FORECASTING LAKE WAIKAREMOANA WATER AVAILABILITY FOR HYDRO POWER

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Abstract

Lake Waikaremoana is a high-altitude, large-volume lake located within the rugged terrain of the Urewera National Park. At the lake outflow a rapid elevation change of nearly 450 metres in 8 kilometres facilitates the lake's use as the upper intake portal for the Waikaremoana Hydro Power Scheme. At the time of this study, Genesis Energy operated the Waikaremoana Power Scheme in response to a water availability model based on daily lake level differencing from which daily generation capacity is predicted, allowing strategic bidding into the electricity market. However, when river flows are low this model is subject to error, as small changes in lake level sometimes cannot be determined accurately beyond background noise on daily timescales.

This project develops a method of estimating both current day and day-ahead water availability of Lake Waikaremoana, independent of lake levels using simple hydrological models, thereby improving operational efficiency of the Waikaremoana Power Scheme. The forecasting is developed specifically for the lower inflow conditions when the lake level differencing approach is most error prone.

It has long been recognised that a significant volume of Lake Waikaremoana water leaks through the ancient landslide dam which created the lake. Previous to this study, it was considered that an inaccurate estimation of this leakage rate combined with evaporative losses might contribute to the error within the existing water availability model. A modified catchment water balance and simple regression approach was applied to Lake Waikaremoana to estimate the lake water loss not accounted for by recorded outflows. Estimating this unrecorded loss translates to estimating the intercept of a linear regression relation, where the assumption is made that there is a linear relationship between the discharge of the Aniwaniwa Stream and the net lake water balance (excluding known outflows) under low inflow conditions. On the basis of the confidence intervals about the intercept, the balance term (constant background lake inflow minus leakage and evaporative loss) is estimated to within the range of 2.89 and -1.17 m^3s^{-1}

suggesting that the unknown portion of leakage and evaporative losses are not significant contributors to model error. A useful consequence of the regression was that regression coefficients could be used as a means of upscaling to give net lake storage change for low-flow conditions. This enabled day-ahead water availability forecasts to be acquired from Aniwaniwa Stream discharge day-ahead forecasts.

Two forecasting methodologies are developed to forecast the Aniwaniwa Stream discharge: a finite mixture rainfall-runoff model, and a multiple linear regression method. The rainfall-runoff model is formulated initially as a many-parameter model which is then subjected to a lasso-based model simplification concurrent with model calibration. The simplified model forecasts next-day inflows by using a weighted linear combination of hydrograph forms which best match the previous observed discharges in the calibration set where the various weights are linear functions of recent rainfalls. An auto-recalibrating version of the rainfall-runoff model was also developed where model simplification and calibration is carried out for each forecast, with the greatest fitting weights most likely on the most recent discharges to allow for changing catchment conditions.

The rainfall-runoff model was calibrated under a range of lasso-based parameter elimination pressures to determine the number of parameters which gave the best validation fit as quantified by the Nash-Sutcliffe fit. The highest validation fit using the original rainfall-runoff model was 50.7%. Using the auto-recalibrating rainfall-runoff model a slightly better maximum validation fit of (52.3%) occurred at an elimination pressure giving 14 final parameters from an initial 300. However, a validation fit which is not much lower (46.8%) is achieved at a higher elimination pressure yielding just 6 final parameters, demonstrating a trade-off between model simplification and validation fit. As expected, the rainfall-runoff model was more successful at predicting low to medium flows because forecasting focus was on the lower flows. Higher discharges were consistently under-predicted. Validation fits of the rainfall-runoff model could probably be improved by increasing the range of possible hydrograph forms available for selection at the expense of model simplicity.

The multiple regression technique was applied to forecast ‘next-day’ Aniwaniwa inflows in a simpler way, in this case using just current daily rainfall and discharges as independent variables. The discharge forecasts derived from both techniques are then scaled using the regression equation mentioned earlier to give net storage change estimates into Lake Waikaremoana for low to medium inflows. The regression approach was the more successful for overall day-ahead Aniwaniwa flow forecasts. The final prediction for current day storage change is:

$$\Delta S = 0.399(A_Q) + 0.59 \qquad [1]$$

Where A_Q is the observed daily total discharge of the Aniwaniwa Stream. Day-ahead Aniwaniwa Stream forecasts can be approximated by equation [2] then scaled to storage change using equation [1]

$$A_{Q(\text{Next-day})} = 0.095(T_{rain}) + 0.558(T_Q) + 0.611 \qquad [2]$$

Where T_{rain} is current day total rainfall and T_Q is current day total discharge. This single equation gave higher calibration fits than separate regressions based on season. Using only current rainfall and current discharge as independent variables, the Nash-Sutcliffe validation fits were as high as 66%.

The linear regression approach gives the most useful inflow estimates to Lake Waikaremoana for the current day, based on upscaling the Aniwaniwa Stream discharges for low to medium flows. Estimating the day-ahead lake inflows is then equated to estimating day-ahead Aniwaniwa discharges for conditions outside of high flows. For this day-ahead forecasting the regression technique proved better than the rainfall-runoff models. It is thus recommended that the multiple regression technique is applied at the Waikaremoana Power Scheme.

Acknowledgements

First thanks must of course go to my supervisor Associate Professor Earl Bardsley, without whom this research would not have been possible. Thank-you Earl for your genius, enthusiasm and passion for research.

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Chapter 1 - Introduction

1.1 Background

The hydro power potential of Lake Waikaremoana has been recognised since the 19^{th} century (Natusch, 2004). In 1904 Hay (cited in McPike, 1980) reported of the power generation opportunity that would exist at Waikaremoana should leakage through its naturally formed landslide dam be controlled. An indication of the amount of generation that could be achieved, and a layout for a power scheme, was produced by Anderson in 1916 (cited in McPike, 1980).

Tuai power station, the first of the three stations to be built which make up the Waikaremoana scheme, was commissioned in 1929 with an installed capacity of 60 Megawatts (MW). Piripaua power station was later commissioned in 1943 with an installed capacity of 42MW and Kaitawa power station was commissioned in 1948 with an installed capacity of 36MW. At maximum capacity the scheme is capable of contributing 138MW to the national grid (Genesis Energy, 2006, Natusch, 2004). The completed scheme (Figure 1) transports water from Lake Waikaremoana via tunnels to Kaitawa Power Station before discharging into Lake Kaitawa, the water then passes through Tuai Power Station and is discharged into Lake Whakamarino. From there, water is transported to Piripaua Power Station by tunnel and discharged into the Waikaretaheke River (Natusch, 2004).

In the 1980s a substantial restructuring of the New Zealand electricity industry was undertaken, with generation and transmission assets transferred to the Electricity Corporation of New Zealand (ECNZ), which was created under the State Owned Enterprises Act 1986. In the 1990s the ECNZ was split into four companies, the privatised Contact Energy, and three state owned enterprises: Meridian Energy, Genesis Energy, and Mighty River Power. Genesis Energy obtained the Waikaremoana Power Scheme as part of their portfolio in 2000.

The Waikaremoana Power Scheme is an important part of North Island generation. The scheme provides voltage support for Gisborne and Tokomaru Bay

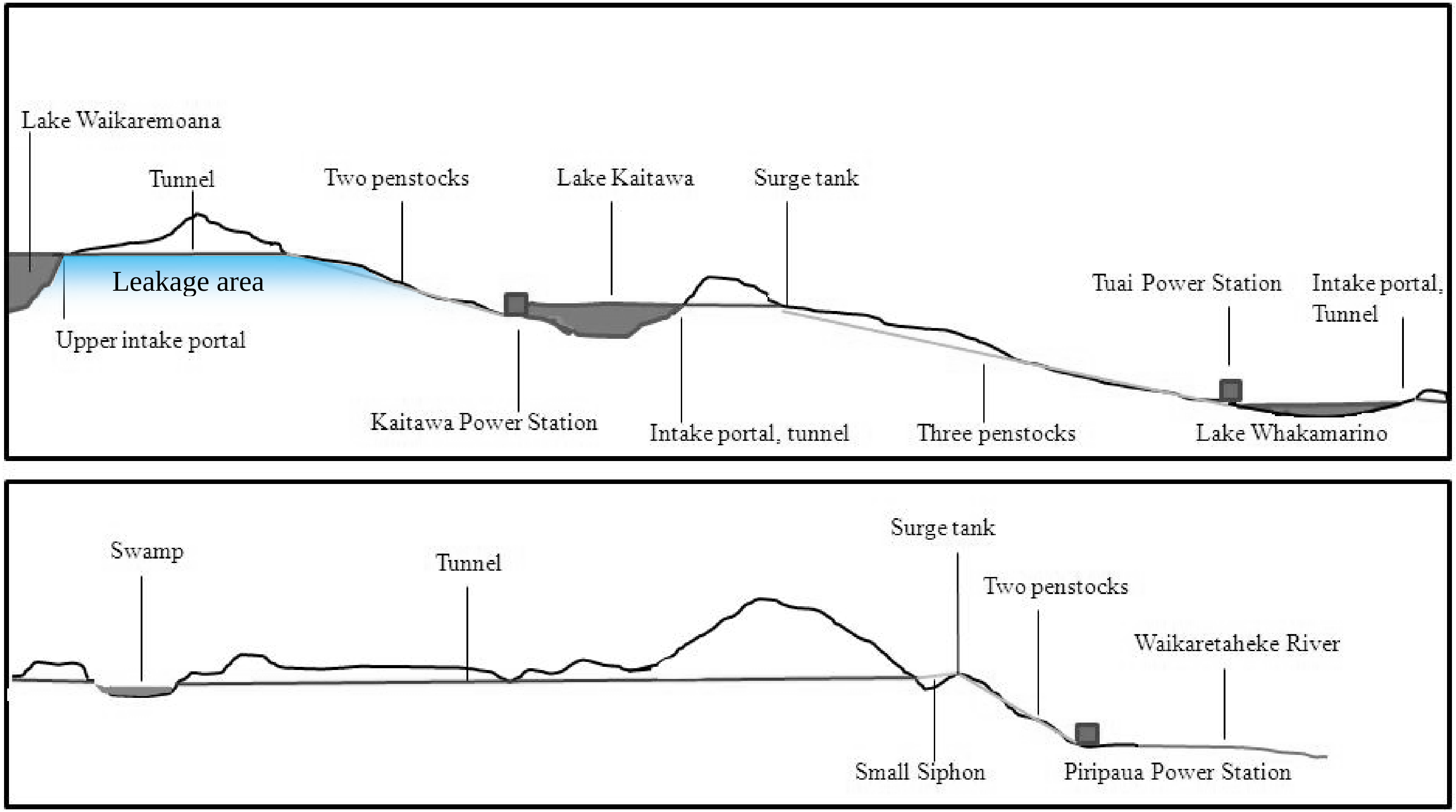

Figure 1: Cross Section of Waikaremoana Power Scheme showing important features. Bottom image follows on from the right of the top image. Modified from Natusch, (2004).

Transpower transmission circuits. It is also in the best position to provide power to the East Cape area should it lose its connection to the national grid. The proximity of the Waikaremoana Scheme in relation to Gisborne results in lower transmission losses, somewhat reducing the overall national need for generation (Genesis Energy, 2009).

A number of constraints exist in the Waikaremoana Scheme which means that effective water management must be applied. These constraints include in particular, the location of the scheme in the conservation land of the Urewera National Park. Also the small storage capacity of Lakes Kaitawa and Whakamarino requires the three stations to be run in tandem. Another constraint derives from leakage of the natural dam which holds back Lake Waikaremoana. This leakage water was originally used to supply the Tuai and Piripaua power stations prior to the commission of the Kaitawa power station. This substantial leakage through the dam has the ability to quickly fill Lake Kaitawa, thus the scheme must constantly be run at a minimum of 12 MW (Genesis Energy, 2006).

The daily operational efficiency of the Waikaremoana scheme requires estimation of lake water availability for hydro power generation on a per day basis. At the time of this study, net daily water availability of Lake Waikaremoana is estimated using a mathematical model of net storage change obtained from lake water level changes. This model uses daily lake water level differencing after correcting for the volume extracted for power generation and known lake losses to estimate net daily lake inflows. The model is used as opposed to direct measurement of river inflows due to the impracticality of gauging the large number of small tributaries and direct groundwater inflows which supply the lake. The water availability estimate is sometimes subject to error when changes in lake level are small, giving rise to negative estimates which may indicate errors in level differencing or inaccurate estimation of leakage. Under low flow conditions the unknown portion of lake losses may be not insignificant relative to inflows, thus in these instances the model approximates storage change.

The model includes an estimation of the leakage rate through the natural dam based on measurement of the discharge of the Waikaretaheke Stream at Kaitawa weir, a stream almost entirely derived from leakage and it is possible that an inaccurate estimation of leakage loss which does not pass though the weir could cause some of the error within the water availability model. Also, when there is little change in lake level the effect of brief water level fluctuations which result from waves and wind set up becomes large relative to lake level differences.

Genesis Energy therefore required an improved water availability model for low flows to allow increased operational efficiency of the Waikaremoana hydro power scheme as measured by income generated. Optimal income generation requires accurate estimates of how much electricity can be generated when bidding into the electricity market particularly for low flow conditions.

1.2 Objectives

The main intention of this thesis is to create an improved net daily water availability model for Lake Waikaremoana to better estimate how much power can be generated from the Waikaremoana power scheme on a given day under low flow conditions. This will be achieved through three specific objectives:

1. Create an improved low flow model of river inflows into Lake Waikaremoana using two forward (next-day) prediction approaches: multiple regression and a lasso simplified rainfall-runoff model.
2. Make a water balance based estimate of leakage loss from Lake Waikaremoana and detect any possible difference from earlier estimates.
3. Combine the results of objectives 1 and 2 to create an improved estimation of net daily water availability under low flow conditions.

1.3 Thesis Outline

This thesis is structured into a number of chapters on different aspects of this study.

Chapter 2 presents an overview of the Lake Waikaremoana catchment including its location, the geomorphology, geology and climate. It presents detail on the origin of Lake Waikaremoana and its relevance to this study through the formation of a landslide dam and associated natural leakage. Chapter 2 also describes the findings of previous studies on local catchment hydrology and catchment modifications for hydro power.

Chapter 3 describes the data available for this study from various sources.

Chapter 4 investigates total lake water losses from Lake Waikaremoana through the combined effects of evaporative loss and leakage of lake water through Lake Waikaremoana’s natural dam. This estimation is derived from a simple hydrological model based on a modified catchment water balance equation and linear regression.

Chapter 5 utilises a regression relation developed as a consequence of hydrological modelling in Chapter 4 to estimate net storage change of Lake Waikaremoana under low flow conditions, based on the discharge of the Aniwaniwa Stream.

Chapter 6 involves the use of two finite mixture rainfall-runoff models for forecasting future inflows of the Aniwaniwa Stream into Lake Waikaremoana, which can then be extrapolated to the wider Waikaremoana catchment using the regression relation developed in Chapter 5.

Chapter 7 uses a multiple regression technique to forecast next-day Aniwaniwa Stream inflows as a simple method of inflow estimation, which may be more practical for operational use at the Waikaremoana Power Scheme.

Chapter 8 compares the results from the three techniques used to model day-ahead inflows of the Aniwaniwa Stream into Lake Waikaremoana. Chapter 8 also compares the inflow estimates of the three models scaled to net storage change to a storage change record in order to determine which method provides both the most accurate and practical method for operational use at the Waikaremoana Power Scheme.

Chapter 9 presents conclusions and recommendations.

Chapter 2 - Study Area

2.1 Introduction

This chapter presents an overview of previous studies and the characteristics of the Lake Waikaremoana area. It focuses on aspects of the study area which are particularly relevant to hydro electric development and operation, and leakage through the natural dam.

Lake Waikaremoana, 'the sea of rippling waters' is situated 80 km south east of Lake Taupo in the North Island of New Zealand among the rugged unmodified terrain of the Urewera National Park (Urewera National Park Board, 1975). It lies at approximately 600m elevation above sea level amid thick temperate rainforest (Koyama et al., 1989, Matthews, 1992) (Figure 2). The large surface area and high altitude facilitates the use of Lake Waikaremoana for hydro power (Keam, 1958). The three power stations at Waikaremoana utilise the steep fall of nearly 450 m in 8 km to generate electricity which is distributed to the national grid for public supply (Read, 1979).

2.2 Geomorphology

Lake Waikaremoana is a drowned valley system with topography at its eastern end consistent with infilling and damming by debris from a large ancient landslide (Main, 1976). The catchment is steep, with 65% of the catchment classified as moderately steep to steep (slopes of 21° -35°) and 10% of the catchment classified as very steep with slopes greater than 35° (Newnham et al., 1998). The elevations in the Urewera National Park are typically high, with maximum elevations up to 1300m above sea level (Matthews, 1992). There are just two minor wetlands in the Waikaremoana catchment (Newnham et al., 1998).

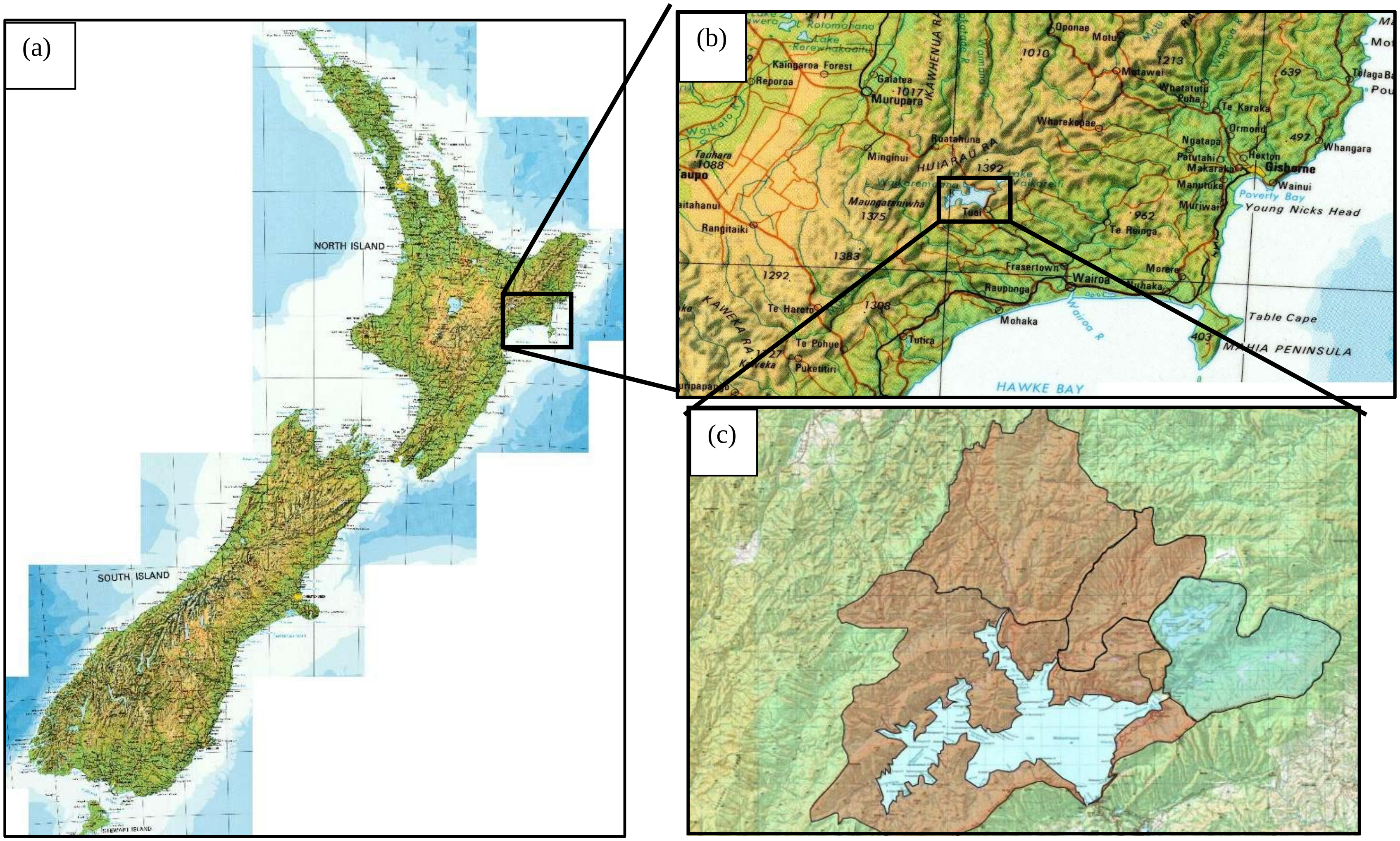

Figure 2: Location of Lake Waikaremoana within New Zealand (a) and Northern Hawkes Bay (b). (c) shows a detailed view of Lake Waikaremoana where Lake Waikaremoana catchment is outlined in red and blue where blue is the Aniwaniwa sub-catchment. (Source: InfoMap 266 New Zealand, NZMS 265-1 North Island, NZMS 260 W18 Waikaremoana).

While evidence of debris avalanches exists in the form of erosion scarps, other erosion is minimal due to the presence of dense native forest cover (Urewera National Park Board, 1976). Sediment from debris avalanches reaches Lake Waikaremoana during storms via the Hopuruahine and Mokau Streams whose catchments have major erosion features which are not as prevalent in other, less steep catchments (Matthews, 1992). Lake Waikaremoana and Lake Whakamarino both act as sediment traps. At Lake Whakamarino high sediment accumulation may limit the operational flexibility and the economics of the Waikaremoana hydro power scheme. This occurred in 1986 when dredging of Lake Whakamarino was required (Chester, 1986).

2.3 Geology

The Urewera National Park landforms are geologically young, but basement rocks range from Urewera Greywacke from the Upper Jurassic period through to tertiary surface geology (Grindley et al., 1960, Johnson, 1976). The park is composed of a depression named the Wairoa Basin, a mountain backbone, and part of the Rotorua-Taupo volcanic zone (Johnson, 1976) (Figure 3).

The Waikaremoana area is underlain by uplifted marine sedimentary rocks with a stratigraphic thickness of at least 12,000 m (Grindley et al., 1960). The dominant lithologies present are siltstone, mudstone and sandstone, where the sandstone commonly contains calcareous beds (Figure 4). The sedimentary sequence dips to the south-east at angles up to 20°. Several locally significant faults with north-east trends similar to the major faults of the North Island are present. The steep topography of the area is a result of its relatively recent uplift. Much of the area is mantled with volcanic tephra from the Taupo Volcanic Zone (Read et al., 1992).

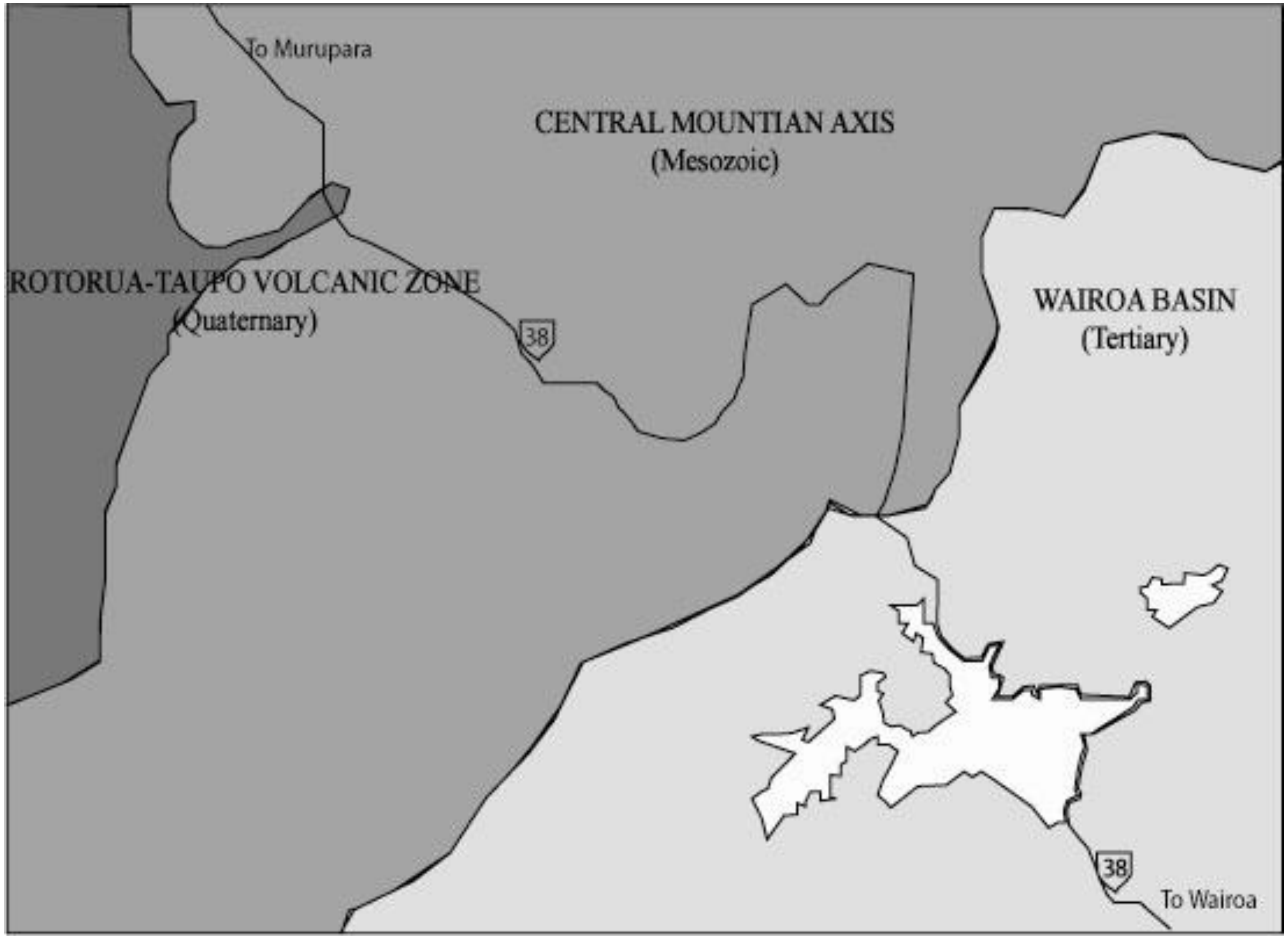

Figure 3: Location of Lake Waikaremoana in relation to the physiographic units of the Wairoa Basin, mountain axis and the Rotorua-Taupo Volcanic Zone. Modified from Urewera National Park Board (1976).

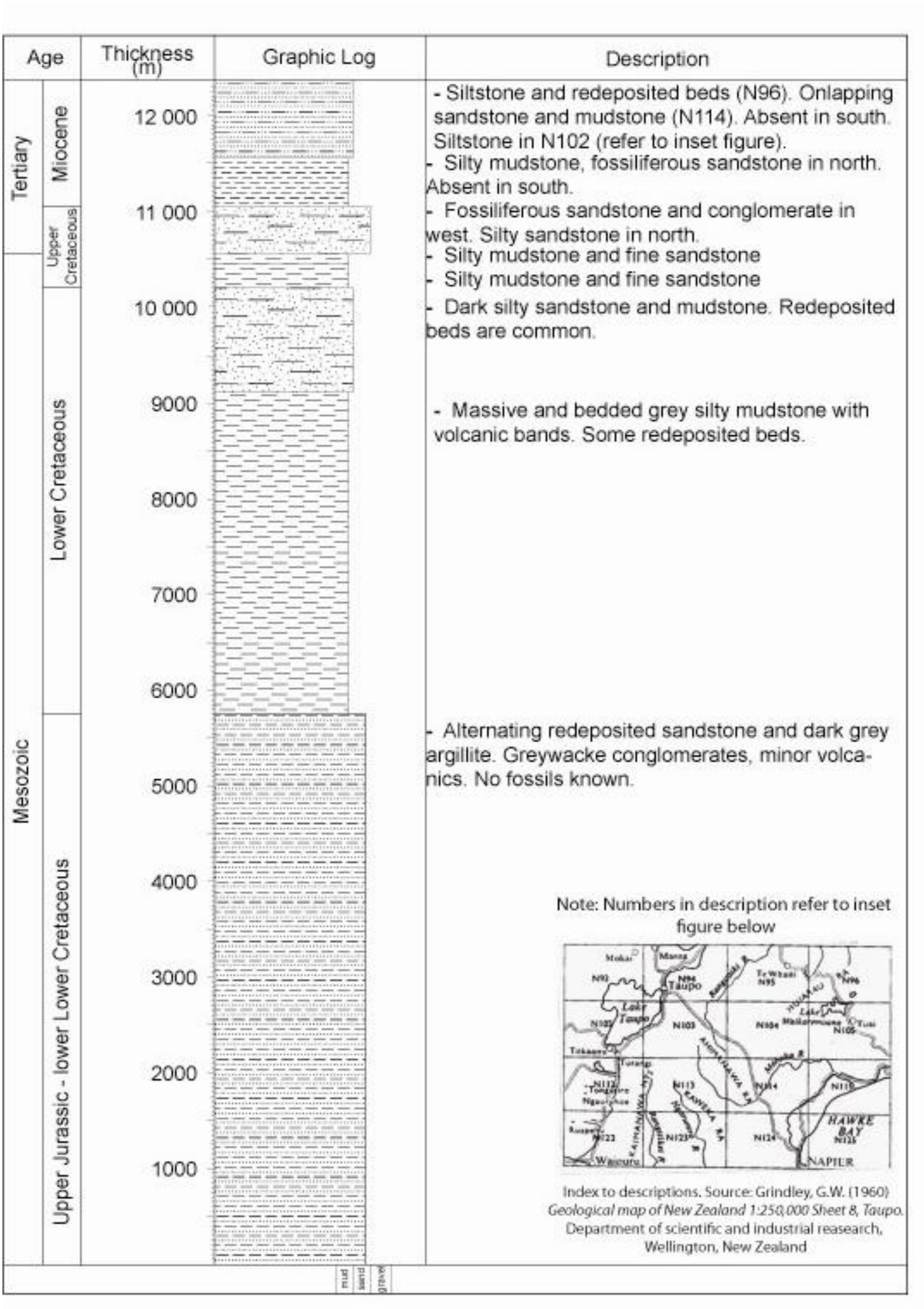

Figure 4: Simplified stratigraphic column of the Waikaremoana area (based on Grindley et al., 1960)

2.4 Origin of Lake Waikaremoana

The origin of Lake Waikaremoana was unknown for a number of years, prompting discussion in the scientific literature. The first study of its origin was carried out by Smith in 1876 (cited in Ongley, 1932) who simply concluded that its origin was ‘not glacial’. Later in 1876 Cox of the Geological Survey (cited in Ongley, 1932) found that its origin was ‘not glacial and not volcanic’. In 1892 Hector (cited in Ongley, 1932) concluded that the lake occupied the depression of the downthrow side of a great fault. This was disproved in 1897 when Smith (cited in Ongley, 1932) recognised that the origin of the lake was a large slip. Smith commented that this was ‘obvious’ despite his earlier comments on the origin as simply ‘not glacial’. In 1912 Marshall suggested that Lake Waikaremoana had been formed by solution of rock leaving large cavities into which the overlying rock collapsed. This suggestion was made despite never having been to the lake (cited in Ongley, 1932). Lambert challenged the idea that the lake origin was ‘not volcanic’ in 1925 concluding that it was a crater lake formed by a ‘great volcanic outburst’ and that landslides had contributed to the formation of the basin (cited in Ongley, 1932).

Today it is accepted that Lake Waikaremoana was formed following a landslide, possibly triggered by a large earthquake, which blocked the flow of the Waikaretaheke River forming a natural dam (Davies et al., 2006, Riley and Read, 1992) (Figure 5). The landslide has an area of 18 km^2 and a volume of approximately 2.2×10^9 m^3, ranking it as one of the biggest landslides in the world (Davies et al., 2006). The landslide dam is approximately 400 m thick, with an average surface slope of 6° and a maximum thickness of 425m. It extends for 8 km along the Waikaretaheke Valley (Riley and Read, 1992). The landslide debris is made up of tertiary age sandstone and siltstone blocks up to tens of meters in diameter supported by a fine grained matrix of sand, silt and pumice. The blocks are randomly oriented and vary in shape (Read et al., 1992). Numerous large cavities exist between clasts (Figure 6). The sliding surface of the block is thought to be within a sandstone layer (Davies et al., 2006).

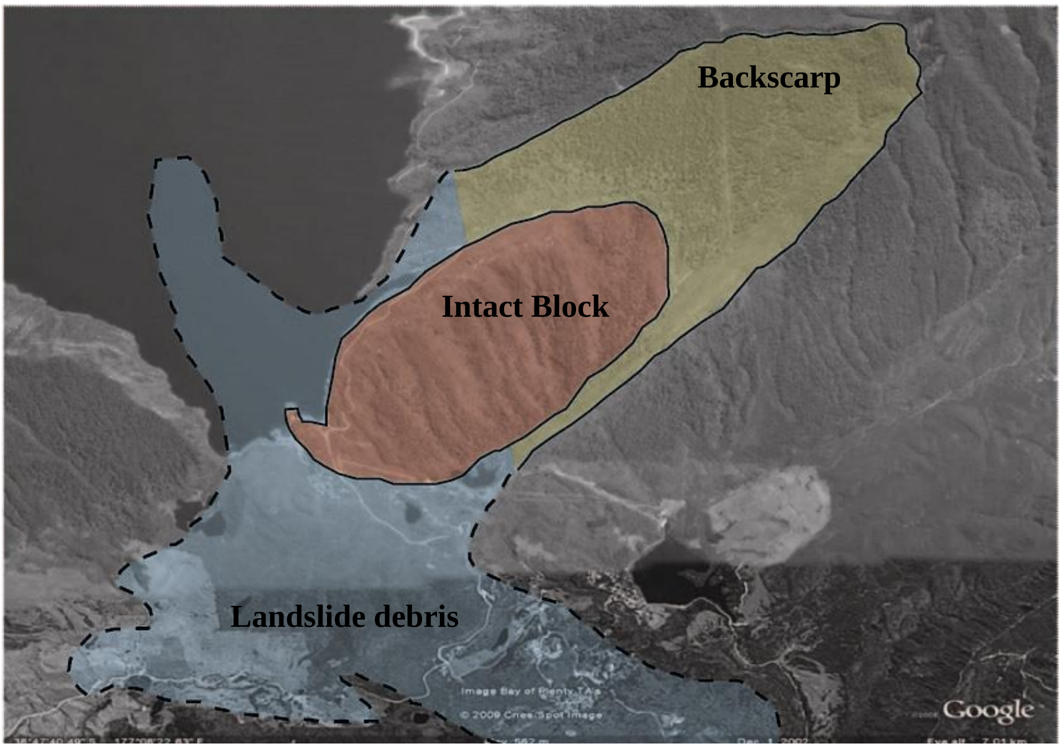

Figure 5: The natural dam at Lake Waikaremoana formed by an ancient landslide showing intact block (red), backscarp (yellow) and debris (blue). Modified from Riley and Read (1991) and Davies et al., (2006).

While landslide lakes are generally short lived, Lake Waikaremoana is known to be at least 2,200 years old, based on carbon dating of dead trees found within the lake (Matthews, 1992, Natusch, 2004, Read et al., 1992, Riley and Read, 1992). However, the presence of the Waimihia Tephra on the landslide debris and exposed slide scarp shows that the landslide occurred at least 3,300 years ago (Allan et al.,2002, Soons and Selby, 1992).

In 1927 Marshall recognised that the landslide occurred in two phases. The first phase was composed of a rock avalanche which blocked the Waikaretaheke Valley. This was followed by a block glide which fractured as it was brought to rest, creating pressure ridges (Riley and Read, 1992). The south eastern part of the landslide dam is formed from landslide debris and intact block forms the north west side. It was later suggested that the landslide occurred in three stages (Read, 1979).

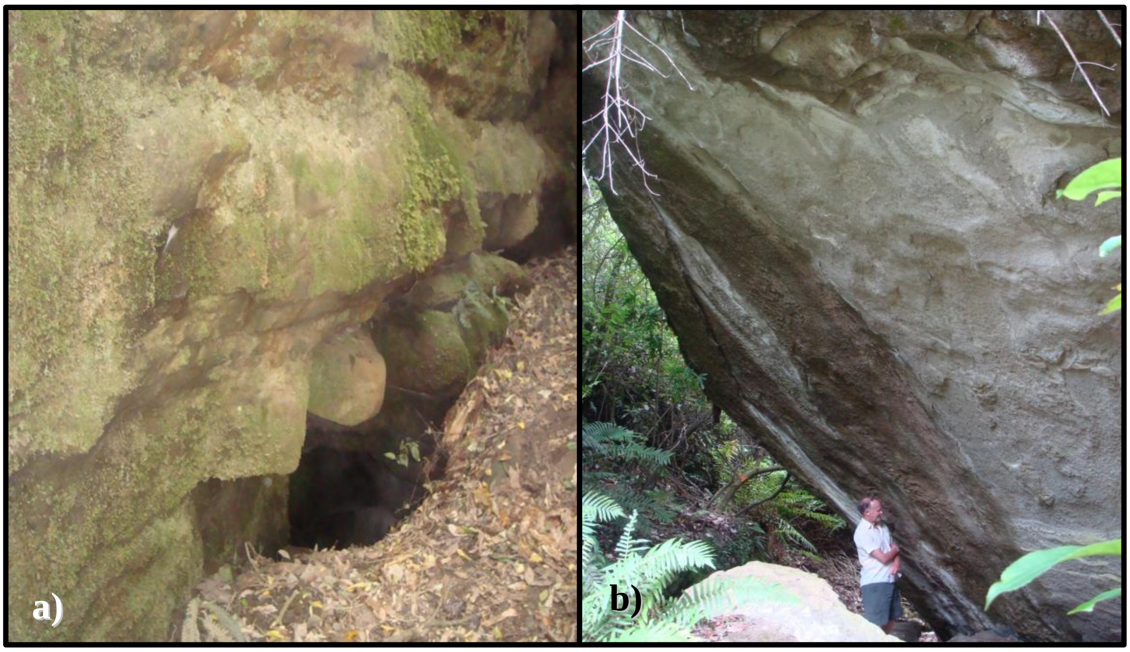

Figure 6: a) An example of the numerous cavities within the landslide debris b) example of the large blocks which make up the landslide debris (note scale).

The first phase is differentiated from the second by its increased mobility which was identified by its morphology, wider areal extent and smaller thickness of debris (Read, 1979).

The landslide barrier appears to leak substantially though its upper levels. Prior to hydro electric development the leakage rate was estimated to be as high as 12 m^3s^{-1}. This was reduced to approximately 5 m^3s^{-1} by upstream sealing works in the Te Whara Whara Bay area (Riley and Read, 1992).

2.5 Climate

Lake Waikaremoana has a temperate climate with a mean annual temperature of 11°C. Summer daily maximum temperatures are approximately 25°C and winter daily minima are approximately-5°C. The catchment is a high rainfall area, with annual rainfall at the lake outlet exceeding 2000 mm/year, tending to occur as infrequent high intensity events (Table 1). Snowfall and ground frosts occur regularly in winter months. The predominant strong wind directions are from the north and north west sectors (Newnham et al., 1998).

Table 1: Annual mean, minimum, and maximum annual rainfall in millimetres for sites gauged by Hawkes Bay Regional Council in the Waikaremoana area.

Catchment	Record begins	Mean annual rainfall (mm)	Min annual rainfall (mm)	Max annual rainfall (mm)
Erepeti Met	1928	1825.1	1165.3	2619.7
Aniwaniwa	1977	2232.4	1750.5	2892.7
Nga Tuhoe	1985	1683.6	1263.5	2255.0
Upper Waiau	1985	1224.4	745.5	1547.5
Bushy Knoll	1986	1447.4	785.0	2352.5
Rocky Pad	1989	2144.2	1575.2	2754.0
Mt Manuoha	1989	2879.7	2164.0	2352.5
Waimaha	2000	1215.9	948.5	1466.3

Evaporation from Lake Waikaremoana has been estimated by Finklestein (1973) who calculated open water evaporation rates for New Zealand using a modified Penman equation. Finkelstein (1973) gives evaporation rates for a large number of sites in New Zealand, including Onepoto, Waikaremoana. At Lake Waikaremoana evaporation was measured directly using an electric type sunken pan (Table 2). Finkelstein (1973) found that over the period of a year, pan evaporation is generally consistent with lake evaporation.

Table 2: Average monthly lake evaporation and total annual evaporation in millimetres. Modified from Finkelstein (1973).

Month	Average Monthly Evaporation (mm)	Month	Average Monthly Evaporation (mm)
January	91	July	22
February	68	August	25
March	58	September	33
April	40	October	50
May	30	November	75
June	22	December	81
Total			**595**

2.6 Hydrology

Lake Waikaremoana is the North Island's deepest lake with a maximum depth of 248 m, an average depth of 93 m, and a surface area of 56 km^2 (Riley and Read, 1992). In terms of physical classification the lake has been defined as warm monomictic and oligotrophic (Main, 1976).

The Lake Waikaremoana catchment consists of a large number of small streams (approximately 114) which flow into the lake. The nature of the terrain and the large number of streams mean that inflows are impractical to measure directly. However, a low-flow study carried out by Hawkes Bay Regional Council found that of the largest streams in the catchment, the highest low-flow specific discharges occurred in the Aniwaniwa and Mokau catchments (9.8 $l/s/km^2$ and 13.8 $l/s/km^2$ respectively). It was thought that the highest low flow specific discharges occurred in the Aniwaniwa and Mokau catchments due to high baseflow produced by the fractured nature of the surface of the landslide which formed Lake Waikaremoana. The lowest specific discharges occurred where the subsurface geology was hard, impermeable unfractured rock (Black, 1992).

While Lake Waikaremoana currently has no natural surface channel outflow, lake overflow occurred approximately 50% of the time prior to hydroelectric development (Read, 1979). It has long been recognised that outflow also occurs in the form of lake leakage through the natural dam, and exits as springs and streams on the landslide surface. The leakage is thought to travel through cavities in the landslide debris formed by the haphazard placement of very large clasts during the lake-forming landslide event. Water passage through the natural dam has been found to be complex and widely dispersed. Tracer studies have produced breakthrough curves with long tails and lag times, suggesting that each spring may be fed by a number of leaks with multiple and intersecting paths (McPike, 1980). Tracer testing carried out in 1931 and 1932 found that the dispersion of water from individual leaks along different fractures was considerable and appeared to be controlled by fracture direction (Read, 1979).

Riley and Read (1992) hypothesised that water conduits which exist in open fissures or bedding planes may be constricted at their downstream limits by landslide debris and could cause high pressures to develop within or beneath the landslide mass, resulting in artesian fissure pressures.

Read et al., (1979) divided the springs in the Waikaremoana area into ‘warm springs’ and ‘cold springs’. Warm springs were found to have up to a 5 degree annual temperature variation, while cold springs had a smaller temperature range, in the order of 2 degrees (McPike, 1980). Warm springs (also known as primary springs) included all major springs located within 300 m of the lake outlet at Te Whara Whara Bay. The water in these springs was thought to have travelled through a zone of fissured sandstone and siltstone and accounted for >85% of the leakage from the lake prior to sealing. The cold springs were found to be distributed throughout the landslide area. Cold water springs were thought to be derived from source water below thermocline within the lake, while warm water springs were believed to have a source above the thermocline (Read et al., 1979). Under conditions of maximum stratification the top of the thermocline occurs at approximately 15-20 m depth (Howard-Williams et al., 1986, Mylechreest, 1978).

Other miscellaneous springs in the Waikaremoana area, including those labelled in the study by Read (1979) as ‘U group and associated springs’ are not thought to have been affected by the sealing of the dam, and are colder than both the warm and cold springs previously mentioned. Thus it is unlikely that Lake Waikaremoana is their source. No evidence has been found to suggest that leakage from Lake Waikaremoana occurs through undisturbed rock beyond the landslide area (Figure 7).

The Kaitawa weir measures the flow of the Waikaretaheke Stream, a stream almost entirely derived from Lake Waikaremoana leakage via the primary and U group springs. A slight increasing trend in discharge has been recorded at the Kaitawa weir (Figure 8). This increasing trend may be due to inaccurate weir readings as a result of debris accumulating on the weir over time, or due to an

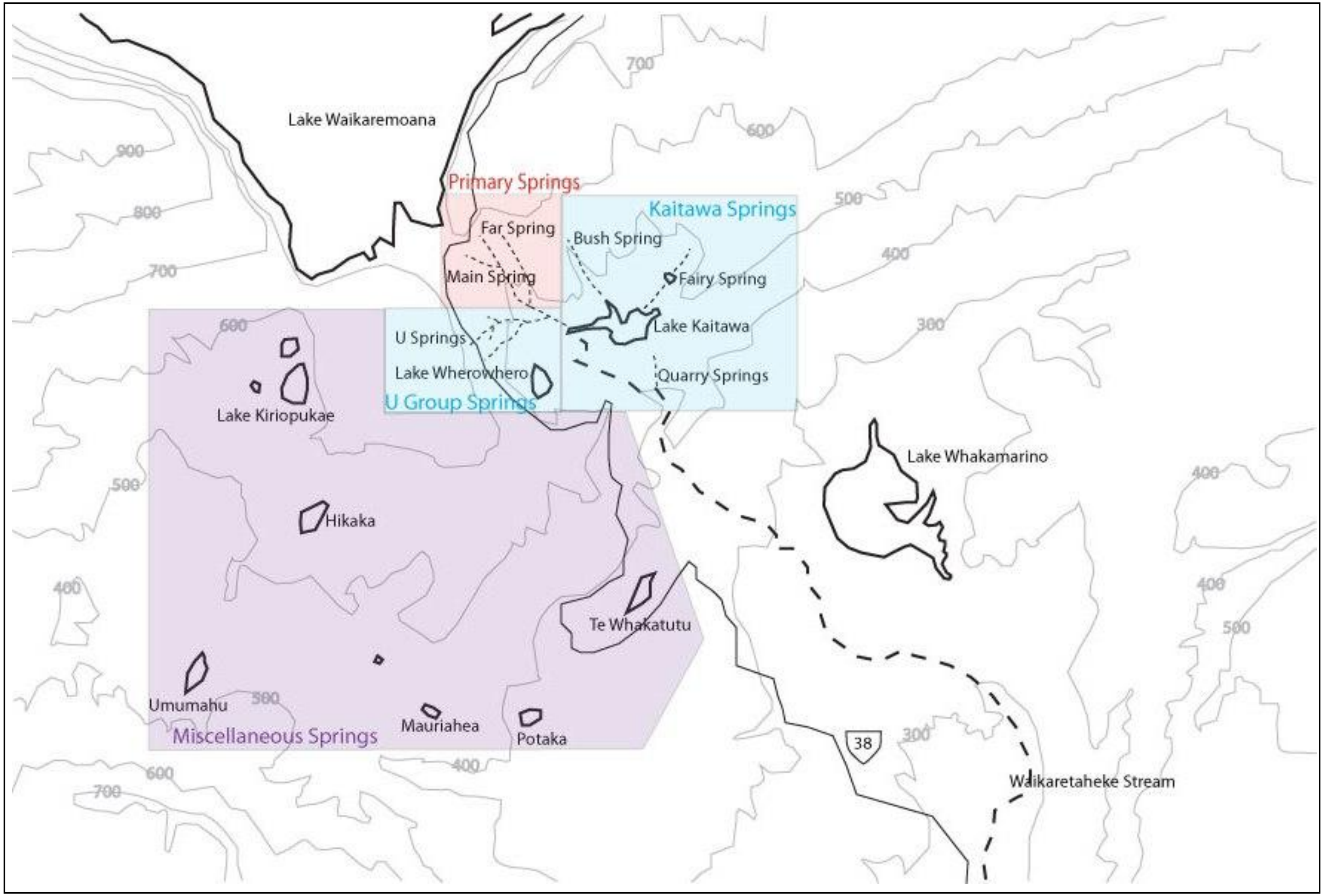

Figure 7: Locations of warm springs (pink), cold springs (blue) and miscellaneous springs (purple).

increase in leakage rate over time as the leakage pathways erode due to the passage of water.

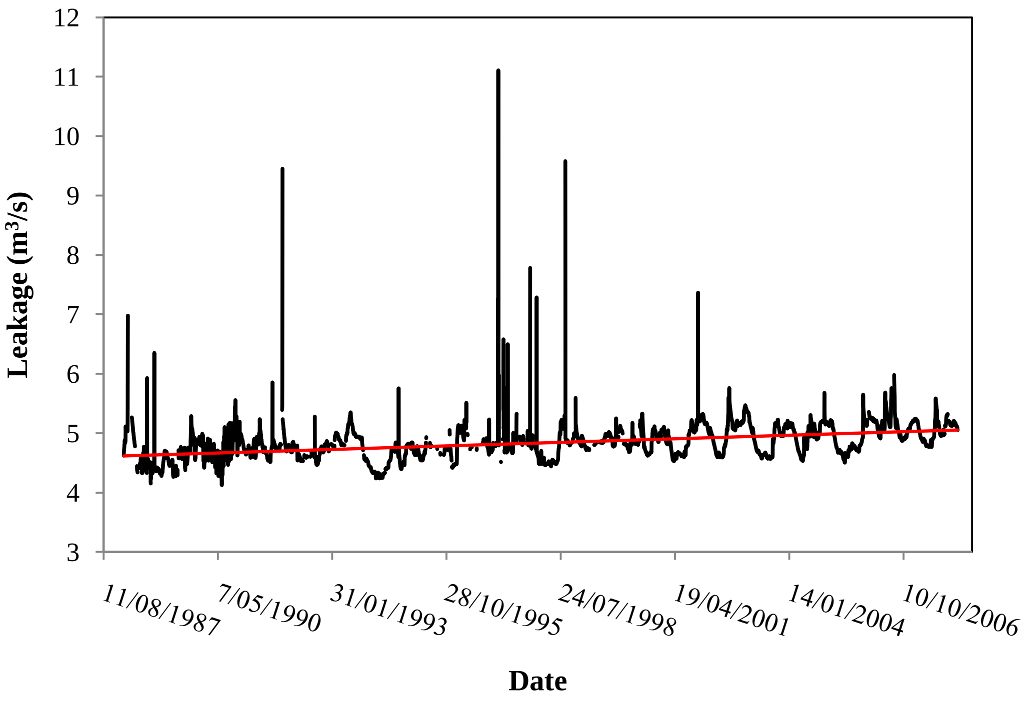

Figure 8: Measured leakage at Kaitawa weir showing a slight increase in leakage over time, and large peaks associated with siphon use. Leakage data has been corrected for lake level.

Leakage rate is also affected by lake level (Figure 9). This may be due to a seasonal effect where increased rainfall which leads to a higher lake level also leads to higher groundwater inputs, or that a higher lake level means that more leakage pathways may be utilised. Alternatively the relationship between leakage rate and lake level may be due to a hydraulic effect where a higher lake level results in increased leakage due to an increased head, or a combination of these two ideas. Freestone et al., (1996a) estimated that leakage increased by 0.2 m^3s^{-1} per meter of lake level rise.

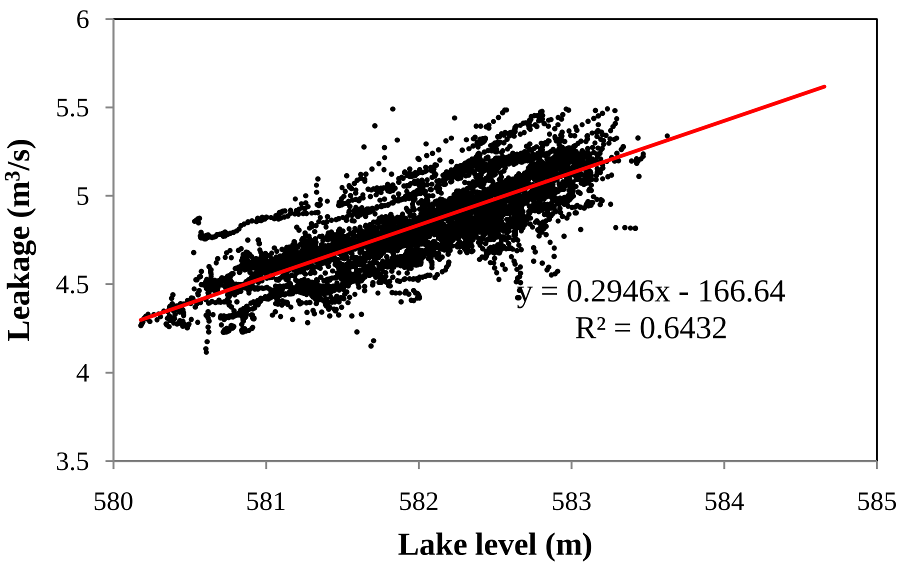

Figure 9: Regression of daily mean lake level and leakage rate as measured at Kaitawa weir where siphon discharge into the Waikaretaheke Stream has been removed. This shows that lake level and leakage rate are related.

2.7 Modifications from Hydro Power

Lake Waikaremoana's waters have been used for hydroelectric power generation since 1929 resulting in modification of the lake environment. Prior to development for hydroelectric generation, lake outflow in the form of leakage through the natural dam occurred at a much higher rate, and reappeared as springs which collectively formed the Waikaretaheke River (Freestone et al., 1996a). In 1946 modification of the natural overflow area began as a result of the construction of Kaitawa Power Station in order to deliver water to its penstocks.

In the late 1940s, partial sealing of the lake bed was carried out in order to reduce the leakage from the lake through its natural dam to prevent leakage water from by-passing Kaitawa Power Station representing a missed generation opportunity. Prior to this sealing the majority of the leakage originated in the area of Te Whara Whara Bay at a rate approximately 50% greater than occurs today (Read, 1979). The Te Whara Whara Bay area is also the location of lake overflow, which occurred approximately 50% of the time prior to hydroelectric development, with discharge into the Waikaretaheke River (Read, 1979).

Despite sealing works in the late 1940s, leakage still exists into the landslide dam. As a result the landslide debris is essentially saturated, indicated by the presence of streams and springs on most of the landslide surface (Figure 10). Most of the major springs are located on the intact block where the water table levels are closer to the surface (Riley and Read, 1992).

In 1978 and 1979, a further investigation showed additional leakage derived from an area of the lake which was deeper and to the north of other areas previously examined (McPike, 1980). This area was beyond the diving capabilities of the 1940s, although it was identified as a possible leakage source in the 1930s through temperature data. Sealing of this area was not carried out as a result of economic limitations and problems with the method of sealing. The economic limitations were overcome in the 1950s due to an increase in the value of electricity, and in the 1970s power shortages prompted feasibility studies into further sealing. Further sealing work was not carried out however, due to the possibility of the reduction in the availability of stock water supplied by springs and the effect on the local natural character of the Urewera National Park (McPike, 1980).

Figure 10: Fairy Spring, an example of one of the many springs on the landslide surface.

Feasibility studies for further sealing have investigated a number of well known springs, such as Bush Spring, Fairy Spring and Quarry Spring which are thought to be derived from Lake Waikaremoana. Concerns have been raised that further sealing may affect these springs, which have importance to the natural character of the Urewera National Park. Read (1979) found that Bush spring is partially a result of subterranean flow from Lake Waikaremoana, as well as from local runoff. This conclusion was drawn as the flow from Bush Spring varied with lake level prior to sealing, and post sealing its flow volume was reduced from 50-85 litres per second to 20 litres per second. Fairy Spring and Quarry Spring appear to be interrelated. They are both recharged by local rainfall and Fairy Springs were slightly affected by sealing of the lake and by fluctuations in lake level. However, the effect of lake sealing on Fairy Springs has not been quantified. Quarry Springs showed no significant variation following sealing or in response to lake level fluctuation. Quarry Springs may be more closely related to the level of Lake Kaitawa (McPike, 1980).

A number of springs in the Waikaremoana area are thought not to be connected to Lake Waikaremoana, these include Lake Kiriopukae, Lake Whakatutu, and the Hikaka group (Figure 7). Lake Hikaka and adjacent springs are thought to be interconnected with Lake Kiriopukae. Other small springs such as Lake Pakiaka are likely to be fed from Lake Hikaka or Mangaone stream. This may also be the source of springs such as Lake Whakatutu. Lakes Umuamahu, Mauriahea, and Pataka Lagoon are formed on areas of ponding of the Mangaone Stream outside the landslide debris and are considered to be recharged locally (Read, 1979).

The construction of Kaitawa Power Station and subsequent modification of the lake inlet allowed for control of lake level and resulted in lake level lowering by 4.7 m below its mean natural level (Figure 11). This was carried out to aid the stability of the natural dam, and to provide flood protection to downstream areas by enhanced storage (Howard-Williams et al., 1986).

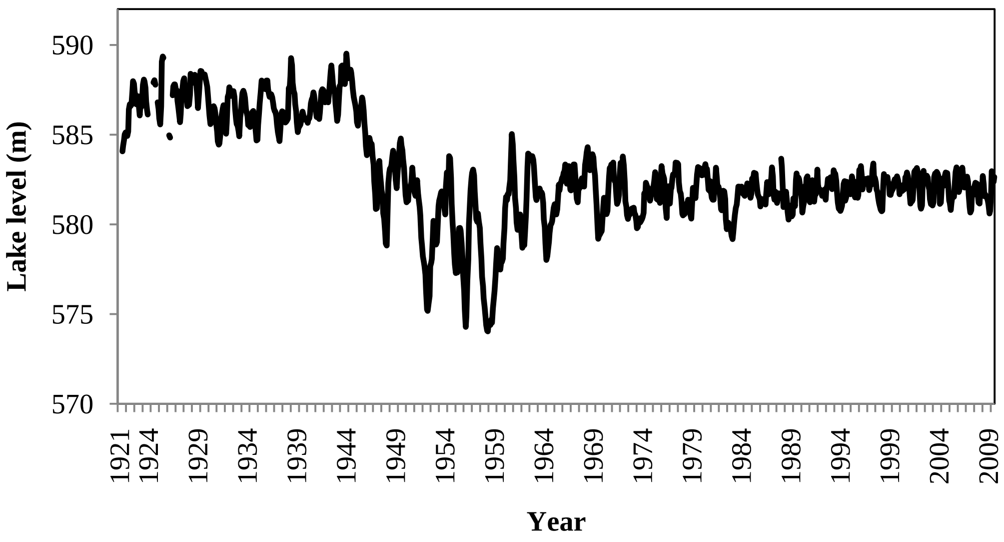

Figure 11: Monthly average lake level in meters from (1921-2009) showing the decrease in lake level by 4.7m in 1946.

Lake level variation has also been modified by hydroelectric generation. From the beginning of the record in 1921 until the construction of siphons and the lowering of lake level in 1946, lake level was controlled solely by the catchment water balance, even though generation using water sourced from lake leakage has been carried out since 1929 at Tuai Power Station. From 1946 the annual range in lake level extremes had an average of 3.1 m, a minimum of 1.0 m and a maximum of 9.0 m. Such a large maximum range is a result of the 4.7 m lake level reduction in 1946, as well as power shortages which followed the end of World War II from 1946 to 1965. Since the conclusion of the power crisis in 1965 the annual operating range has been constrained to a maximum range of 5.640 m with an average of 2.561m (Freestone et al., 1996b).

Modifications in lake level fluctuation associated with hydro power generation were reported in an early study by Mylechreest (1979). Mylechreest (1979) graphically showed the changes in lake level in response to hydro generation. A reproduction of lake level analysis by Mylechreest (1979) has been produced with the addition of more recent lake level data for the period 1921 to 2009 (Figure 12).

Mylechreest (1979) showed that prior to hydroelectric development (for the period 1921 to 1945), lake level varied naturally with season such that the highest lake levels occurred in winter in response to high rainfall inputs, and the lowest lake levels occurred during the summer months. For the period 1966 to 1973 seasonal variation showed a reversed trend, where high lake levels occur in summer as a result of storage of water in order to meet the demand in winter months. The lowest lake levels then occur during the winter months to supply peak demand (Figure 12). This reversed seasonal trend is similar to the approach adopted at South Island hydro lakes (Harding et al., 2004).

The period 1946 to 1965 follows the same seasonal variation pattern as that prior to hydro electric development but with a reduced lake level. This is due to the lowering of the lake level by 4.7 meters in 1946. There is also a wider operating range due to the post World War II power crisis. The natural seasonal pattern continues due to the stable power demand at all times during the year.

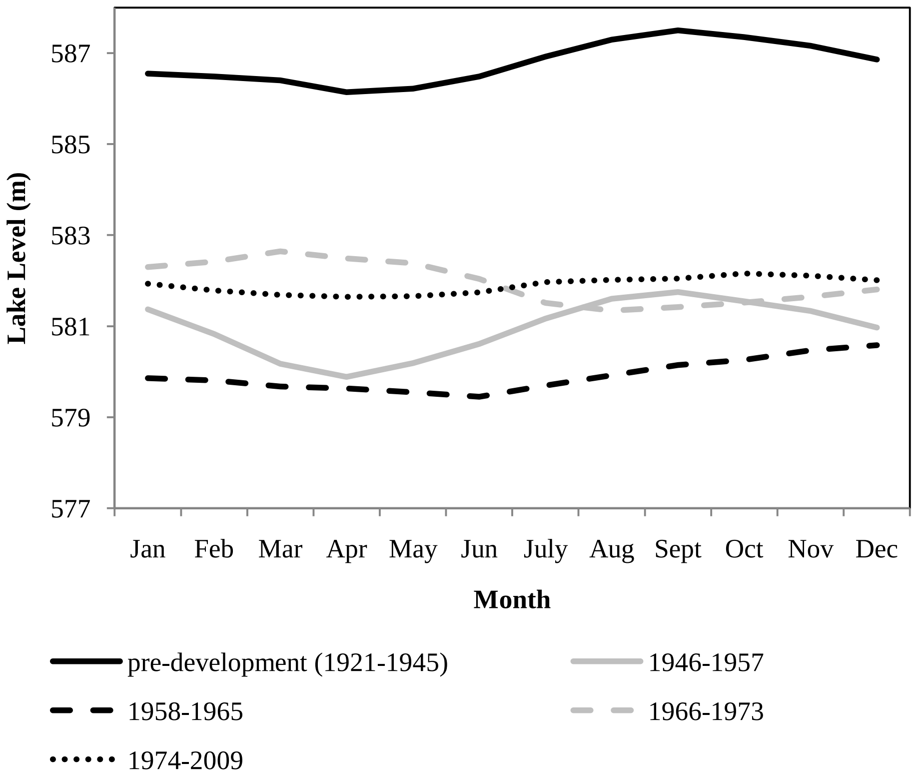

Figure 12: Seasonal (mean monthly) lake level variation for five periods from before hydro electric development (1921-1945) to (2009). Modified from Mylechreest (1979).

In the following period, from 1958 to 1965 the lake level exists at a constantly lower level and has a reduced operating range. Seasonally, minimum lake levels occur in winter, and peak lake levels in summer. This follows the end of the Second World War power crisis, where the operating range was restricted within smaller limits and the 'power use in winter, storage in summer' trend begins to reappear. The most recent period of the graph, from 1974 to 2009, has the smallest operating range due to restrictions imposed by resource consent conditions. It also has a slight seasonal variation with minor winter maxima and summer minima.

While hydro electric development has modified lake level variation, at present the natural seasonal pattern of maximum lake levels occurring during winter months in response to high inflows and minimum lake levels occurring in summer still exists. However, this seasonal variation has a much smaller range than prior to hydro electric development (Figure 13).The lower range is a result of the resource consent conditions imposed on the scheme, which limit lake level variability in order to protect shoreline morphology and vegetation (Genesis Energy, 2009).

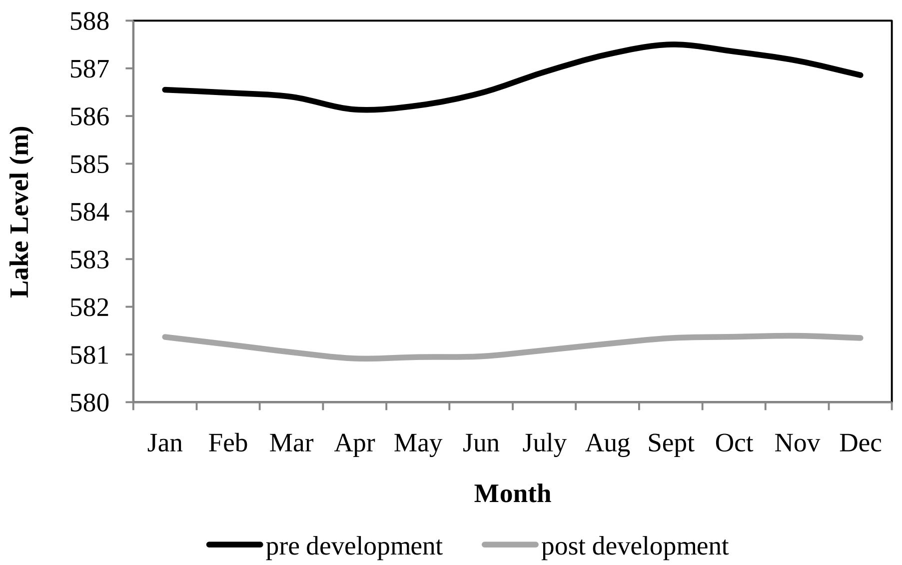

Figure 13: Mean monthly lake level variation, showing variation before (1921-1945) and after (1946-2009) hydroelectric development. Modified from Mylechreest (1979).

Daily lake level fluctuates naturally in response to the effects of waves and wind set up which results in high frequency noise in the lake level record (Figure 14). This noise is reduced by utilising the three hourly average of lake level data (Figure 15) however, it is likely that sufficient noise still exists within the data set to be a significant source of error.

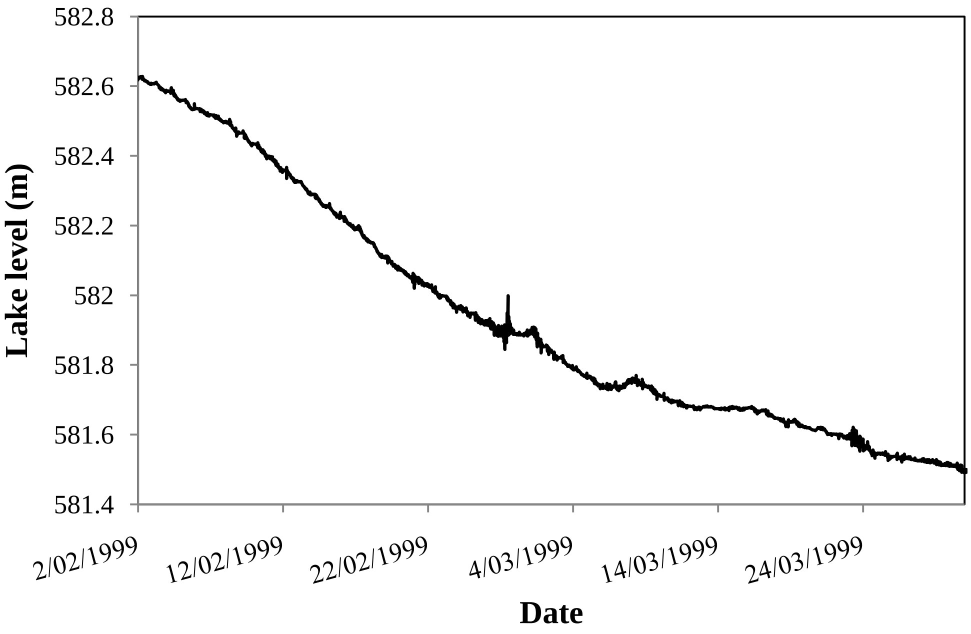

Figure 14: Raw lake level data for the period 2 Feb 99 – 24 Mar 99 showing high frequency noise.

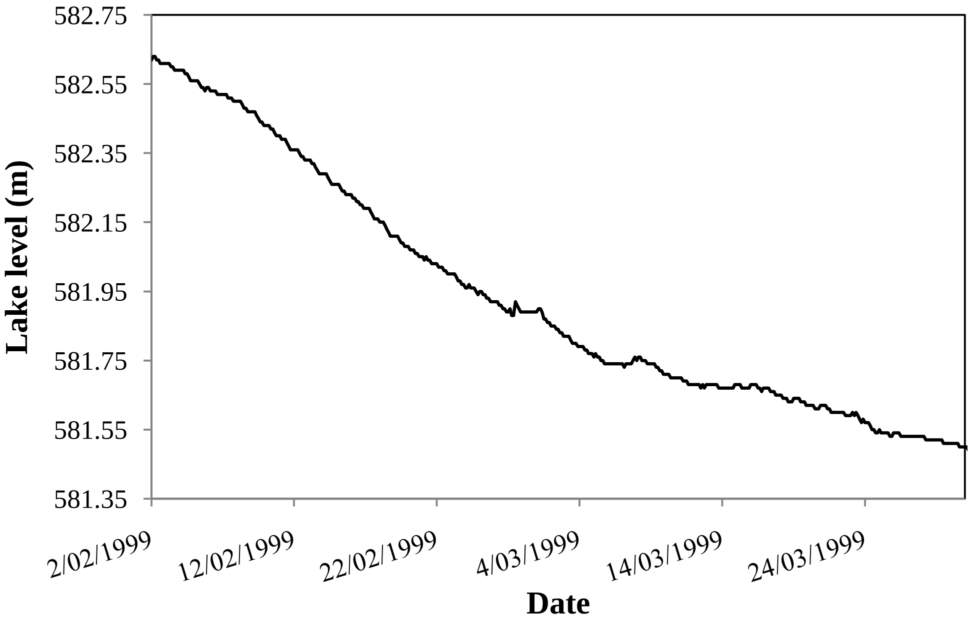

Figure 15: Three hourly averaged lake level data for the period 2 Feb 99 – 24 Mar 99 showing reduction in high frequency noise.

A number of other modifications have been made in the Waikaremoana area to facilitate the generation of hydro power. These modifications include the initiation of a new sequence of shoreline development due to the modification of lake shore platforms caused by the lowering of the lake level in 1946 (Allan et al., 2002), and the creation of small new headpond lakes to serve as storage: Lake Kaitawa and Lake Whakamarino (Chester, 1986, Genesis Energy, 2009).

Many other environmental modifications have also occurred as a result of hydroelectric development, such as to terrestrial vegetation, aquatic vegetation, trout, water quality and erosion. These are monitored by Genesis Energy such that mitigating action can be taken should the power scheme result in any adverse environmental effects (Genesis Energy, 2009).

Chapter 3 –Data Sources

3.1 Introduction

Data availability is a critical aspect of any field study, and was particularly important during this research due to the heavy reliance on historical data sets. During this study a large amount of data including rainfall, river flow, lake level, and power station operation was available for use. Rainfall and river inflow data was obtained from Hawkes Bay Regional Council. Lake level, limited rainfall data, and power station operation was available from Genesis Energy. However, data availability limited this study in some aspects.

3.2 Rainfall and River Inflows

Eight rain gauges (Aniwaniwa, Erepeti Met, Bushy Knoll, Nga Tuhoe, Waimaha, Upper Waiau, and Mt Manuoha) and four stream flow recorders (Aniwaniwa, Te Kumi, Mokau and Hopuruahine) monitor inflow into Lake Waikaremoana (Figure 16, Figure 17). Many of these were initially installed by Hawkes Bay Regional Council between 1928 and 2000 to allow the allocation of water permits and to set lake levels under the Water and Soil Conservation Act of 1967 (Black,1992). The results from this gauging show that Lake Waikaremoana lies in a high rainfall area (Figure16). Of these rainfall sites, only the Aniwaniwa and Mt Manuoha are located within the catchment of Lake Waikaremoana (Figure 17). However, other sites close to the catchment still provide an indication of rainfall in the Waikaremoana catchment (Sansom and Thompson, 2008).

The Waikaremoana catchment has an approximate area of 283 km^2. Of this, inflows originating from 169.0 km^2 are measured by Hawkes Bay Regional Council, making 59% of the catchment area gauged (Figure 17). River inflows are recorded for the Aniwaniwa Stream, Te Kumi Stream, Mokau Stream and the Hopuruahine Stream.

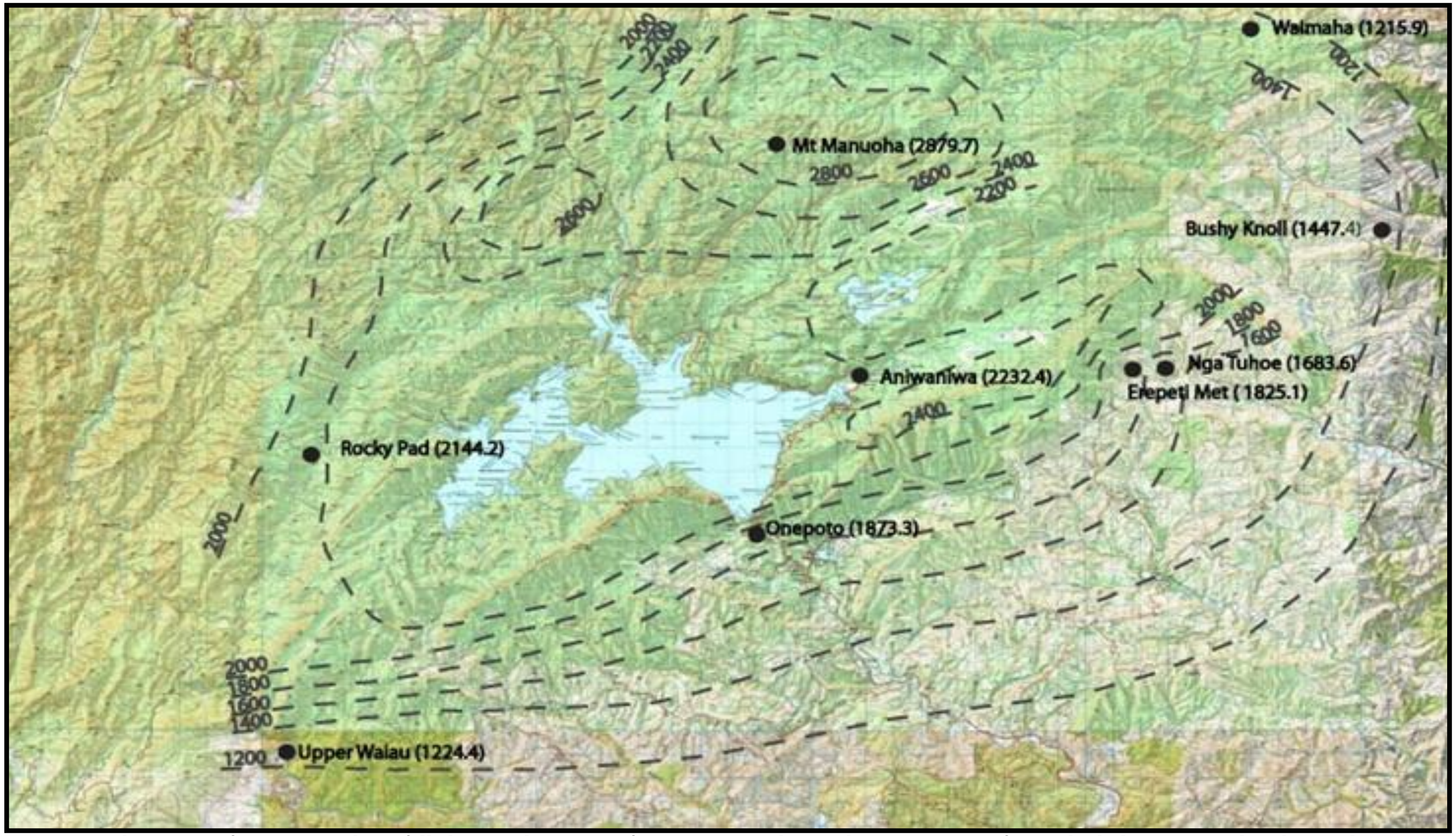

Figure 16: Isohyet map of mean annual rainfall showing locations of raingauges in the Waikaremoana area from which data was used in this study. Contours modified from Black (1992).

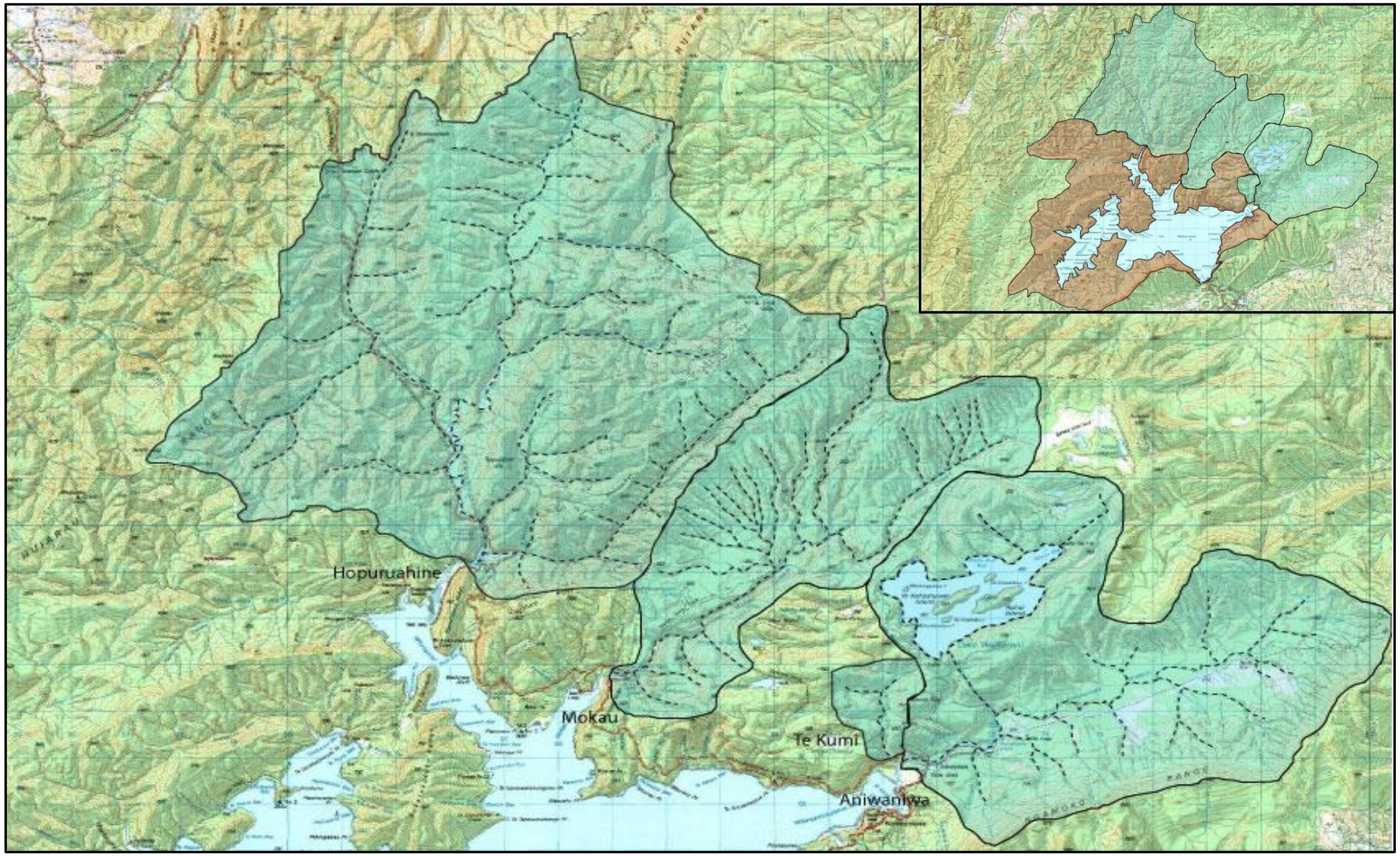

Figure 17: Catchment areas of streams from which inflow data was used in this study. Inset: Gauged catchment area (blue) and ungauged area (red) of the Lake Waikaremoana catchment.

Despite a large amount of data, data availability limited this study. Inflow data for the Aniwaniwa stream was the only data set used of the available stream data due to the data for the other three streams not being available and/or continuous throughout the required time periods. The Aniwaniwa flows were available from 1988 to 2009. Inflows for the Mokau catchment were available for 1990 to 2001, Hopuruahine from 1989 to 2000, and the Te Kumi from 2000 to 2009.

Of the 9 rain gauges in the Waikaremoana region, Mt Manuoha, Rocky Pad, Nga Tuhoe, Waimaha, Upper Waiau, Bushy Knoll and Onepoto are telemetered. That is, the data is received in real time. This data is received at Hawkes Bay Regional Council, with the exception of the Onepoto raingauge which is monitored by Genesis Energy. The Aniwaniwa raingauge is non-telemetered and the data must be periodically downloaded by staff. The Erepeti Met site is a daily manual Met Service site where the data is supplied to Hawkes Bay Regional Council by Met Service once per year.

Data from these rain gauges are available at hourly resolution from 1928, 1977, 1985, 1985, 1986, 1989, 1989 and 2000 for Erepeti Met, Aniwaniwa, Nga Tuhoe, Upper Waiau, Bushy Knoll, Rocky Pad, Mt Manuoha and Waimaha respectively.

3.3 Lake Levels

Lake level data was available from Genesis Energy in two forms, raw instantaneous data, and Three-hourly averages. Three-hourly averages are used to reduce the effects of noise such as seiching and wind waves. Three hourly average data was used in all instances where lake level input data was required during this study as well as in Genesis Energy’s existing water availability model.

3.4 Power Station Operation

Data related to operation of the Waikaremoana Power Scheme was made available by Genesis Energy. Available data included flow through Kaitawa Power Station, the first of the three power stations in the Waikaremoana Scheme, and flow through Onepoto Siphons 1 and 2.

Kaitawa Power Station data was available in two forms: ‘Opus’ power station data for the period 1995 to 1998, and ‘current’ power station data for the period 1998 to 2009. ‘Opus’ data comes from prior to Genesis Energy taking over the operation of the Waikaremoana Power Scheme, with discharge through the power station calculated using a combination of headwater level, tail water level and generation. The ‘current’ calculations are a rating derived from load versus flow. The differences are thought to be very small. However, only ‘current’ data was used in this study.

The Lake Waikaremoana spillway is capable of both manual and automatic spill. Automatic spill occurs via the Onepoto siphons which discharge into the Waikaretaheke Stream when the lake level reaches 585.51 m asl. However as the lake rarely reaches this level, automatic spill is a rare occurrence. The Onepoto siphons are also used for manual lake water spill when lake level approaches the maximum resource consent limit for lake level of 583.29 m asl in order to control the lake level. The siphons are also used periodically to test for correct operation. Data for siphon operation is available from 2002 to 2009.

3.5 Leakage

Some measure of leakage through the natural dam is available from Genesis Energy in the form of discharge through the Kaitawa Weir on the Waikaretaheke River. The Waikaretaheke River emerges from its river bed as a spring derived entirely from leakage from Lake Waikaremoana. No streams run into the Waikaretaheke River upstream of Kaitawa weir. However, since the Onepoto siphons discharge into the Waikaretaheke River when in use, this data has large peaks which represent siphon operation rather than leakage. Discharge data of the Waikaretaheke River at Kaitawa weir is available from 1988 to 2009.

Estimations of the average leakage rate are also available from a number of earlier studies as described in detail in Chapter 4. These estimates range between 4 and 6 m^3s^{-1}.

3.6 Waikaremoana Water Quality Buoy

A water quality buoy was installed in Lake Waikaremoana in late 2009 as part of a joint water quality monitoring programme involving The University of Waikato, Genesis Energy, Fish & Game and a number of other parties concerned with the ecology of Lake Waikaremoana. This buoy collects a variety of water quality information, but also collects some meteorological data. This meteorological data includes wind speed, direction, air temperature, relative humidity, barometric pressure, rainfall, hail, and buoy orientation. However, due to the short length of the record data from the Waikaremoana Water Quality Buoy was not used in this study.

Chapter 4 –Lake Water Loss Estimation

4.1 Introduction

Leakage through Lake Waikaremoana's natural dam has been well recognised since as early as 1916 due to observations of a combination of falling lake levels, calm weather vortices and the sound of water moving through subterranean passages (McPike, 1980). Since then, numerous studies have observed and sought to measure this leakage. Prior to hydroelectric development in the Waikaremoana area various studies estimated leakage through the natural dam to be within the range of 10 m^3s^{-1} at low lake levels and 18 m^3s^{-1} at high lake levels (Freestone et al., 1996, McPike, 1980). This substantial leakage rate would limit the operational efficiency of the Waikaremoana Power Scheme as there would be less water available for electricity generation as leakage water emerges below the intake of the Kaitawa Power Station. Thus, in the late 1940's sealing works were carried out in Te Whara Whara Bay to reduce leakage (Read, 1979).

Following the completion of the sealing operation in the early 1950's, various studies were carried out in order to determine its success by estimating the reduction in leakage rate. Carter (1952) provided the first estimation of the reduced leakage rate stating that leakage had been reduced by 51% with the current total leakage rate 4 m^3s^{-1} (cited in Read, 1979). In 1979 Read suggested a total leakage rate of 4.4 m^3s^{-1}. This rate was estimated on the basis of a review of a range of published information including maps and aerial photographs; studies involving tracer testing, flow and temperature monitoring, drilling, sealing operations, oxygen 18/deuterium isotope analysis, and reports produced in association with the construction of the Piripaua Power Station and Kaitawa intake tunnels.

In 1980 McPike estimated a total leakage rate of approximately 4 m^3s^{-1} using some measurement of flows and a review of the literature. A chemical tracer study was also carried out in order to investigate leakage pathways and dispersion (McPike, 1980). That study used 3 types of chemical tracers: rhodamein wt, fluorescein, and salt, and produced comparable results to a chemical tracer test carried out prior to sealing in the 1930s, where the nature of the pathways as interconnected and widely dispersed was discovered (McPike, 1980). In 1994 leakage was calculated using the sum of flow gaugings of known springs and streams derived from Lake Waikaremoana, producing a total leakage rate of 4.3 m^3s^{-1} (Freestone et al., 1996). Freestone et al., (1996) concluded that the leakage rate varied between 4.0 m^3s^{-1} and 6.0 m^3s^{-1} and fluctuated in response to a change in lake level.

Mylechreest (1979) suggested that since the lake bed sealing had only reduced leakage from Lake Waikaremoana rather than stopping it completely, the project could be considered only partially successful. After the initial sealing works were carried out it was not considered economically feasible to continue with further sealing. However, the prospect of further sealing became viable in the 1970s due to power shortages and a dramatic increase in the price of electricity. Further leakage studies were carried out at this time. However, no further sealing was carried out as local residents were concerned that sealing would have an effect on springs and streams which were important for stock watering. The Urewera National Park board also had concerns that sealing might affect the local natural character of the National Park by altering springs and streams, in particular Fairy Spring (McPike, 1980).

It is possible that an inaccurate estimation of leakage and/or evaporative loss is a significant contributor to error in Genesis Energy’s current water availability model. The aim of this chapter is to present independent estimates of the combined effect of leakage and evaporative loss using a simple regression model based on a modified catchment water balance equation such that the combined role of leakage and evaporation in the error of storage change estimates might be determined with minimal assumptions while avoiding field measurement error. This chapter will first give an overview of selected literature of lake water balance studies in other catchments. The methods used in estimating leakage and evaporative loss at Lake Waikaremoana, the results gained, and the implications that this has for further water availability modelling will then be discussed.

4.2 Selected Lake Water Balance Studies in Other Catchments

A wide range of techniques have been used to estimate unknown components of lake catchment water balances. An estimation of catchment water balance for a closed basin lake can be calculated most simply by direct measurement of hydrological and meteorological variables to find the balance of catchment inputs and outputs where the remainder is equal to change in storage, as seen by a change in lake level. However, in many cases there is little or no hydrological or meteorological record and direct measurement of water balance variables may be impractical. For this reason, the majority of lake water balance studies use direct measurement of some water balance variables, in combination with various techniques of estimation of others. In many cases, evaporation, groundwater flux and ungauged inflow are unknown components of the catchment water balance (Gibson, 2002, Gurrieri and Furniss, 2004, Wale, 2009).

A wide number of techniques for estimating lake water balance variables are available and widely used. These include mathematical techniques, numerical modelling, chemical and/or isotopic mass balances or a combination of these approaches.

Lake evaporation is not known accurately in the vast majority of studies due to the difficulty of its direct measurement. In these instances, surface water evaporation is often estimated using one of many available equations. The Penman equation or a variation of the Penman equation has been used in a number of lake water balance studies (Chebud and Melesse, 2009, Gurrieri and Furniss, 2004, Shanahan et al., 2007, Wale et al., 2009), as has the Priestly-Taylor equation (Shanahan et al., 2007, Stets et al., 2010) and the energy or radiation balance (LaBaugh et al., 1997, Shanahan et al., 2007). In Shanahan et al., (2007) a number of equations including the Priestly-Taylor, penman-combination, and radiation balance approaches were used in order to achieve the best estimation of evaporation. This then allowed the water balance to be solved, and the results compared to a reconstructed lake level for each evaporation method, where the best matching results were used. Similarly, Chebud and Melesse (2009) estimated evaporation by three methods, the Penman, Meyers and Thornwaite’s techniques, where the Penman and Meyers methods were used for estimation of the monthly water budget, while the Thornwaite’s method was applied to the annual water budget (Chebud and Melesse, 2009).

Lake groundwater flux has been estimated using flow nets drawn from a networks of wells and Darcy’s law (LaBaugh et al., 1997), chemical mass balances (Holzbecher et al., 1999, Schmidt et al., 2010), isotope studies (Schuster et al., 2003, Stets et al., 2010, Vallet-Coulomb et al., 2006), or numerical modelling techniques (Ayenew and Gebreegziabher, 2006, Chebud and Melesse, 2009, Zuo et al., 2006). However, construction of a network of wells is often beyond the scope or resources of many lake studies (LaBaugh et al., 1997).

Another approach for estimating lake groundwater flux is through the use of numerical models. Holzbecher et al., (1999) used a 2d steady-state numerical model to model the subsurface flow pattern, at Lake Stechlin, Germany and Aneyew and Gebreegziabher (2006) calculated the net groundwater flux by calculation of the residual of other water balance components using a model simulation. The water balance of Lake Tana in Ethiopia was estimated using a numerical model where groundwater inflow was an unknown variable (Chebud and Melesse, 2009).

Kebede et al., (2006) calculated the annual water balance of Lake Tana, Ethiopia using a numerical model using lake level simulation at a monthly timestep. A differential water balance equation was used which was integrated with simulated lake level over a monthly timestep. This equation was then solved iteratively using Excel SOLVER. Inflow and outflow volumes of Lake Bosten, China, were calculated using a numerical model as functions of known variables from which the water balance could then be calculated (Zuo et al., 2006). A study by Wale et al., (2009) calculated the contribution of ungauged catchments to the water balance of Lake Tana using a regionalisation procedure which established relationships between water balance parameters and catchment characteristics based on gauged catchments, the parameters were then transferred to ungauged catchments based on catchment size. The HBV-IHMS model was then used to simulate catchment runoff (Wale et al., 2009). Unknown water balance components of evaporation and runoff of Lake Bosumtwi in Ghana were calculated in a study by Shanahan et al., (2007) using a rainfall-runoff calculation based on a simple rainfall-evapotranspiration balance model in order to determine a runoff parameter.

Stable isotopes of oxygen have also been widely used as a method for estimation of unknown water balance variables. In Stets et al., (2010) stable isotopes of oxygen-18 were used to calculate surface and groundwater fluxes. Isotopes were also calculated for precipitation, evaporation and stream inflow however, these were constrained by direct measurement of these variables. Since stable isotope methods are typically only effective in lakes with long residence times a time series model of oxygen-18 stable isotope signature was applied to 6 lakes, two of which were closed basin (Stets et al., 2010).

Stable isotopes were used in two separate studies of the closed basin Williams Lake in Minnesota, USA. Schuster et al., (2003) used stable isotopes to calculate groundwater flux, which was estimated to be approximately equal to half the annual water input to the lake. The isotope mass balance in the pore water of sediment was also used to determine the amount of mixing of lake water and groundwater in the littoral zone. Isotope analysis of the same lake by LaBaugh et al., (1997) found that 79% of annual inflow was a result of groundwater inputs.

While isotope studies are generally steady-state in nature, some situations require non-steady-state conditions. In 2004, Gurrieri and Furniss applied a non-steady-state model to the alpine lakes of Montana, USA. A non-steady-state model was required since the entire volume of the lakes are replaced every spring as a result of snowmelt, therefore, the lakes themselves never reach a steady-state. However, the isotope component of this study did not perform well. A non-steady isotope mass balance was also used in Gibson (2002) in shallow arctic lakes which undergo fluctuations in heavy isotopes seasonally due to the extreme seasonality of water balance processes in this region. This study produced much more successful results.

Similar to the isotope mass balance method is a radon mass balance approach. In Canada, Schmidt et al., (2010) used the radon 222 mass balance of two small lakes to determine their groundwater influxes. Radon 222 can be used for measuring groundwater processes within a time scale of approximately 15 days, due to its half life of 3.8 days. Radon 222 can be used because in some geological settings where groundwater readily comes into contact with material containing radon, whereas lake water does not. Thus, groundwater discharge into a lake results in elevated radon concentrations in lake water.

Chemical mass balances can also be used to solve unknown water balance components, and can include mass balances of Ca 2+, K+, Mg2+, K+ and Cl- among others. These types of study are often used in conjunction with isotope studies (Gurrieri and Furniss, 2004, LaBaugh et al., 1997). A chemical mass balance study was used at Williams Lake, Minnesota, USA for Na+, Mg2+, Cl, and dissolved organic carbon in conjunction with an isotope study (LaBaugh et al., 1997). A combined water balance and chemical mass balance equation was also used to solve for groundwater inflow in alpine lakes of Montana, USA by Gurrieri and Furniss (2004).

In summary, there are a number of different techniques available for estimation of unknown variables of the catchment water balance for closed basin lakes which are applied in order to solve the catchment water balance. It seems that in many instances more than one technique is applied in order to ensure reliable results. It also seems that both mathematical/modelling techniques are used equally as widely as experimental techniques. However, many such experimental techniques are not effective for water balance studies at the daily time scale.

It should be noted that all previous leakage estimation studies carried out in the Waikaremoana area have used physically based methods which involve some measurement of known springs and streams. It is unknown whether sealing of lake leakage was truly as effective as indicated by previous studies or of the leakage was simply forced to take a new path such that it exited at some unknown spring or stream. In this study, a statistical approach is used which has the ability to determine whether leakage has reduced to the level reported in these studies or has simply taken a new path to exit at an unknown location.

4.3 Method

4.3.1 Lake Data Investigation

Lake water loss by leakage and evaporation was estimated using a modified lake water balance equation based on a lake volume change time series derived from differencing a sequence of lake level changes which are greater than noise effects of waves and wind set-up. Prior to construction of the lake water balance an initial data investigation was carried out as a quality control measure.

3-hour average lake level plots were created in order to carry out a visual check that the lake level points chosen for lake level differencing were indeed greater than noise (Figure 18). From examination of these plots it is clear that noise in lake level occurs at a scale of approximately 0.025 m - 0.05 m. It is important that chosen lake level points are greater than noise since this ensures that the variation in lake level is large compared to error when it is multiplied over the area of the lake. Chosen lake level points are never less than 0.1 m so are much greater than data noise.

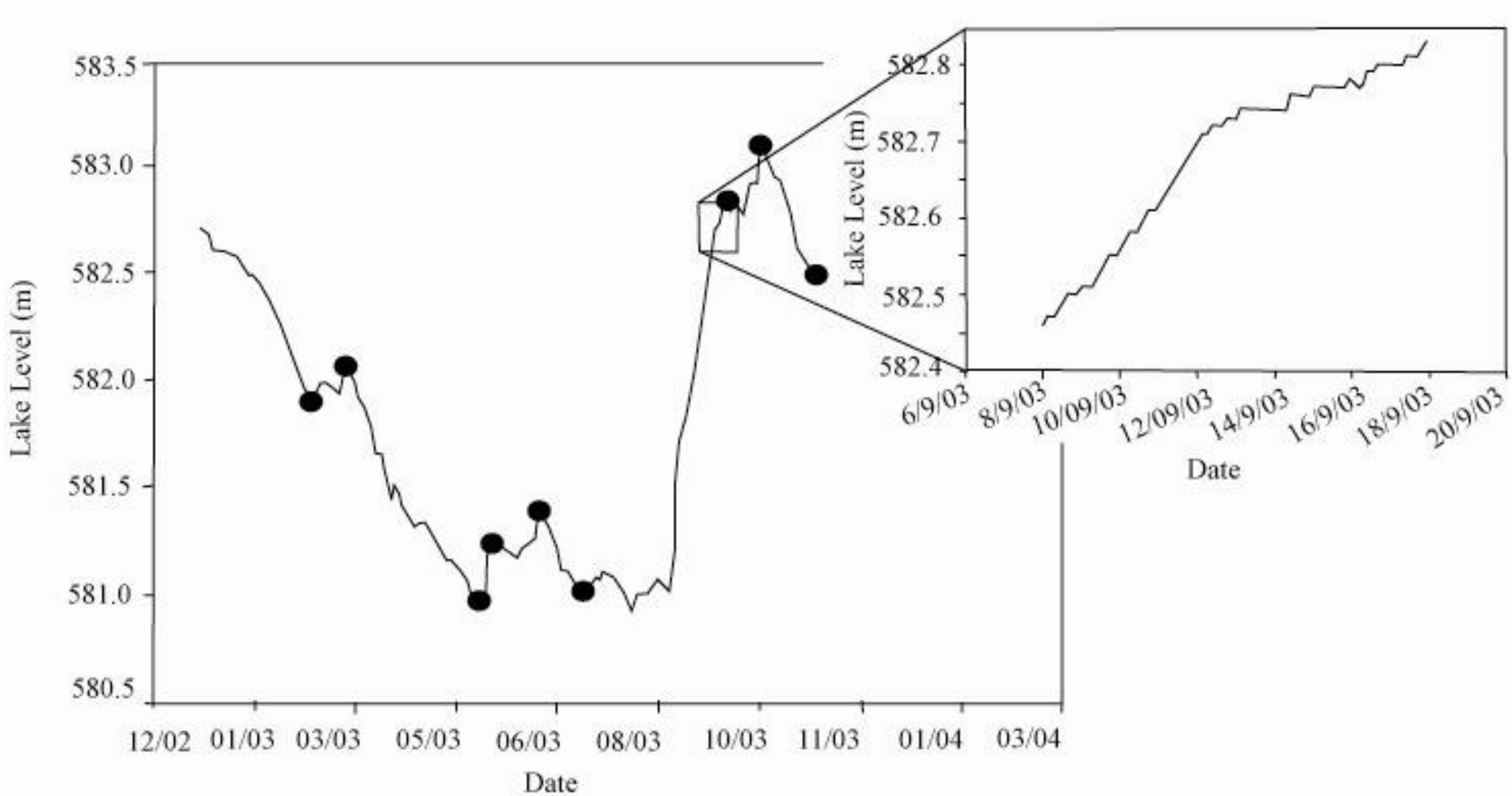

Figure 18: Quality control plot showing that points chosen for lake level change are much greater than that of random noise.

4.3.2 River Inflow Comparisons

The consistency of inflows from the Aniwaniwa Stream are compared with other gauged streams in the Waikaremoana catchment. The inflows of the Aniwaniwa Stream and Te Kumi Stream appear to be consistent with one another at low inflows, and less consistent at higher inflows where there is most probably increased spatial variation (Figure 19). This is observed as increased scatter in scatterplots of Aniwaniwa Stream and Te Kumi Stream discharges at higher inflows. It must also be noted that Figure 19 compares a small catchment with a much larger one, thus it is expected that they will only have similarity for low flows.

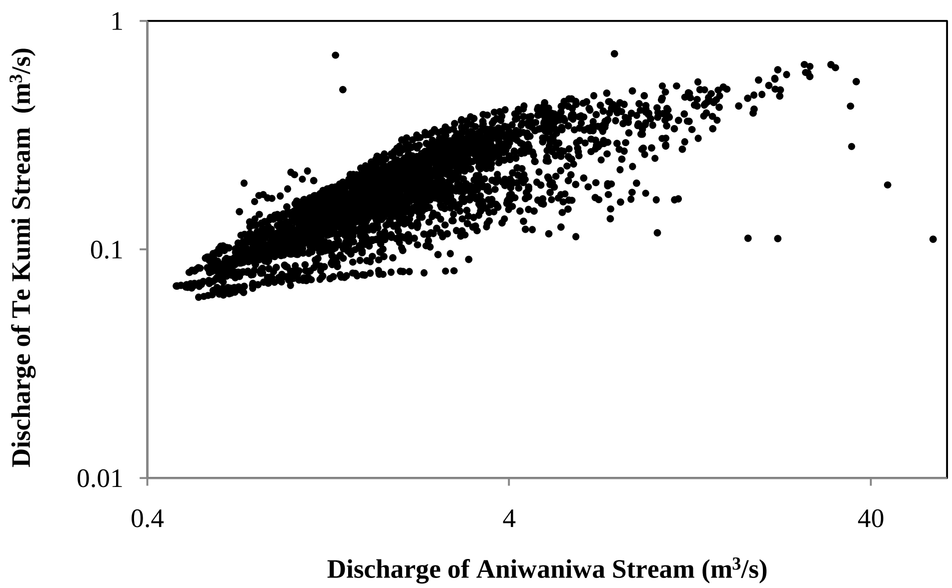

Figure 19: Log-log plot of Te Kumi Stream against Aniwaniwa Stream showing the consistency of inflows with high inflows corresponding to high spatial variation and less consistency of inflows.

Similarly, the discharge of the Aniwaniwa Stream with the Mokau and Hopuruahine Streams, both of which are more similar in size to the Aniwaniwa Stream show consistency of inflows at low flows, but not at high flows due to an increased spatial variation in rainfall (Figure 20, 21).

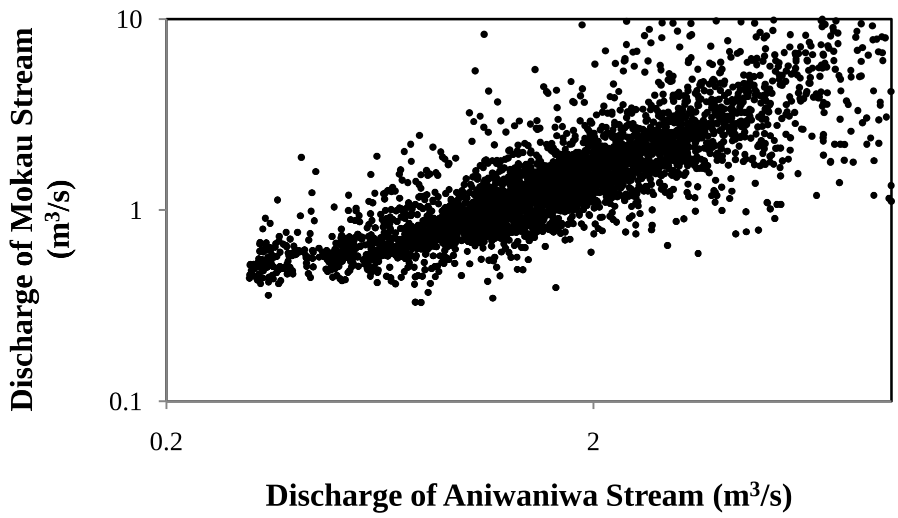

Figure 20: Log-log plot of discharge of the Aniwaniwa Stream and Mokau Stream (m^3s^{-1}) showing consistency of inflows at low flows.

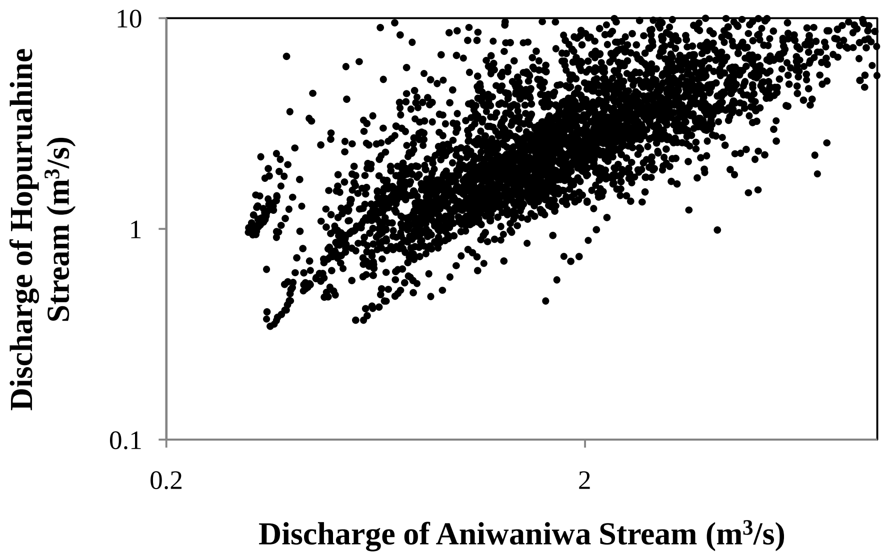

Figure 21: Log-log plot of discharge of the Aniwaniwa Stream and Hopuruahine Stream (m^3s^{-1}) showing consistency of inflows at low flows.

Both these streams are less consistent with the Aniwaniwa Stream than the Te Kumi Stream. It is likely that this is because they are located a greater distance away from the Aniwaniwa Stream and are thus influenced by spatial rainfall variations. Thus, scatter within scatterplots of the Aniwaniwa Stream against the Mokau and Hopuruahine Streams is more significantly reduced when flows which correspond to a rise in lake level are removed (Figure 22, 23).

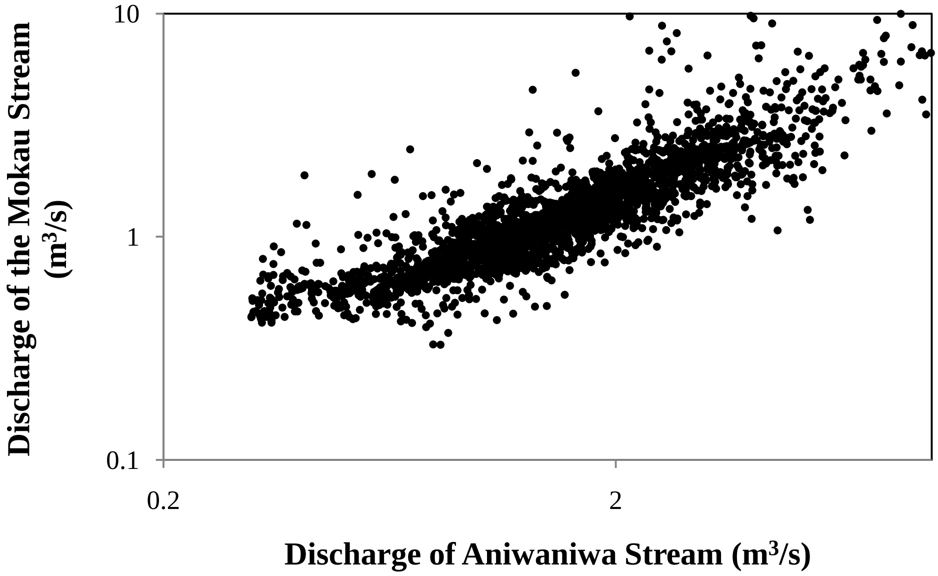

Figure 22: Log-log plot of discharge of the Aniwaniwa Stream and Mokau Stream (m^3s^{-1}) showing consistency of inflows at low flows. Scatter is reduced when flows corresponding rises in lake level are removed.

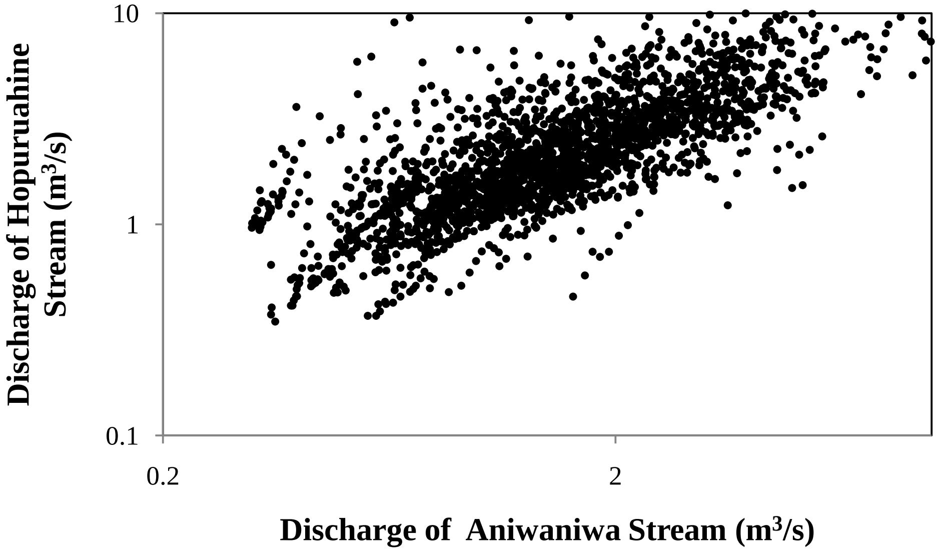

Figure 23: Log-log plot of discharge of the Aniwaniwa Stream and Hopuruahine Stream (m^3s^{-1}) showing consistency of inflows at low flows. Scatter is reduced when flows corresponding rises in lake level are removed.

4.3.3 Method Utilised for Loss Estimation

Leakage and evaporative loss from Lake Waikaremoana under low flow conditions was estimated using a simple hydrological model based on a modified lake water balance. The basic lake water balance equation can be written:

$$\text{Loss} = \text{Inflow} - \Delta\ \text{Storage} \qquad [1]$$

However, since total inflow into Lake Waikaremoana is unknown, loss cannot be deduced from storage change. Thus, a modified catchment water balance equation was created for this study.

As a starting point for estimation of the lake water balance, a storage change time series was created by lake level differencing over consecutive time intervals. Lake level data was first plotted in a time series in order to identify a sequence of changes in lake levels which are much greater than high-resolution noise effects such as waves and wind set-up. These changes were converted to storage volume changes by scaling via the lake surface area.

From this volume change sequence, corresponding lake outflow volumes from discharge through Kaitawa Power Station were added, giving the modified volume sequence defined as L_i. A second modified volume sequence, L_k was calculated as lake volume change + volume discharge through Kaitawa Power Station + volume leakage measured at the Waikaretaheke Stream. These volumes are all with respect to the time sequence of lake level changes mentioned earlier. The second modified volume sequence was created to give an estimate of the unknown leakage and evaporative component of the water balance since the initial volume sequence provides an estimate which includes known leakage as measured at the Kaitawa weir on the Waikaretaheke Stream. Because the periods over which the changes in lake level were taken were not equal in length, L_i and L_k were divided by their associated days durations in order to standardise leakage on an averaged per day basis for each period of lake level change, giving $L_i/\Delta t_i$ and $L_k/\Delta t_i$.

Thus, on an averaged daily basis within a given storage change period, loss can be calculated as:

Change in lake volume - measured outflow volume = inflow volume – (any additional leakage + evaporation loss). [2]

For the special case of low inflows, the assumption is made that the total lake inflow volume from all streams and direct groundwater input is proportional to the Aniwaniwa Stream discharge. Equation [2] can therefore be rewritten as:

Change in lake volume - measured outflow volume = α (Aniwaniwa inflow volume) – (additional leakage + evaporation loss) [3]

Where α is a proportionality factor to be estimated.

Therefore, if the terms in equation [3] are on a per day basis, both daily leakage and evaporative losses are approximated as roughly constant over time. So a plot of change in lake volume - measured outflow volume should appear as a linear plot with gradient α and intercept of total daily loss rate. The loss rate was calculated for the period 1998-2008 due to the availability of power station outflow data.

Initially, a simple scatterplot was created using $L_k/\Delta t_i$ as the dependent variable, and the daily inflow of the Aniwaniwa Stream (Aniwaniwa inflow/ Δt_i) as the independent variable. $L_i/\ \Delta t_i$, was then plotted in place of $L_k/\ \Delta t_i$ to determine whether this would provide a better estimation (Table 3). However, the error of the intercept was relatively large on both plots (Figure 24, Figure 25). In order to reduce error width, volume sequence data derived only from falling lake levels was used to reduce the effect of spatial variation of heavy rainfall and resulting high flows, which are likely to violate the assumed linear approximation.

Table 3: Results of linear regression showing large intercept error width.

Dependent variable	**Independent variable**	**Intercept (m^3s^{-1})**	**R^2**	**p of estimate**
$L_i/\ \Delta t_i$	Aniwaniwa inflow/ Δt_i	-2.22 ± 2.61	0.78	< 0.0001
$L_k/\ \Delta t_i$	Aniwaniwa inflow/ Δt_i	2.71 ± 2.60	0.78	< 0.0001

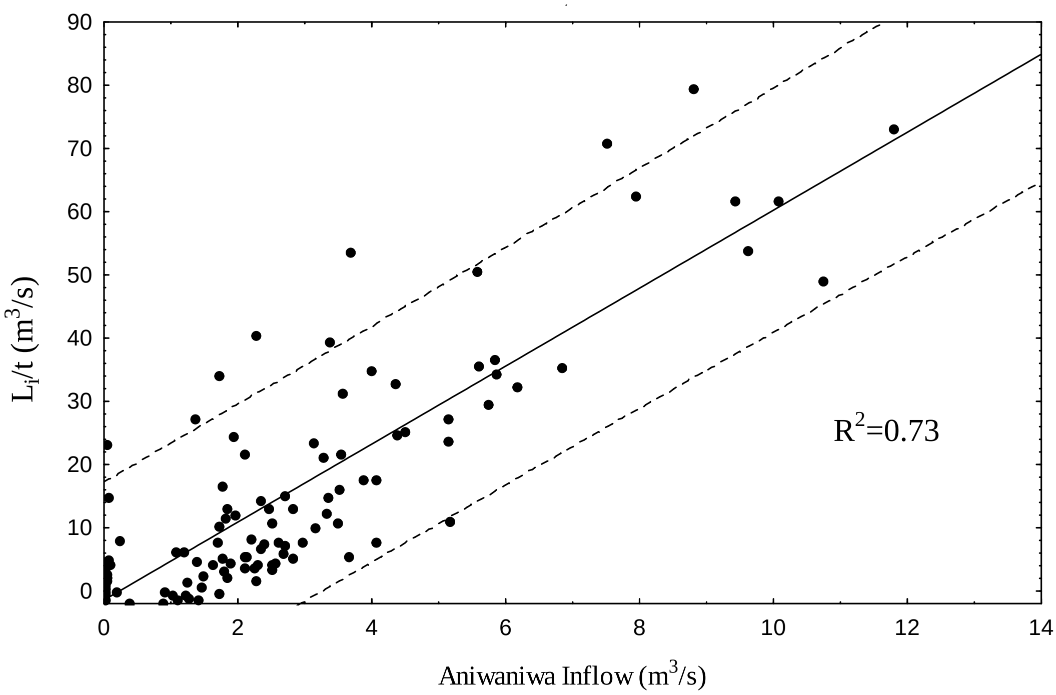

Figure 24: Scatterplot of $L_i/\Delta t_i$ and inflow/Δt_i with 95% prediction interval.

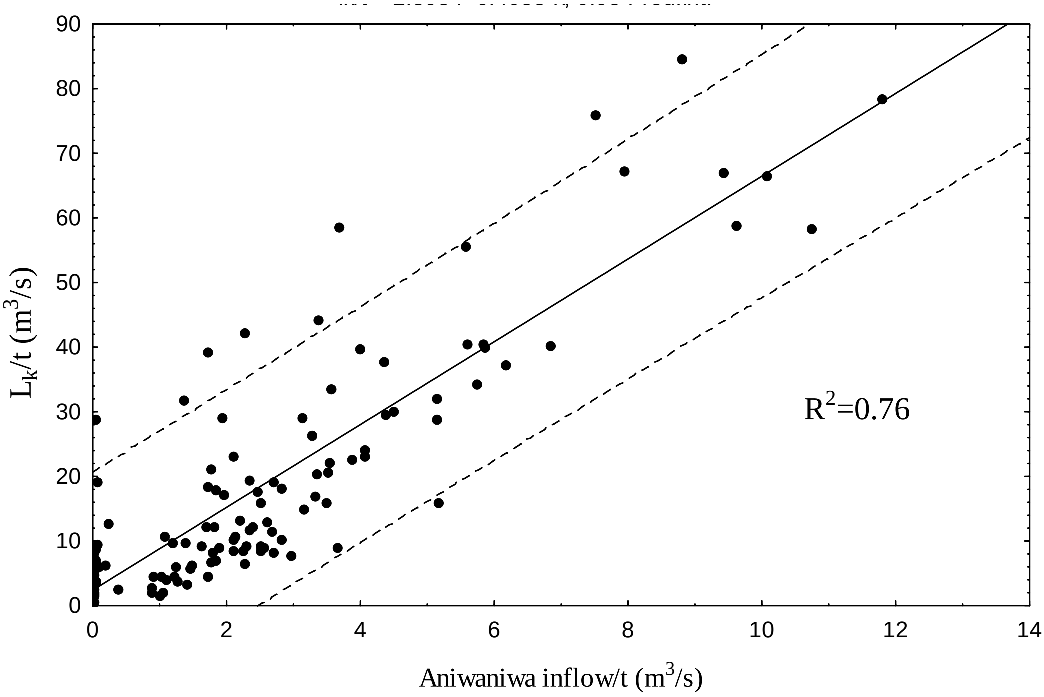

Figure 25: Scatterplot of $L_k/\Delta t_i$ and inflow/Δt_i with 95% prediction interval.

This was successful in reducing the error of the intercept, indicating that a component of scatter was derived from rainfall situations (Figure 26).

In order to reduce scatter further, the data was reduced to that for which the corresponding river inflows were both low and decreasing, such that the error arising from any rainfall spatial variation was further reduced. It was thought that if inflows are low and falling, there is most likely no rainfall which is the dominant causal factor of spatial variation in inflows. However, this idea was difficult in its application since many of the periods of lake level decline included both flows which were low and falling, and flows which were high and/or rising. Using only the periods where the flows were only low and falling reduced the volume of the data significantly that little was left to plot. As a result, the standard errors of these plots were higher because of the reduced number of data points. Consequently, this idea was abandoned. Instead, data which corresponded to a decrease in lake level was used for further investigation.

In an attempt to improve the accuracy of the intercept a multiple regression was used with the long term evaporation average now incorporated as a second independent variable in addition to Aniwaniwa inflow. The intercept of the regression line therefore becomes solely unmeasured leakage. The evaporation variable was calculated as a weighted average to allow for lake level change periods which extend over month boundaries. Mean evaporation values were based on monthly average values of open water evaporation from Onepoto, Waikaremoana from Finkelstein (1973) who calculated average monthly open water evaporation using a modified form of Penman’s equation. Finkelstein (1973) used data for more than 20 years of evaporation pans for locations all over New Zealand. The evaporation pan situated at Lake Waikaremoana was in use from 1956 to 1970.

In a further attempt to define the intercept mean lake level above the minimum operating range allowed by Genesis Energy and measured leakage from Kaitawa weir were also used as independent variables. A suite of different combinations of each of these independent variables were then used in a multiple regression against both dependent variables $L_i/\Delta t_i$ and $L_k/\Delta t_i$ in order to find the best estimation of lake water loss.

4.4 Results

The most useful result from the regression analysis was deemed to be the regression of $L_k/\Delta t_i$ as the dependent variable, and Aniwaniwa inflow/ Δt_i as the independent variable, as this estimate includes only the unknown portion of leakage and evaporative losses. The $L_k/\Delta t_i$ and Aniwaniwa inflow/ Δt_i estimate also meets conditions of having a small intercept error, acceptable R^2 value, statistical significance in terms of its **p** value, and has independent variables of which all are significant. The most useful result has an intercept of 0.59 ± 2.3 m^3s^{-1} ($\pm$ 2 standard errors) with an R^2 value of 0.57 and a **p** value of the regression gradient of < 0.001 (Figure 26).

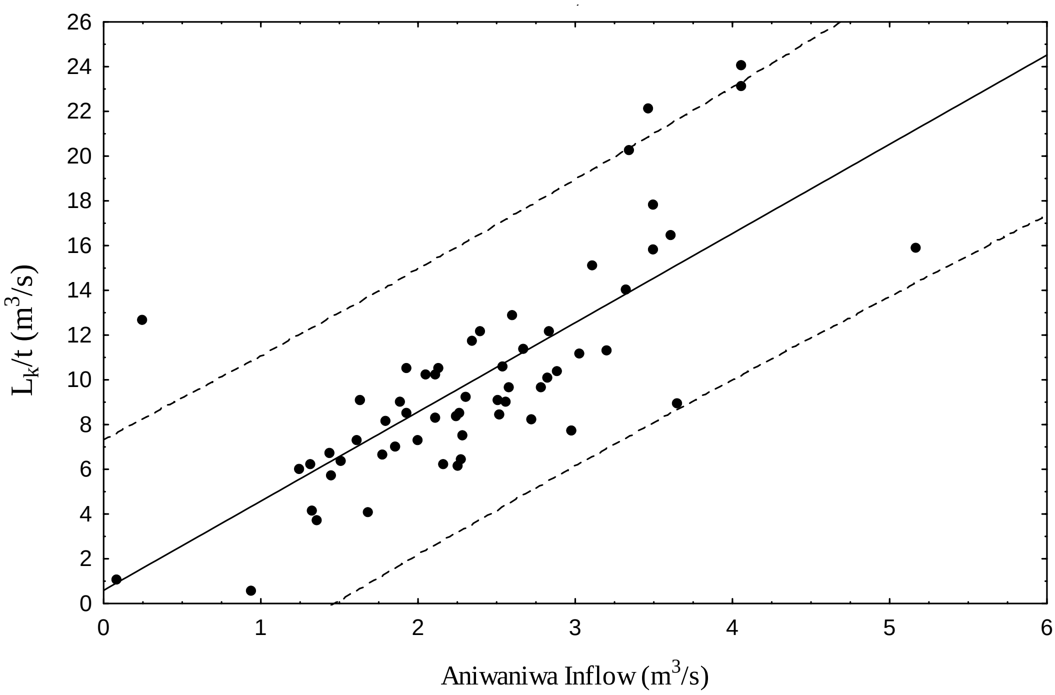

Figure 26: Regression of $L_k/\Delta t_i$ and Aniwaniwa inflow on a per day basis, where the intercept is equal to daily loss volume, showing 95% prediction interval.

The regression equation here is

$$L_i/\Delta t_i = 5.1 \times 10^4 + 3.99\chi \qquad [4]$$

where 5.1×10^4 is the leakage and evaporation loss rate in m^3 per day, 3.99 is the constant which relates the flow of the Aniwaniwa Stream to the total catchment inflow under low flow conditions, and χ is the inflow of the Aniwaniwa Stream.

Regression analyses which included independent variables of evaporation and known leakage were generally found not to be significant and the standard error of the estimate derived from using evaporation and known leakage as independent variables was high. Lake level was found to be significant as an independent variable, however, it also produced results where the associated coefficient standard error was high. The lake level coefficient was positive, indicating that higher lake levels result in a greater leakage loss.

4.5 Discussion

The intercept value of 0.59 ± 2.3 m^3s^{-1} (± 2 standard errors) implies that the combination of unknown leakage and evaporative loss in the Waikaremoana catchment is likely to be within the range of 0 to 1.71 m^3s^{-1}. A positive intercept indicates that the estimated unknown portion of leakage loss is not significantly different from zero, suggesting that the leakage rate is sufficiently small that it may be ignored. If real, the positive intercept has the physical meaning that under very dry conditions with zero river inflow direct groundwater inflow is still greater than the unknown leakage and evaporative loss. The leakage and evaporative loss estimate is not far removed from the estimates made using physical means in numerous previous studies. The estimate represents evaporation and lake water leakage which does not pass through Kaitawa weir on the Waikaretaheke Stream, a stream almost entirely derived from leakage.

While a large proportion of the total leakage from Lake Waikaremoana is measured at the Waikaretaheke Stream, this known leakage did not serve as an independent variable during the regression analysis. It is possible that measured leakage was not a significant variable due a slight increasing trend in weir readings over time, or that the maximum and minimum leakage rates are not too different from each other (*see Section 2.6 Hydrology*). Extreme peaks in the flow measured at Kaitawa weir which is usually solely lake leakage are observed and may also account for some of the lack of correlation with this variable. These peaks arise from siphon usage, since the Waikaremoana spillway discharges into the Waikaretaheke Stream. As the siphon discharge record begins as late as 2002, not all of these extreme peaks could be removed from the leakage rate record.

In many of the regression analyses lake level was a significant though minor variable. It is thought that this may be due to seasonal or hydraulic effects, or a combination of these two ideas (*see Section 2.6 Hydrology*). However, the correlation of lake level may simply be a proxy for some other variable.

Evaporation was not found to be a significant variable during the regression analysis. Evaporation may not have improved estimates due to the limitations of open pan evaporation measurement and because evaporation estimates were in the form of average monthly estimates, from which daily evaporation can vary significantly depending on meteorological conditions. Evaporation may also not be significant as it has a very minimal contribution to daily storage change (mean annual evaporation is 1.6mm).

The best estimate of lake water loss gave a confidence interval width of ± 2.3 m^3s^{-1} suggesting that the leakage rate is less than 1.71 m^3s^{-1}. Since this is relatively small, that suggests that unmeasured leakage and evaporation are not big factors in the production of negative inflow values in Genesis Energy's current water availability model, and that it is more likely to be a result of the error which accumulates in water level differencing.

4.6 Conclusion

Leakage plus evaporative loss from Lake Waikaremoana can be estimated using the regression equation $L_k/\Delta t_i = 5.1 \times 10^4 + 3.99\chi$ where the value of the intercept is equal to unknown daily leakage plus evaporative loss. This gives a leakage and evaporative loss rate of 0.59 ± 2.3 m^3s^{-1}. Since estimated lake leakage and evaporation is not significantly different from zero and the absolute value of the confidence interval is small it can be concluded that leakage and evaporation are not big factors in producing error within Genesis Energy's current water availability model. It is more likely that lake level differencing is the cause of the error, with noise large relative to consecutive levels.

Chapter 5 – Application of estimation of net storage change in Lake Waikaremoana under low flow conditions

5.1 Introduction

For effective operation of the Waikaremoana Power Scheme Genesis Energy estimates water availability for hydro electric generation in the Lake Waikaremoana catchment. Currently, this water availability estimation consists of a lake level differencing model which predicts total lake inflows when inflows are large relative to losses (excluding known outflow) and losses can be neglected. Under low flow conditions, the water availability model in fact estimates net storage change as there is a possibility that unknown losses may not be small relative to inflows. Lake inflows are not measured directly due to the large number of small streams which enter the lake and possibly direct groundwater inflow, as well as the large area and rugged nature of the terrain.

However, the existing water availability model has been found to be error prone under low flow conditions, producing negative estimates of net storage change (excluding known outflow) (Figure 27). In order to allow for more strategic bidding into the electricity market, thereby increasing the operational efficiency of the Waikaremoana Power Scheme an improved estimation of net storage change of Lake Waikaremoana at low flows has been created.

Two possible causes of the negative estimates were considered:

1. An inaccurate estimation of leakage rates through Lake Waikaremoana's natural dam.
2. The effect of lake level error derived from waves and wind set up such that when lake level changes are small, the size of the error is large.

In the previous chapter, leakage was found to be within the range of leakage estimates used by Genesis Energy in the existing model and therefore is not likely to be a significant factor in the production of negative inflows. This means that the cause of the negative estimates is likely to be a result of lake level differencing.

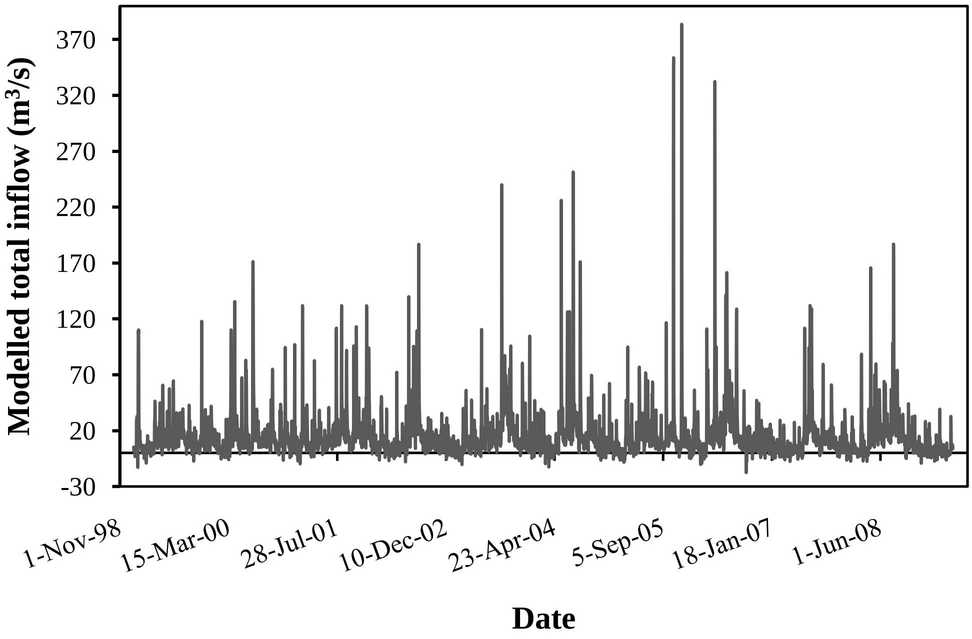

Figure 27: Modelled 'inflows' using Genesis Energy's estimation technique showing negative estimations.

It is expected that under low flow conditions and in the absence of rainfall, streams (with a minor groundwater component) will generally follow the shape of a recession curve. Since groundwater inputs are low in the Lake Waikaremoana catchment, this assumption is likely to hold. A recession curve pattern is generally not observed in the existing model which produces large fluctuations in inflow which are not observed in the gauged streams in the Waikaremoana catchment (Figure 28). However, the existing model has the ability to estimate inflows under medium to high flow conditions when lake level changes are large (Figure 29).

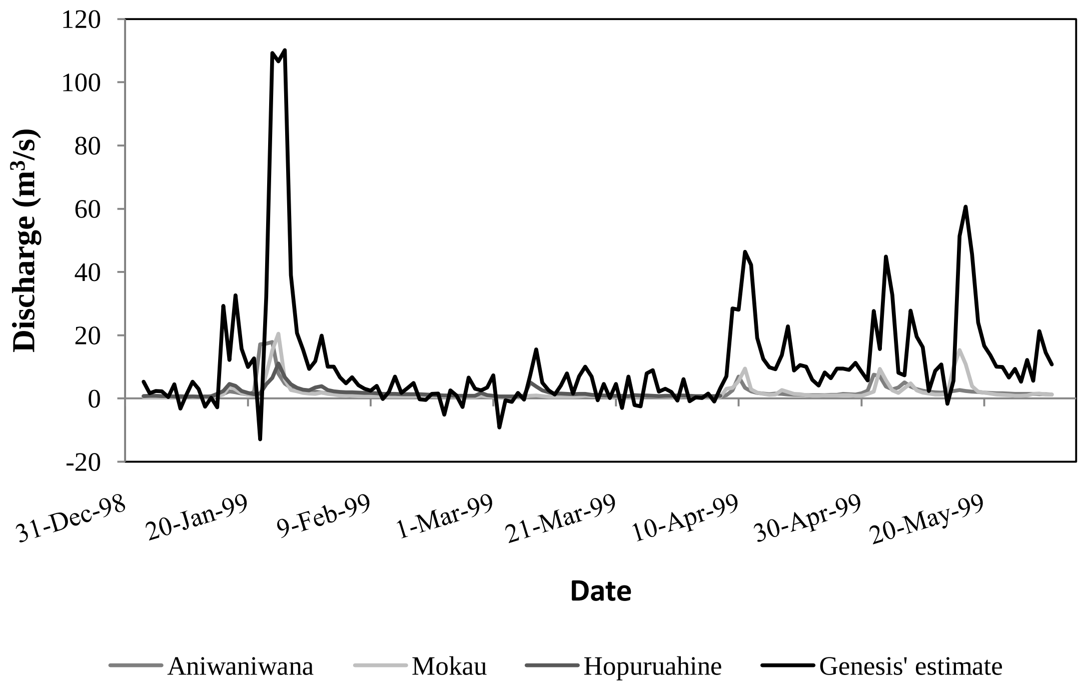

Figure 28: Genesis Energy's 'inflow' estimation compared to gauged inflows from the Aniwaniwa, Mokau, Hopuruahine and Mokau streams under low flow conditions.

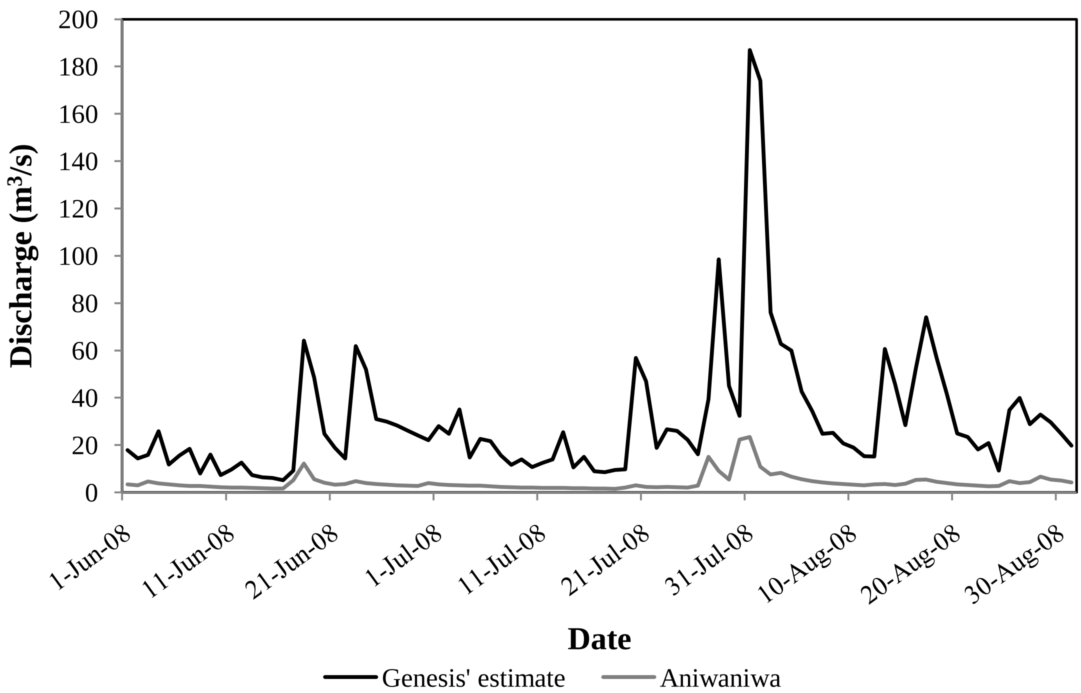

Figure 29: Genesis Energy's estimate of 'inflows' compared to the Aniwaniwa Stream under normal to high flow conditions.

5.2 Method

Inflow data is not available for the vast majority of the streams which flow into Lake Waikaremoana, consequently net 'inflow' must be estimated. A simple linear model was constructed on the basis that at low flows in the absence of rainfall the true total inflow has a linear association with the recorded inflow of the Aniwaniwa Stream. This approximation is likely to hold under low inflow conditions only since this allows for minimal effect of errors arising from spatial variation of rainfall.

The regression technique applied for the estimation of unknown leakage and evaporative loss in the previous chapter produced a regression equation which related the discharge of the Aniwaniwa Stream during periods of low, decreasing lake levels to the net storage change of the Waikaremoana catchment at low flows. This regression equation is:

$$L_k/\Delta t_i = 5.1 \times 10^4 + 3.99\chi \qquad [4]$$

Where 5.1×10^4 is the volume of leakage over a 24 hour period, 3.99 is the scaling factor and χ is the inflow from the Aniwaniwa catchment. Using this estimation of the relationship between the discharge of the Aniwaniwa Stream and the total catchment, estimation of net 'inflow', or net storage change of Lake Waikaremoana (excluding known outflow) is:

$$\text{Net inflow}_{\text{(at low flow)}} = 0.59 + \alpha\,(\text{Aniwaniwa inflow}) \qquad [5]$$

Where 0.59 is the estimate of leakage and evaporation rate in m^3s^{-1}.

Since this relationship holds only for low flows, a definition of 'low flow' must be used. Two situations have been modelled: low flow defined by the upper bound of 5 m^3s^{-1} and low flow defined by the upper bound of 7 m^3s^{-1}.

5.3 Results and Discussion

Using two definitions of low flow, that where low flow is defined by the upper bound of 5m^3s^{-1} and that where low flow is defined by the upper bound of 7 m^3s^{-1} modelled net 'inflows' have been compared to 'inflows' previously modelled by Genesis Energy (Figure 30).

The new net inflow model involves multiplying a positive scaling factor by the measured inflow of the Aniwaniwa Stream, and the addition of a positive intercept value which means that modelled net discharge can never be negative. This removes a large amount of fluctuation from the modelled data (Figure 31). In reality the wide confidence intervals mean that negative net discharges may occur, representing periods where unknown leakage and evaporative loss is greater than true inflows.

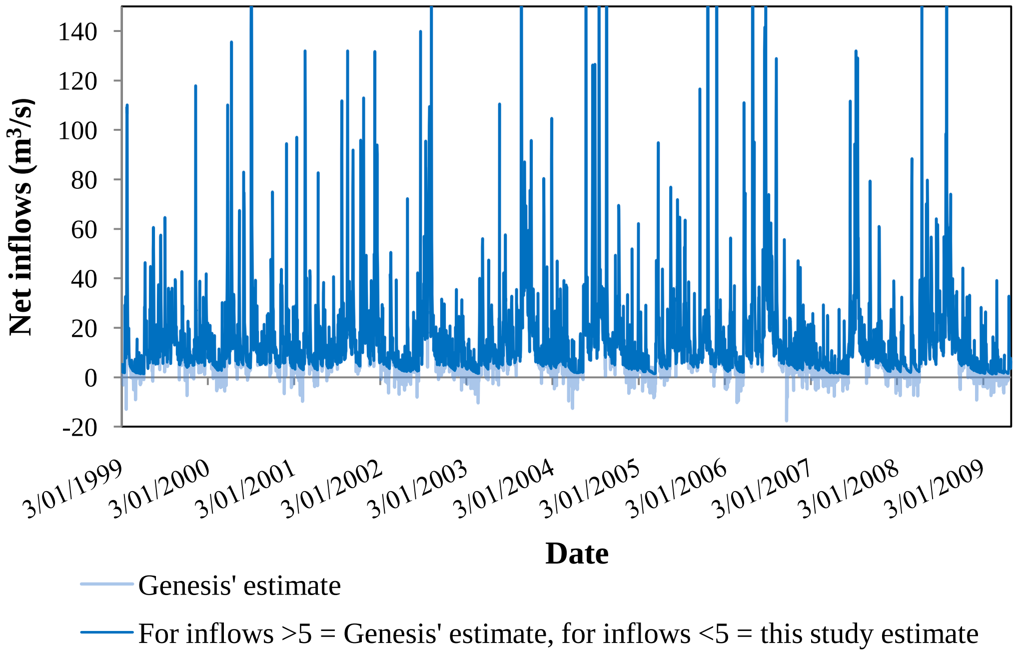

Figure 30: Genesis Energy's estimate of net inflows for the period 99-09 and the situation where for inflows greater than 5 m^3s^{-1} Genesis Energy's estimate is used, and where inflows are less than $5m^3s^{-1}$ this study estimate is used.

At higher resolution, the difference between Genesis' estimate and the new estimate can be seen clearly for the situations where low flows are defined by the upper bound of 5 m^3s^{-1} (Figure 31) and 7 m^3s^{-1} (Figure 32). The new estimate more closely resembles a recession curve, and eliminates many of the large fluctuations observed in the existing model. The situation where low flows are defined by the upper bound of 7 m^3s^{-1} more closely resembles a recession curve than the upper bound of 5 m^3s^{-1} estimate due to the elimination of fluctuations in the estimate.

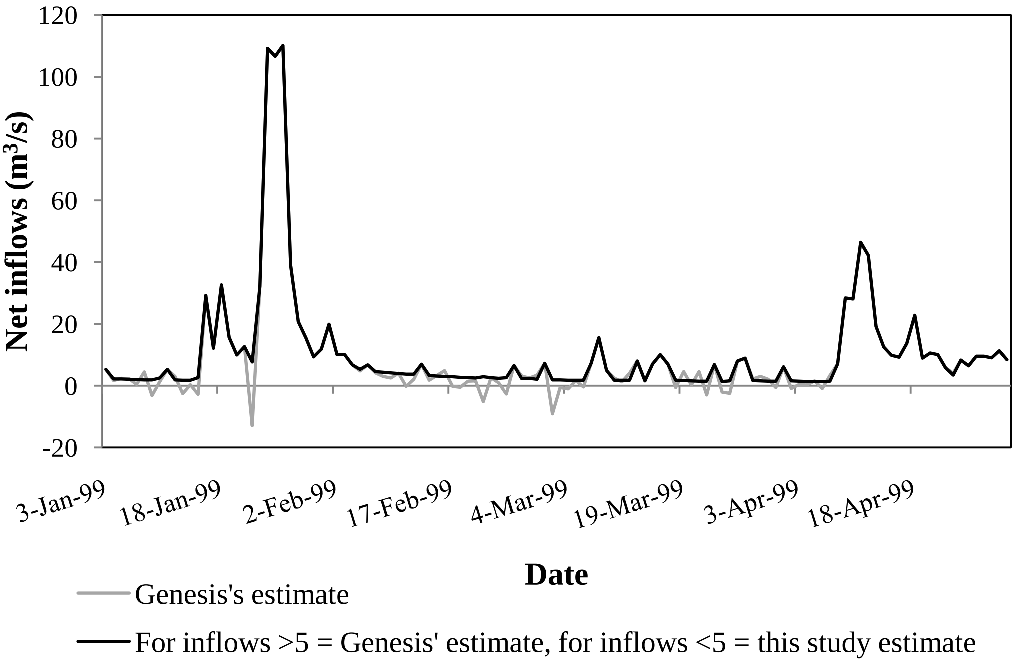

Figure 31: Genesis Energy's estimate and the situation where for Aniwaniwa inflows greater than 5 m^3s^{-1} Genesis Energy's estimate is used, and where Aniwaniwa inflows are less than $5m^3s^{-1}$ this study estimate is used for the period 3 Jan 99 to 31 May 99.

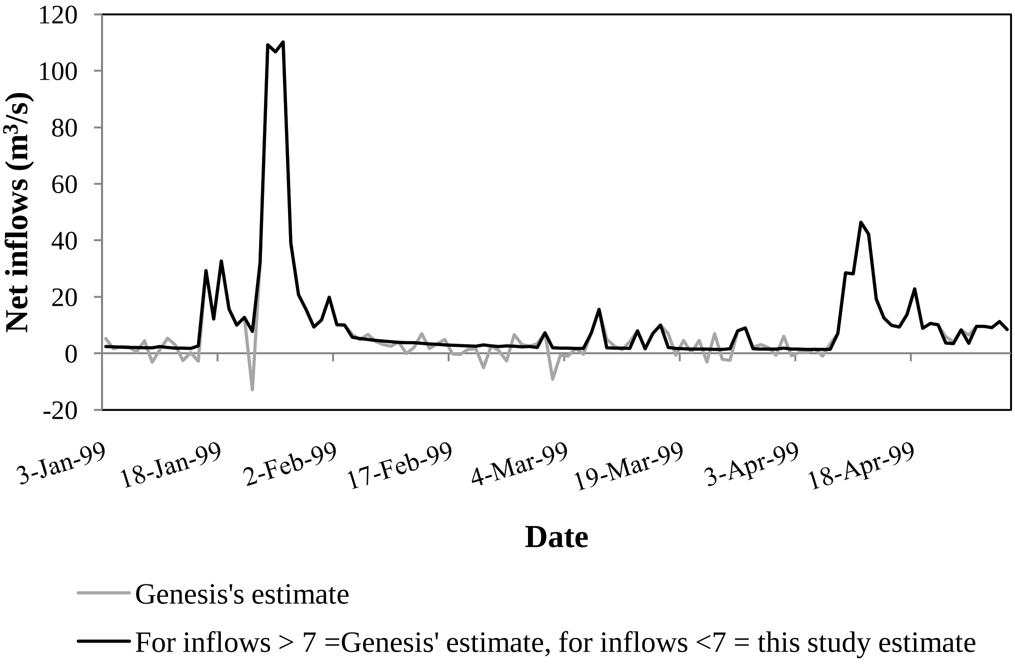

Figure 32: Genesis Energy's estimate and the situation where for Aniwaniwa inflows greater than 7 m^3s^{-1} Genesis Energy's estimate is used, and where Aniwaniwa inflows are less than 7 $m^3s\text{-}^{1}$ this study estimate is used for the period 3 Jan 99 to 31 May 99.

In order to test whether fluctuations in the estimated data are false or are due to rainfall modelled net inflows have been plotted against recorded rainfall for both the 5 m^3s^{-1} (Figure 33) and 7 m^3s^{-1} situations (Figure 34). The 7 m^3s^{-1} upper bound definition provides the most accurate estimation of low flow conditions, as the majority of the false fluctuations are eliminated, leaving only those fluctuations which relate to rainfall inputs.

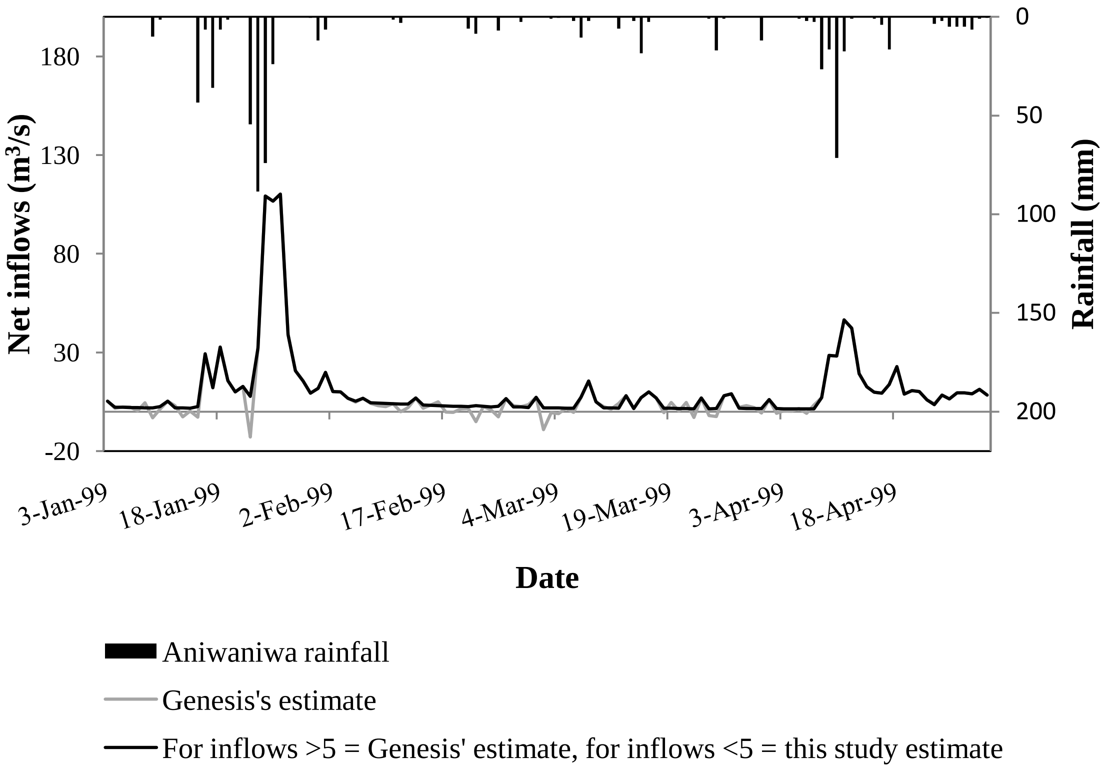

Figure 33: Genesis Energy's estimate and the situation where for Aniwaniwa inflows greater than 5 m^3s^{-1} Genesis Energy's estimate is used, and where Aniwaniwa inflows are less than 5 m^3s^{-1} this study estimate is used for the period 3 Jan 99 to 31 May 99 and rainfall from the Aniwaniwa raingauge.

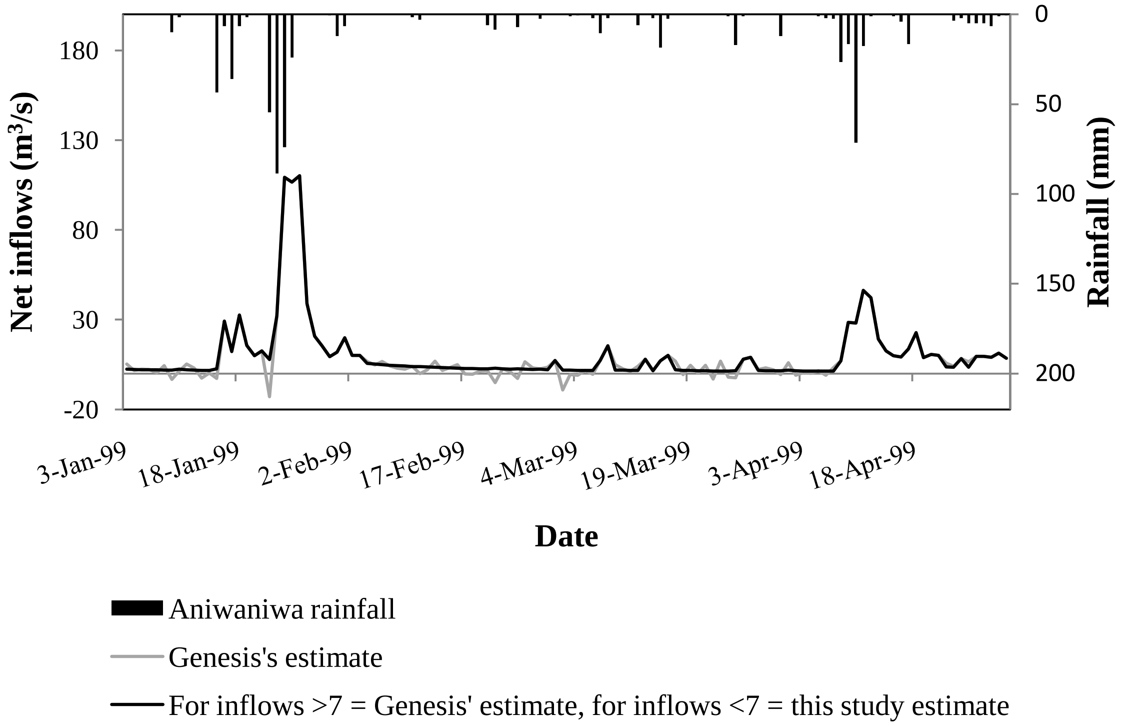

Figure 34: Genesis Energy's estimate and the situation where for Aniwaniwa inflows greater than 7 m^3s^{-1} Genesis Energy's estimate is used, and where Aniwaniwa inflows are less than 7 m^3s^{-1} this study estimate is used for the period 3 Jan 99 to 31 May 99 and rainfall from the Aniwaniwa raingauge.

5.5 Conclusion

An improved estimate of net inflows into Lake Waikaremoana under low flow conditions has been created. This estimation happens to never yield negative 'inflows' as the intercept is greater than zero. However, given the confidence interval it appears that sometimes negative net inflows do occur in reality. The low flow conditions defined by the upper bound of 7 m^3s^{-1} has proven to give a more accurate estimation of inflows at low flows than the upper bound of 5 m^3s^{-1} definition as it eliminates the majority of fluctuations that are not caused by rainfall.

Chapter 6 –Rainfall – Runoff Model

6.1 Introduction

A rainfall-runoff model has been developed in order to provide an improved prediction of daily inflows into Lake Waikaremoana such that water availability for the Waikaremoana Power Scheme can be estimated with particular emphasis on next-day low flow conditions. The model is used to forecast next-day inflow of one of the largest streams in the Waikaremoana catchment, the Aniwaniwa Stream. The Aniwaniwa Stream is utilised as opposed to another of the approximately 114 streams which discharge into Lake Waikaremoana because it has the most complete discharge record. A scaling factor relating inflows of the Aniwaniwa Stream to net water storage change into Lake Waikaremoana was derived in Chapter 5, which can be used to extrapolate the discharge of the Aniwaniwa Stream to the entire Waikaremoana catchment, thus predicting net day ahead net lake storage change as defined by inflows minus evaporation and leakage not already accounted for in the observed leakage discharge.

The net water storage change for Lake Waikaremoana was estimated in Chapter 5 using a regression relation derived from a modified catchment water balance and linear regression technique used to estimate lake water loss in Chapter 4. However, as the net storage change estimation was made based on daily totals of input variables, it could be applied only to predict present day inflows, rather than next-day inflows as is the case here. The net inflow predictions in Chapter 5 also held under low flow conditions only, as the assumed linear relationship between the discharge of the Aniwaniwa Stream and net inflows into Lake Waikaremoana could not be assumed to hold under higher flows due to spatial variation of heavy rainfalls. This limitation will also exist when extrapolating results from a rainfall-runoff model to the entire catchment. Nevertheless, prediction of ‘next-day’ inflows will allow for further increased operational efficiency of the Waikaremoana Power Scheme by allowing for improved water availability estimates and therefore generation capacity.

There is concern among various authors of hydrological literature that hydrological models have become fraught with over-complexity such that uncertainty within the models is increased (Beven, 2002a, Jakeman and Hornberger, 1993, Kirchner, 2006, Perrin et al., 2001, Sivakumar, 2008b, Wagener et al., 2001). This chapter demonstrates the use of a model simplification technique, the “lasso”, in an over-parameterised model with the aim of reducing model complexity and computational time. The lasso technique is widely applied in the statistical community although it appears not to have been widely used in hydrology (Bardsley et al., under review).

The aims of this chapter are:

1. To forecast day-ahead Aniwaniwa Stream inflows, which can then be extrapolated to estimate net storage change in Lake Waikaremoana.
2. To demonstrate the model simplification tool, the lasso in a finite mixture rainfall-runoff model.

6.2 Literature Review

6.2.1 Introduction

Numerical models have been applied to hydrological science in some form for over 150 years (Beven, 2001). Rainfall-runoff models, models which predict streamflow based on a precipitation-runoff relationship have been important in the last few decades due to their numerous real-world applications, including water availability for regional water allocation, hydro power and studies involving the effects of land use and climate change (Beven, 2002a).

However, in recent years hydrologists have noted a lack of progress being made in catchment-scale hydrologic modelling (Jakeman and Hornberger, 1993). Over time, hydrological models have become increasingly complex in response to advances in our understanding of small-scale physical processes and significantly increased computational power (Sivakumar, 2008a). Various authors have expressed concern that this increased complexity is not resulting in better predictions or further advances in understanding of hydrological systems, but rather in increasing uncertainties (Beven, 2002a, Jakeman and Hornberger, 1993, Kirchner, 2006, Perrin et al., 2001, Sivakumar, 2008b). This section will briefly discuss the current state of catchment runoff modelling as reported in the literature.

6.2.2 Are Complex Models Better Than Simple Models?

While some hydrological models are developed for the primary purpose of increasing scientific understanding of complex hydrological systems or processes, many are created for ‘real-world’ practical applications such as hydro power, water resource allocation or land use change (Kirchner, 2006). In these applications, the over-complexity of hydrological models becomes particularly relevant since it is more computationally efficient and cost effective to use the simplest model which can explain the data. Any unnecessary complexity simply allows another avenue for uncertainty (Bardsley et al., under review). Thus, an acceptable level of model complexity should be determined during the initial stages of any hydrologic modelling project in relation to the purpose of the model to ensure that the model does not become anymore complex than necessary.

6.2.3 Model Structure

The level of model complexity is often, in part, a result of the model structure applied. Physically based hydrological models require a set of governing equations which describe physical processes and calculate the behaviour of each process in response to other processes within the system across an area represented by a grid (Beven, 2001).

Physical models often apply the upward mechanistic approach to modelling where a number of small-scale physical processes are represented using physical equations which are then scaled to represent a catchment-wide process taking into account as much natural heterogeneity within the catchment as possible. This leads to a model which is highly complex, as it is composed of large number of parameters and governing equations. In recent years, catchment models have tended towards incorporating more and more detail about each physical process, leading to physical models becoming increasingly complex (Beven, 2002a).

A common assumption within many physical models is that micro-scale processes will scale up to catchment scale. However, this is not always the case. For example, Darcy’s law for unsaturated subsurface flow is applicable at small scales but not at large scales. This assumption limits the well known and widely applied ‘blueprint’ for physical hydrological models created by Freeze and Harlen (1969) (Beven, 2002b).

A criticism of the upward approach to hydrological modelling is that its application is not limited to scientifically based studies of which the focus is to gain an understanding of hydrologic systems. Often, our purpose in hydrology is to predict the behaviour of a system rather than to understand its elements and processes in detail. In these instances the upward mechanistic approach may not be the most appropriate choice of model structure (Sivakumar, 2008b). Sivakumar (2008b) recognises that physically based models may not always be appropriate for prediction studies and suggests that ‘understanding does not necessarily lead to better prediction’.

The attempt to capture physical processes and represent them in a way which is true to their actual form means that physical models are limited by the current understanding of physical processes and their interactions (Kirchner, 2006). Even a physical process which is well understood may be difficult to translate into a model in a way which can be considered a true representation. This is particularly so since the catchment is an open system, within which each process has unique characteristics and boundary conditions which may be difficult to define (Beven, 2002a). However, in support of the use of physical models in hydrology is the notion that should the model give a good result then it is ‘the right answer for the right reasons’ (Kirchner, 2006). This may be particularly important when trying to predict beyond circumstances represented in the calibration data such as extreme events, land use change and climate change (Kirchner, 2006).

Conceptual catchment models, often described as the ‘black box’ approach, require input data which is then manipulated by a set of equations which attempt to approximate the behaviour of the overall system rather than individual processes. The model then produces an output. The processes which take place inside the ‘black box’ are not necessarily any true representation of real processes (Sivakumar, 2008b). Beven (2002a) argues that while conceptual models will be ‘wrong’ in terms of their representation of hydrological processes within the model, and they will be 'known to be wrong but still have the possibility of being approximately realistic'.

6.2.4 Problems with Complex Models

6.2.4.1 Less is More – The Problem of Over-Parameterisation

Over-parameterisation is the situation where a large number of parameters are included in a model where many of the parameters have little to no predictive power and their inclusion in the model increases model uncertainty. Perrin et al., (2001) is of the opinion that over parameterisation is one of the root causes of model output uncertainty, and is inherent in the majority of complex models. Over parameterisation is of particular concern when input or comparison data is noisy or limited, as is often the case in hydrology. As the number of free parameters is increased, uncertainty within the model increases non-linearly (Kirchner, 2006). In 1989 Beven expressed the 'great danger of over-parameterisation', a trap many modellers fall into when attempting to simulate all hydrological processes thought to be relevant.

Various authors have shown that for prediction purposes very simple models can perform almost as well as models with a large number of parameters. Mein and Brown (1978) showed that in their modified 13 parameter SFB model a drastic reduction in the number of optimised parameters only caused a slight reduction in model performance. Chew and McMahon (1994) showed that all of the 19 parameters used in their model were not necessary and that sufficient estimation of stream flow could be achieved with only 9 of them (cited in Jakeman and Hornberger, 1993). Hooper (1988) examined a very simple model with 6 parameters and found it to be over-parameterised (cited in Jakeman and Hornberger, 1993). Beven (1989) found than '3 to 5 parameters should be sufficient to reproduce most of the information in the hydrological record.'

In 1993 a study was conducted to investigate how much complexity was warranted in a rainfall-runoff model (Jakeman and Hornberger, 1993). Jakeman and Hornberger concluded that the limitations of the observed data placed restrictions on the complexity of a rainfall-runoff model such that most data are sufficient only to justify models of limited complexity. Nash and Sutcliffe (1970) also expressed the need for simplicity in hydrological models and suggested that adding components to a model is only acceptable ‘if they substantially increase model accuracy and robustness’.

6.2.4.2 Parameter Identifiability

Parameter identifiability is a model property which, if satisfied, means that model inference is possible. That is, that it is possible to learn about the underlying model parameters through model outputs (Kotz et al., 2006). Parameter identifiability is important in hydrology as it enables us to improve both our understanding of hydrological systems and our prediction ability. Parameter identifiability is particularly important in physical models where all parameters supposedly represent real-world physical processes (Kotz et al., 2006). The result may be that a lack of identifiability in model parameters limits the use of models in studies which involve parameter regionalisation, and land use change or climate change (Wagener et al., 2001). Wagner et al., (2001) argue that there is a ‘need to balance model performance and identifiability of parameters’ as a model which performs well but has unidentifiable parameters is less hydrologically relevant (in a sense that we can learn from it) than a model which performs moderately well but has highly identifiable parameters. Over-parameterisation also makes parameter identification more difficult, thus parameter identifiability may be more difficult in complex models than in simple models (Wagener et al., 2001).

6.2.4.3 Calibration and Validation

Model calibration, the process of modifying a model to increase fit with observed data and model validation, the process of assessing a models predictive ability are critical components in all types of environmental modelling. A models’ predictive capacity can be identified by the success of calibration and validation fits. Complex models, both physical and non-physical are more flexible in fitting data during calibration, giving the appearance that they predict better than simple models (Schoups et al., 2008). However, over-complex models encounter the problem of over-fitting during calibration where a model is over-parameterised such that many different sets of parameters, and many different models will give almost identical fits to calibration data (the equifinality problem). When an over-parameterised model is validated, the model gives very poor data fits, demonstrating poor predictive power (Schoups et al., 2008). Simple models are generally not prone to calibration over-fitting, and thus may provide a better validation prediction in some cases.

In order to test whether a model has encountered the equifinality problem a split calibration-validation test can be performed. A split calibration-validation test involves the creation of a split data set where the model is calibrated on part of the data, then validated on the remaining part. Ideally, the validation set should include extreme events to test the models predictive power under situations not encountered in calibration. This is a common test which is performed in many modelling situations (Schoups et al., 2008). Another, more difficult calibration-validation test is the differential split calibration-validation test where the model is required to validate data which has been subjected to climate or land use change. These tests often fail, indicating inflexible models (Kirchner, 2006).

Schoups et al., (2008) found that in a non-physical polynomial model calibration fit increased with model complexity but validation fit decreased with complexity due to over-fitting. However, when physical principles were applied to the model to limit it, for example a storage-discharge relationship, then validation fit did not decrease with model complexity.

6.2.4.4 Failure Opportunity

The lack of progress in hydrological modelling noted by Jakeman and Hornberger (1993) may be a result, in part, of the approach taken towards hydrological modelling. Hydrological modelling should be undertaken by the setting of a hypothesis, and the creation of a simple model with few enough parameters that the model will fail when the hypothesis is incorrect (Kirchner, 2006, Sivakumar, 2008b). Failure of the model allows for opportunities to learn about hydrological processes, improving both our understanding of hydrological systems and our ability to forecast them. Giving models the ability to fail also provides an important tool for recognising a model which does not perform well and may encourage revision of the model, which may be beneficial in making progress in hydrological modelling. However, in modern day hydrology model failure is generally not considered acceptable (Beven, 2002a). Perhaps, as Beven (2002a) suggests ‘our reluctance to reject our models is because complete model rejection is not a good strategy in writing a thesis, journal article, or reporting to a client’.

Gupta et al., (2008) argues that in order to detect model failure, more sophisticated approaches to model evaluation are required. In most hydrological models validation is represented as graphical plots of observed vs. simulated hydrographs accompanied by fit statistics such as the Nash efficiency and correlation coefficient (Gupta et al., 2008). Gupta et al., (2008) contends that the Nash efficiency summarises model efficiency to a relatively weak benchmark. It is also suggested that an increased ability to diagnose the problems in our models is required (Gupta et al., 2008).

6.2.5 Data Quality and Quantity

The quality and quantity of data is a significant factor in the success of any model. Due to the nature of hydrology as a science, and the expense of collecting data, many data sets in hydrology can be considered 'sparse and noisy' (Schoups, 2008). For more accurate, identifiable models more emphasis must be placed on the value of data. This is most likely to be achieved in situations where data is collected for specific purposes (Kirchner, 2006).

6.2.6 For the Future

There is discussion in hydrological literature that progress in the field of hydrological modelling requires a change in attitude among hydrological modellers from the current notion which Sivakumar (2008b) describes as being that 'complex models and new concepts are better than simple models and old concepts'. This existing mindset has lead to the development of hydrological models which are fraught with over-complexity which may not be warranted. The modelling mindset needs to move towards what Sivakumar (2008b) describes neatly that 'something is better than nothing, but nothing is better than nonsense'.

The future of hydrological modelling appears to be to move away from the idea of 'modelling everything' and towards 'capturing the essential features' as this will reduce the risk of over-parameterisation thereby decreasing model uncertainty (Sivakumar, 2008b). Beven (2008) argues that the future of environmental modelling should place more emphasis on 'parametrically simple robust models, carefully designed for specific purposes'. Similarly, Sivakumar (2008b) argues that 'complex models may only be better where adopted scientific concepts are correct, and the data is reliable in information, and of sufficient quantity. This is rarely the case in hydrology'.

There is agreement in the literature that in order for hydrological modelling to progress as a science, there must be a change in attitude among the hydrological community to dismiss the belief that failure of a model is a failure in science, since it is when we admit that our models do not perform well that we may learn from our mistakes and progress, both in terms of improvement in prediction ability and understanding (Kirchner, 2006, Sivakumar, 2008b).

6.3 The Lasso Methodology

The lasso technique is one of many different methods of model shrinkage. Put simply, the lasso technique works by selecting a subset of linear predictor parameters, and discarding the remaining parameters (Hastie et al., 2009). The lasso has the capability to select variables with predictive power during model calibration, with the particular practicality of being able to handle a large number of contender variables (Bardsley et al., under review).

The lasso technique originally appeared in the Journal of the Royal Statistical Society in 1996, for the purpose of linear model simplification for the development of interpretable models (Tibshirani, 1996). That is, if models which have a very large number of parameters can be simplified so that only those which have the greatest effects on the system remain then models should be easier to interpret as the parameters may have increased identifiability (Tibshirani, 1996). The lasso technique was also developed to address dissatisfaction among statisticians at the time with ordinary least squares estimates which produced models which in general, had low bias but high variance. In these situations it is common to attempt to increase prediction accuracy and reduce variance by setting some co-efficient to zero. However, this introduces bias as a trade off for a better prediction (Tibshirani, 1996).

Model simplification can be achieved by methods other than shrinkage methods. The most common of these is subset selection. However, subset selection has the disadvantage of being a discrete process since variables are either retained or eliminated; this results in high variance within models such that the prediction error may not be reduced. Subset selection also has a heavy calculation load which limits variables. Shrinkage methods exhibit less variability since they are continuous (Hastie et al., 2009). The lasso was originally designed based on another shrinkage method, the non-negative garrotte which was proposed by Breiman in 1993. The non-negative garotte uses non-negative factors to shrink ordinary least squares estimates. However, the garotte is limited in that its solution depends on the sign and magnitude of the ordinary least squares estimate, consequently the garrotte may perform poorly when the ordinary least squares estimate is overfit. The lasso avoids this drawback by not depending explicitly on the ordinary least squares estimate (Hastie et al., 2009).

Presently, two standard techniques for the improvement of ordinary least squares estimates exist. These include best subsets regression and ridge regression. However, best subsets regression is limited in that it is too discrete. This allows small variations within a data set to give vastly different results. Ridge regression is a continuous technique like the lasso, but simply 'shrinks' parameters without setting any to zero, meaning that the total number of parameters are retained. This may make model interpretation difficult due to lack of parameter identifiability. The lasso technique however has the disadvantage that unlike best subsets regression the remaining selected parameters are not necessarily 'best'. However, best subsets regression is unable to cope with a large number of potential parameters like the lasso can (Bardsley et al., under review).

The lasso technique has been compared to subset regression and ridge regression in terms of prediction accuracy under three scenarios, a small number of large effects, small to moderate number of moderate effects, and a large number of small effects (Table 4). Subset selection performs best for a small number of large effects, followed by the lasso and then ridge regression, the lasso performs best for a small to moderate number of moderate effects, followed by ridge regression then subset regression, and the ridge regression does best for a large number of small effects followed by the lasso then subset regression, so it is the most versatile of the three (Tibshirani, 1996).

Table 4: Relative performance of subset selection, the lasso and ridge regression under different scenarios (based on text from Tibshirani, 1996).

Performance	Small number of large effects	Small-moderate number of moderate effects	Large number of small effects
Best	Subset selection	Lasso	Ridge regression
Intermediate	Lasso	Ridge regression	Lasso
Worst	Ridge regression	Subset regression	Subset regression

The lasso technique was proposed as an intermediate between the two aforementioned techniques, retaining the positive features of both. There is suggestion of the power of the lasso methodology in its wide application in the statistical community as a method of variable elimination in a least-squares regression (Tibshirani, 1996). The original lasso paper by Tibshirani, 1996 has been cited over 1,400 times as of the 8th of January 2011 across a wide range of scientific fields.

The original lasso is defined in least squares form as:

Letting $\beta = (\beta_1 \ldots \beta_p)^T$ the lasso estimate (α, β) is defined by

$$(\alpha,\beta) = \arg\min \left\{ \sum_{i=1}^{N} \left(y_i - \alpha - \sum_j \beta_j x_{ij}\right)^2 \right\} \text{ subject to } \lambda \sum_j |\beta_j| \leq t \qquad [6]$$

Where (x^i, y_i), i=1,2,….N is the data, $x^i = (x_{i1} \ldots, x_{ip})^T$ are predictor variables and y_i are the responses. The assumption is made that y_i is either independent or conditionally independent given standardised x_{ij} so that $\sum_i x_{ij} / N = 0$, $\sum_i x^2_{ij} / N = 1$. $t \geq 0$ applies elimination pressure to the parameters, and thus determines the amount of shrinkage which is applied. Forcing variables to zero thus removes less informative variables (Tibshirani, 1996).

The lasso technique uses a parameter, λ which applies elimination pressure to the β parameters. As λ is increased more variables are forced towards zero. This means that variables which have poor prediction of the data are forced to zero during calibration, and variables which have good fit to the data are reduced in size but are not eliminated. The result is a set of non-zero parameters which may be constrained to be positive, depending on the model formulation. A second calibration is then carried out where λ is set at zero and consequently there is no elimination pressure. Any variables which went to zero in the previous calibration will remain at zero. The remaining variables are then subjected to a standard calibration, increasing the values of the variables which have been shrunk during the initial calibration towards the observed data. Therefore, there is a trade-off between model simplification and fitting to data since as the model becomes simpler the calibration fit decreases.

The lasso method has to date not been widely applied in hydrology although a wide range of possible applications exist. For example, the lasso method can be applied to finite mixture rainfall runoff models, and may have a number of other hydrological applications.

6.4 Method Used

A lasso-simplified finite mixture rainfall-runoff model was used to predict the day-ahead inflow of the Aniwaniwa Stream into Lake Waikaremoana. The rainfall-runoff model utilised the lasso technique in an initially over-parameterised rainfall runoff model as a method of model simplification. The model requires a complete record of rainfall data as an input. Initially some data exploration was carried out to determine which raingauges were the most appropriate to use as parameters for model input.

6.4.1 Data Organisation

The rainfall data used for input into the rainfall-runoff model is from a single raingauge in the Aniwaniwa catchment as it is the closest raingauge to the Aniwaniwa Stream, being in the catchment itself. However, the actual record of Aniwaniwa rainfall is not complete. Therefore, rainfall from another raingauge in the Waikaremoana area must be used to patch in missing rainfall data.

In order to determine which of the 7 other raingauges in the Waikaremoana area is most suitable for patching into the Aniwaniwa record the rainfall-runoff relationships with the Aniwaniwa Stream were compared. The lag time between rainfall events and observed peaks in the Aniwaniwa Stream were compared in order to determine which raingauge behaved most similarly to the Aniwaniwa raingauge (Figure 35).

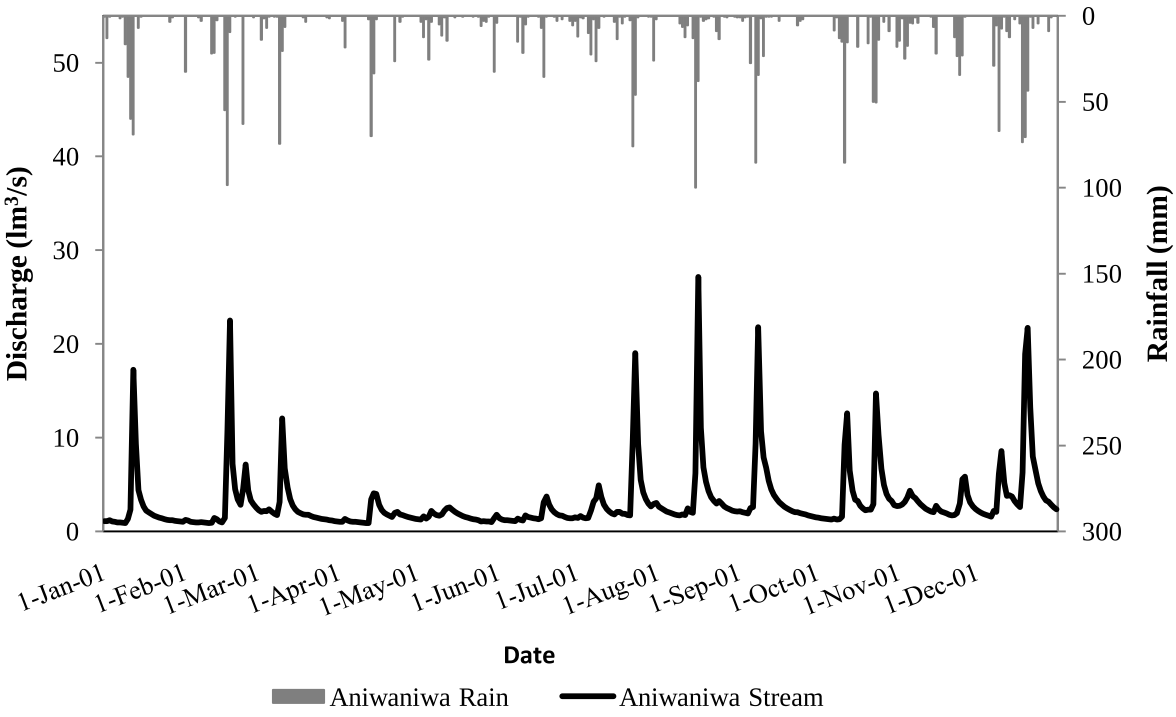

Figure 35: Example hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Aniwaniwa rainfall (mm) for 2001.

While the rainfall and runoff relationship for each raingauge was compared over a large time scale, some short time scale plots of a large rainfall event in August 2001 are shown here for ease of comparison (Figure 36). While only one large rainfall event is shown, there are often rainfall events almost as large at other dates.

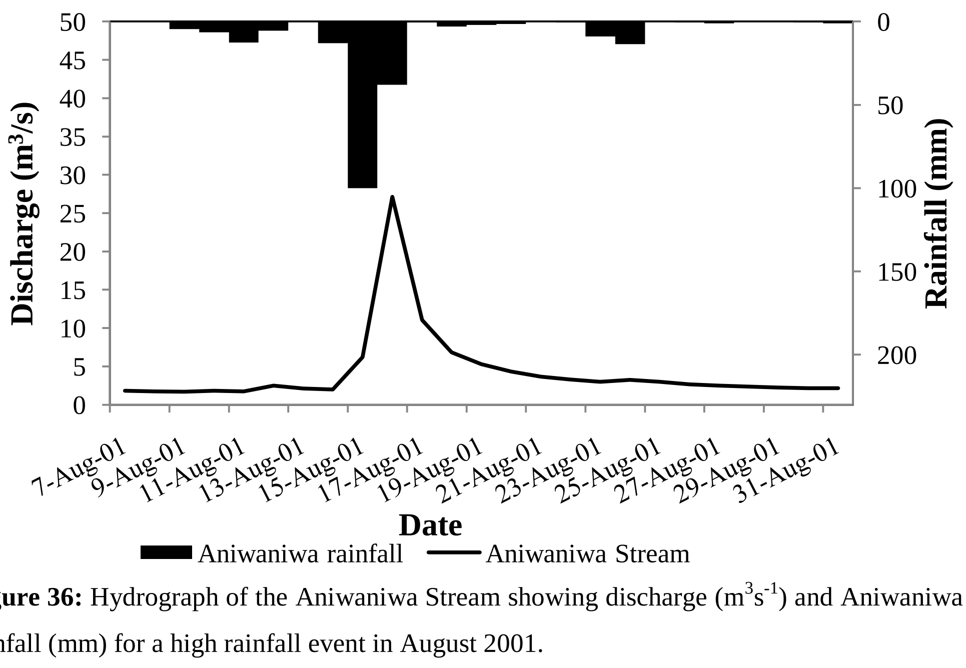

Figure 36: Hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Aniwaniwa daily rainfall (mm) for a high rainfall event in August 2001.

The Aniwaniwa stream responds to Aniwaniwa rainfall fairly rapidly with the peaks occurring either on the same day or on the following day. Situations where the hydrograph peak occurs on the day following recorded rainfall may be a result of night time rainfall such that a runoff response time of a few hours means that the hydrograph peak occurs the following day. It may also be a result of low catchment wetness state such that the soil moisture stores are filled first, delaying the hydrograph peaks.

The Erepeti Met raingauge is located on the other side of a topographic ridge from the Aniwaniwa catchment, approximately 6km from the mouth of the Aniwaniwa Stream (Figure 16). River flows in the Aniwaniwa Stream tend to lag the recorded rainfall by a period of one day. Rainfall peaks at this rain gauge tend to be smaller than at the Aniwaniwa raingauge, possibly due to a rain shadow effect of the ridge between the two catchments (Figure 37). The Nga Tuhoe raingauge is situated close to the Erepeti Met raingauge and also lags the river flows by 1 day. Both raingauges are outside the Waikaremoana catchment. In both Erepeti Met and Nga Tuhoe raingauges the size of the rainfall peaks relative to the size of the river flow peaks are not as closely related as for the Aniwaniwa raingauge (Figure 38).

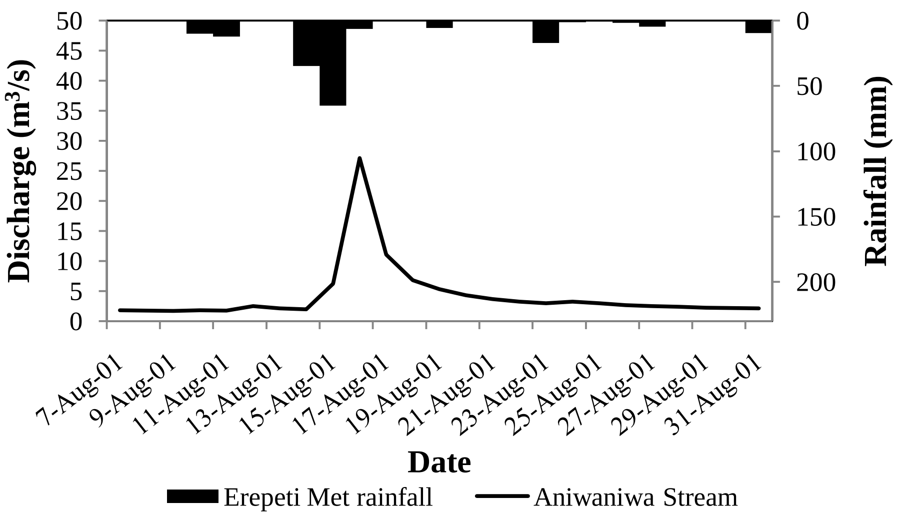

Figure 37: Hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Erepeti Met daily rainfall (mm) for a rainfall event in August 2001.

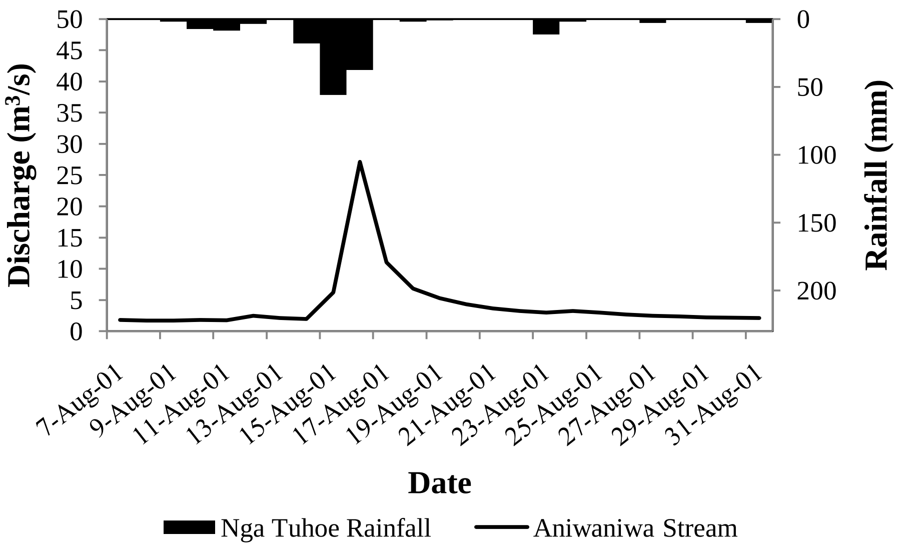

Figure 38: Hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Nga Tuhoe daily rainfall (mm) for a rainfall event in August 2001.

The Upper Waiau raingauge is located on the opposite side of Lake Waikaremoana to the Aniwaniwa catchment, approximately 20 km from the mouth of the Aniwaniwa Stream and is separated from the Waikaremoana catchment by the Panekiri Range. Rainfall peaks recorded at the Upper Waiau raingauge occur either on the same day as discharge peaks of the Aniwaniwa Stream or lag the peaks by one day. However, the magnitude of rainfall peaks is only moderately well related to those of the Aniwaniwa raingauge (Figure 39). The Upper Waiau raingauge receives less rainfall than many of the other catchments.

The Bushy Knoll raingauge is located approximately 23 km NNE of the Aniwaniwa Stream. Discharge in the Aniwaniwa Stream lags Bushy Knoll rainfall by one day. This is to be expected as Bushy Knoll is located some distance from the Waikaremoana catchment. However, the rainfall magnitude of rainfall peaks are fairly similar to that of the Aniwaniwa raingauge (Figure 40).

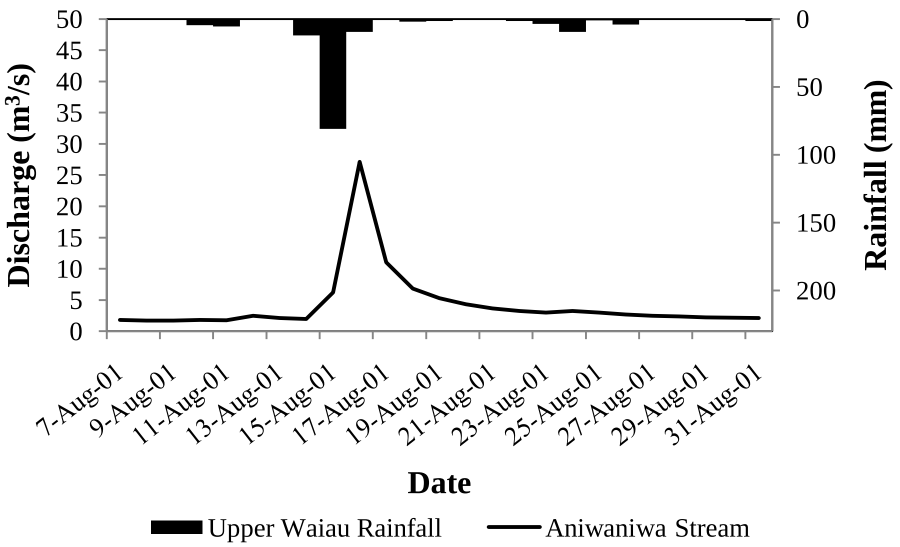

Figure 39: Hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Upper Waiau daily rainfall (mm) for a rainfall event in August 2001.

Mt Manuoha is located 10 km to the NNW of the mouth of the Aniwaniwa Stream. It is a topographic peak some 670 m higher than the mouth of the Aniwaniwa Stream. High rainfall events appear to be more frequent at the Mt Manuoha raingauge, possibly due to the orographic effect of high topography. River flows in the Aniwaniwa Stream lag Mt Manuoha rainfall by 2 days (Figure 41).

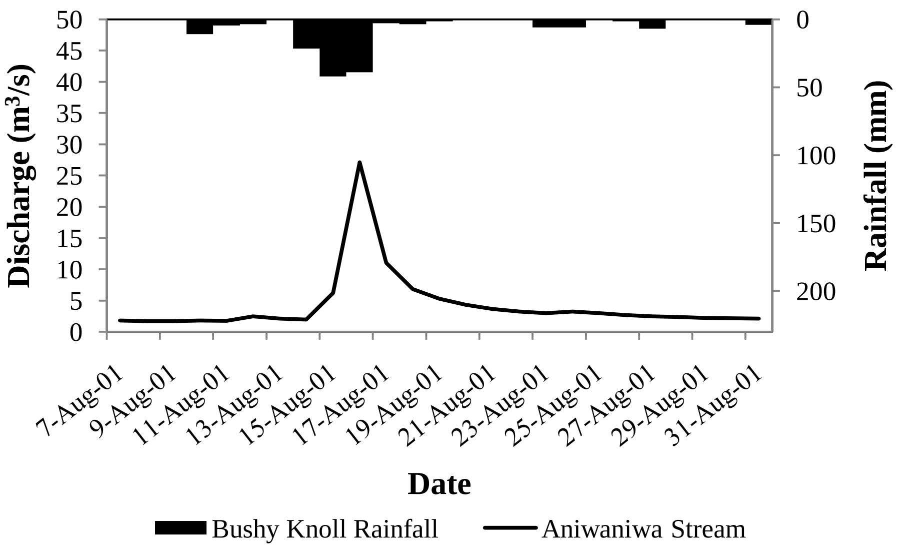

Figure 40: Hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Bushy Knoll daily rainfall (mm) for a rainfall event in August 2001.

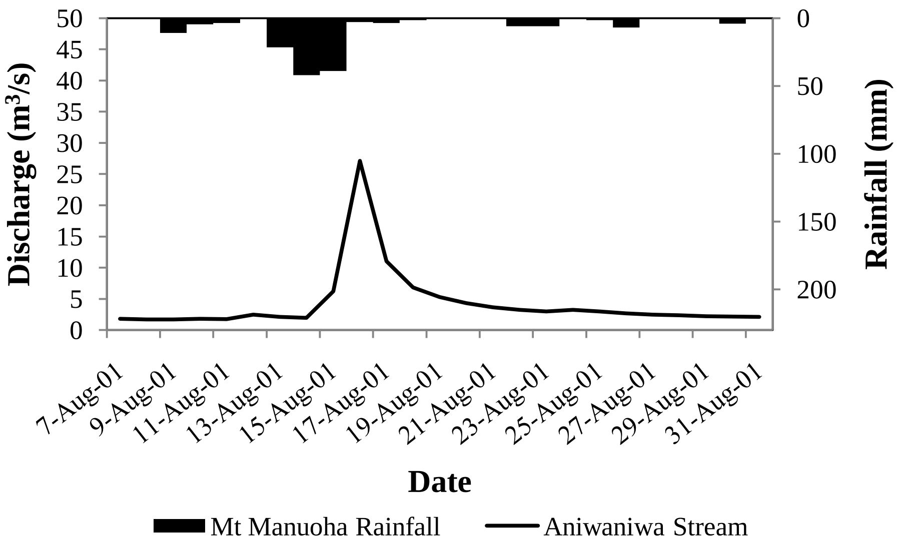

Figure 41: Hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Mt Manuoha daily rainfall (mm) for a rainfall event in August 2001.

Rocky Pad is located across Lake Waikaremoana from the Aniwaniwa catchment, approximately 21 km from the mouth of the Aniwaniwa Stream. Rainfall peaks at the Rocky Pad raingauge and river peaks in the Aniwaniwa Stream match moderately well. Rainfall occurs on either the same day, or river flow lags rainfall by one day (Figure 42).

The Waimaha raingauge is located approximately 20 km to the North East of the Aniwaniwa Stream. The Waimaha raingauge has the shortest rainfall record which is only 9 years long. River flow peaks and rainfall peaks match quite well but the absolute value of rainfall are much lower in the Waimaha catchment compared to the Aniwaniwa catchment. Aniwaniwa discharge lags rainfall by one day (Figure 43).

The Onepoto raingauge is located 7 km to the south west of the Aniwaniwa Stream, and Aniwaniwa discharge lags Onepoto rainfall by 1 day. The Onepoto rainfall record also has large amounts of missing data (Figure 44).

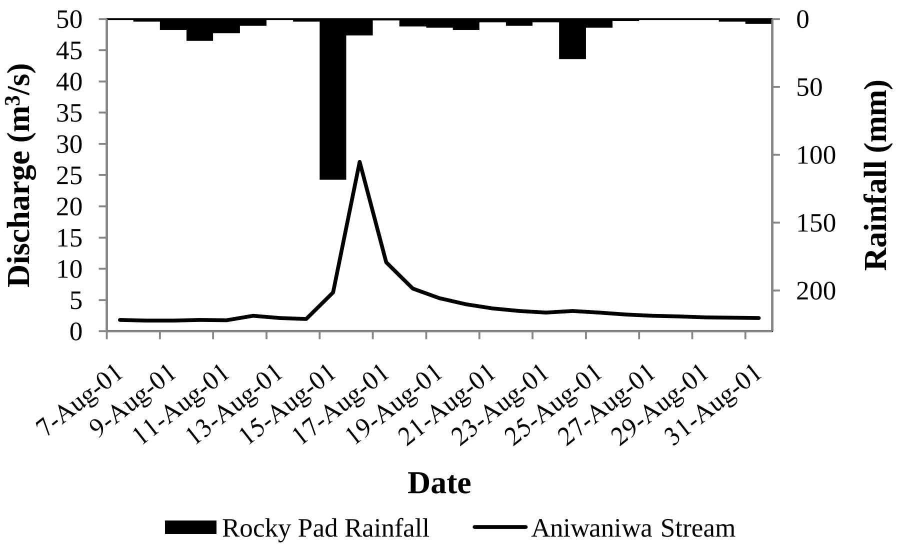

Figure 42: Hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Rocky Pad daily rainfall (mm) for a rainfall event in August 2001.

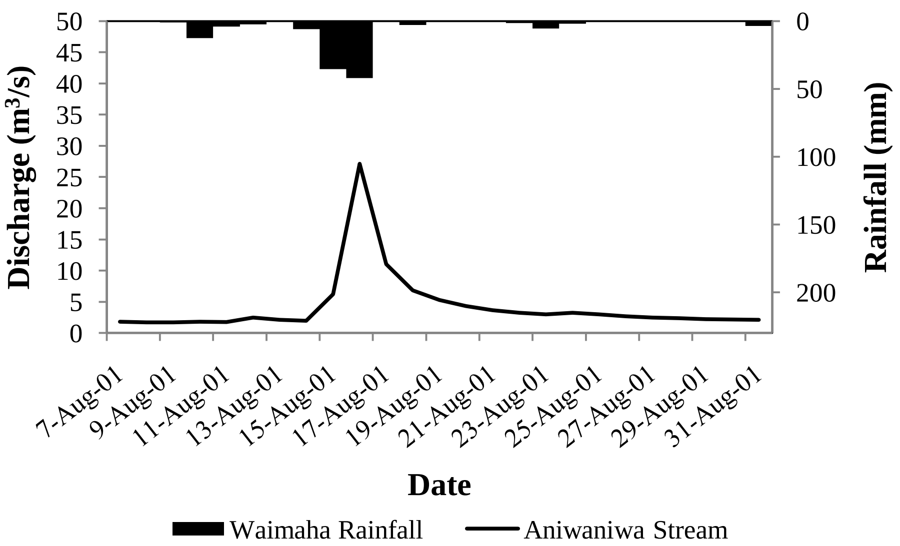

Figure 43: Hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Waimaha daily rainfall (mm) for a rainfall event in August 2001.

Monthly rainfall totals for each raingauge were compared to determine which raingauge has the closest monthly rainfall totals to the Aniwaniwa raingauge, and which raingauges had the same relative seasonal variation in rainfall (Figure 45). Onepoto rainfall is not included in Figure 45 due to the large amount of missing data.

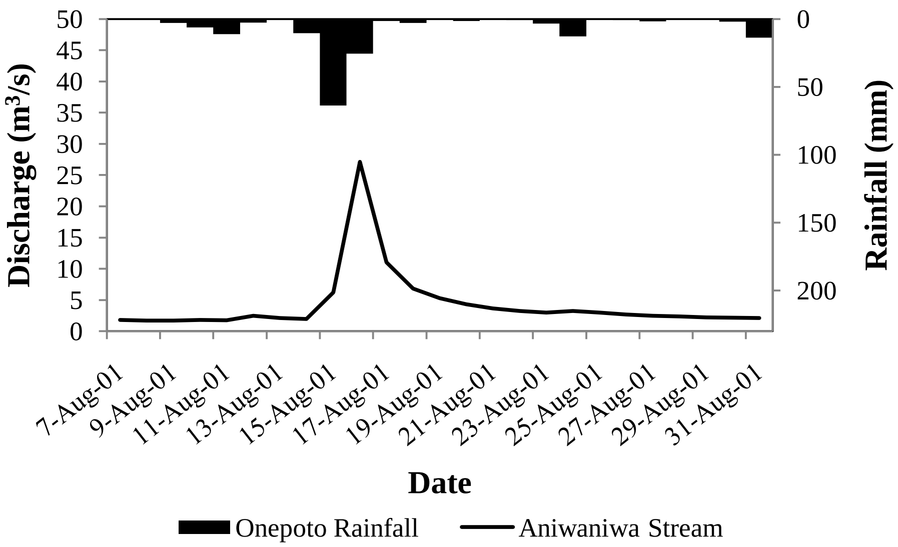

Figure 44: Hydrograph of the Aniwaniwa Stream showing discharge (m^3s^{-1}) and Onepoto daily rainfall (mm) for a rainfall event in August 2001.

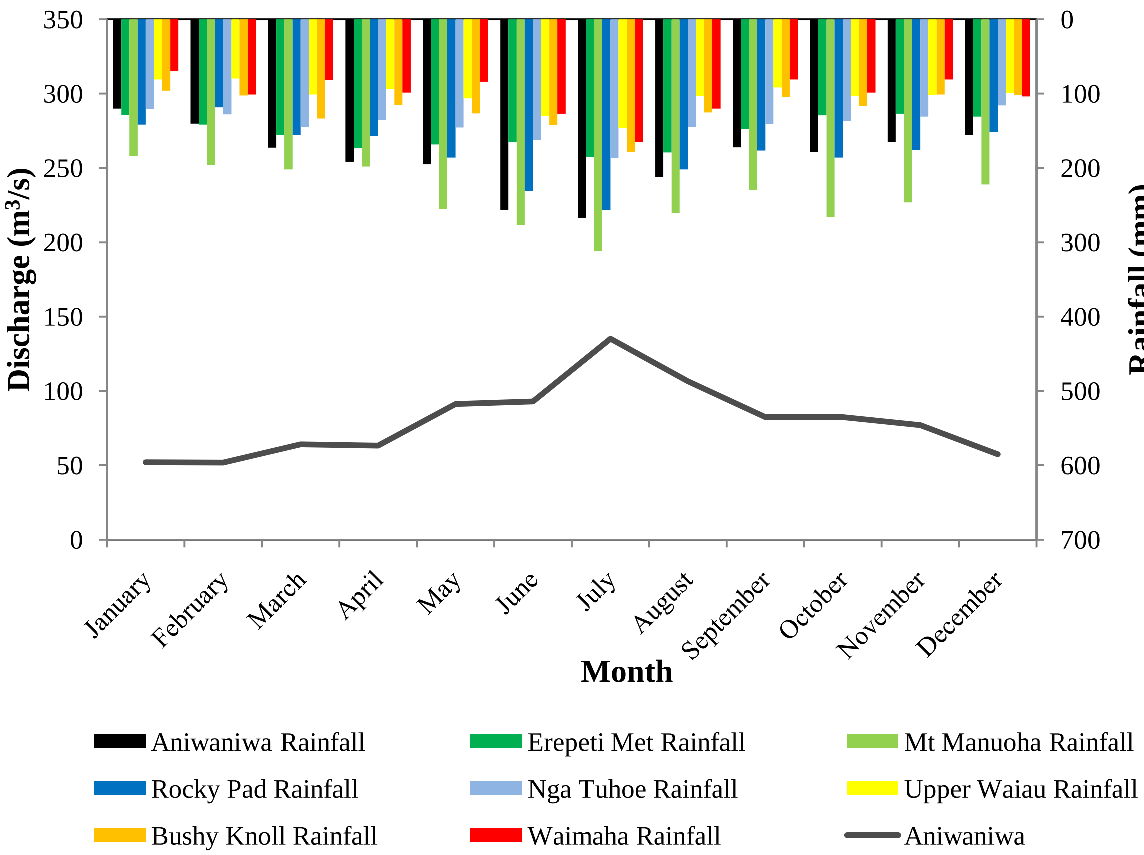

Figure 45: Monthly rainfall totals and average monthly discharge of the Aniwaniwa Stream (m^3s^{-1}).

It was found that the Aniwaniwa rainfall consistently had the second highest rainfall total each month for the year until September. During September to December Aniwaniwa rainfall is matched or slightly exceeded by Rocky Pad rainfall. The Mt Manuoha raingauge had the highest rainfall totals each month. This is likely due to an orographic effect caused by high topography.

The closest monthly rainfall totals to the Aniwaniwa rainfall are Rocky Pad, Erepeti Met and Nga Tuhoe which are within ± 93 mm of rainfall over the entire year. The other raingauges considered are ± 130 mm of rainfall each month compared to Aniwaniwa rainfall (Table 5). Thus, at a monthly scale it is clear that the Rocky Pad rainfall is most closely matched to the Aniwaniwa rainfall.

Table 5: Deviation of monthly rainfall totals from Aniwaniwa rainfall totals (%)

	Jan	Feb	Mar	Apr	May	Jun
Erepeti Met	7.1	1	-9.9	-9.5	-13.6	-35.7
Mt Manuoha	53	39.8	17	3.2	30.8	7.9
Rocky Pad	17.8	-15.6	-10	-18.1	-4.6	-9.8
Nga Tuhoe	0.7	-8.9	-16	-29.3	-25.4	-36.6
Upper Waiau	-32.6	-43.3	-41.4	-51	-45.4	-49
Bushy Knoll	-20	-26.9	-22.5	-40	-35.1	-44.5
Waimaha	-42.3	-27.8	-52.8	-48.5	-56.9	-50.5

Table 5 continued.

	Jul	Aug	Sep	Oct	Nov	Dec
Erepeti Met	-30.5	-15.6	-14.4	-27.5	-23.1	-15.7
Mt Manuoha	16.9	22.9	33.7	49.1	49.1	43.1
Rocky Pad	-3.8	-4.8	2.6	4.2	6.4	-2.5
Nga Tuhoe	-30.1	-31.6	-18.3	-23.5	-20.9	-25.3
Upper Waiau	-45.2	-51.5	-46.7	-42.4	-38.2	-36
Bushy Knoll	-33.2	-41	-39.4	-34.5	-38.7	-34.4
Waimaha	-38.2	-43.4	-52.9	-44.7	-50.9	-33.3

The various raingauges were also compared on a daily scale using a scatterplot of Aniwaniwa rainfall and each of the contender raingauges (Figure 46), the R^2 values of the plots could then be compared (Table 6). The Nga Tuhoe raingauge had the highest R^2 value followed closely by the Onepoto raingauge.

Table 6: R^2 value and Nash-Sutcliffe coefficient for comparison of Aniwaniwa rainfall to each of the 8 raingauges in the Waikaremoana catchment.

Raingauge	R^2
Erepeti Met	0.377
Nga Tuhoe	0.840
Upper Waiau	0.627
Bushy Knoll	0.724
Mt Manuoha	0.515
Rocky Pad	0.68
Waimaha	0.697
Onepoto	0.827

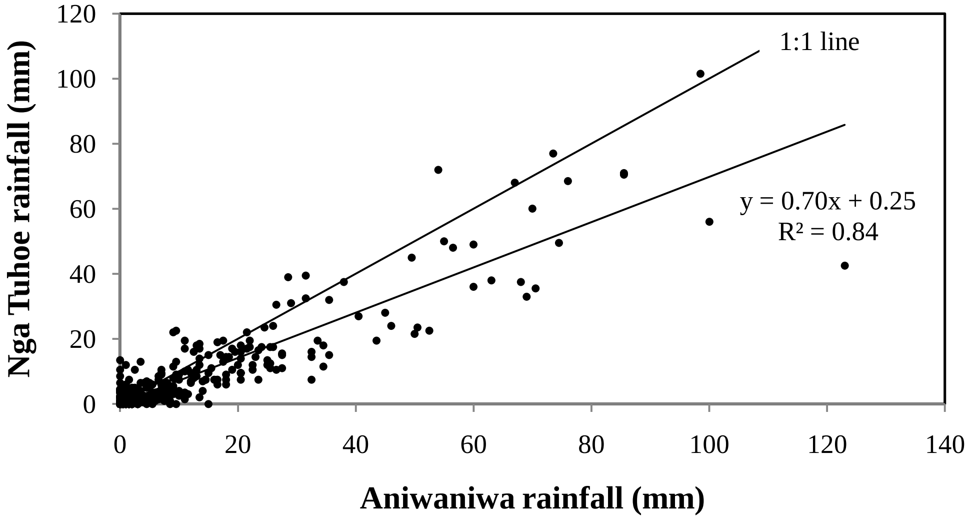

Figure 46: Scatterplot of Aniwaniwa daily rainfall (mm) and Nga Tuhoe rainfall showing linear relationship.

The Nga Tuhoe raingauge appears to be the most correlated to Aniwaniwa rainfall as it has the highest R^2 value, similar monthly rainfall totals, and a similar lag time when compared to Aniwaniwa rainfall.

The seasonality of the rainfall-runoff relationship was investigated prior to model development (Figure 47). This may be important in the Waikaremoana catchment, as strong seasonal variation in spring may denote snowmelt unrelated to rainfall events which may make runoff more difficult to predict during this time.

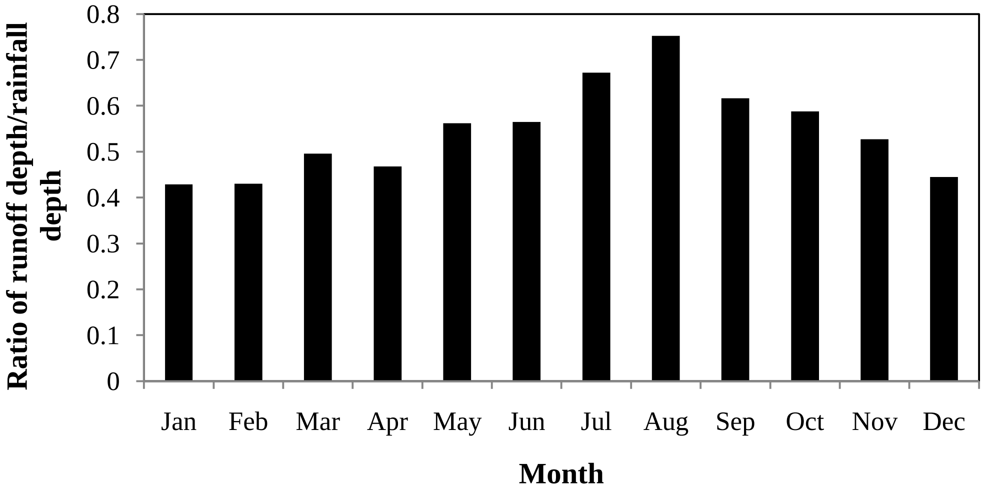

Figure 47: Ratio of average monthly runoff and average monthly rainfall.

Seasonal variation in average monthly runoff and average monthly rainfall changes is indicated by a change in the runoff/rainfall ratio. Seasonal variation in the Waikaremoana catchment is apparent, with the ratio of runoff to rainfall increasing to a peak in August, with summer minima. As the larger ratios occur in mid to late winter, this suggests a reduced evaporation loss as well as the soil already having a high moisture content, allowing infiltration capacity to be exceeded much more quickly than during other times of the year. Higher ratios in September and October compared to June and July could also be a result of this, but could also be related to snow melt.

6.4.2 Method

The lasso methodology is used to develop a simplified model to forecast daily inflows of the Aniwaniwa Stream into Lake Waikaremoana. The model is run using linear programming routines set up and called from COMSOL. The model is set up for calibration/simplification using linear programming model where an input file created and edited in Microsoft Excel is read into the model. The input file contains the observed daily discharge of the Aniwaniwa Stream, as well as Aniwaniwa daily rainfall. Included are 5 other rainfall variables which represent the rainfall of the Aniwaniwa catchment at different lags, for example 1 day, 2 day, 3 day and 4 day lags. This is included to give the model information about the catchment wetness state since previous rainfall is likely to affect hydrograph form. Where rainfall data was not available for certain (small) periods, data from the Nga Tuhoe raingauge, was patched in. Rainfall input data was standardised as a requirement of the model by dividing by the no-zero mean such that rainfall values fluctuate around 1.0. This has the effect of removing any very large input values after rainfall is squared, since these values will be preferentially eliminated from the model which may produce bias.

The data set used ranges from the beginning of 1995 to March 2009. Although a longer data set is available, this period was used because there is no missing discharge data during this period. The calibration/simplification computational time is approximately 20 minutes.

Since the lasso technique requires linear inputs, and rainfall-discharge relationships are rarely linear, a pseudo-linear approach has been taken. A finite mixture rainfall-runoff model has been created where a number of hydrograph forms (25 in this case) are made available to the model. A large range of pre-calculated forms must be available such that all possibilities may be predicted. That is, there must be forms which can approximate the peaks, and forms which can approximate long recession tails (Figure 48). The forms are given a more or lesser weight via the algorithm depending on the intensity of the rain event, and the previous 5 days rainfall to allow for catchment wetness state. Therefore, the shape of the hydrograph is related to the catchment variables by the relative weight of chosen hydrograph forms which serve as shape parameters.

The weights also serve as scale parameters so results are independent of units of measurement. This approach does not attempt to represent the physical processes between hydrological variables such as rainfall and runoff beyond representative forms of hydrograph components but simply selects hydrographs as an empirical function of past rainfall events. Therefore, any hydrological interpretation is carried out after modelling rather than as part of the model input.

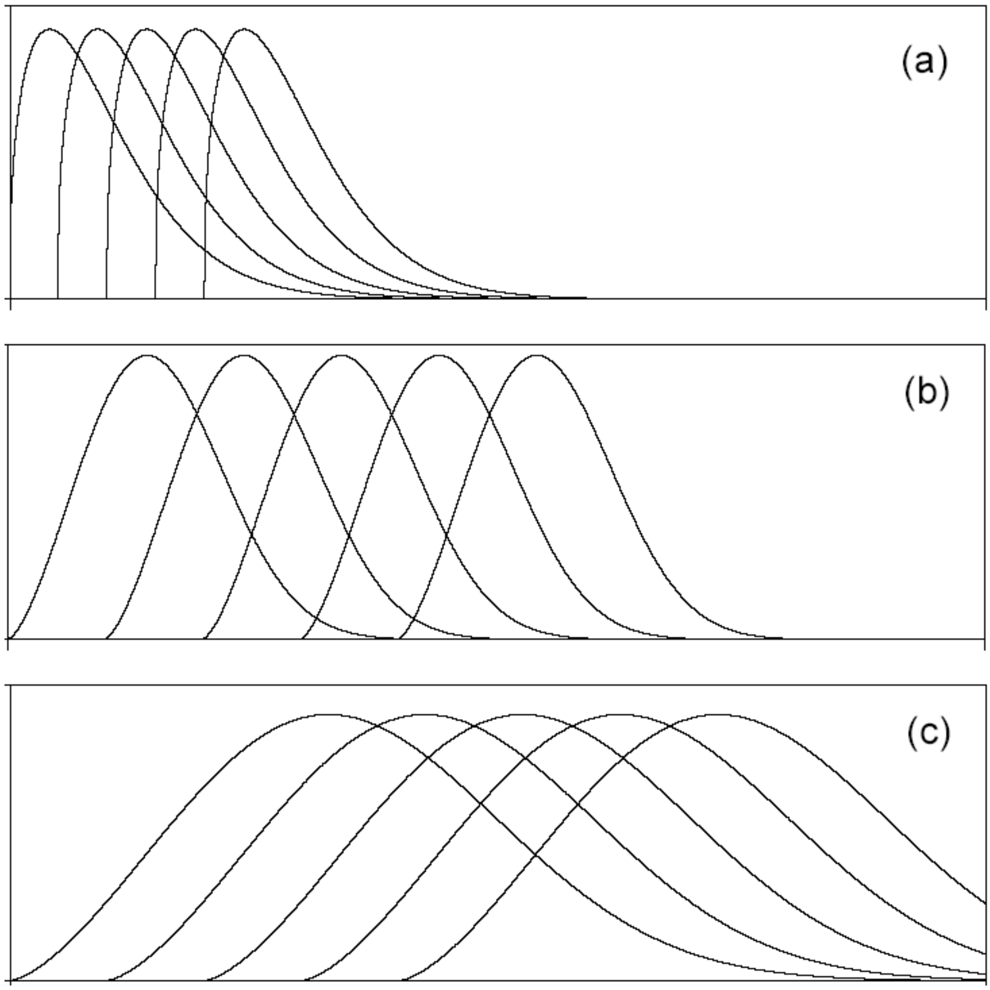

Figure 48: Illustrative example of the possible hydrographs which may be selected for the rising limb (a) peak (b) and recession tail (c) of a hydrograph.

A modified form of the original least squares lasso equation is used here (Wang et al., 2006). This enables the use of the lasso in linearly constrained models using standard linear programming techniques which produce a single global minimum during calibration.

$$min \sum_{i=1}^{N} \left| Y_i - (\beta_0 + \sum_{j=1}^{M} X_{i,j}\beta_j) \right| \quad + \lambda \sum_{j=1}^{M} \left| B_j \right| \qquad [7]$$

where values of β are coefficients associated with independent variables, Y_i are the N data values of the model which are being approximated by the model, β_0 is a constant term which is not minimised as it is not used in prediction, $X_{i,j}$ are the M standardised independent variables. The parameter λ a user supplied value, provides elimination pressure.

The weights of pre-calculated hydrograph forms are linked to rainfalls through quadratic functions with coefficients constrained to non-negative values. Constraining the quadratic coefficients to be non-negative gives non-negative weights and avoids the possibility of negative discharges. The use of quadratic coefficients can be used to represent nonlinear processes of runoff such as rapidly increasing discharge as a result of infiltration capacity being exceeded. This does not violate the requirement of linearity since both calculation of the hydrograph forms and raising them to powers is a pre-calculation. There is no explicit representation of causal mechanisms between hydrological variables such as rainfall and runoff. The pre-calculated forms are linked to physical reality by the large set of hydrograph forms available which are selected by the user.

Thus, the model takes a large number of different hydrograph forms and rainfall inputs thereby creating a highly over-parameterised constrained linear model, in excess of 300 parameters. The model is then subjected to calibration/simplification using the lasso technique. Here, a λ parameter is selected by the user to determine the elimination pressure. That is, as λ increases the number of non-zero variables decreases by reducing the size of the parameters such that some parameters become zero. Even when the λ parameter = 0 and there is no elimination pressure some parameters will still move to zero, as they contribute best to the fit when set to zero. Since all of the parameters have been subjected to elimination pressure during the first round of calibration causing them to move towards zero, a second round of calibration is carried out to allow the parameters to adjust to best match the original calibration set, reducing the under-prediction bias. Any parameters which were forced to zero during the simplification will remain at zero. Any parameters which try to change sign will be eliminated.

Initially the model was run at $\lambda = 0$ which reduced the number of parameters from 300 to 45. The λ value was then increased incrementally to λ =2500 giving 9 parameters, λ =2750 giving 6 parameters, λ =3000 giving 4 parameters. The model parameter 'maximum hydrograph baselength' was set at 50 hours. While the maximum hydrograph baselength is generally not very important, it needs to be long relative to the length of the recessions in the recorded hydrograph. If the maximum hydrograph baselength is set too short, then the modelled hydrograph tail will fall to a constant baseflow after the number of hours set as the hydrograph baselength following the hydrograph peak. This is avoided by setting a longer baselength. Alternatively, this can be avoided by including a range of heavy-tailed distributions amongst the forms available for selection. A Gumbel scale parameter can also be set by the user, however, setting of the Gumbel scaling factor is thought to not be too important as the rainfall-runoff model has the ability to shuffle the Gumbel scale parameter during calibration

The Nash-Sutcliffe coefficient of observed vs. predicted inflows was used to observe validation fit.

6.5 Results

The rainfall-standardised model was initially run with no elimination pressure on the parameters, that is, λ was set to zero. This produced a model with 45 parameters, a significant reduction from the original 300 contender parameters. This means that many of the potential parameters did not have predictive ability and thus contributed best to fit when they were set to zero under standard calibration.

As anticipated, the number of parameters in the model decreased as elimination pressure, λ was increased (Figure 49). The elimination pressure was increased incrementally between λ =0 and λ =3500, when the number of parameters was reduced to zero. Parameter reduction was not found to occur linearly with increasing elimination pressure, rather, small ‘bumps’ or peaks are observed where the number of parameters increases temporarily with elimination pressure. Explanation of this non-linearity is beyond the scope of this study.

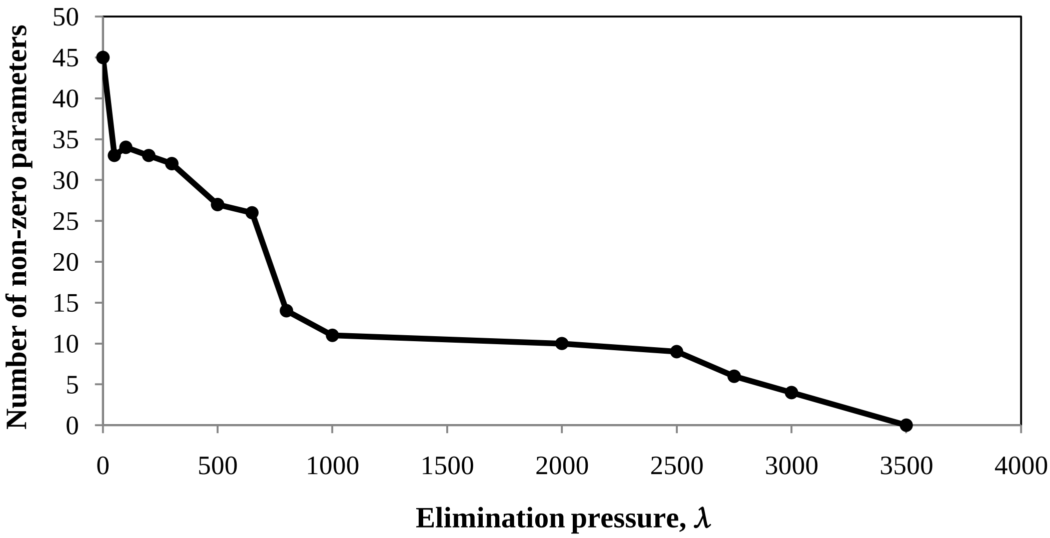

Figure 49: Number of parameters and elimination pressure showing a non-linear decrease in number of parameters with increasing elimination pressure.

A visual examination of time series plots of observed and predicted inflows was carried out to check where the model fits were best and worst. When the elimination pressure, λ, is set to zero the model appears to over-predict some low flow periods, particularly the tails of the hydrographs, and under-predicts peak flows quite severely (Figure 50, Figure 51).

As elimination pressure is increased and more model parameters are eliminated, calibration fit decreases. This can be observed visually through time series plots of observed and predicted flows. As elimination pressure is increased the peak flows are predicted more and more poorly, that is, they are more severely under-estimated and the baseflows are more severely over-estimated (Figure 52). Some peaks are predicted very poorly even when λ=0. This may be caused by increases in discharge which are not related to rainfall, such as snow melt or may be due to a temporary change in the relationship between rainfall and runoff, such as flashy hydrophobic behaviour. Hydrograph peaks are often difficult to predict using rainfall-runoff models due to the high spatial variability of heavy rainfall.

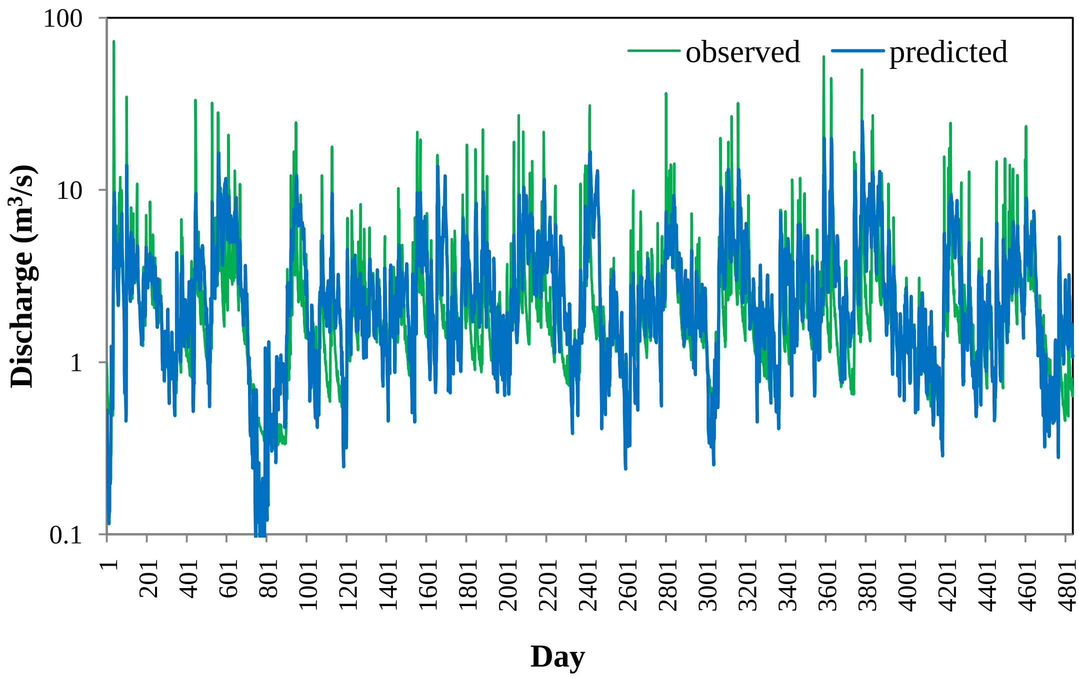

Figure 50: Observed flows (green) and predicted flows (blue) for the entire data set under no elimination pressure. This plot is for illustrative purposes only and is not a calibration set.

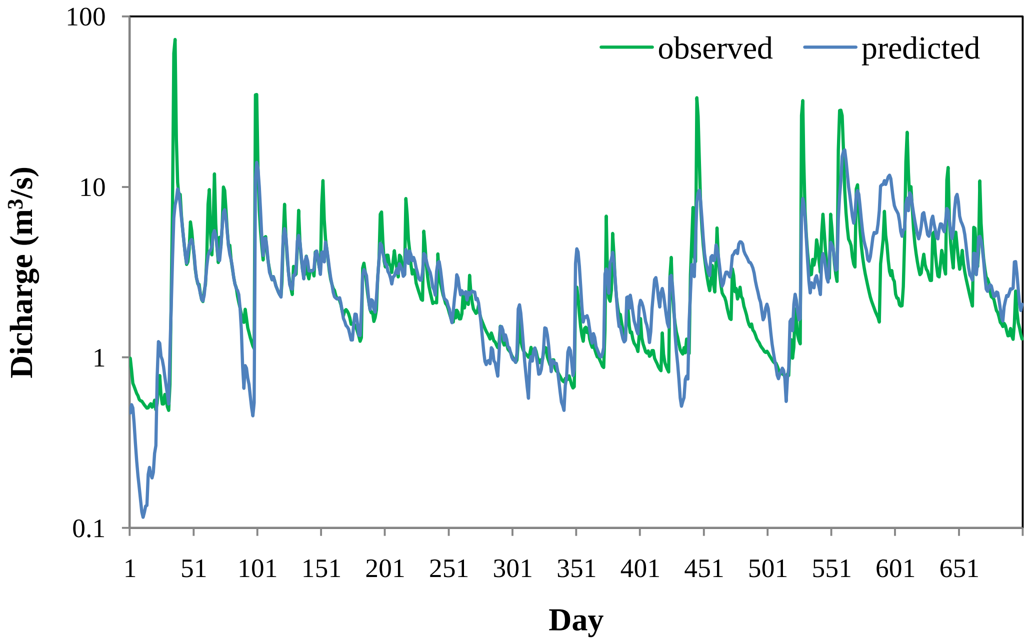

Figure 51: Observed flows (green) and predicted flows (blue) under elimination pressure, λ=0 for 700 days of data. This plot is for illustrative purposes only and is not a calibration set.

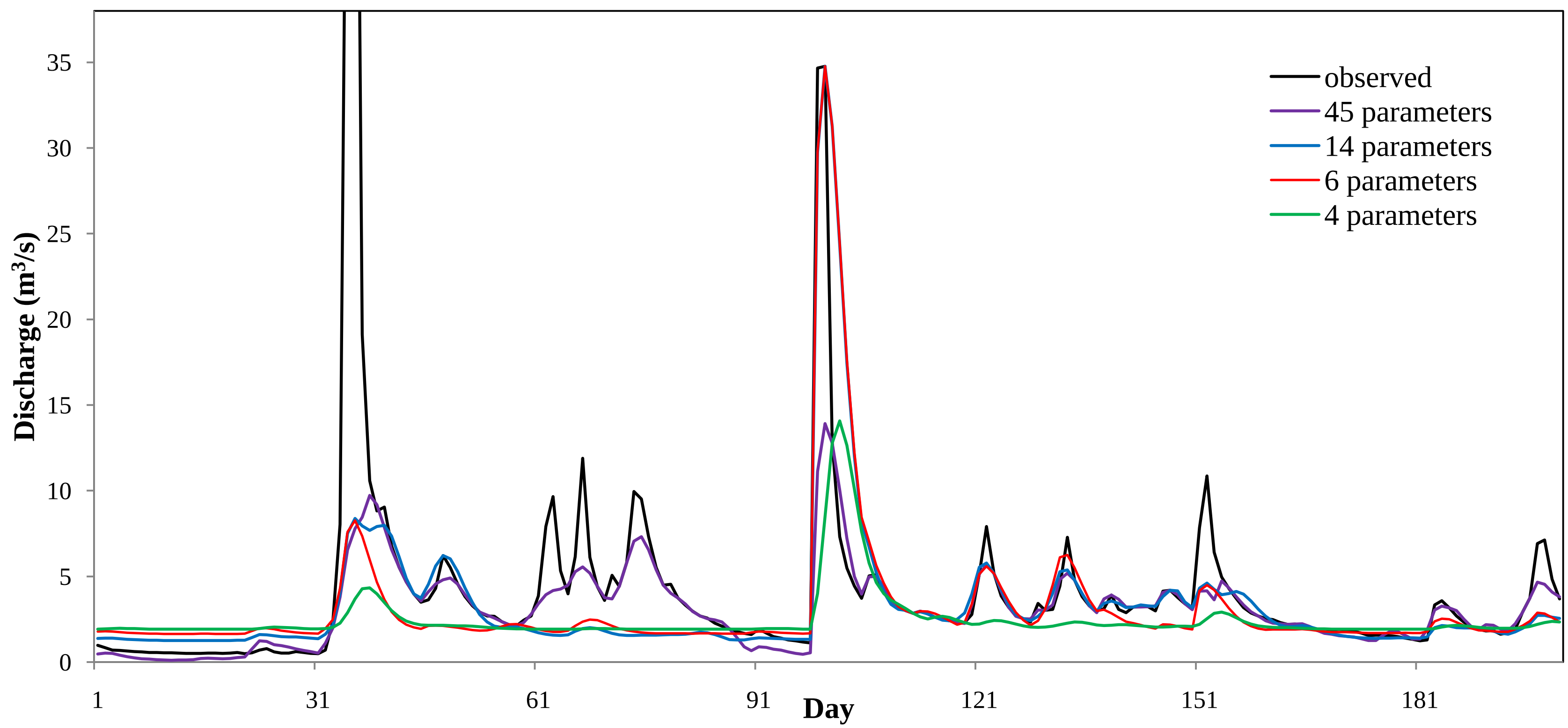

Figure 52: Observed dicharge (green) and predicted discharge of the Aniwaniwa Stream under a range of elimination pressures, resulting in 45, 14, 6 and 4 parameters. Showing the increased under-prediction of peak discharges and over prediction of low flows with increasing elimination pressure.

It was expected that calibration fit would increase with the number of parameters, but that validation fit would decrease with increasing number of parameters due to calibration over-fitting. However, the models with a large number of parameters had a reasonably high validation fit (Figure 53, 54). Relatively high validation fits were achieved with a large number of model parameters because the non-linear relation has been made discrete in effect by a large number of combinations. The validation fit then began to decline at approximately 35 parameters, but rose to a peak where the elimination pressure, λ was 800 with 14 parameters. Validation fit then plateaus although elimination pressure still increases and the number of variables decrease. The highest elimination pressure on this plateau is λ=2750, where there are 6 parameters. Validation fit then decreases rapidly with increasing elimination pressure. The validation peak at 14 parameters suggests that it is over-parameterised above this value.

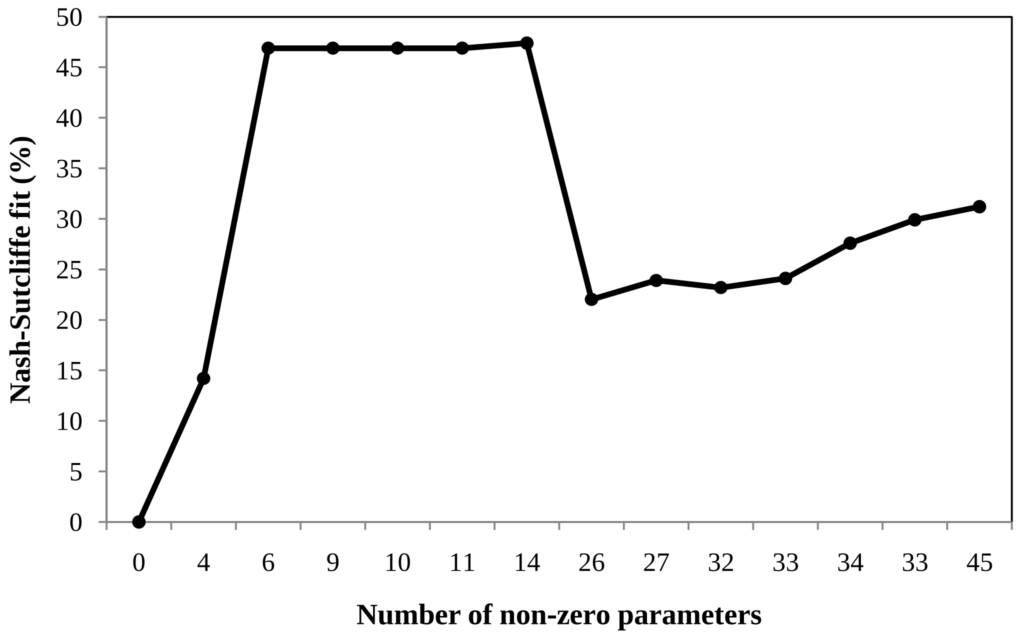

Figure 53: Number of non-zero model parameters and Nash-Sutcliffe validation fit (%).

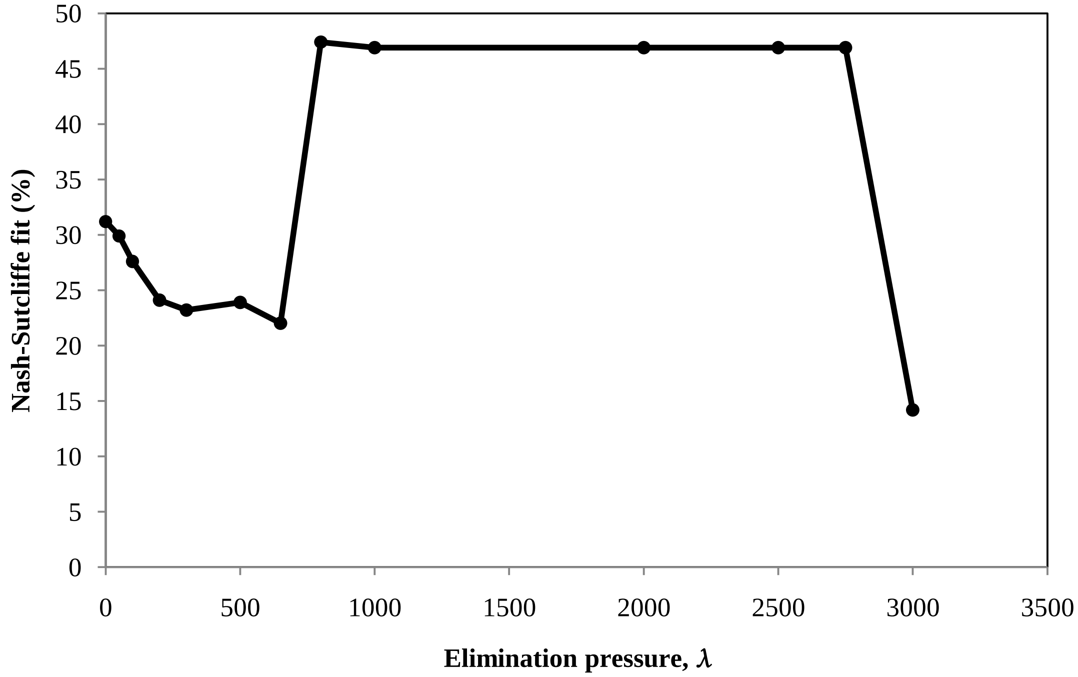

Figure 54: Validation fit as measured by the Nash-Sutcliffe coefficient (%) and elimination pressure, λ.

Validation fit can also be observed visually through scatterplots of observed and predicted discharge. The highest validation scores were obtained for λ=800 (14 parameters) and λ=2750 (6 parameters) using the Nash-Sutcliffe coefficient. However, quite a lot of scatter exists within the data (Figure 55). As observed discharge values increase, however, the model under-predicts peak flows quite severely suggesting that the prediction of the low-medium flows may be better than the validation score suggests. In the λ=2750 (6 parameters) under-prediction of peak flows is more severe than for λ=800 (14 parameters) (Figure 56). The peak flows become more poorly estimated as parameters are dropped from the model.

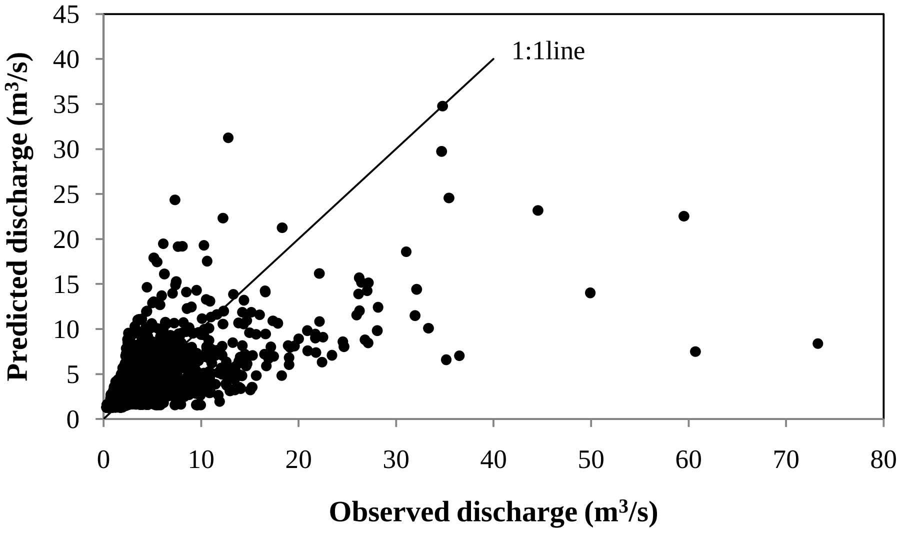

Figure 55: Scatterplot of observed vs. predicted discharge (m^3s^{-1}) and 1:1 line when λ=800 (14 parameters).

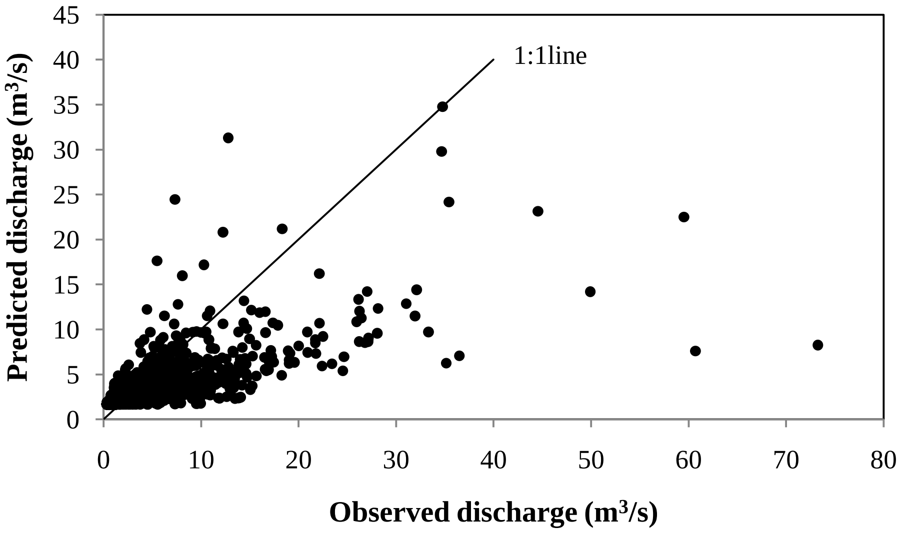

Figure 56: Scatterplot of observed vs. predicted discharge (m^3s^{-1}) and 1:1 line when λ=2750 (6 parameters).

6.6 Discussion

The finite mixture rainfall-runoff model used in this chapter was created in order to forecast the inflow of the Aniwaniwa Stream, which is in turn to be used to anticipate storage change of Lake Waikaremoana. The rainfall-runoff model is also used to demonstrate a use of the lasso technique as a model simplification tool in rainfall-runoff modelling.

Forecasting of Aniwaniwa Stream inflows into Lake Waikaremoana was of moderate success. Under all model variations tested peak flows were under-estimated. This may have been due to the model being composed of a limited number of hydrograph forms available as well as spatial variation of heavy rainfall. That is, there may not have been enough ‘flashy’ hydrographs among the pre-calculated forms. More steep hydrograph forms could be added to the model to improve the prediction of peak flows, however, this would be at the expense of model simplicity since the number of contender parameters would be significantly increased. The ability to predict peak flows decreased with increasing elimination pressure, the most likely reason for this is as elimination pressure was increased not enough hydrograph forms were available to match the well defined peaks resulting in more forms being selectively removed. It is important to note here however, that the focus of this study is on forecasting medium to low discharges.

In very few cases, the model failed to predict discharge peaks at all. There is the possibility that during these periods high discharges were a result of snow melt, or a situation where the soil moisture stores were full meaning that a much larger proportion of rainfall became quickflow as opposed to baseflow compared to the normal rainfall-runoff relationship in this catchment.

Low flows were generally predicted well under low λ values but predictions of low flows became increasingly poor as λ was increased. This occurred because as the elimination pressure was increased the model preferentially eliminated forms which did not contribute to peak flows. This lead to over-predictions of tail portions of the hydrographs and under-predictions of periods of little to no rainfall. The addition of heavy-tailed hydrograph forms may increase the prediction of lows and hydrograph tails, but as is the case with peak flows, this is at the expense of model simplicity.

Therefore, the model was of moderate success in terms of prediction ability. It predicted peak flows poorly, and low flows fairly well at moderate levels of elimination pressure. The model is thus of use for predicting low to medium flows of the Aniwaniwa Stream but of little use for predicting the magnitude of high flows. However, the model does have the ability to give indication of the timing of peak flows.

The use of the lasso technique of model simplification has been demonstrated in a finite mixture rainfall-runoff model. The model was found to be highly successful at parameter elimination, having the ability to reduce the number of model parameters from over 300 to 1 while still maintaining some prediction ability. Calibration without implicit elimination pressure, just a non-negative constraint reduced model parameters to 45. The lasso technique was successful at further eliminating parameters. The model was able to be used to locate the λ value where the best validation fit occurred. Thus meaning it is possible to use the model to detect where it is no longer over-parameterised. The best validation fit was obtained using an elimination pressure of 800 which produced a model with 14 parameters.

6.6.1 Limitations

As outlined in the literature review section of this chapter, in order to observe progression in hydrological modelling, modellers must aim to produce the simplest model which can fulfil its purpose with minimum uncertainty. In order to achieve this a number of conditions must be met, the model parameters must be identifiable, the model must not be over-parameterised, and the model must have the ability to fail among others. The model used in this chapter broadly meets the majority of these conditions.

It should be noted that the finite mixture rainfall-runoff model will always ‘fail’ in terms of parameter identifiability since the model is composed of many very similar pre-calculated hydrograph forms. Therefore, the model may select different hydrograph forms based on very small variations or errors in the data. Small errors in the data could mean the difference between a model parameter being small and positive, or being zero. However, the model can be deemed to have a consistent behaviour as long as the predicted forms do not differ greatly when calibration is carried out on the same rainfall data. Parameter identifiability is not as important here as it is in many models since any input rainfall data is summarised in a graphical form, as a hydrograph rather than as a physically meaningful parameter.

Krichner, 2006 suggested that attempting to model non-linear hydrological processes in a linear way may cause a model to be subject to great error and uncertainty. However, in this case, a pseudo-nonlinear method has been used such that nonlinear processes are pre-calculated to satisfy the requirement of the lasso technique of being a linear framework.

The model can be said to be successful at reducing over parameterisation. The model was reduced from 300 parameters to a situation where maximum validation fit occurred at 14 parameters. However, as with any rainfall-runoff model the model is also limited in that for a true forecast of river flows into the future forecasted rainfall would also be required.

6.7 Next-Day Forecasting

In the previous section of this chapter, a lasso-simplified finite mixture rainfall-runoff model was used to forecast daily inflows of the Aniwaniwa Stream into Lake Waikaremoana given the condition that rainfall data was available for the time period to be forecasted. In this section, a modified rainfall-runoff modelling methodology is developed to forecast 'next-day' Aniwaniwa Stream inflows in the absence of future rainfall data.

A 'next-day' inflow prediction is relevant for operational use at the Waikaremoana Power Scheme as a one day in advance water availability estimation will allow for more strategic bidding into the electricity market. Predicting only one day ahead removes the need for rainfall forecasting as may be the case if long term forecasting was carried out.

After obtaining a 'next-day' inflow forecast of the Aniwaniwa Stream the regression relation developed in Chapter 5 can then be used to scale Aniwaniwa Stream inflows to the entire Waikaremoana catchment such that net storage change of Lake Waikaremoana is estimated.

6.7.1 Method

An auto-recalibrating finite mixture rainfall-runoff model was run using COMSOL Script 1.2. The rainfall-runoff model is similar to the model mentioned earlier where a hydrograph is created in response to current and previous rainfall by selection of a combination of hydrograph forms of varying weight from a suite of pre-calculated forms. The model uses linear programming and a double calibration where the initial round of calibration makes use of the lasso, which applies an elimination pressure causing less descriptive variables to be forced towards zero. A second, standard round of calibration is then applied during which any variables which went to zero in the previous round of calibration remain set at zero and all remaining parameters are calibrated to fit the observed data. The auto-recalibrating model differs from the original model mentioned previously in that it makes one inflow prediction only following the calibration/simplification/calibration process –that of the 'next-day'. The model then auto-recalibrates moving down the calibration data by one line in order to predict inflow for the following day. The model is simplified from an initial state where it has in excess of 300 parameters. These parameters are all initially necessary to allow the model a wide range of possible hydrograph forms from which it may select the most descriptive parameters.

As in the model mentioned previously in this chapter, an elimination pressure is applied to allow for model simplification by forcing model parameters towards zero. In the auto-recalibrating model a different number of parameters are used for each individual prediction under the same elimination pressure, due to a different number of parameters being required to describe different parts of the hydrograph. For example, approximation of a hydrograph peak may require 5 hydrograph forms while the model may only require 3 hydrograph forms to approximate a low flow period under the same elimination pressure. In order to further allow for catchment wetness state and improve validation fit two new variables are introduced into the model which are used to apply an increased weight to more recent calibration data.

A number of model runs were carried out using various user selected variables. The 'best' result of these trials was selected by comparing the validation scores derived from the Nash-Sutcliffe model efficiency coefficient. Due to the relatively long computational time required to carry out the calibration/simplification process the model was initially run through 86 predictions. This was felt to be a sufficiently long period that the model would encounter a large enough variety of conditions to allow it to gain experience predicting both high and low flows. After the selection of the model settings with the best validation fit for the Aniwaniwa

Stream a small suite of much longer model runs were carried out in order to achieve an improved validation fit by increasing the models experience.

6.7.2 Results

The rainfall-runoff model was run under a range of elimination pressures, λ, from 0 to 3500. This was carried out in order to determine the magnitude of λ which produced the model with the highest validation fit as measured by the Nash-Sutcliffe model efficiency coefficient. As was the case with the original finite mixture rainfall-runoff model used earlier in this chapter, validation fit was relatively high during the initial model run under only non-negativity elimination pressure that is, $\lambda = 0$. As expected, even when no elimination pressure was applied many variables were eliminated from the model during calibration since these parameters contribute best to fit when they are set to zero thus reducing the maximum number of model parameters from 300 to 65 with an average of 52 parameters. The highest validation fit was achieved under an elimination pressure of λ =650 (14 parameters) (Figure 57).

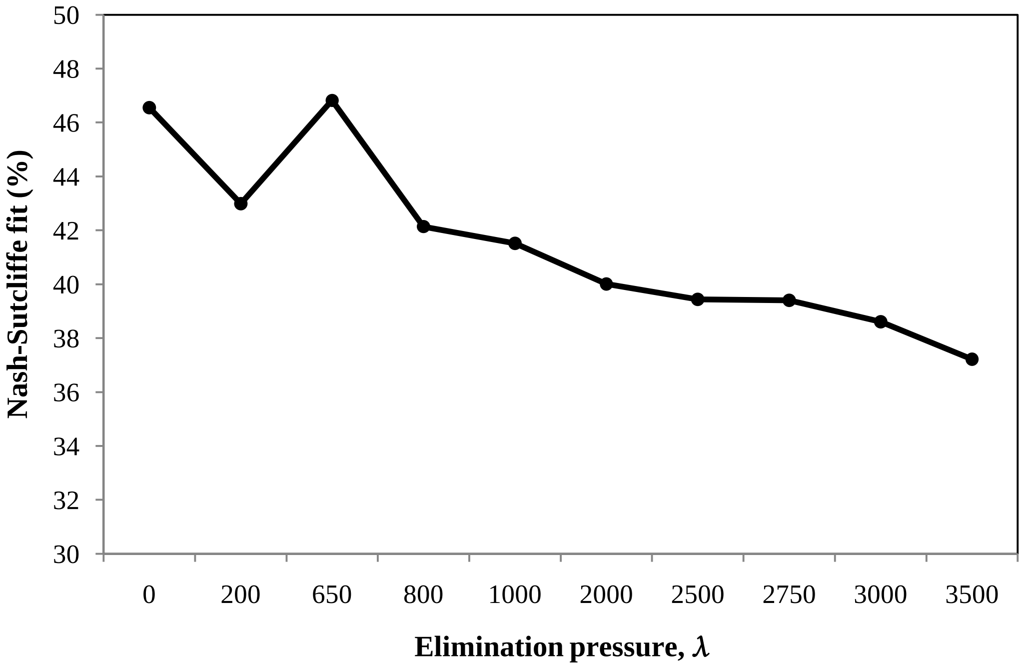

Figure 57: Elimination pressure, λ and validation fit as measured by the Nash-Sutcliffe coefficient showing peak validation fit occurring at $\lambda = 650$ (14 parameters).

The day-ahead nature of the rainfall-runoff model means that the model is re-calibrated prior to each prediction made. Therefore the number of parameters used to make each prediction may not be the same for a given set of user selected model parameters. The range of parameters for any given elimination pressure, λ fluctuates by up to 21 parameters at low values of λ, and the range generally decreases with increasing elimination pressure (Figure 58). As in the previous rainfall runoff model elimination pressure increases as the average number of parameters per model run decreases.

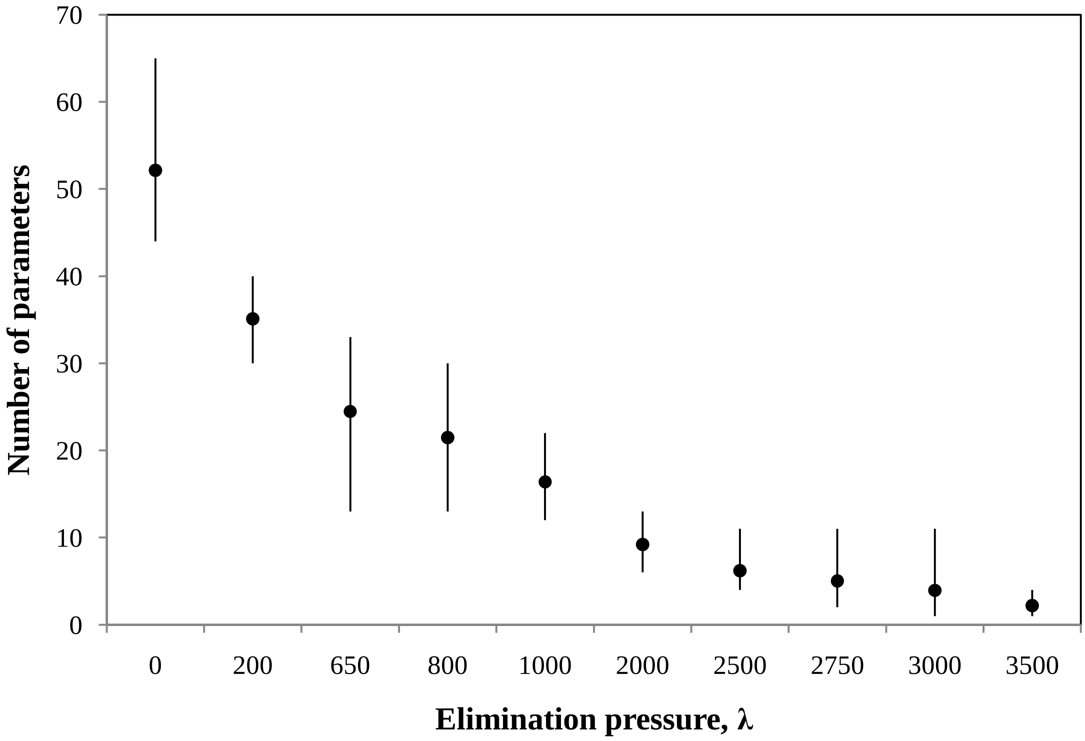

Figure 58: Elimination pressure, λ and number of parameters showing average (circle) and maximum and minimum (bar).

The highest validation fit is achieved using the λ = 650 (14 parameter) model as determined using the Nash-Sutcliffe efficiency. Time series plots of observed and predicted discharges were also used to compare the prediction success of different areas of the hydrograph between models with different numbers of parameters. All models were found to significantly under predict large peak flows. Time series plots of models with the two highest Nash-Sutcliffe validation fits (λ=650 and λ=2750) were compared. The 14 parameter model (λ=650) was found to significantly under-predict peak flows and slightly under-predict low flows while the parameter model (λ=2750) was found to under-predict both areas of the hydrograph to a greater extent (Figure 59).

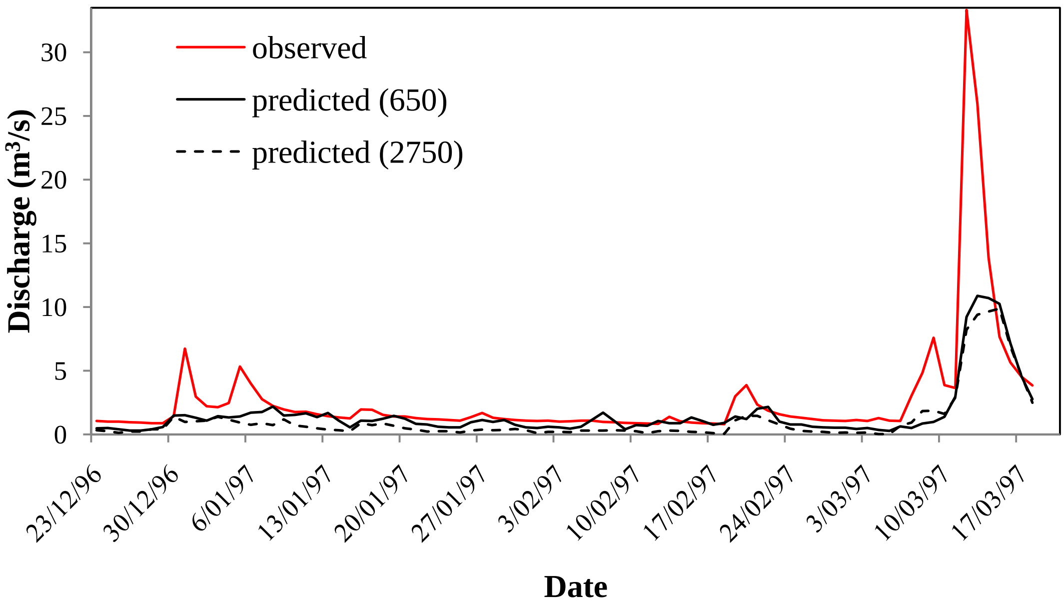

Figure 59: Time series plot of observed discharge of the Aniwaniwa Stream (red) and predicted discharges under elimination pressure of 650 with 14 parameters (black solid) and 2750 with 6 parameters (black dashed).

The auto-recalibrating model allows the user to adjust the weight of more recent environmental input data as a proxy for catchment wetness state. As expected, both validation fit and the average number of parameters per prediction increased slightly as increased weight was put on more recent environmental input data. In the λ =650 model validation fit decreased when weight was increased to 20 times due to an increased lag in the predicted hydrograph. The validation fit then increased at a weight of 40 due to a less severe under-prediction of peak flows and a reduced lag. Under an elimination pressure of 2750 the model validation fit rose steadily with increasing weight without experiencing decreases in validation fit as was observed in the λ = 650 model.

Similarly to the weight variable, increasing the number of days for which an increased weighting is applied results in an increased validation fit. A maximum validation fit is achieved at 30 days, beyond which validation fit is decreased in both the λ = 650 and λ = 2750 models.

6.7.3 Discussion

The model which gave the highest validation fit had an elimination pressure of 650, maximum hydrograph baselength of 50 hours, an increased weighting of 40 times for the most recent 30 days of data and a Gumbel scaling factor of 2. This model has a Nash-Sutcliffe efficiency of 52.3%.

As elimination pressure was increased, the number of model parameters were reduced, and in general, validation fit was decreased. However, validation fit increased to local maxima at an elimination pressure of 650, and a smaller maximum at an elimination pressure of 2750. Validation fit at λ =650 (46.8%) with an average 14 parameters per prediction was greater than the validation fit when no elimination pressure was applied (44.5%) where there was an average of 45 parameters. It is likely that the reduction in parameters resulted in an increased validation fit as the model was over parameterised at greater than 14 parameters. The small peak in validation fit at λ = 2750 may be due to the elimination of less informative parameters which contribute more to uncertainty within the model than to fit. As maximum validation fit was achieved at an elimination pressure greater than zero, the lasso technique can be seen as successful in simplifying the model such that an improved validation fit occurs.

The increased weighting of more recent rainfall and river flow inputs can be considered to be a proxy variable for catchment wetness state. The length of the increased weighting was found to be important as validation fit decreased as time was increased past 30 days. 30 days was the optimal time for increased weight in both the λ =650 and λ =2750 plots supporting the theory that length and magnitude of the weight variable can be considered as a proxy for catchment wetness state.

6.8 Model Evaluation

The auto re-calibrating rainfall-runoff model was expected to perform much better than the original rainfall-runoff model in terms of validation fit due to the addition of the weight parameter allowing for catchment wetness state. However, the auto re-calibrating rainfall-runoff model performed to a similar level as the original rainfall-runoff model, achieving validation fits of up to 52.3%.

The highest validation for the original rainfall-runoff model was achieved under an elimination pressure of 800 and a maximum hydrograph baselength of 40 hours with a validation fit of 50.7%. The highest validation fits achieved for the auto re-calibrating rainfall-runoff model occurred at an elimination pressure of 650 with a weight of 40. A validation fit of 52.3% was achieved (Table 7). It is interesting to note that the highest validation fit was achieved with 14 parameters in both the original and auto-recalibrating rainfall-runoff models.

Table 7: Validation fits and model parameters of highest scoring models using the original rainfall-runoff model and the auto re-calibrating rainfall-runoff model.

Model	λ	Weight	Validation fit (%)
Original	2750	N/A	47.0
	800	N/A	50.7
Auto re-calibrating	2750	10	46.8
	650	40	52.3

Both models give fairly low validation fits, suggesting that they may not be suitable for operational use. Validation fit of peak flows has been observed to be very low through timeseries plots of observed and predicted inflows due to severe under-estimation. While prediction of low flows is also under-estimated at high elimination pressures time series plots suggest that the validation fit may be higher if peak flows were removed from the data. It is likely that poor prediction of peak flows masks the difference in non-peak validation fit between the original and auto re-calibrating rainfall-runoff models.

Both the original and modified rainfall-runoff models can be considered to be somewhat successful in terms of model simplification ability as the validation fits of the models were improved at elimination pressures greater than zero. Thus, the use of the lasso technique of model simplification has meant that the model was both simplified and its fit was improved. An approach which may be used to improve the validation fits of both the original and auto-recalibrating models may be to create a wider range of available hydrograph forms. The model currently only uses 25 possible hydrograph forms. This could be increased to 50 forms. For example, hydrograph forms which are flashier may allow for better prediction of hydrograph peaks and a range of heavy tailed distributions may allow for better prediction of hydrograph tails. However, this would also mean that there would be a much larger initial number of model parameters which would have to be removed from the model using the lasso simplification. Therefore there is a trade off between model simplification and fitting to data.

6.9 Conclusion

The lasso methodology was applied to two finite mixture rainfall-runoff models in order to forecast inflows into the Aniwaniwa Stream which can then be usefully extrapolated using the regression relation developed in Chapter 5 to give net Lake Waikaremoana storage change. Rainfall-runoff modelling was partially successful, the original rainfall-runoff model was able to predict inflows with some accuracy at low to medium flows with 14 parameters. The auto-recalibrating finite mixture rainfall-runoff model achieved similar validation fits as the original rainfall-runoff model, with a maximum validation fit of 52.3% with 14 parameters.

The problem of over-complexity of hydrological models is identified and the notion which is commonly asserted in the literature that the future of hydrological models is not in more and more complex models with more and more parameters but in simple models which predict well is addressed. This is a driving factor in the use of the lasso methodology as a technique of model simplification.

While the method used has limitations in that parameter identifiability may be difficult, the methodology is concluded to be successful in reducing model parameters to tackle the problem of over-parameterisation of hydrological models which have been previously formulated in a linear context. The use of the lasso methodology allowed for the number of model parameters to be reduced beyond that of standard calibration such that an optimal validation result at a reduced number of parameters (14) was found which may otherwise have been unidentified.

Chapter 7 –Multiple Regression for Forecasting Aniwaniwa Stream Inflows into Lake Waikaremoana.

7.1 Introduction

As a simpler alternative to the finite mixture rainfall-runoff models presented in Chapter 6, a multiple regression technique is applied in order to forecast inflows of the Aniwaniwa Stream into Lake Waikaremoana to allow estimation of net lake inflows. A regression technique may be more suitable for operational use at the Waikaremoana Power Scheme than the finite mixture rainfall-runoff model due to lower computational demands in terms of both software requirements and computational time. There is also the possibility that a regression approach may produce next-day inflow forecasts which are at least as accurate as the rainfall-runoff models used in the previous chapter. Use of multiple regression also satisfies an underlying theme in this thesis, that modelling of a hydrological system for practical application should be no more complex than necessary.

7.2 Method –Multiple Regression

Seventeen years (1992-2009) of Aniwaniwa Stream daily discharge data, and Aniwaniwa rainfall data was available for use in a multiple regression. However, the discharge record was complete for only 14 years, therefore discharge and rainfall data for the period (1995-2009) was used. As the rainfall data was not a complete record, rainfall readings from a nearby raingauge, the Nga Tuhoe raingauge was used to patch in missing rainfall data.

The data set was split into a 9 year calibration (1995-2004) and 5 year validation set (2005-2009). These time periods were chosen for the calibration and validation sets as the validation set was chosen to contain the largest peak flow to give an indication of the models' ability at predicting peaks beyond its experience (Figure 60).

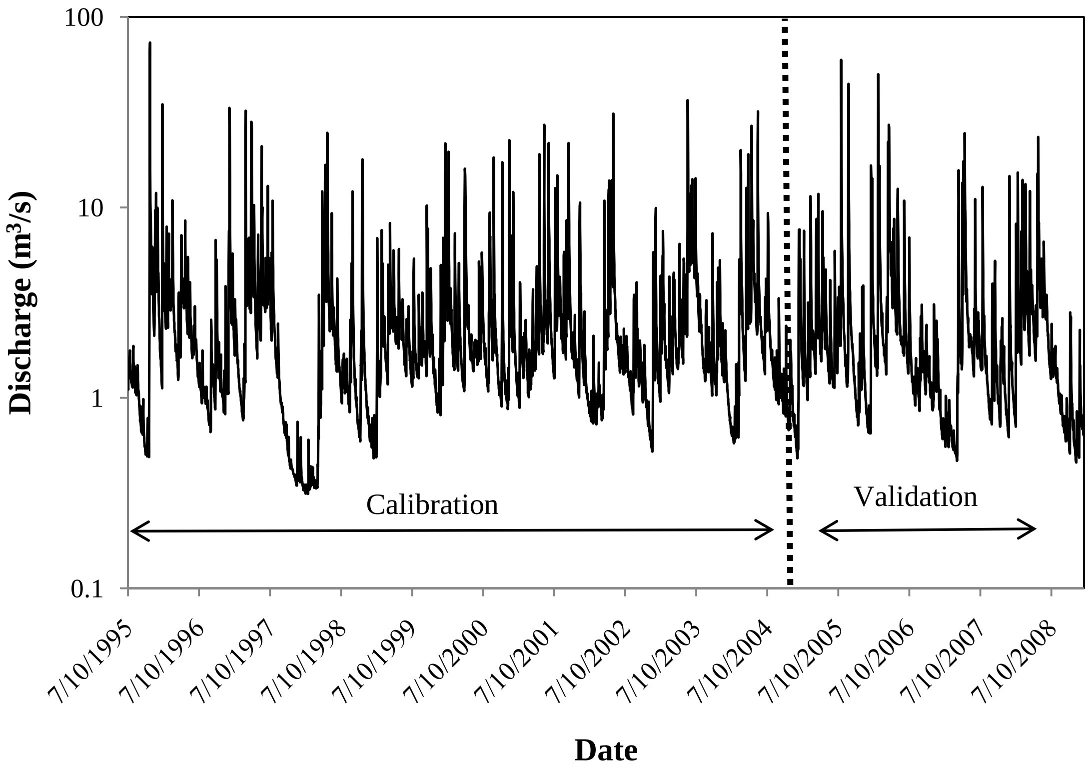

Figure 60: Time series plot of Aniwaniwa Stream inflows showing calibration and validation periods. Note logarithmic vertical scale.

A suite of independent variables were selected for use in multiple regression against the dependent variable of 'next-day' inflow. These independent variables were current day inflows (T_Q); previous day inflows (Y_Q); current day rainfall (T_{rain}); previous day rainfall (Y_{rain}); next-day rainfall (ND_{rain}); the differences between current day and previous day rainfall and discharge ($T\text{-}Y_Q$, $T\text{-}Y_{rain}$); and between next day and current day rainfall ($ND\text{-}T_{rain}$). 38 combinations of these variables were used in a suite of single or multiple regressions using the calibration data set. Of the 38 combinations the 10 results which gave the lowest standard error and the highest R^2 /multiple R^2 values in the calibration set were selected. Observed Aniwaniwa inflows and inflows predicted using the various regression equations were compared using the Nash-Sutcliffe model efficiency coefficient.

7.3 Results

Of the 38 combinations of independent variables all gave a **p** value of less than 0.001 suggesting that the correlation with the dependent variable is statistically significant to the 99% level (Table 8). In all but 5 cases, all of the independent variables used were also statistically significant. The regression equations which gave the 10 lowest standard error values, the 10 highest R^2/multiple R^2 values and where all independent variables were significant were selected for further analysis and the remaining regressions were discarded (Table 9).

The regression coefficients of the 'top three' regression equations as determined by comparing calibration fits were then used to create regression equations from which 'next-day' predictions of Aniwaniwa Stream inflows were calculated (Table 10).

Of the 10 regression equations, 6 gave negative predictions of Aniwaniwa discharge due to either a negative regression co-efficient or negative input values in the case of $T\text{-}Y_Q$ and $T\text{-}Y_{rain}$ where previous day discharge/rainfall is greater than current day discharge/rainfall respectively. A rule was therefore applied which stated that if the model gives a negative discharge prediction, then the prediction is set to zero as negative discharges are considered hydrologically incorrect.

Table 8: Suite of independent variables used in single/multiple regressions with the dependent variable ND_Q in calibration data set.

Dependent	R^2	mR^2	p	Standard error	Intercept
T_Q	0.54	0.73	<0.001	2.4	0.699
T_{rain}	0.41	0.64	<0.001	2.73	1.69
ND_{rain}	0.22	0.47	<0.001	3.11	1.93
T_{rain}, ND_{rain}	0.49	0.7	<0.001	2.52	1.37
$T\text{-}Y_{rain}$	0.04	0.19	<0.001	3.47	2.64
$T\text{-}Y_Q$	0.18	0.42	<0.001	3.21	2.64
T_{rain}, T_Q	0.65	0.8	<0.001	2.1	0.611
T_Q, Y_Q	0.57	0.75	<0.001	2.33	0.87
T_Q, Y_{rain}	0.54	0.74	<0.001	2.39	0.681
T_Q, ND_{rain}	0.69	0.83	<0.001	1.96	0.23
Y_{rain}, T_{rain}	0.46	0.68	<0.001	2.6	1.44

T_Q, Y_Q,T_{rain}, Y_{rain}	0.65	0.81	<0.001	2.08	0.642
T_Q, T-Y_{rain}	0.63	0.79	<0.001	2.16	0.592
T_Q, T-ND_{rain}	0.55	0.74	<0.001	2.38	0.622
T_{rain}, ND_{rain}	0.49	0.76	<0.001	2.52	1.37
T_Q, Y_Q, T_{rain}	0.65	0.81	<0.001	2.1	0.662
T_Q, Y_Q, T_{rain}, Y_{rain}	0.65	0.81	<0.001	2.1	0.643
T_Q, Y_Q, T_{rain}, Y_{rain}, ND_{rain}	0.75	0.87	<0.001	1.76	0.281
T_Q, T_{rain}, Y_{rain}, ND_{rain}	0.75	0.87	<0.001	1.77	0.23
T_Q, Y_{rain}, ND_{rain},	0.69	0.84	<0.001	1.94	0.21
T_Q, ND_{rain}, T-Y_Q	0.71	0.84	<0.001	1.9	0.38
T_Q, T-Y_Q, T-Y_{rain}	0.63	0.8	<0.001	2.15	0.69
T_Q, T-Y_{rain}	0.57	0.75	<0.001	2.33	0.87
T_Q, T-Y_{rain}, T-ND_{rain}	0.68	0.82	<0.001	2.01	0.35
Y_Q	0.18	0.43	<0.001	3.2	1.51
Y_Q, T_{rain}	0.53	0.73	<0.001	2.42	0.80
Y_Q, T_{rain}, Y_{rain}	0.54	0.73	<0.001	2.4	0.81
Y_Q, T_{rain}, Y_{rain}, ND_{rain}	0.63	0.79	<0.001	2.19	0.46
Y_Q, Y_{rain}	0.22	0.49	<0.001	3.09	1.45
Y_Q, T-Y_Q	0.56	0.75	<0.001	2.33	0.87
T_{rain}, Y_{rain}	0.46	0.75	<0.001	2.6	1.44
T_{rain}, Y_{rain}, ND_{rain}	0.55	0.74	<0.001	2.37	1.10
T_{rain}, Y_{rain}, ND_{rain}, T-Y_Q	0.56	0.75	<0.001	2.35	1.24
T_{rain}, T-Y_Q	0.42	0.65	<0.001	2.69	1.79
Y_{rain}	0.17	0.41	<0.001	3.07	2.02
Y_{rain}, T-Y_Q	0.28	0.53	<0.001	2.93	2.13
ND_{rain}, T-Y_Q	0.35	0.6	<0.001	2.84	2.00
ND-T_{rain}	0.02	0.14	<0.001	3.504	2.64

Table 9: 'Top 10' results selected on the basis of lowest standard error, highest R^2/multiple R^2 and where all independent variables are significant.

Dependent	R^2	mR^2	p	Standard error	intercept
T_Q, Y_Q, T_{rain}, Y_{rain}, ND_{rain}	0.75	0.87	<0.001	1.76	0.28
T_Q, T_{rain}, Y_{rain}, ND_{rain}	0.75	0.87	<0.001	1.77	0.23
T_Q, *Y_{rain}, ND_{rain},	0.69	0.84	<0.001	1.94	0.21
T_Q, ND_{rain}, T-Y_Q	0.71	0.84	<0.001	1.9	0.38
T_Q, ND_{rain}	0.69	0.83	<0.001	1.96	0.23

T_Q, $T\text{-}Y_{rain}$, $T\text{-}ND_{rain}$	0.68	0.82	<0.001	2.01	0.34
T_Q, Y_Q, T_{rain}, Y_{rain}	0.65	0.81	<0.001	2.08	0.64
T_{rain}, T_Q	0.65	0.8	<0.001	2.1	0.61
T_Q, Y_Q, T_{rain}	0.65	0.81	<0.001	2.1	0.66
T_Q, Y_Q, T_{rain}, Y_{rain}	0.65	0.81	<0.001	2.1	0.64

The forecasts of the 'top 10' regression equations were compared to observed discharges of the Aniwaniwa Stream for the validation period using the Nash-Sutcliffe model efficiency coefficient. Three of these regression equations gave high calibration fits (Table 11).

Table 10: Regression coefficients and intercept of the top 3 regression equations.

Equation #	Parameters	Regression coefficients	Intercept
1	ND_{rain}	0.097	0.376
	T_Q	0.642	
	$T\text{-}Y_Q$	0.187	
2	T_Q	0.690	0.230
	ND_{rain}	0.101	
3	T_{rain}	0.095	0.611
	T_Q	0.558	

Table 11: Nash-Sutcliffe coefficient for the top 3 calibration fits results.

Dependent	Calibration fit	Validation fit
T_Q, ND_{rain}, $T\text{-}Y_Q$	71.02	69.48
T_Q, ND_{rain}	69.43	69.42
T_{rain}, T_Q	64.69	66.16

From inspection of the Nash-Sutcliffe coefficients equation 1 gives a slightly better forecast of next day inflows, followed by equation 2. However, equation 3 is used for further analysis as the reliance of equations 1 & 2 on next day rainfall may introduce error (*see 7.4 Discussion*). It is encouraging that the validation fits of all three of the regression equations are similar to, or higher than the calibration fits.

Inspection of scatterplots of observed and predicted discharges for calibration and validation of regression equation 3 shows that the model under-predicts peak discharges (Figures 61 & 62). This is shown by the large number of points which occupy space below the 1:1 line.

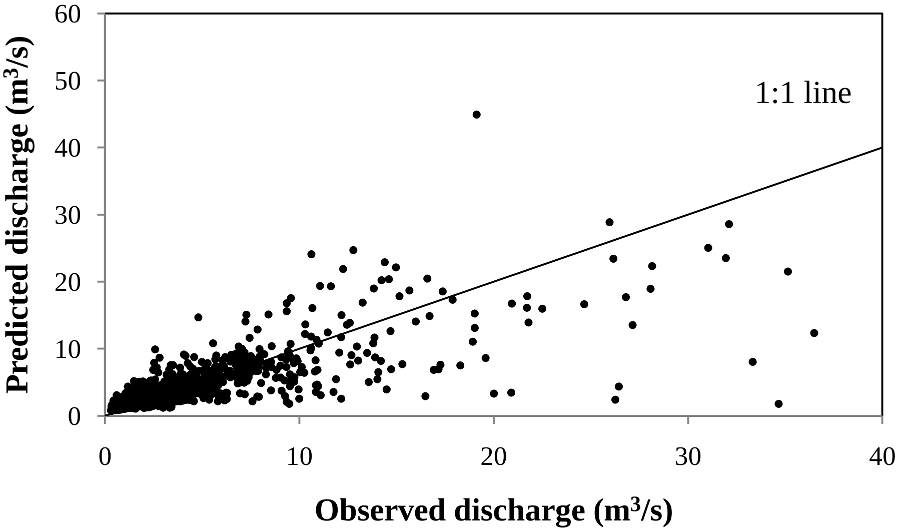

Figure 61: Scatterplot of observed and predicted calibration data for regression equation 3 showing under-prediction of peak flows.

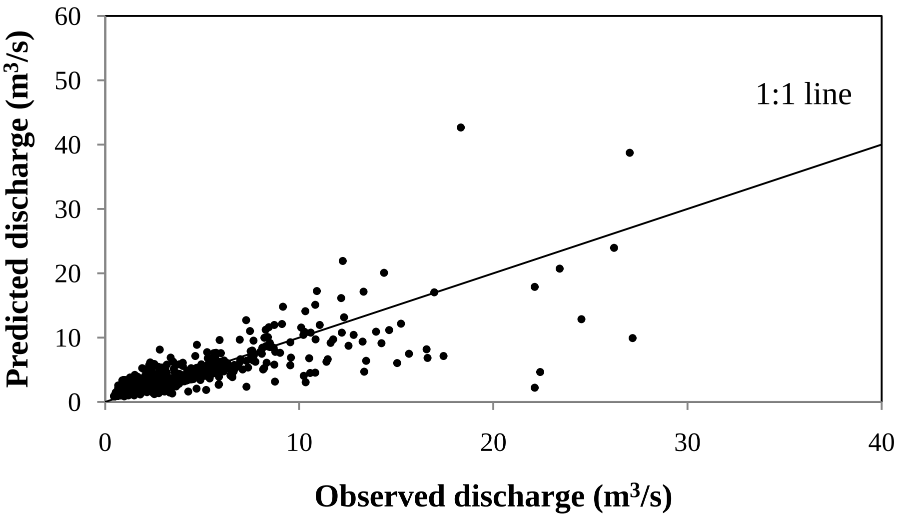

Figure 62: Scatterplot of observed and predicted validation data for regression equation 3 showing under-prediction of peak flows.

A time series plot of observed and predicted inflows further shows that while the model predicts inflows reasonably well, large hydrograph peaks are under-predicted. The model also predicts some small hydrograph peaks in areas where no peak occurs in the observed data as a result of the model responding to minor rainfall inputs which do not impact the following days discharge (Figure 63).

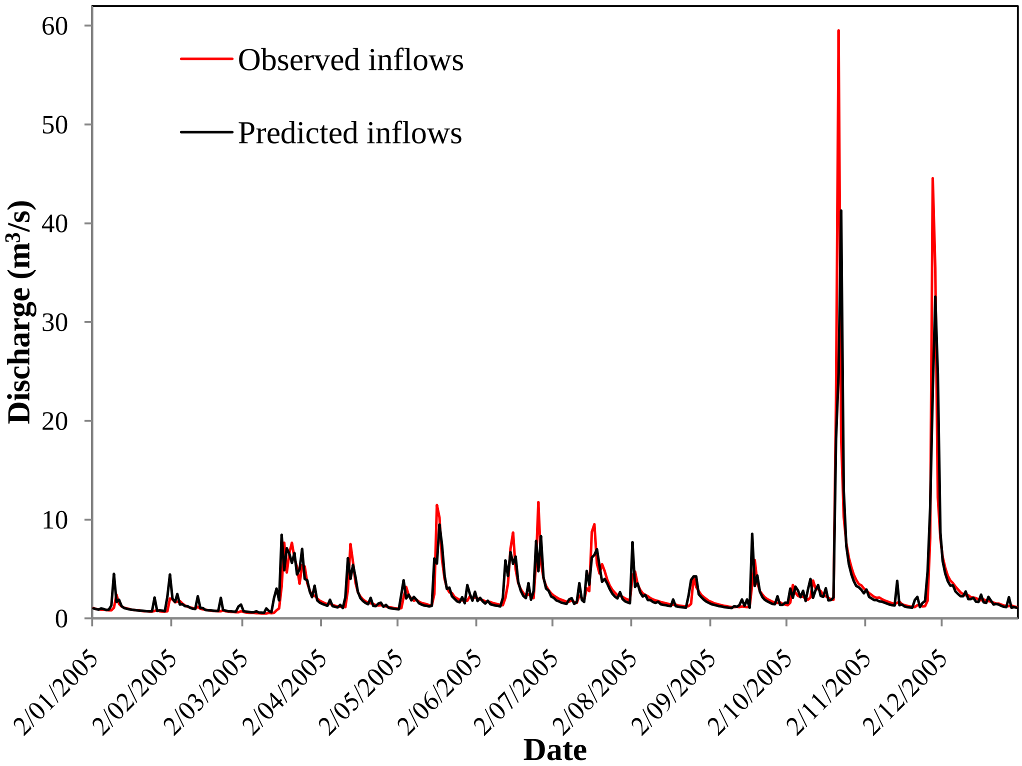

Figure 63: Time series plot of observed and predicted discharge using validation data of regression equation 3.

It was shown in Chapter 6 that the rainfall/runoff ratio varied seasonally in the Waikaremoana catchment, therefore a seasonal regression analysis was carried out using the independent variables of regression equation 3 (Current day rainfall, current day discharge). However, higher calibration and validation fits were in fact achieved using the full data record (Table 12). It is possible that seasonal data may not apply as large discharges may have a dominating effect on the means of seasonal discharges.

Table 12: Nash-Sutcliffe calibration and validation fit for each season using independent variables of current day rainfall and discharge.

Season	Calibration fit	Validation fit
Summer	34.3	50.5
Autumn	35.7	32.2
Winter	52.9	55.9
Spring	53.6	30.4

7.4 Discussion

Regression equation 3, which had independent variables of T_{rain} and T_Q was selected as the most appropriate for all year operational use at the Waikaremoana Power Scheme despite regression equations 1 and 2 having higher validation fits. Regression equations 1 and 2 both utilise 'next-day' rainfall as independent variables and would therefore require rainfall forecasts for operational use. While day-ahead rainfall can be forecasted, error associated with rainfall forecasting would introduce further error into the inflow model resulting in lower validation fits. As the Nash-Sutcliffe coefficient of regression equation 3 is not much lower than regression equations 1 and 2 it is suggested that regression equation 3 will be less error prone when applied.

Regression equation 3 predicts low to medium flows reasonably well, while peak flows are under-predicted. It is likely that this under-prediction is caused by only having the current day rainfall information since heavy future rainfalls are not accounted for. This is supported by the fact that hydrograph peaks are under-predicted less severely when regression equation 2 is applied (Figure 64).

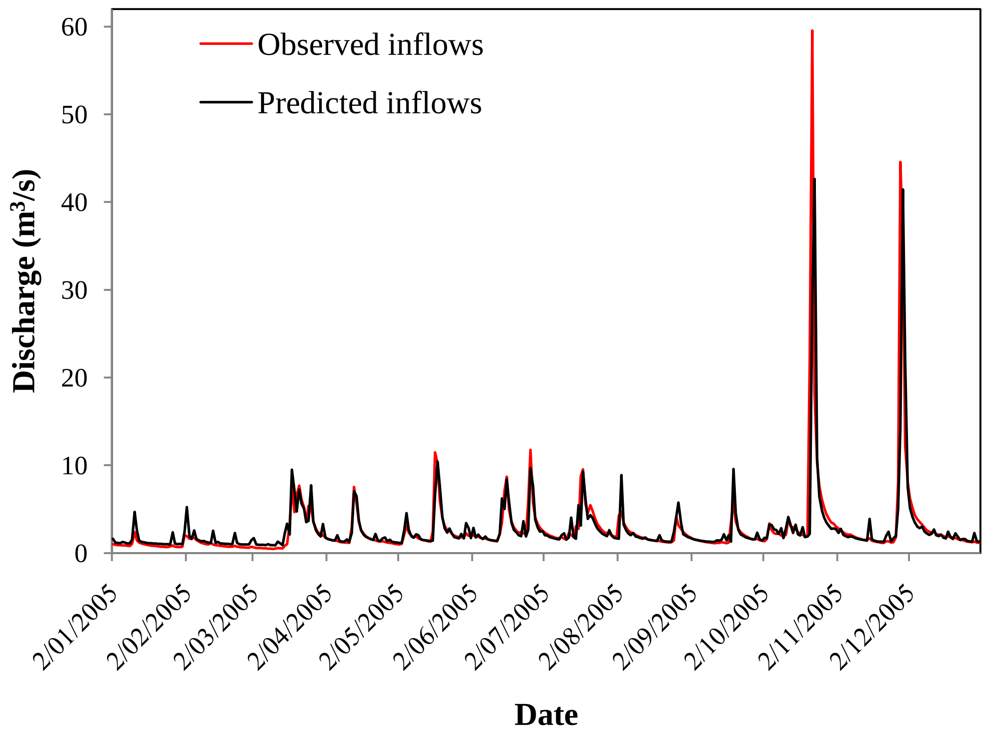

Figure 64: Time series validation plot of observed and predicted discharges from regression equation 2.

The prediction of some small hydrograph peaks which are not observed in the discharge record may be the result of the model translating some small current day rainfalls into hydrograph peaks which do not actually affect next-day discharge. These small hydrograph peaks may also arise as a result of a lack of catchment wetness state information such that the model may predict hydrograph peaks as the result of small rainfalls during dry periods which is reality may contribute to replenishing soil moisture stores or subject to high evaporation rates.

7.5 Conclusion

A multiple regression technique has been applied in order to forecast next-day Aniwaniwa Stream inflows. Of a possible 38 combinations of various independent variables with the dependent variable of next-day inflows, three regression equations were generated which had Nash-Sutcliffe validation fits within the range of 66.2 - 69.5. The two highest calibration fits obtained both utilised next-day rainfall as independent variables. Use of next-day rainfall as a coefficient in practical use is not desirable due to error associated with rainfall forecasting. The third highest calibration fit was achieved using independent variables of current day discharge and current day rainfall. The third regression equation was thus considered the most suitable for practical application at the Waikaremoana Power Scheme.

Chapter 8 - Comparison of Modelling Techniques

8.1 Introduction

Three hydrological modelling techniques were evaluated in this thesis in order to forecast the inflow of the Aniwaniwa Stream into Lake Waikaremoana. The best of each of these methods can then be used to extrapolate net storage change of Lake Waikaremoana using a regression derived inflow scaling factor (Chapter 5). The three modelling techniques are finite mixture rainfall-runoff model (Chapter 6), an auto-recalibrating finite mixture rainfall-runoff model for next-day prediction (Chapter 6) and multiple regression for next day inflows (Chapter 7). The aim of this chapter is to compare the results of these three modelling techniques in order to:

1. determine which technique preformed the best in terms of the most accurate forecasts.
2. determine which technique is most suitable in terms of both practicality and prediction ability for operational use at the Waikaremoana Power Scheme.

8.2 Comparison of Modelling Techniques

The 'best' model developed using each of the three modelling techniques applied in this thesis were compared. The 'best' model was considered to be the model which gave the highest validation fit as measured by the Nash-Sutcliffe model efficiency coefficient. Validation fit was compared using two separate data sets. Initially the Nash-Sutcliffe coefficient was calculated for each model using the validation data set of that model (Table 13). However, as the validation data sets for each model are not identical such that they do not all cover the same time period as a result of different input and output requirements the Nash-Sutcliffe coefficient of the overlapping region between the three validation sets was also calculated. This ensured that comparison between the three models was fair as each model would be required to forecast the same observed data set (Table 14).

The multiple regression technique gives the highest validation score when compared to the two rainfall-runoff modelling techniques using the Nash-Sutcliffe coefficient. This was followed by the finite mixture rainfall-runoff model forecasts and finally by the looping finite mixture model (Table 13). The multiple regression model also outperforms both finite mixture rainfall-runoff models when the overlapping region of validation data is compared (Table 14).

Table 13: Validation scores for 'best' result from each model.

Model	Nash-Sutcliffe coefficient
Original rainfall-runoff model	52.2
Auto-recalibrating rainfall-runoff model	47.3
Multiple regression model	61.5

Table 14: Validation scores using only the overlapping region of the validation data.

Model	Nash-Sutcliffe coefficient
Original rainfall-runoff model	53.4
Auto-recalibrating rainfall-runoff model	47.9
Multiple regression model	59.7

A time series plot of observed Aniwaniwa inflows and predicted inflows for each of the three models is compared in order to identify areas where one model outperforms another (Figure 65). All of the models were found to under-predict very large peak flows. However, the multiple regression model under-predicts the least, followed by the original rainfall-runoff model then the auto-recalibrating rainfall-runoff model.

In some areas medium sized peaks are predicted by the multiple regression model which translate to small peaks or do not exist in observed data. The auto-recalibrating rainfall-runoff model under-predict medium sized peaks most severely of all the models, while the multiple regression model tended to slightly over predict medium sized peaks. Low flow periods are over-predicted by the original rainfall-runoff model, and under predicted by the auto-recalibrating rainfall-runoff model but are predicted well by the multiple regression model.

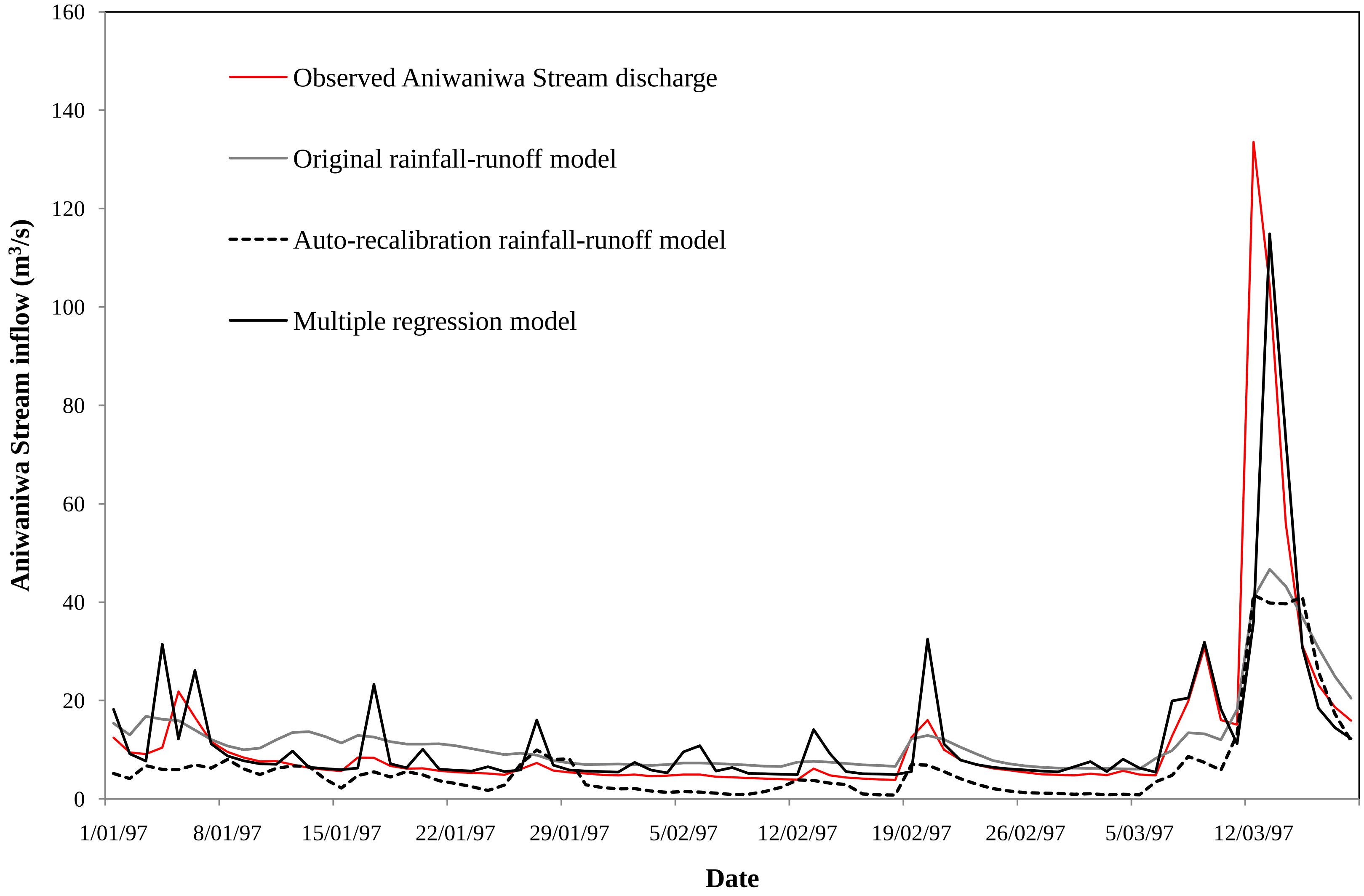

Figure 65: Representative example time series plot of observed Aniwaniwa Stream inflows and predicted inflows for each of the three modelling techniques.

The three models used in this study were also compared by scaling up the predicted inflows of the Aniwaniwa Stream to net inflows into Lake Waikaremoana using the simple linear regression equation developed in Chapter 5. The models were also compared to both observed Aniwaniwa Stream data scaled using the regression relation and lake volume change data derived from the lake level record (Figure 66).

The comparison shows a similar pattern to when comparing the results of the Aniwaniwa forecasts and discharges, where peak flows are under-predicted. It follows that large increases in lake volume are also under-predicted. Under-prediction of peak flows is likely to be in large part a consequence of the high spatial variation of heavy rainfalls. This under-prediction problem further compounded in storage change modelling as the regression relation of Chapter 5 holds only under low flow conditions.

It is noted that in some cases prediction of an increase in lake storage proceeds actual storage increase, while the shape of the increase in time series is approximated well. This may also be due to spatial variation of rainfall representing rainfall moving across the catchment east to west or south to north such that the Aniwaniwa Stream is affected by rainfall earlier than the rest of the catchment.

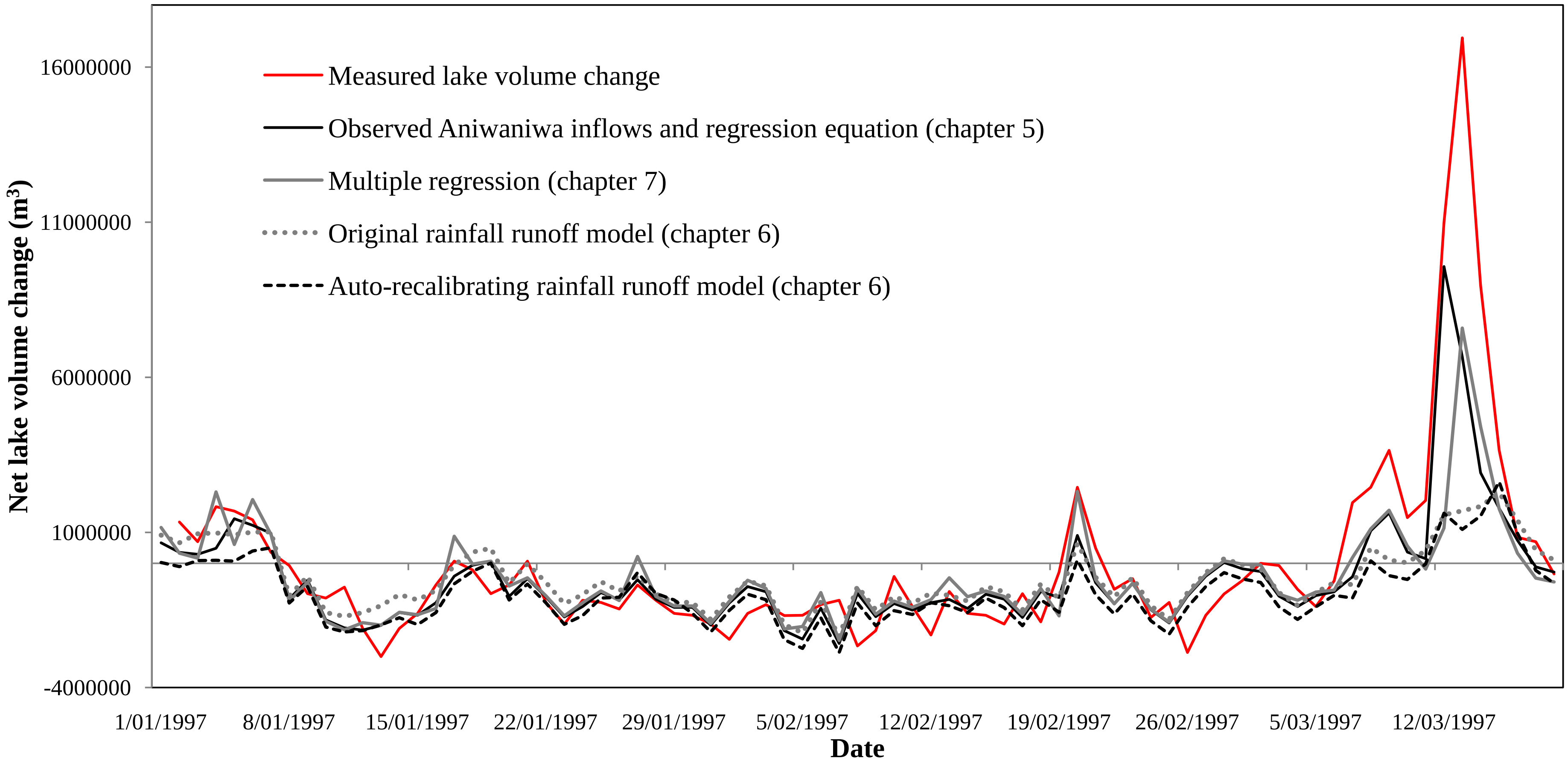

Figure 66: The original rainfall-runoff model, auto-recalibrating rainfall-runoff model, multiple regression model, and observed Aniwaniwa Stream inflows are scaled to net volume change using the regression relation of Chapter 5. These models are compared to net lake volume change from the lake level record.

8.3 Discussion

The highest Nash-Sutcliffe coefficient of forecasted Aniwaniwa Stream inflows is obtained using the multiple regression model. The multiple regression model provides a good prediction of low to medium sized Aniwaniwa inflows, but occasionally fails where medium sized inflows are predicted in the absence of a peak in observed data. While under-prediction of inflows is likely to occur as a result of spatial rainfall variation, the prediction of small hydrograph peaks in the absence of peaks in the observed record may be a result of the models' lack of catchment wetness state information. Prediction of these peaks may also be due to the daily resolution of the input data such that the model will not respond differently to a light rainfall which lasts 12 hours compared to a heavy rainfall lasting 30 minutes with the same total volume of rainfall.

Both rainfall-runoff models under-predict peak flows more severely than the multiple regression model due to the restricted availability of hydrograph forms during the model calibration process and due to the spatial variation of rainfall. The multiple regression model also provides more reliable estimations of low flows as the rainfall-runoff models under-predict low flows as hydrograph forms which do not contribute to peak flows are preferentially dropped from the model as elimination pressure is applied. It is suggested that prediction of low and medium flows is more important for operational use at the Waikaremoana Power Scheme than prediction of peak flows as the existing lake level differencing model provides a reliable estimation of net inflow under peak flow conditions. Thus, the multiple regression model provides the most useful prediction of Aniwaniwa Stream inflows into Lake Waikaremoana.

For current day inflows the most accurate measure of net change in storage in Lake Waikaremoana is observed Aniwaniwa Stream discharge scaled to net inflows using the regression relation developed in Chapter 5. For forecasts of day-ahead inflows net storage change is best approximated using the multiple regression model to forecast Aniwaniwa Stream inflows which are then scaled to net inflows using the regression relation from Chapter 5.

Differences between net storage as calculated from the lake level changes record, and estimated net storage calculated using the techniques developed in this study, arise due to a number of possible factors:

- **Spatial variation of rainfall:** The high spatial variation of rainfall is particularly important in this study as a single stream is being used to forecast inflows from a very large catchment. The Waikaremoana catchment encompasses approximately 114 streams, of which 3 major streams drain 59%. Of these streams only the Aniwaniwa Stream had a record which was both long and complete enough to use in this study. The remaining streams in the Waikaremoana catchment which drain 41% of the catchment are short and steep and are likely to have a higher runoff : rainfall ratio because of this, further increasing the problem of spatial variation.

  Spatial variation may be a particularly large factor in error where the three inflow models give very similar forecasts for the Aniwaniwa Stream which do not match storage change as derived from lake level when scaled.

- **Scaling:** The scaling of forecasted inflows to net inflows means that any errors in Aniwaniwa Stream forecasts may become very large once scaled.

- **Errors in lake level differencing:** It is likely that during some low flow periods where model forecasts do not match net storage estimations derived from the lake level record that error arises from lake level differencing when changes in lake level are small. This may be caused by the effects of waves and wind set up become significant in accurately determining lake level. This error is compounded when storage change volume is calculated over the large lake surface area.

8.4 Practicality

The three modelling techniques used in this thesis are compared here for practicality of operational use at the Waikaremoana Power Scheme. The finite mixture rainfall-runoff models both require the use of an expensive specialist package COMSOL Multiphysics. This is a numerical computing and programming package with similar syntax to MATLAB. The cost of purchasing this software package in order to run the rainfall-runoff model is high leading to this option being somewhat impractical.

The original rainfall-runoff model described in Chapter 6 has a computational time of approximately 20 to 30 minutes. The auto-recalibrating rainfall-runoff model however, has a computational time of approximately 8 hours further making operational use of the rainfall-runoff models impractical at the Waikaremoana Power Scheme.

The multiple regression model is very practical in its application. The model requires any simple spreadsheet package such as Microsoft Office Excel or Statistica. Microsoft Office Excel is currently installed at Genesis Energy. The multiple regression model can also be run through a Microsoft Excel macro creating a user-friendly environment. Therefore, the multiple regression model is considered to be the most practical in terms of operational use.

8.5 Conclusion

In a comparison of the two rainfall-runoff models and the multiple regression model used to forecast Aniwaniwa Stream inflows into Lake Waikaremoana using the Nash-Sutcliffe validation fit and a visual examination of time series plots of observed and predicted discharges, the multiple regression model is found to be the most suitable for operational use at the Waikaremoana Power Scheme.

When scaled to net inflows and compared to both scaled observed Aniwaniwa Stream inflows and net lake volume change as calculated using the lake level record, scaled observed Aniwaniwa Stream inflows is most suitable for current day storage estimation, and the multiple regression is most suitable for day ahead forecasts. The multiple regression model is also the most suitable for operational use at the Waikaremoana Power Scheme as both computational requirements and the cost of practical application is low.

Chapter 9 – Conclusions

Daily estimates of water availability at Lake Waikaremoana are required for efficient operation of the Waikaremoana Power Scheme. The current water availability model operated by Genesis Energy is subject to error when changes in lake level are small and supposed inflow estimates are in fact net lake balances, with the possibility of the negative term being derived from lake level error. The aim of this thesis was to resolve this issue.

Prior to this research it was considered that an inaccurate estimation of lake water loss in the form of a combination of evaporation and leakage through the ancient landslide dam which formed Lake Waikaremoana could be the cause of negative net 'inflow' estimates. This hypothesis was tested using a modified catchment water balance model to estimate the unknown lake water loss rate where the loss rate was calculated as the intercept of a simple regression. The assumption was made that under low flow conditions the inflow of the Aniwaniwa Stream is linearly related to net lake water balance. The unknown lake water loss rate measured in this way was not found to be significantly different from zero and the absolute value of the confidence interval was small, suggesting that unknown leakage and evaporative losses are not significant in the production of negative 'inflow' estimates. It may be in fact that total losses per day never exceed inflows, though this can't be proven. It is suggested that negative estimates are more likely to arise as the result of the error effect of waves and wind set up during lake level differencing when changes in lake level are small.

As a positive consequence of using a regression approach to estimate unknown lake water loss was the development of a regression relation which could be used to relate the flow of the Aniwaniwa Stream to net inflows into Lake Waikaremoana. This not only allowed current day estimates of net inflows to be calculated from observed Aniwaniwa Stream inflows but also allowed day-ahead estimates to be obtained by forecasting Aniwaniwa Stream inflows.

Inflows of the Aniwaniwa Stream were forecasted using three different models in an attempt to develop a forecasting methodology that was both practical for operational use and would give a reasonable prediction of inflows. The three modelling techniques were a finite mixture rainfall-runoff model, an auto-recalibrating finite mixture rainfall-runoff model and a multiple regression.

Both rainfall-runoff models were subjected to an established technique of linear model simplification, the lasso. While widely applied in the statistical community, the lasso has not been widely applied in hydrology to date. The lasso technique is used to simplify initial many-parameter models using an elimination pressure to force uninformative model parameters to zero thereby simplifying the model. The first of these rainfall-runoff models achieved a maximum validation fit at an elimination pressure of 800, giving a Nash-Sutcliffe coefficient of 50.7% with 14 parameters. A validation fit which is not much lower (46.9%) was achieved with an elimination pressure of 2750 and 6 parameters demonstrating the trade off between validation fit and model simplicity.

The second rainfall-runoff model, an auto-recalibrating finite mixture rainfall-runoff model also simplified by lasso reached a peak validation fit (52.3%) under an elimination pressure of 650 with an average of 14 parameters and an increased weighting of 40 times on the last 30 days of environmental input data. Similarly to the original model a validation fit not much lower was achieved under an elimination pressure of 2750 with 6 parameters (46.8%).

Both rainfall-runoff model generally under-predicted peak flows and over-predicted hydrograph tails. Poor peak flow prediction is thought to be a result of spatial variation of rainfall and because of the limited range of hydrograph forms available for selection. To improve peak flow prediction a wider range of hydrograph forms could be made available to the model at the expense of model simplicity. Under-prediction low flows also occurred at very high elimination pressures as the model preferentially dropped out hydrograph forms which did not contribute to peak flow prediction.

An increased weight was also set on the last 30 days of calibration data in the auto-recalibrating rainfall-runoff model as a proxy for catchment wetness state. While this rainfall-runoff model was expected to outperform the original rainfall-runoff model in terms of validation fit due to its increased weighting on most recent rainfalls, validation fit (52.3%) was found not to be significantly different to that of the original rainfall-runoff model (50.7%). This is likely to be due to a masking effect as a result of poor prediction of peak flows.

The lasso technique was found to be successful at simplifying down complex initial finite mixture rainfall-runoff models, reducing model parameters from 300. The lasso appears to be successful at reducing over parameterisation in the rainfall models as higher validation fits were achieved at elimination pressures greater than zero with the highest validation fit being achieved at 14 parameters in both models. While the rainfall-runoff models gave reasonable predictions of low flows under lower elimination pressures, the models were not considered practical for operational use at the Waikaremoana Power Scheme due to computational requirements.

A multiple regression technique was applied in order to forecast day-ahead inflows of the Aniwaniwa Stream into Lake Waikaremoana in a way which may be practical for operational use at the Waikaremoana Power Scheme. A suite of single and multiple regressions were carried out, resulting in three regression equations with the highest Nash-Sutcliffe validation fits. Both the regressions with the highest and second highest Nash-Sutcliffe validation fits (69.5% & 69.42%) made use of 'next-day' rainfall as an independent variable. As forecasting of next-day rainfall would be required for the use of these regression equations the regression with the third highest validation fit (66.16%) was used. This regression equation uses current day rainfall and discharge as coefficients.

The multiple regression equation also under-predicted inflows of the Aniwaniwa Stream, however under-prediction was less severe than in the rainfall-runoff models. The multiple regression equation gave reasonable predictions of medium to low flows.

A comparison of the three forecasting techniques used in this study was made in Chapter 8. The models were compared both in terms of their prediction ability and practicality for operational use at the Waikaremoana Power Scheme. The multiple regression technique was found to be the most practical for operational use as the only software requirements are Microsoft Excel or another basic statistical package, the model only takes seconds to run, and the model interface is user-friendly.

Prediction ability of the three models was assessed by comparing the Nash-Sutcliffe model efficiency coefficient of observed and predicted inflows calculated from the three models for an overlapping validation period. The multiple regression model was found to produce the results with the highest Nash-Sutcliffe validation fit. The three models were also compared by a visual examination of a time series plot to determine the areas under which each model performs well or poorly. The multiple regression model was found to predict all areas of the hydrograph more accurately than the rainfall-runoff models.

Results of the three Aniwaniwa Stream forecasting models were scaled to represent net storage volume of Lake Waikaremoana using the regression relation derived in Chapter 5. These results were then compared to scaled observed Aniwaniwa Stream discharges and storage change derived from the lake level record. The scaled observed Aniwaniwa Stream inflows gave a reasonable prediction for current day storage, while the scaled multiple regression model gave the most useful approximation of net storage of all the models used in this study. Spatial variation of rainfall, scaling and errors in lake level differencing are thought to account for the majority of error in net storage prediction.

Thus, it is recommended that observed Aniwaniwa Stream inflows, scaled to net storage of Lake Waikaremoana using the regression relation developed in Chapter 5 (Equation 5), are used for estimation of current day net storage for operational use at the Waikaremoana Power Scheme. For day-ahead forecasts it is recommended that regression equation 3 of the multiple regression models is used to forecast inflows of the Aniwaniwa Stream which can then be scaled.

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