768300	6100500	492
Woodville STP at Secondary oxpond waste	2752300	6092100	2,054

Appendix H. Python Script for Nutrient Generation Model

Appendix H presents the python script that was developed to carry out the processes of the nutrient generation model described in Section 4.3.

```
import pandas as pd
import numpy as np
import os

#import all water balance files
path=r'G:\Shared drives\Projects\Bears Home Project Management Ltd\WWLA0321_Muriwai Downs
Golf Project\Technical\Models\APSIM\Models'
allfiles=glob.glob(os.path.join(path,'*.out'))

IF=[c for c in allfiles if ('interflow' in c)]
QF=[c for c in allfiles if ('quick flow' in c)]
SF=[c for c in allfiles if ('slow flow' in c)]
GW=[c for c in allfiles if ('groundwater percolation' in c)]

IFdict=()
for file in IF:
  SC=os.path.basename(file).split('_')[2]
  df=pd.read_csv(file,delim_whitespace=True,skiprows=3)
  df['Date']=pd.to_datetime(df['Date'], dayfirst=True)
  df = df.set_index(df['Date'])
  df.drop(['Date'], axis = 1, inplace = True)
  monthly_df = df.resample('M').sum()
  IFdict[SC]= monthly_df['flow'].values

QFdict=()
for file in QF:
  SC=os.path.basename(file).split('_')[2]
  df=pd.read_csv(file,delim_whitespace=True,skiprows=3)
  df['Date']=pd.to_datetime(df['Date'], dayfirst=True)
  df = df.set_index(df['Date'])
  df.drop(['Date'], axis = 1, inplace = True)
  monthly_df = df.resample('M').sum()
  QFdict[SC]= monthly_df['flow'].values

SFdict=()
for file in SF:
  SC=os.path.basename(file).split('_')[2]
```

```
  df=pd.read_csv(file,delim_whitespace=True,skiprows=3)
  df['Date']=pd.to_datetime(df['Date'], dayfirst=True)
  df = df.set_index(df['Date'])
  df.drop(['Date'], axis = 1, inplace = True)
  monthly_df = df.resample('M').sum()
  SFdict[SC]= monthly_df['flow'].values

GWdict=()
for file in GW:
  SC=os.path.basename(file).split('_')[2]
  df=pd.read_csv(file,delim_whitespace=True,skiprows=3)
  df['Date']=pd.to_datetime(df['Date'], dayfirst=True)
  df = df.set_index(df['Date'])
  df.drop(['Date'], axis = 1, inplace = True)
  monthly_df = df.resample('M').sum()
  GWdict[SC]= monthly_df['flow'].values


#import Overseer leaching
Overseer=pd.read_csv(".......")

#import functional unit, and SC rainfall classification
FU=pd.read_csv("  ")
SC_rainfall=pd.read_csv("  ")

#create a file for each SC and functional unit

allN=[]
keys=[]
data=np.zeros([16071,1])

for key,a in IFdict.items():
  print(key)

  QF=QFdict.get(key)
  SF=SFdict.get(key)
  GW=GWdict.get(key)

  #Calculate quick flow conc
  Totalflow=IF+SF
  Totalconc=(Overseer*1000)/(Totalflow/1000*10000)
  IF_load=(Totalconc/1000)*(IF/1000*10000)
  QF_conc=(IF_load*1000)/(QF/1000*10000)

  #calculate slow flow conc
  SF_load=(Totalconc/1000)*(SF/1000*10000)
```

```
  TSF_load=SF_load.sum()
  TSF=SF.sum()
  SF_conc=(TSF_load*1000)/(TSF/1000*10000)

  N2=N.reshape(16071,1)
  data=np.hstack([data,N2])

  newkey='Concentration'

  keys.append(newkey)
  allN.append(N)

Nseries=dict(zip(keys,allN))
```

Appendix I. Mitigation Model Parameters

Appendix I presents a description of the parameters used in the wetland mitigation model (Section 4.5.3.3)

Table 33. Wetland model parameterisation.

Parameter	Description	Units	Default
C*	The background concentration of quick flow	mg/L	1.3
C*-slow flow	The background concentration of baseflow	mg/L	1.3
Surface area - quick flow	Surface area of filter model for surface flow component	m^2	60,000
Surface area - slow flow	Surface area of filter model for the baseflow component	m^2	60,000
Cin	Input concentration	mg/L	60,000
k	Areal decay rate constant	m/yr	500
k-slow flow	Areal decay rate constant for slow flow	m/yr	500

Appendix J. Flow Calibration Results

Appendix J presents the statistics, hydrographs and flow duration curves for the calibration of modelled flow to measured data.

Table 34. Model performance statistics for primary flow monitoring sites in the Tararua Catchment for both the calibration (1999 to 2007) and validation (2008 to 2016) periods.

Monitoring Location	NSE		PBIAS		RMSE		R^2	
	Calibration	Validation	Calibration	Validation	Calibration	Validation	Calibration	Validation
Manawatū at Hopelands	0.8	0.7	-4.1	-5.0	14,252	14,672	0.9	0.9
Manawatū at Upper Gorge	0.8	0.6	-5.0	-5.9	58,281	59,031	0.9	0.8
Manawatū at Weber Road	0.8	0.8	-7.6	-8.7	29,315	30,021	0.9	0.9
Mangahao at Ballance	0.7	0.6	-1.3	-3.4	21,865	22,725	0.9	0.8
Mangatainoka at Pahiatua	0.6	0.6	13.2	16.8	13,027	13,857	0.9	0.9
Tiraumea at Ngaturi	0.8	0.7	-7.5	-10.2	8,373	8,570	0.9	0.9

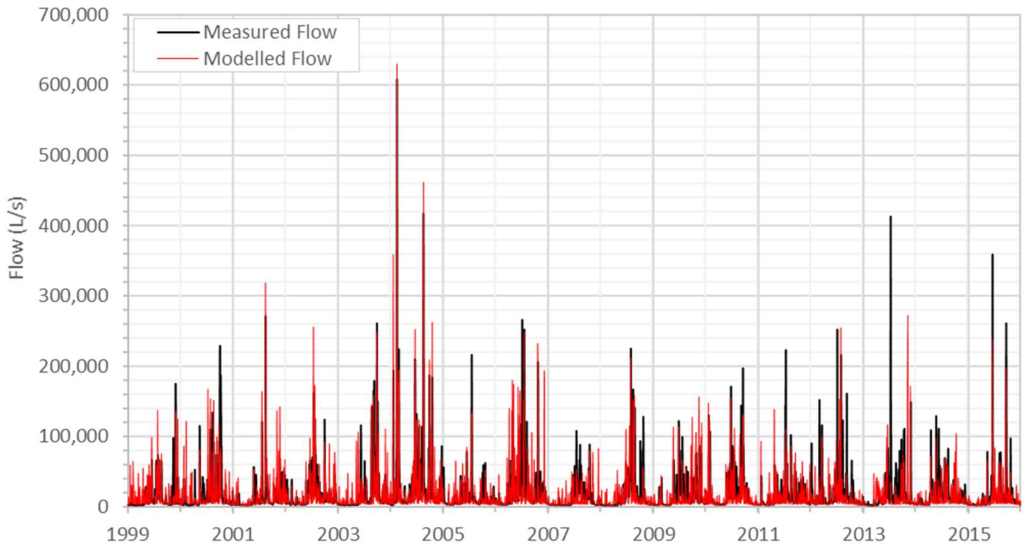

Figure 48. Hydrograph of measured and modelled flow at Tiraumea at Ngaturi.

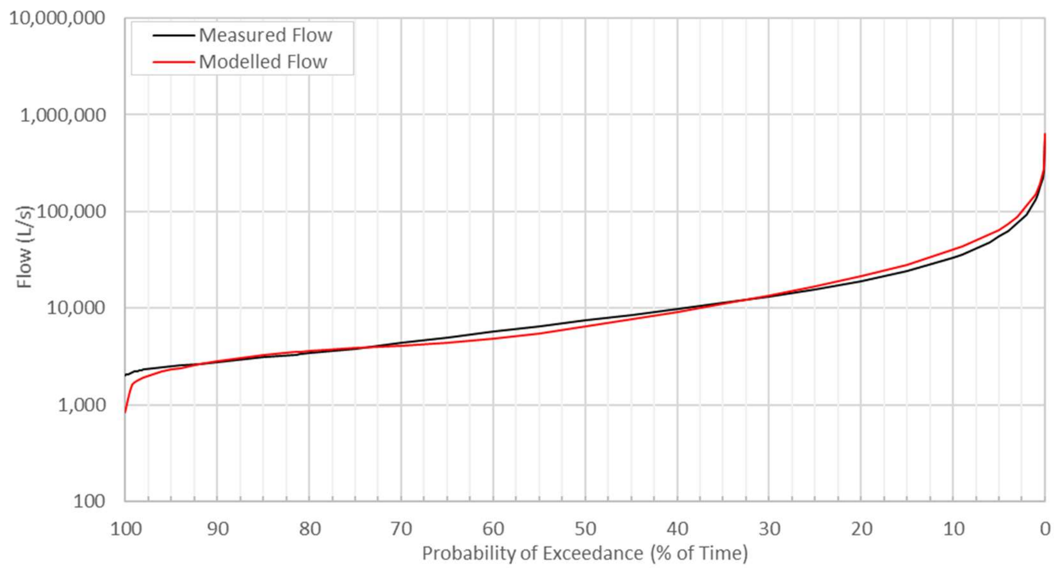

Figure 49. Flow duration curve of measured and modelled flow at Tiraumea at Ngaturi.

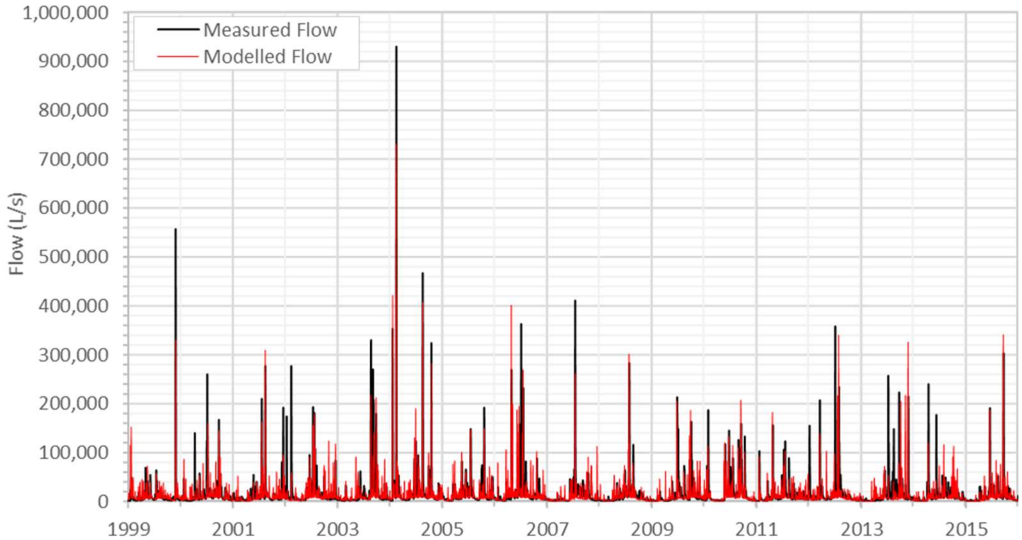

Figure 50. Hydrograph of measured and modelled flow at Manawatū at Weber Road.

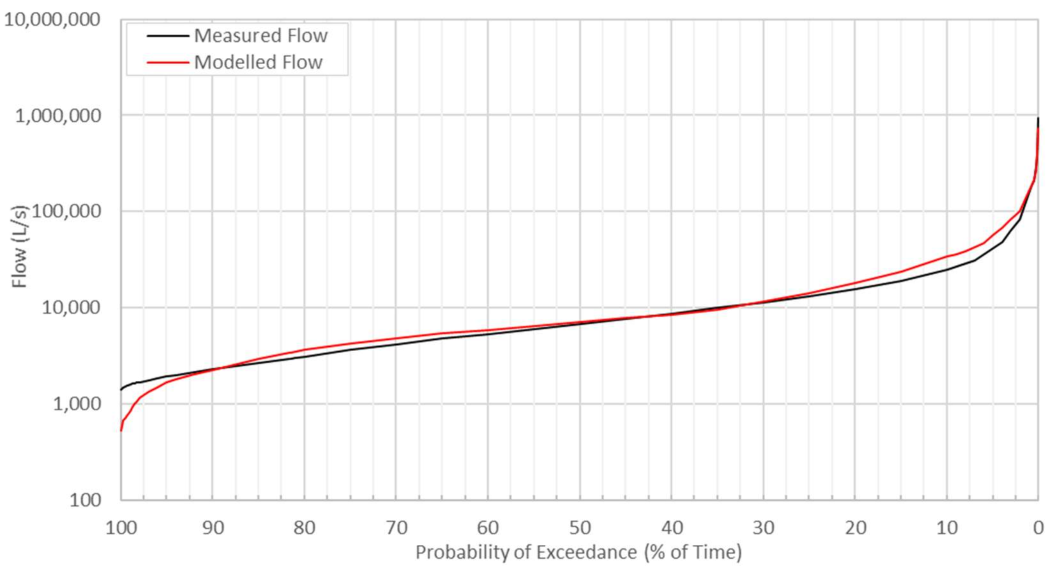

Figure 51. Flow duration curve of measured and modelled flow at Manawatū at Weber Road.

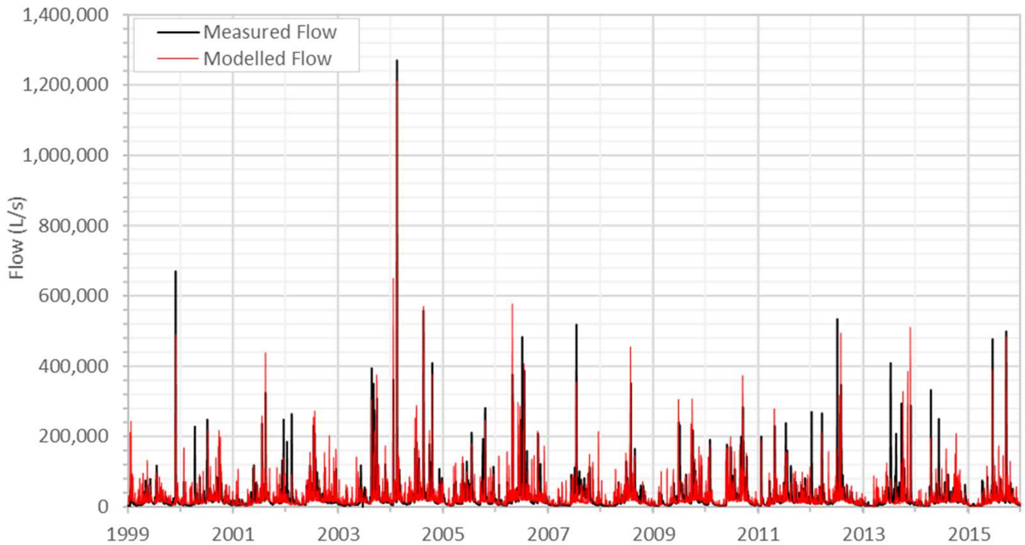

Figure 52. Hydrograph of measured and modelled flow at Manawatū at Hopelands.

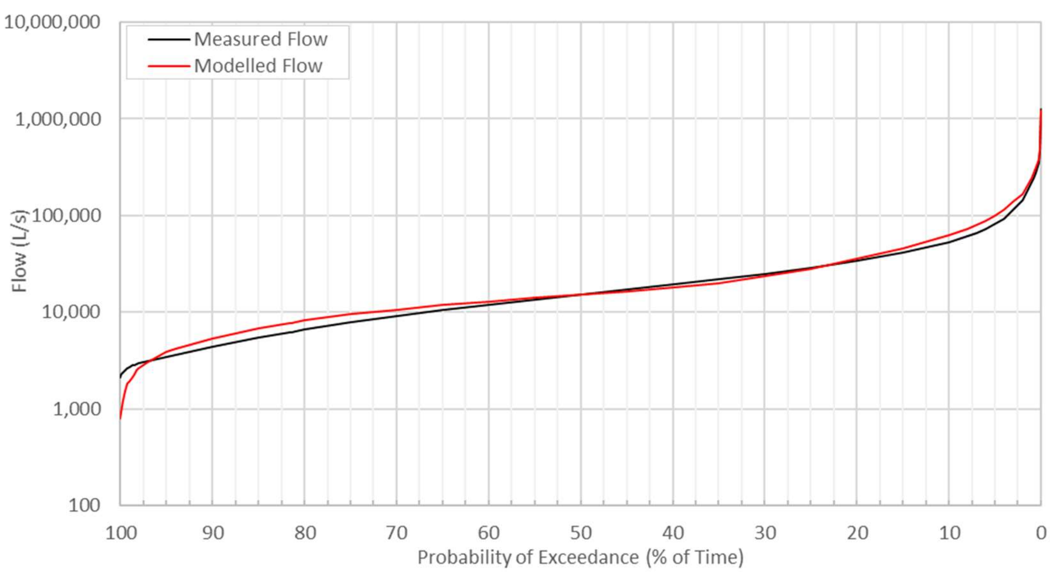

Figure 53. Flow duration curve of measured and modelled flow at Manawatū at Hopelands.

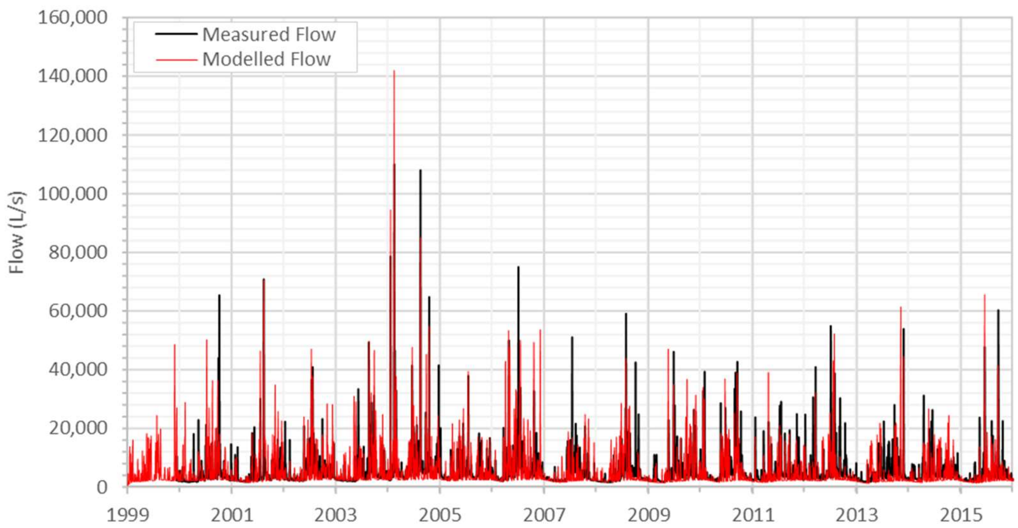

Figure 54. Hydrograph of measured and modelled flow at Makuri at Tuscan Hills.

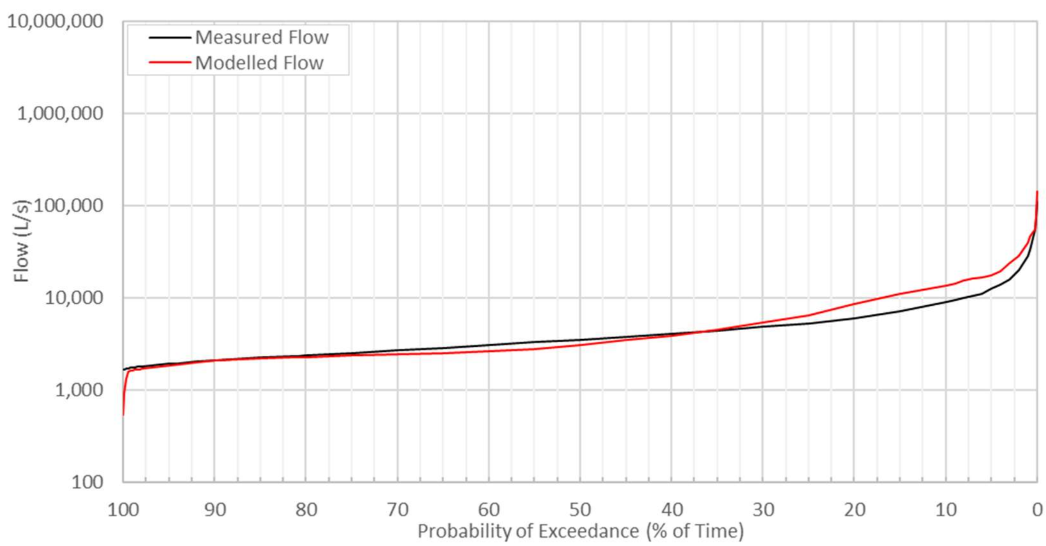

Figure 55. Flow duration curve of measured and modelled flow at Makuri at Tuscan Hills.

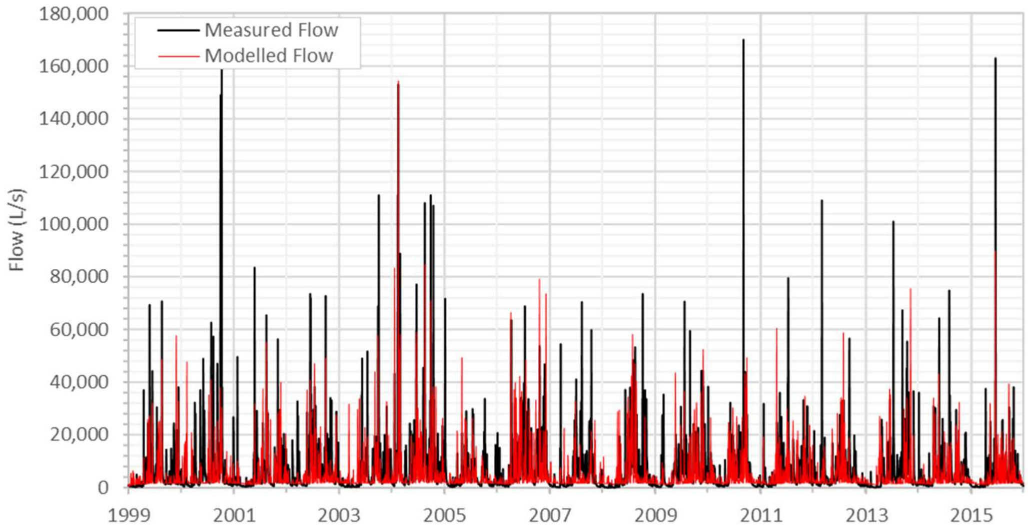

Figure 56. Hydrograph of measured and modelled flow at Makakahi at Hamua.

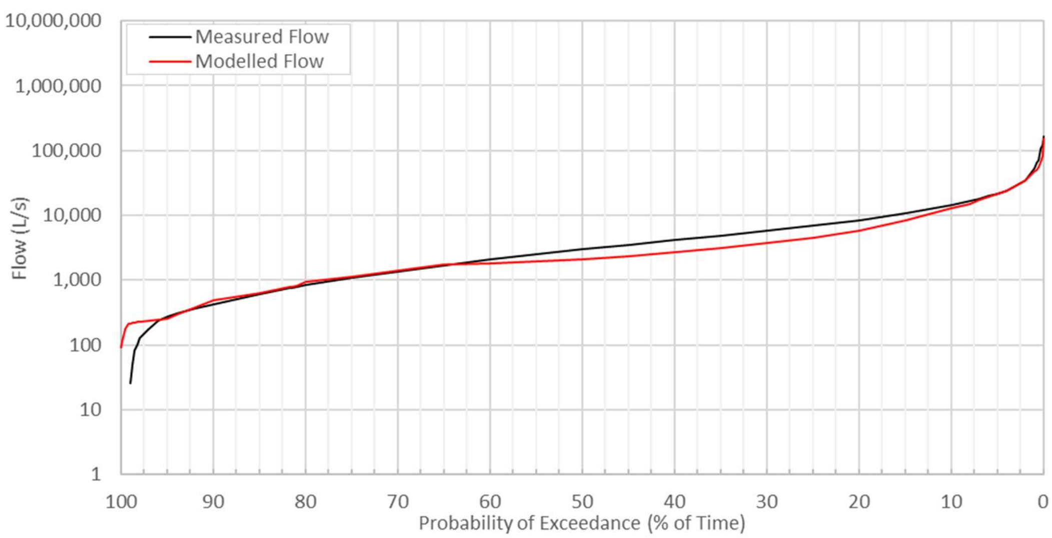

Figure 57. Flow duration curve of measured and modelled flow at Makakahi at Hamua.

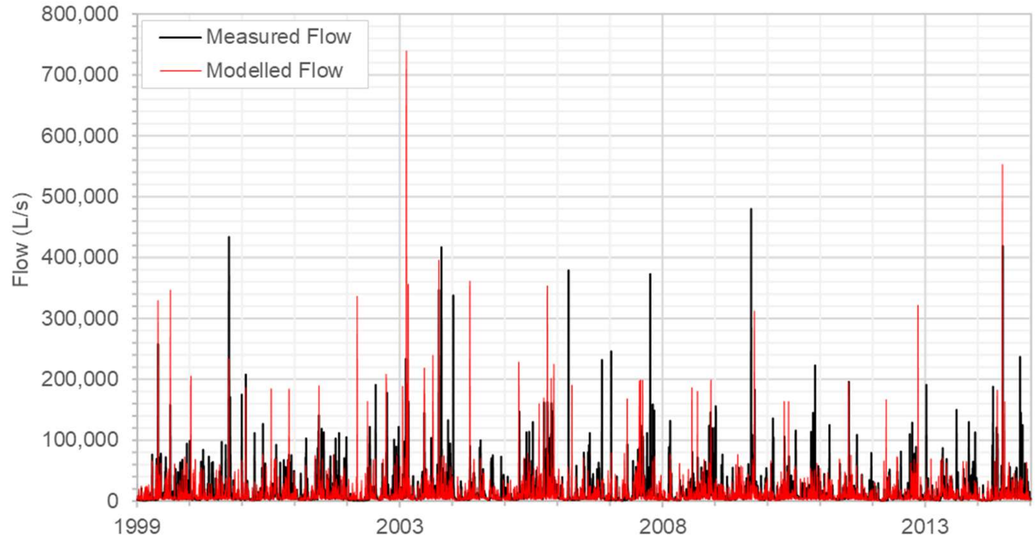

Figure 58. Hydrograph of measured and modelled flow at Mangahao at Ballance.

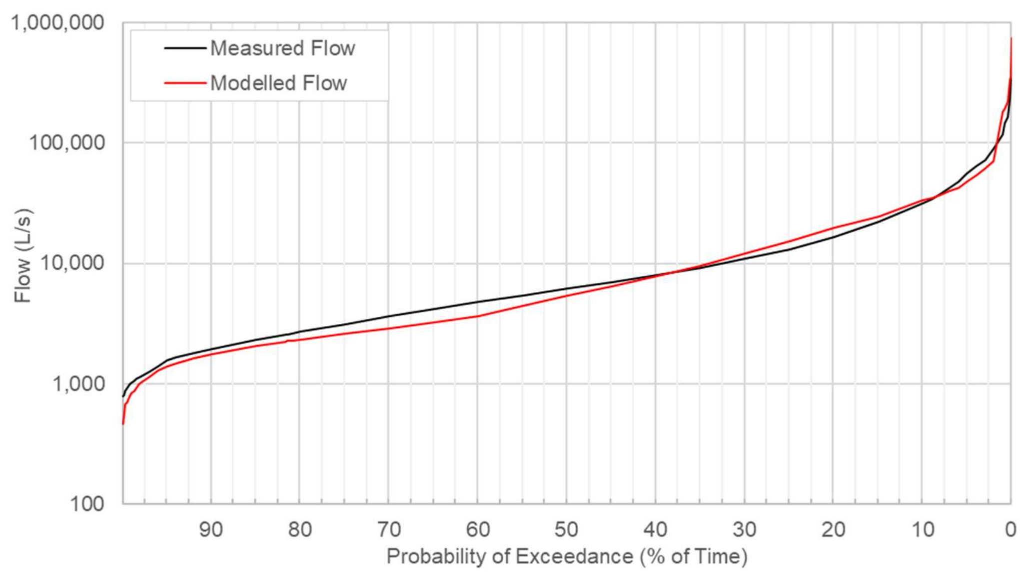

Figure 59. Flow duration curve of measured and modelled flow at Mangahao at Ballance.

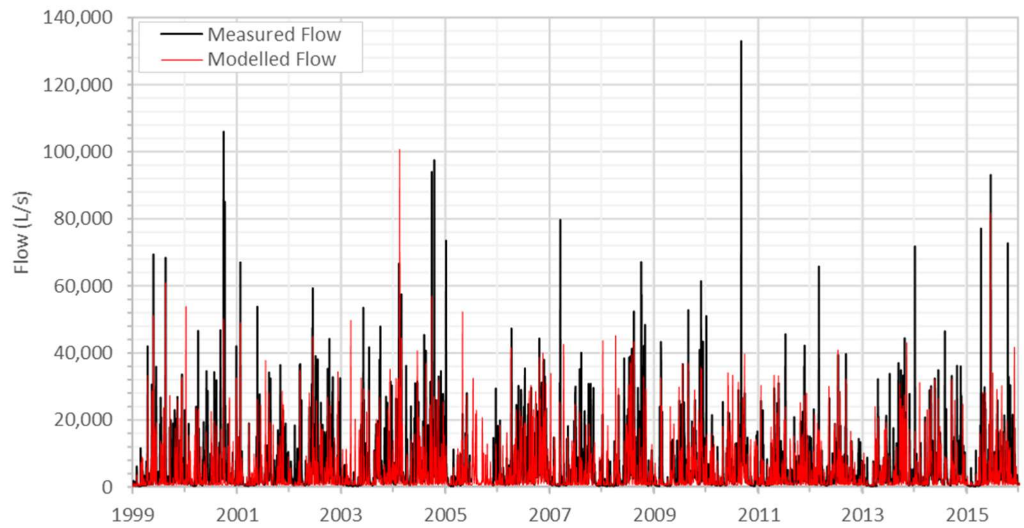

Figure 60. Hydrograph of measured and modelled flow at Mangatainoka at Larsons Road.

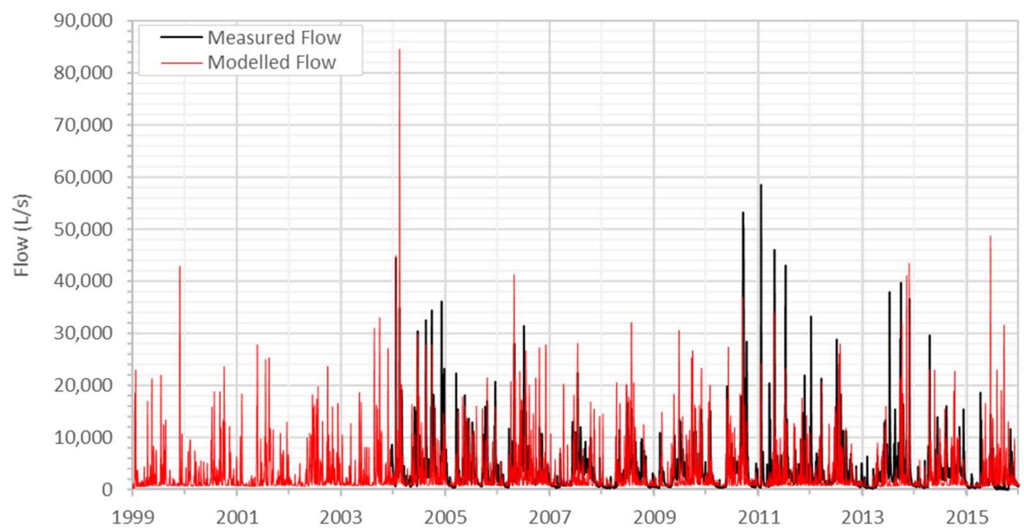

Figure 61. Hydrograph of measured and modelled flow at Tamaki at Stephens.

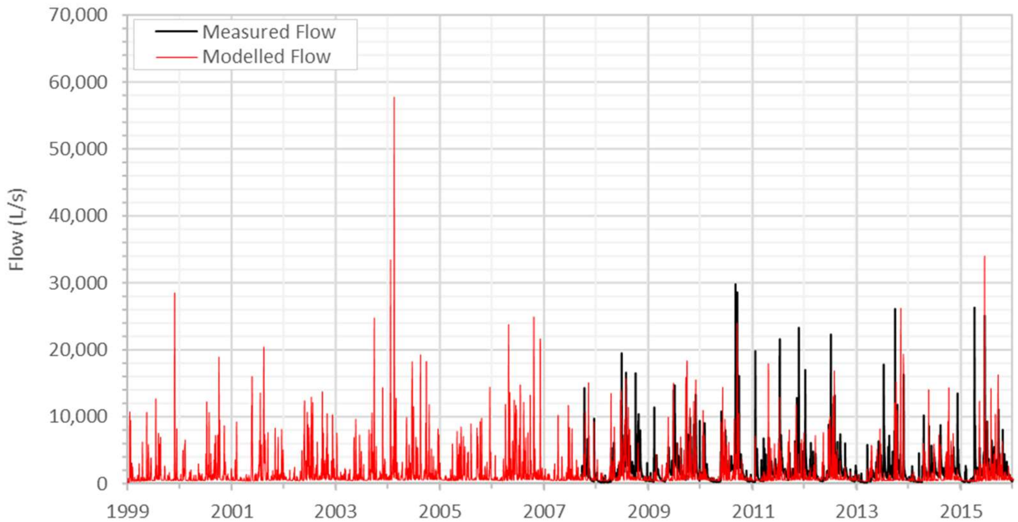

Figure 62. Hydrograph of measured and modelled flow at Oruakeretaki at SH2 Napier.

Appendix K. Water Balance

Appendix K presents the key components of the SIMHYD water balance in mm. Note that functional unit notation is Landuse_Geological Permeability_Soil Texture. SS, IT, CT and FT refer to stony soils, intermediated textured soils, coarse textured soil, and fine textured soils, respectively.

Table 35. Modelled annual average water balance for each functional unit in the average rainfall regime within the Tararua sub-catchments.

Functional Unit	Precipitation (mm)	Interception Loss (mm)	Runoff (mm)	Soil evaporation (mm)	Percolation to groundwater (mm)
Dairy_High_CT	1219.1	83.3	164.8	507.6	463.4
Dairy_Low_CT	1219.1	109.4	296.2	491.5	322
Dairy_Medium_CT	1219.1	139.5	219.4	444.9	415.3
Dairy_High_FT	1219.1	83.8	142.7	485.3	507.3
Dairy_Low_FT	1219.1	113.7	97	514.4	494
Dairy_Medium_FT	1219.1	140.4	99.2	538.5	441
Dairy_High_IT	1219.1	140.1	289.9	532.9	256.2
Dairy_Low_IT	1219.1	84.2	325.3	608.6	201
Dairy_Medium_IT	1219.1	100.9	335.5	557.5	225.2
Dairy_High_SS	1219.1	109.8	36.3	424	649
Dairy_Low_SS	1219.1	76.6	102.1	442.9	597.5
Dairy_Medium_SS	1219.1	105.8	89.7	414.6	609
Forest_High_CT	1219.1	210.2	150.5	493.8	364.6
Forest_Low_CT	1219.1	235.4	283.8	451.6	248.3
Forest_Medium_CT	1219.1	220.5	220.5	485.8	292.3
Forest_High_FT	1219.1	230.6	340.4	540.1	108
Forest_Low_FT	1219.1	244.4	365.8	540.1	68.8

Functional Unit	Precipitation (mm)	Interception Loss (mm)	Runoff (mm)	Soil evaporation (mm)	Percolation to groundwater (mm)
Forest_Medium_FT	1219.1	247.7	373.1	514.8	83.5
Forest_High_IT	1219.1	249.1	279.9	475.7	214.4
Forest_Low_IT	1219.1	240.3	339.5	467.7	171.6
Forest_Medium_IT	1219.1	250.1	310.4	468.1	190.5
Forest_High_SS	1219.1	217.2	20.9	490.8	490.2
Forest_Low_SS	1219.1	211.2	106	460.2	441.7
Forest_Medium_SS	1219.1	224.2	94.7	427.7	472.5
SheepBeef_High_CT	1219.1	113.1	151.7	510.4	443.9
SheepBeef_Low_CT	1219.1	105	303.2	488.9	322
SheepBeef_Medium_CT	1219.1	113.3	204.1	484.7	417
SheepBeef_High_FT	1219.1	98.4	395	574.6	151.1
SheepBeef_Low_FT	1219.1	115	522.3	529.1	52.7
SheepBeef_Medium_FT	1219.1	126.8	401.6	603.1	87.6
SheepBeef_High_IT	1219.1	105.9	295.9	550.9	266.4
SheepBeef_Low_IT	1219.1	109.3	347	546.8	216
SheepBeef_Medium_IT	1219.1	119.3	331.5	565.7	202.6
SheepBeef_High_SS	1219.1	113.5	39.3	411.2	655.1
SheepBeef_Low_SS	1219.1	104.8	114	431.9	568.4
SheepBeef_Medium_SS	1219.1	95.3	92.3	421	610.5
Urban	1219.1	32	1154.8	18	9.3

Table 36. Example monthly water balance for SC 10_SheepBeef_Medium_IT.

Month	Infiltration excess runoff (mm)	Interflow runoff (mm)	AttSurfRunoff (mm)	Quick flow (mm)	PercT (mm)	GW flow (mm)	Slow Flow (mm)
January	9.00	9.63	18.64	18.64	7.47	15.58	15.58
February	9.10	8.73	17.83	17.83	4.67	15.49	15.49
March	12.78	9.47	22.24	22.24	4.78	15.38	15.38
April	14.27	10.27	24.53	24.53	6.15	15.27	15.27
May	18.91	12.84	31.75	31.75	9.93	15.18	15.18
June	25.91	16.12	42.03	42.03	16.90	15.15	15.15
July	34.81	16.44	51.25	51.25	25.72	15.21	15.21
August	26.83	15.27	42.10	42.10	30.92	15.36	15.36
September	21.32	14.41	35.73	35.73	29.31	15.55	15.55
October	15.77	13.14	28.91	28.91	23.52	15.70	15.70
November	11.68	11.96	23.64	23.64	15.71	15.77	15.77
December	13.62	11.73	25.35	25.35	10.32	15.76	15.76

Appendix L. Overseer Nitrate Loads

Appendix L presents the Overseer outputs that were used as an input to the nutrient generation model.

Table 37. Overseer estimated average annual nitrate losses (N kg/ha/yr).

Rainfall Regime	Dairy SS	Dairy CT	Dairy IT	Dairy FT	S & B CT	S & B IT
Low	47	43	41	36	17	15
Medium	61	57	54	50	22	18
High	85	72	64	60	23	22

Appendix M. Nutrient Generation Model Results

Appendix M presents the results of integrating the Overseer outputs with SIMHYD to produce quick flow and slow flow concentrations.

Table 38. The nutrient integration generated input nitrogen quick flow concentrations (mg/L) for different functional units in SC19 (medium rainfall regime).

Month	Dairy	Dairy	Dairy	Dairy	S & B	S & B
	High	High	High	High	Medium	Low
	SS	CT	IT	FT	CT	IT
January	8.4	4.3	2.1	1.3	1.0	1.5
February	6.5	6.1	3.1	3.2	0.7	1.5
March	6.6	5.4	2.1	1.0	1.2	1.1
April	10.5	8.9	8.5	2.5	2.5	1.1
May	9.5	10.6	8.4	1.9	3.0	1.2
June	5.4	10.0	7.2	6.0	2.6	1.2
July	5.1	7.8	8.1	17.6	2.4	1.1
August	5.0	7.1	8.9	25.0	2.4	1.3
September	7.4	9.5	7.1	4.7	2.7	1.3
October	7.9	8.9	8.3	4.1	3.3	1.5
November	6.3	8.4	6.2	2.1	1.4	1.7
December	4.1	4.7	3.8	2.1	0.8	1.5

Table 39. The nutrient integration generated input nitrogen slow flow concentrations (mg/L) for different functional units in SC19 (medium rainfall regime).

Month	Dairy High SS	Dairy High CT	Dairy High IT	Dairy High FT	S & B Medium CT	S & B Low IT
January	4.0	7.6	5.4	9.5	2.3	1.3
February	4.3	5.4	3.3	9.1	2.2	1.4
March	6.6	5.5	3.6	8.1	2.7	1.5
April	7.6	6.4	4.5	8.9	3.4	2.3
May	12.3	10.0	7.3	10.2	4.4	2.9
June	17.1	15.2	12.6	11.8	6.1	5.2
July	20.9	24.3	20.5	15.2	8.2	6.8
August	23.6	29.8	25.2	19.9	9.4	7.7
September	16.4	28.3	23.3	20.2	8.6	6.1
October	14.2	22.0	19.0	17.5	7.3	5.0
November	3.8	15.0	12.5	14.0	3.5	3.6
December	3.4	10.3	8.4	11.6	2.3	1.6

Appendix N. Nitrogen Calibration Results

Appendix N presents the calibration of modelled and measured DIN data.

Table 40. A comparison of average monthly river DIN loads (t/yr) at different measurement stations, modelled using no nitrogen attenuation factor applied in Tararua sub-catchments.

Month	Manawatū at Upper Gorge		Manawatū at Hopelands		Manawatū at Weber Road		Mangatainoka at Pahiatua		Tiraumea at Ngaturi		Mangahao at Ballance	
	Measured	**Modelled**	**Measured**	**Modelled**	**Measured**	**Modelled**	**Measured**	**Modelled**	**Measured**	**Modelled**	**Measured**	**Modelled**
January	45.6	274.9	10.5	85.9	3.7	40.7	13.4	50.1	8.6	33.6	1.9	11.9
February	37.1	253.5	10.8	115.3	5.0	52.3	12.9	53.1	9.4	37.4	5.2	16.2
March	44.5	258.1	20.8	119.0	7.2	58.6	15.5	54.2	8.7	36.5	5.2	17.1
April	111.6	315.6	36.2	122.1	12.3	66.8	17.7	55.1	15.9	42.3	6.1	22.0
May	91.3	343.0	43.3	177.3	15.9	72.8	36.9	66.9	21.0	45.9	9.9	22.6
June	232.8	454.4	113.7	211.8	34.4	78.8	75.3	90.0	46.4	80.9	12.9	23.3
July	362.3	490.4	123.6	216.6	66.3	101.3	75.7	88.1	58.1	92.5	16.2	30.6
August	301.9	421.4	110.9	206.2	45.9	105.1	64.1	79.2	46.9	73.5	15.6	26.3
September	286.3	401.3	74.9	206.4	37.9	89.6	64.8	77.2	31.3	63.7	9.7	24.2
October	170.5	375.6	69.5	156.4	22.0	85.8	66.4	72.3	25.0	54.6	9.6	19.5
November	104.9	356.6	43.9	127.2	9.7	77.4	43.0	71.4	16.1	42.5	8.2	19.6
December	77.3	293.7	26.0	92.2	8.2	56.5	30.9	55.2	12.2	38.7	5.8	13.4
Annual	1866.1	4238.5	684.1	1836.4	268.5	885.7	516.6	812.8	299.6	642.1	106.3	246.7

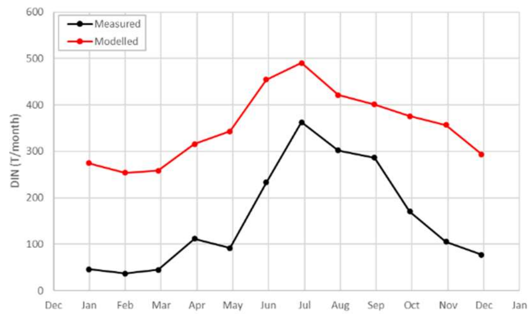

Figure 63. Manawatū at Upper Gorge no attenuation factor calibration.

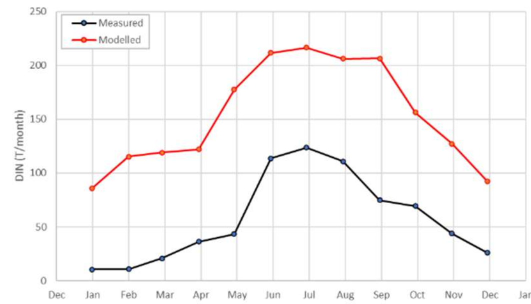

Figure 64. Manawatū at Hopelands no attenuation factor calibration.

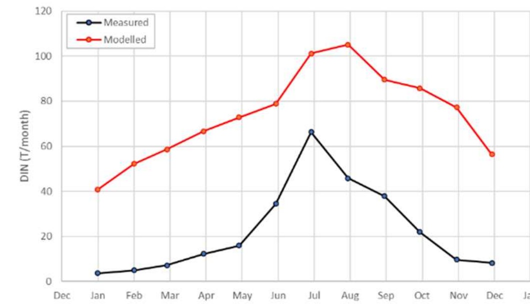

Figure 65. Manawatū at Weber Rd no attenuation factor calibration.

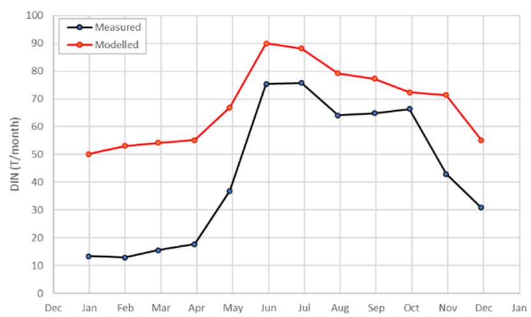

Figure 66. Mangatainoka at Pahiatua no attenuation factor calibration.

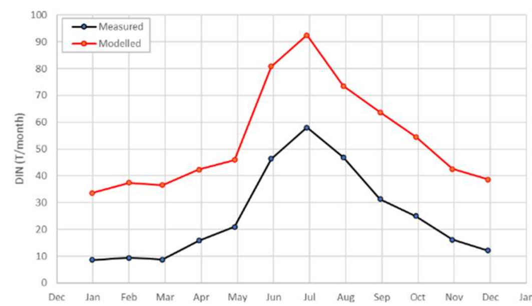

Figure 67. Tiraumea at Ngaturi uniform attenuation factor calibration.

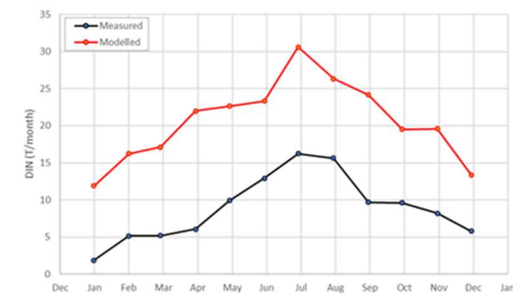

Figure 68. Mangahao at Ballance no attenuation factor calibration.

Table 41. A comparison of average monthly river DIN loads (t/yr) at different measurement stations, modelled using a uniform nitrogen attenuation factor applied in Tararua sub-catchments.

Month	Manawatū at Upper Gorge		Manawatū at Hopelands		Manawatū at Weber Road		Mangatainoka at Pahiatua		Tiraumea at Ngaturi		Mangahao at Ballance	
	Measured	Modelled	Measured	Modelled	Measured	Modelled	Measured	Modelled	Measured	Modelled	Measured	Modelled
January	45.6	119.3	10.5	36.9	3.7	7.7	13.4	20.0	8.6	21	1.9	4.3
February	37.1	107.4	10.8	47.6	5.0	10.7	12.9	10.8	9.4	23.7	5.2	5.6
March	44.5	110.8	20.8	49.6	7.2	15.3	15.5	16.3	8.7	24.6	5.2	6.5
April	111.6	132.8	36.2	52.2	12.3	19	17.7	21.4	15.9	25	6.1	7.3
May	91.3	150.3	43.3	76.2	15.9	21.1	36.9	28.5	21.0	28.5	9.9	8.6
June	232.8	195.1	113.7	90.3	34.4	23	75.3	38.6	46.4	41.7	12.9	8.8
July	362.3	209.5	123.6	93.4	66.3	32.2	75.7	38.0	58.1	47.4	16.2	10.9
August	301.9	181.9	110.9	87.8	45.9	33.4	64.1	34.1	46.9	40.8	15.6	10.4
September	286.3	171.1	74.9	89.1	37.9	28.7	64.8	31.8	31.3	35.5	9.7	8.4
October	170.5	161.8	69.5	67.6	22.0	26.3	66.4	31.0	25.0	31.2	9.6	7.0
November	104.9	154.7	43.9	53.6	9.7	21.9	43.0	28.8	16.1	25.2	8.2	6.6
December	77.3	126.3	26.0	39.2	8.2	14.3	30.9	22.1	12.2	23.9	5.8	4.4
Annual	1866.1	1821.0	684.1	783.5	268.5	253.6	516.6	321.4	299.6	368.5	106.3	88.8

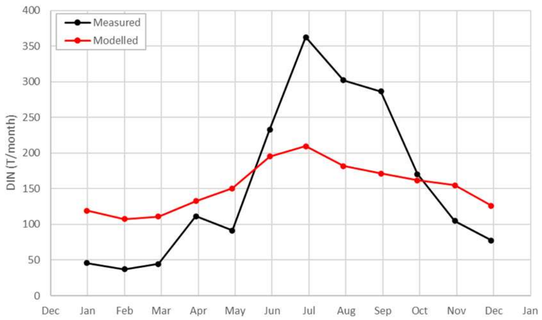

Figure 69. Manawatū at Upper Gorge uniform attenuation factor calibration.

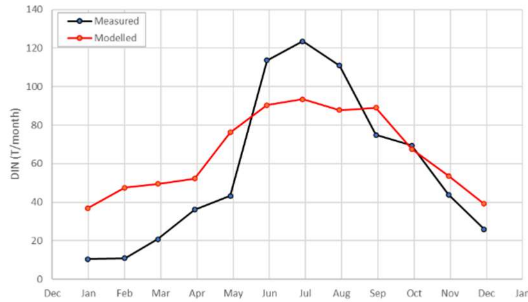

Figure 70. Manawatū at Hopelands uniform attenuation factor calibration.

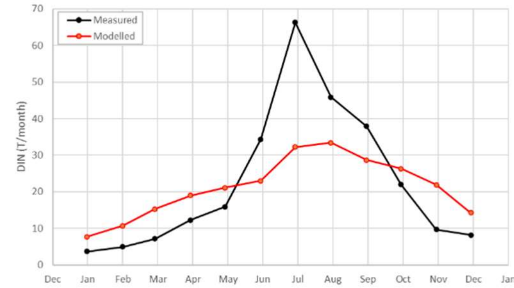

Figure 71. Manawatū at Weber Road uniform attenuation factor calibration.

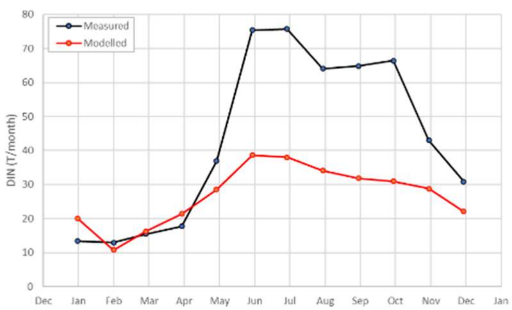

Figure 72. Mangatainoka at Pahiatua uniform attenuation factor calibration.

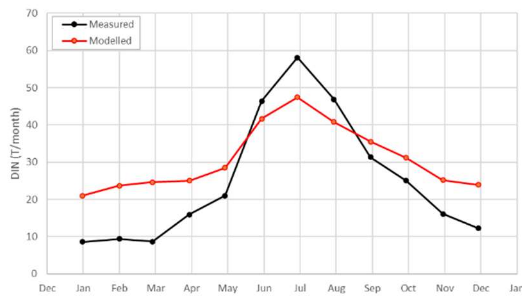

Figure 73. Tiraumea at Ngaturi uniform attenuation factor calibration.

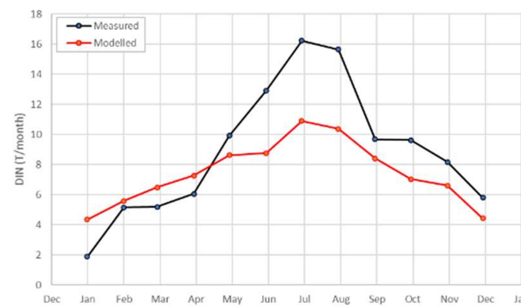

Figure 74. Mangahao at Ballance uniform attenuation factor calibration.

Table 42. A comparison of average monthly river DIN loads (t/yr) at different measurement stations, modelled using a spatially variable attenuation factor applied in Tararua sub-catchments.

Month	Manawatū at Upper Gorge		Manawatū at Hopelands		Manawatū at Weber Road		Mangatainoka at Pahiatua		Tiraumea at Ngaturi		Mangahao at Ballance	
	Measured	Modelled	Measured	Modelled	Measured	Modelled	Measured	Modelled	Measured	Modelled	Measured	Modelled
January	45.6	119.3	10.5	22.9	3.7	7.7	13.4	32.0	8.6	15.5	1.9	6.0
February	37.1	107.4	10.8	39.6	5.0	10.7	12.9	17.3	9.4	14.2	5.2	7.3
March	44.5	110.8	20.8	41.6	7.2	15.3	15.5	26.1	8.7	18.1	5.2	8.2
April	111.6	139.8	36.2	54.2	12.3	19.0	17.7	34.3	15.9	18.5	6.1	9.0
May	91.3	170.3	43.3	71.2	15.9	21.1	36.9	45.6	21.0	24.4	9.9	10.3
June	232.8	195.1	113.7	82.3	34.4	27.0	75.3	61.8	46.4	37.6	12.9	10.5
July	362.3	209.5	123.6	95.4	66.3	38.2	75.7	60.9	58.1	43.3	16.2	12.6
August	301.9	191.9	110.9	79.8	45.9	33.4	64.1	54.6	46.9	36.7	15.6	12.1
September	286.3	181.1	74.9	71.1	37.9	28.7	64.8	50.9	31.3	29.0	9.7	10.1
October	170.5	161.8	69.5	59.6	22.0	26.3	66.4	49.5	25.0	21.7	9.6	8.7
November	104.9	154.7	43.9	35.6	9.7	21.9	43.0	46.1	16.1	18.7	8.2	8.3
December	77.3	126.3	26.0	31.2	8.2	14.3	30.9	35.4	12.2	18.4	5.8	6.1
Annual	1866.1	1868.0	684.1	684.5	268.5	263.6	516.6	514.5	299.6	296.1	106.3	109.2

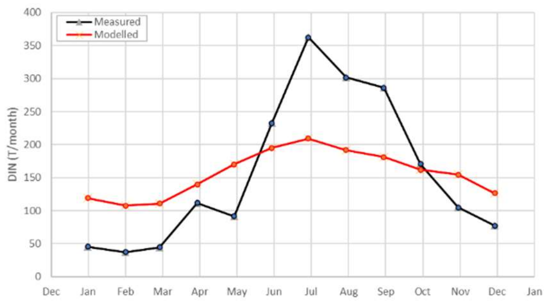

Figure 75. Manawatū at Upper Gorge spatially variable attenuation factor calibration.

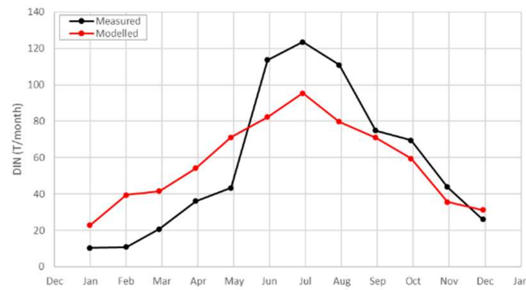

Figure 76. Manawatū at Hopelands spatially variable attenuation factor calibration.

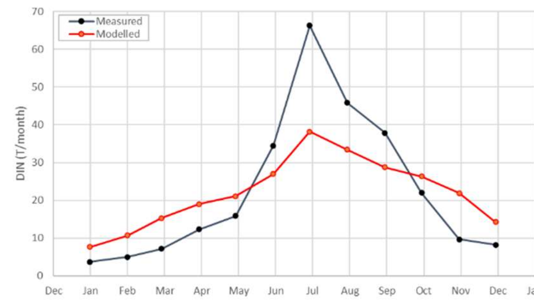

Figure 77. Manawatū at Weber Road spatially variable attenuation factor calibration.

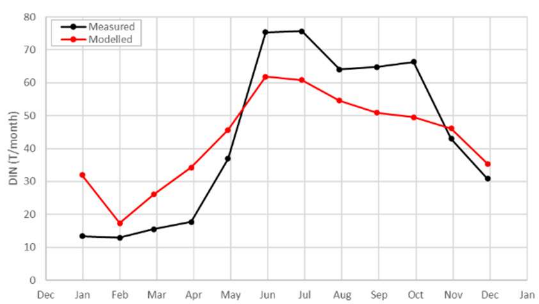

Figure 78. Mangatainoka at Pahiatua spatially variable attenuation factor calibration.

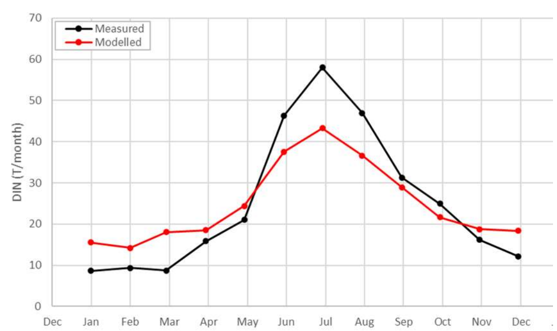

Figure 79. Tiraumea at Ngaturi spatially variable attenuation factor calibration.

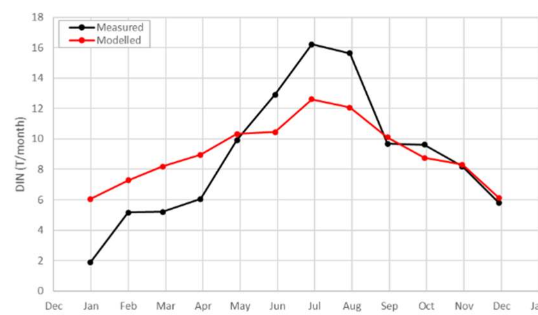

Figure 80. Mangahao at Ballance spatially variable attenuation factor calibration.

Table 43. A comparison of average monthly river DIN loads (t/yr) at different measurement stations, modelled using a spatially variable nitrogen attenuation factor applied to different flow pathways in Tararua sub-catchments.

Month	Manawatū at Upper Gorge		Manawatū at Hopelands		Manawatū at Weber Road		Mangatainoka at Pahiatua		Tiraumea at Ngaturi		Mangahao at Ballance	
	Measured	Modelled	Measured	Modelled	Measured	Modelled	Measured	Modelled	Measured	Modelled	Measured	Modelled
January	45.6	59.3	10.5	12.9	3.7	7.7	13.4	32.0	8.6	6.5	1.9	6.0
February	37.1	47.4	10.8	29.6	5.0	10.7	12.9	17.3	9.4	9.2	5.2	7.3
March	44.5	50.8	20.8	26.6	7.2	11.3	15.5	26.1	8.7	13.1	5.2	8.2
April	111.6	79.8	36.2	39.2	12.3	18.0	17.7	34.3	15.9	13.5	6.1	9.0
May	91.3	230.3	43.3	76.2	15.9	20.1	36.9	45.6	21.0	19.4	9.9	10.3
June	232.8	325.1	113.7	102.3	34.4	37.0	75.3	61.8	46.4	52.6	12.9	10.5
July	362.3	309.5	123.6	125.4	66.3	48.2	75.7	60.9	58.1	64.3	16.2	12.6
August	301.9	251.9	110.9	99.8	45.9	43.4	64.1	54.6	46.9	51.7	15.6	12.1
September	286.3	191.1	74.9	81.1	37.9	27.7	64.8	50.9	31.3	24.0	9.7	10.1
October	170.5	141.8	69.5	49.6	22.0	24.3	66.4	49.5	25.0	16.7	9.6	8.7
November	104.9	114.7	43.9	25.6	9.7	11.9	43.0	46.1	16.1	13.7	8.2	8.3
December	77.3	66.3	26.0	21.2	8.2	9.3	30.9	35.4	12.2	9.4	5.8	6.1
Annual	1866.1	1868.0	684.1	689.5	268.5	269.6	516.6	514.5	299.6	294.1	106.3	109.2

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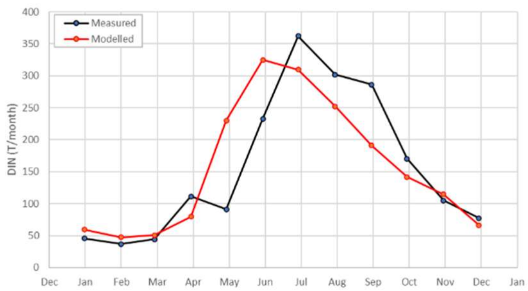

Figure 81. Manawatū at Upper Gorge calibration using a spatially variable attenuation factor applied to different flow pathways.

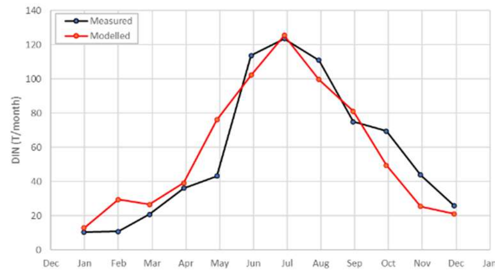

Figure 82. Manawatū at Hopelands calibration using a spatially variable attenuation factor applied to different flow pathways.

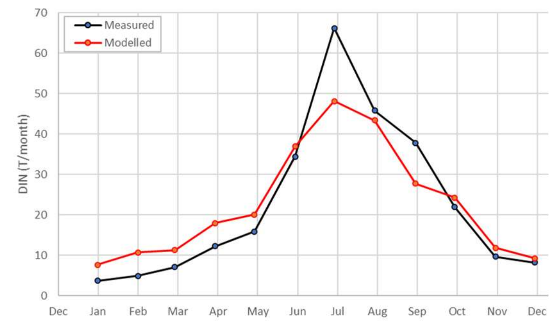

Figure 83. Manawatū at Weber Road calibration using a spatially variable attenuation factor applied to different flow pathways.

Figure 84. Mangatainoka at Pahiatua calibration using a spatially variable attenuation factor applied to different flow pathways.

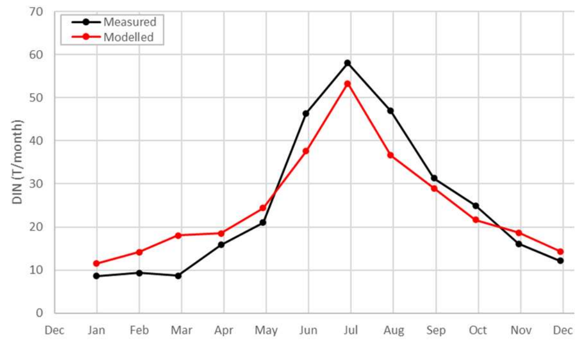

Figure 85. Tiraumea at Ngaturi calibration using a spatially variable attenuation factor applied to different flow pathways.

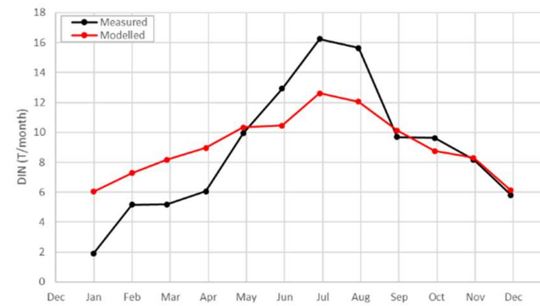

Figure 86. Mangahao at Ballance calibration using a spatially variable attenuation factor applied to different flow pathways.

Appendix O. Mitigation Scenario Results

Appendix O presents the annual average root zone nitrate losses and river DIN loads for the sub-catchment under each mitigation scenario.

Table 44. Estimates of discrete annual average river DIN loads (t/yr) under different water quality mitigation scenarios.

Sub-catchment	Baseline	Land use & Attenuation Matching	Drainage management	Wetlands
1	29.2	24.8	29.2	29.2
2	70.2	43.2	60.4	70.2
3	41.6	29.6	41.6	41.6
4	36.9	23.9	36.9	36.9
5	4.5	4.5	4.5	4.5
6	41.3	33.5	41.3	41.3
7	22.4	26.4	22.4	22.4
8	3.1	3.1	3.1	3.1
9	6.5	6.9	6.5	6.5
10	94.4	83.0	83.0	94.4
11	9.3	9.3	9.3	9.3
12	44.8	41.5	44.8	44.8
13	37.8	41.1	37.8	37.8
14	30.3	30.3	30.3	30.3
15	79.1	49.6	49.1	79.1
16	79.8	59.0	59.0	19.8
17	44.2	40.3	44.2	44.2
18	38.7	39.7	38.7	38.7

Sub-catchment	Baseline	Land use & Attenuation Matching	Drainage management	Wetlands
19	72.4	64.0	72.4	72.4
20	29.6	31.2	29.6	29.6
21	64.4	64.4	59.5	64.4
22	44.3	36.5	44.3	14.3
23	63.9	67.6	63.9	63.9
24	61.8	49.8	61.8	61.8
25	46.2	49.5	46.2	46.2
26	45.3	45.9	45.3	45.3
27	21.2	21.2	21.2	21.2
28	34.9	37.1	34.9	34.9
29	178.6	138.6	105.9	178.6
30	132.8	106.8	55.9	61.8
31	60.1	63.2	60.1	60.1
32	122.1	119.1	63.1	122.1
33	3.7	3.7	3.7	3.7
34	23.5	25.7	23.5	23.5
35	82.1	65.5	82.1	82.1
36	35.2	24.5	35.2	35.2
37	33.3	29.3	33.3	33.3
Total	1869.5	1633.2	1584.0	1708.5

Table 45. Estimates of discrete annual average root zone N losses (t/yr) under different water quality mitigation scenarios.

SC	Baseline, Wetlands, Drainage Management	Matching Land Use Intensity and Attenuation Capacity
1	92.0	86.6
2	220.7	220.7
3	125.1	125.1
4	116.6	116.6
5	8.0	8.0
6	106.1	93.0
7	80.9	80.9
8	7.1	7.1
9	15.0	15.0
10	217.1	207.9
11	30.6	30.6
12	98.5	90.5
13	103.0	135.0
14	74.3	74.3
15	117.6	104.0
16	211.2	198.2
17	113.1	105.3
18	95.9	93.5
19	258.5	247.2
20	68.0	99.0
21	120.4	120.4
22	147.9	135.0
23	176.9	198.9

SC	Baseline, Wetlands, Drainage Management	Matching Land Use Intensity and Attenuation Capacity
24	158.3	146.5
25	152.3	174.3
26	85.8	116.8
27	30.4	30.4
28	80.3	98.3
29	265.0	265.0
30	199.7	199.7
31	72.5	62.5
32	221.0	221.0
33	8.5	8.5
34	28.8	28.7
35	168.2	154.8
36	104.0	90.0
37	99.5	83.3
Total	4238.8	4232.6