NIWA
Taihoro Nukurangi

Impact of hydroelectric power scheme operations on low flows in the Wairau River

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Executive summary

Hydro dams are used for hydropower generation and their operation influences downstream river flow and environmental conditions The Branch River Hydroelectric Power Scheme (Branch HEPS) in the Wairau Valley is a 'run of river' scheme with minor buffering storage. To efficiently manage the river flows in the catchment, Marlborough District Council (MDC) wishes to better understand:

- How does the flow in the Wairau River respond to the operation of Branch HEPS?
- What is the potential impact of its operation on low flows?

Answering these questions using traditional hydrologic modelling is not feasible due to limitations of available data and information. To overcome these limitations, we implemented a machine learning algorithm and a linear regression model to assess the impact of the hydro dam on the low flow. The low flow here is defined as river flow at "Wairau at Barnetts Bank " lower than 60 m^3/s from October to April next year (Note: This is different from MDC's traditional definition – lower than 30 m^3/s from December to May next year, and the increase to 60 m^3/s is simply to allow enough data to construct the machine learning model), with the approval from MDC. Model inputs include flow time series from the upper Wairau River and its tributaries, hydro dam intake and discharge, weather data, and water take data, while the model output is the low flow at a downstream assessment site "Wairau at Barnetts Bank".

The machine learning algorithm "Long-short-term memory" (LSTM) model achieved better performance when simulating low flow at "Wairau at Barnetts Bank" than a linear regression model. LSTM model performance was classified as "very good" using performance evaluation criteria, and therefore suitable for simulating low flow.

Our assessment indicates that improving the performance of the LSTM models in simulating the system following removal of water takes requires better data representing irrigation of pasture and viticulture.

Compared to current operations, removing the hydro dam (Branch HEPS) will generally result in a decrease in low flow, but the change in low flow varies (i.e., increase the flow in some periods while decrease in other periods), and the change will vary according to flow. Although our results suggest that the hydro dam generally has a positive impact on low flow (i.e., generally increasing the low flow), optimal hydro dam operation should account for multiple uses - hydropower generation, irrigation demands, and instream ecological and community values. The LSTM model that we have developed could be further refined and used to improve analysis of complex flow variations.

The performance of the LSTM model could be improved if more extensive data were available for irrigation and other water uses (e.g., stock water, food processing). LSTM models can also be used to simulate flooding and assist with flood management.

1 Introduction

The Branch River Hydroelectric Power Scheme (Branch HEPS) is a 'run of river' scheme with minor buffering storage, consisting of two power stations in Wairau and Argyle. This scheme is operated by Manawa Energy, collectively producing an annual average output of 54.3 GWh. The storage is used to generate at peak demand times, resulting in hydro-peaking effects on the Wairau River downstream of the discharge point. To support the management of the Wairau River below its Branch River confluence, in particular to prevent adverse effects on instream ecological values, Marlborough District Council (MDC) requires information on the impact operation of the Branch HEPS (i.e., water abstraction and release) has on low flows, and the effects of hydro-peaking during periods of low flow. This requires a better understanding of the river's hydrological regimes, including the interaction between surface water and groundwater along the river course.

The traditional water balance model approach cannot be employed to examine the hydrology regimes in this river due to the extent of missing data. Therefore, MDC commissioned NIWA to develop an alternative approach to assess the relationship between the low flows in the Wairau River, Branch HEPS operation water takes and diversions. This report describes the data and methods used along with results and conclusions.

We used two different methods to predict the low flows: a special type of machine learning model called "Long-short-term memory" and a traditional multivariate linear regression method. Performance and predictability of both methods were compared to aid the selection of the right model for low flow prediction.

This work was funded through a grant from Envirolink (Grant No. C01X2116).

1.1 Study area

The Wairau River is located in Marlborough. It rises in the Spenser Mountains and flows for 169 km between the St. Arnaud and Raglan Ranges, entering Cloudy Bay of Cook Strait. Together with its principal tributaries — the Goulter, Branch, and Waihopai Rivers — the Wairau River drains a basin of 4,220 km^2 (https://www.britannica.com/place/Wairau-River). In addition to use for hydropower generation, the Wairau River, and the associated Wairau aquifer are the principal water sources for the Marlborough wine industry, pasture irrigation, and municipal water supply for the township of Blenheim. The interaction between HEPS and water takes within the Wairau Valley plays a big role on the low flow dynamics of the Wairau River. Figure 2-1 illustrates the river network, main flow gauging sites, Wairau River gravel bed, and Wairau Valley irrigation zone.

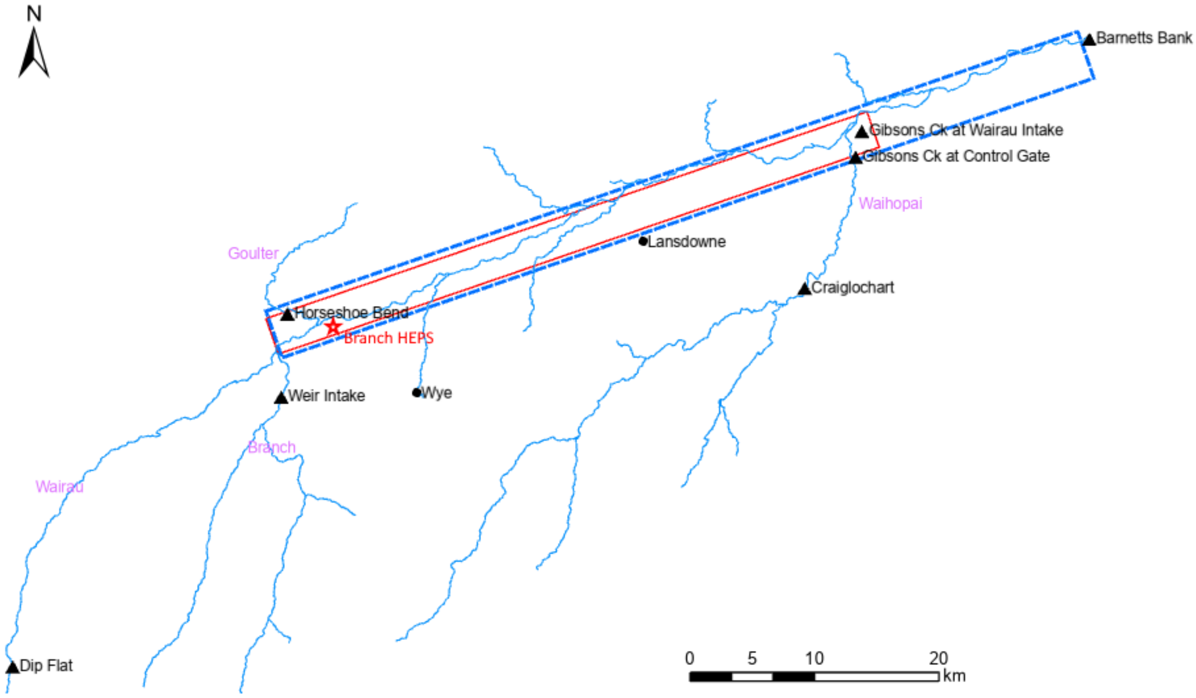

Figure 1-1: Wairau River network. Wairau River gravel bed (dashed blue rectangle), Wairau Valley irrigation zone (solid red rectangle), main flow gauging sites (black triangles) and weather stations (black dots). Station details are listed in Table 2-1.

2 Methodology

2.1 Data

To examine the impact of Manawa Energy's hydropower scheme operation on low flows of the Wairau River, we collated the following data which are also listed in Table 2-1.

- Intake and discharge from Manawa Energy's Wairau hydropower station, comprising water diversion from the Branch River to the hydropower stations and then the discharge to the Wairau River;
- Gibsons Creek intakes; Gibsons Creek at Control Gate (1961 rewatering project), and Gibsons Creek Wairau River intake (2004 Southern Valleys Irrigation scheme and rewatering project);
- Flow data at sites on the Wairau River and from different tributaries (Branch, Goulter, and Waihopai);
- Weather data (rainfall and temperature). These can be indications of flows from ungauged tributaries, and of water consumptions in the Wairau Valley; and
- Water use data. These include water use for pasture and vine irrigation. Owing to limited availability of water meter data for irrigation takes in the Wairau Valley, this study used two representative water meter data records – one each for pasture and viticulture.

Table 2-1: Data collected for low flow modelling. Column "Availability" only indicates data availability in the period from 1/1/2010 to 1/4/2022.

No	Data Type	Site Name	Time step	Availability	Source
1	Observed Flow	Wairau River at Dip Flat	15 minutes	1/1/2010 – 1/4/2022	NIWA
2	Observed Flow	Goulter River at Horseshoe Bend	15 minutes	1/1/2010 – 1/4/2022	MDC
3	Observed Flow	Branch at Weir Intake	15 minutes	1/1/2010 – 1/4/2022	MDC
4	Observed Flow	Branch Hydro Intake	daily	1/1/2017 – 1/4/2022	Manawa Energy
5	Observed Flow	Branch Hydro Discharge	15 minutes	1/1/2017 – 1/4/2022	Manawa Energy
6	Observed Flow	Waihopai at Craiglochart	15 minutes	1/1/2010 – 1/4/2022	MDC
7	Observed Flow	Gibsons Ck at Wairau Intake	15 minutes	1/1/2010 – 1/4/2022	MDC
8	Observed Flow	Gibsons Ck at Control Gate	15 minutes	1/1/2010 – 1/4/2022	MDC

No	Data Type	Site Name	Time step	Availability	Source
9	Observed Flow	Wairau at Barnetts Bank	15 minutes	1/1/2010 – 1/4/2022	MDC
10	Water use for pasture	Representative site	daily	2/6/2018 – 1/4/2022	MDC
11	Water use for vines	Representative site	daily	2/6/2010 – 1/4/2022	MDC
12	Weather	Wye	1 hour	1/1/2010 – 1/4/2022	MDC
13	Weather	Lansdowne	1 hour	1/1/2010 – 1/4/2022	Fire and Emergency NZ

2.2 Problem formulation

The extensive riverbed gravel in the Wairau Valley, downstream of the confluence of the Wairau River and the Branch River, functions as a hyporheic water storage reservoir before it upwells further downstream and is measured at the "Wairau at Barnetts Bank" site. Figure 2-1 presents the water flows from tributaries, and water takes for different purposes in a schematic form. Principal water sources are headwater streams (flows are assumed to represented by the flow at the Dip Flat gauging site) and the main tributaries (Branch, Goulter, and Waihopai). The main water uses include water intake for hydropower generation from the Branch River (Manawa Energy), and the Gibsons Creek intakes from Waihopai and Wairau Rivers, as well as multiple irrigation water takes for pasture and vines in the Wairau Valley zone (solid red rectangle in Figure 2-1). The flow percolation into Wairau Aquifer is assumed to be constant at a rate of 8 m^3/s and therefore it is not considered in the following study.[1]

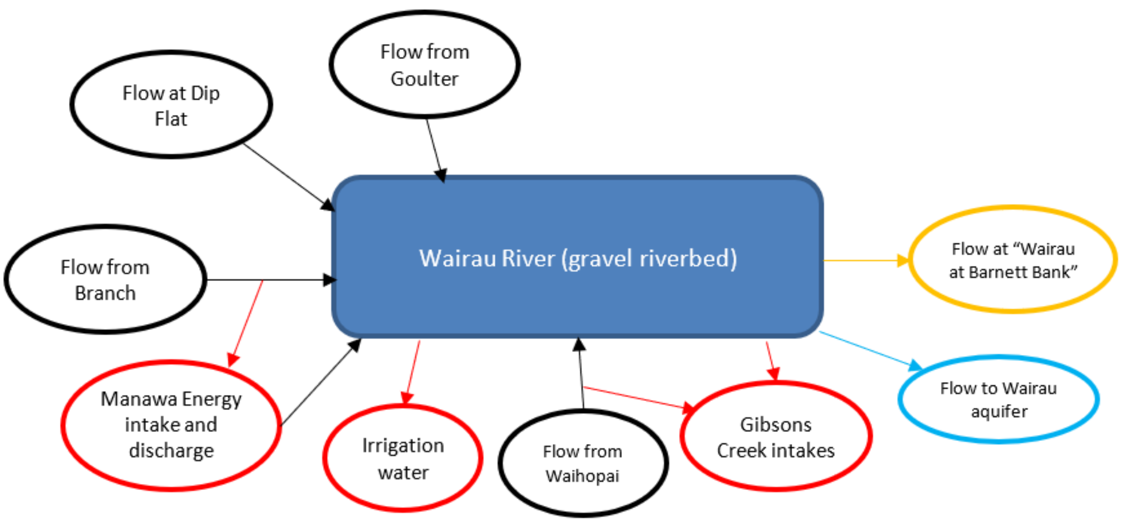

Figure 2-1: Schematic representation of the water flowing into and out of the Wairau Valley. Black arrow: sources of water; Red arrow: water takes; Blue arrow: percolation to the Wairau aquifer.

As the main interest of this study is to model the low flows, we focus on the Wairau River flows at "Wairau at Barnetts Bank" site that are below 60 m^3/s from October to May with the approval from

[1] Personal communication, Val Wadsworth, MDC, Feb 2022.

MDC (Note: This is different from MDC's traditional definition, i.e., flow below 30 m^3/s from November to April, simply to allow enough data for machine learning modelling). The Wairau River flow at site "Wairau at Barnetts Bank" can be predicted with possible influential factors, in the form of:

$$y_t = f(X_{t-1}, X_{t-2},..., X_{t-M}) \tag{1}$$

where y_t is the river flow at the "Wairau at Barnetts Bank" site to be predicted at time step t (Site No 9 in Table 2-1), X is the predictor vector (all data categories listed in Table 2-1, except Site No 9), and M is the memory or maximum time lag between input X and output y.

2.3 Long-short-term memory

"Long-short-term memory" (LSTM) is a machine learning algorithm used in the discipline of artificial neural network. It has feedback connections and is implemented within recurrent neural networks (RNNs). RNNs are designed to analyse temporal patterns by processing time-series data in sequential order (Rumelhart et al. 1985). RNNs have been applied to predict streamflow for several decades (e.g., Carriere et al. 1996). LSTMs have been proposed to improve upon traditional RNNs by identifying long-term dependencies between a response time-series and a set of predictor time-series (e.g., Gers et al. 2000; Tian et al. 2018). LSTMs have also been applied in hydrology to hindcast stream flows (e.g., Kratzert et al. 2018) and groundwater levels (Zhang et al. 2018), and forecast hydrological conditions (Le et al. 2019). Hydrological applications of LSTM have used time-series of antecedent conditions (e.g., time-series of meteorological conditions prior to the date of interest) as predictors of a response (e.g., streamflow on the date of interest). For example, Kratzert et al. (2018) used various meteorological variables (e.g., precipitation, radiation, air temperature) as predictors of streamflow.

To implement LSTM, one needs to determine several factors: the number of LSTM layers (nlayer), the number of cells in each LSTM layer (ncell), an epoch number, where an epoch is defined as the period in which each training sample is used once for updating model parameters (Kratzert et al., 2018), and batch size – the number of training data samples used for model training in each epoch. Model complexity increases as nlayer and ncell increase, requiring more parameters to be estimated. All these factors need to be set up carefully to avoid overfitting (i.e., a model performs very well in the training period while poorly performed in the validation period).

When constructing LSTM models, we varied the number of LSTM layers (nlayer) from 1 to 4, the number of cells at each LSTM layer from 8 to 128, and epoch numbers of 50 to 500, and all data for model input and output (Table 2-1:) were standardised (Flow data at "Wairau at Barnetts Bank" were log-transformed). We chose mean absolute error (MAE; the absolute values of the individual model prediction errors against the observations) as the loss function to optimise LSTM model parameters. The best LSTM model would be the one with the best model performance.

2.4 Linear regression model

LSTM models assume nonlinear relationship between X and y (see Equation (1)), whereas a linear regression model assumes a linear relationship between X and y:

$$y_t = A_1 X_{t-1} + A_2 X_{t-2} + \ldots + A_M X_{t-M} \tag{2}$$

where A_i $(i = 1, \ldots, M)$ is the regression coefficient vector at time lag i.

2.5 Modelling procedure

To implementing the LSTM and linear regression models, the following three-step procedure was used:

1. Data pre-processing

All data were processed to develop time-series at 3-hour time interval. If the time interval is smaller than 3 hours (e.g., flow at "Wairau River at Dip Flat"), data were aggregated into 3-hourly increments by averaging all data in the period; if time interval is longer than 3 hours (e.g., flow at "Branch Hydro Intake"), data were evenly downscaled into 3-hourly estimates by using daily average values.

2. Modelling setup for LSTM and linear regression models

Although we have collected two representative irrigation datasets (for pasture and vines), these two datasets start from 2/6/2018, which is only two thirds of the extent of the other datasets. Thus, in addition to comparison of the performance of LSTM and linear regression models, we also considered whether inclusion of irrigation datasets could improve the model prediction. To model with and without irrigation data, four model setups were implemented as shown in Table 2-2.

Table 2-2: Model setups for low flow modelling.

Simulation	Modelling approach	Datasets
Setup 1	LSTM model	Without irrigation data for pasture and vines
Setup 2	LSTM model	With irrigation data for pasture and vines
Setup 3	Linear regression model	Without irrigation data for pasture and vines
Setup 4	Linear regression model	With irrigation data for pasture and vines

During modelling, the dataset was split into a training dataset (the first 80% of data), and a validation dataset (the remaining 20%). Numbers of LSTM layers, cells in each LSTM, batch size and epochs were determined by trial-and-error, using MAE to assess model performance and select the most suitable model.

3. Performance assessment

Model performance assessment is case dependent and in this study the Nash-Sutcliffe Efficiency metric (NSE; Nash and Sutcliffe, 1970) was used.

$$NSE = 1 - \frac{\sum_i (Q_{si} - Q_{oi})^2}{\sum_i (Q_{oi} - \overline{Q_o})^2} \quad (3)$$

Where Q_{si} and Q_{oi} are simulated and observed flow at site "Wairau at Barnetts Bank" at time i, and $\overline{Q_o}$ the mean observed flow. We also used NSlog, which is the NSE for log-transformed river flow.

To assist with evaluating model performance, criteria developed by Moriasi et al. (2015) were used to classify model performance:

- "Very good" if NSE (NSlog) is larger than 0.8;
- "Good" if NSE (NSlog) is between 0.7 and 0.8;
- "Satisfactory" if NSE (NSlog) between 0.5 and 0.7; and
- "Not satisfactory" if NSE (NSlog) is below 0.5.

4. Scenario analysis on "no-hydro-dam"

This scenario was developed to assess the impact of current operation of the hydro dam on low flows at the "Wairau at Barnetts Bank" site, by assuming there was no Branch HEPS, i.e., removing the hydro dam from the Wairau catchment. This would return all water takes for Branch HEPS ("Branch Hydro Intake" in Table 2-1:) back into the Branch (i.e., No 3 in Table 2-1:), and stop all Branch HEPS discharge ("Branch Hydro Discharge" in Table 2-1:) to the Wairau River.

The developed LSTM model above was then used to run the scenario by modifying the corresponding model inputs (i.e., flows at "Branch at Weir Intake", "Branch Hydro Intake", and "Branch Hydro Discharge"), and produce simulated low flows at "Wairau at Barnetts Bank" (referred to as "Simulation without hydro dam"). Flow estimates derived from the "Simulation without hydro dam" were then compared against the baseline flows - simulated flow used for model training and validation as described above (referred to as "simulation with current hydro dam operation"). Differences between flows for these simulations were analysed at 3-hourly time step and daily average.

3 Result and discussion

3.1 LSTM model

Figure 3-1 shows the LSTM model performance with Setup 1 and Setup 2 (see Table 2-2) runs during the training and validation at 3-hour time step. Mean absolute error (MAE) was used as the loss function to optimise model parameters. Then the best LSTM model was chosen – that with the lowest MAE values – for each setup. It is worth noting that MAE here is calculated after river flow data are log-transformed and then standardised.

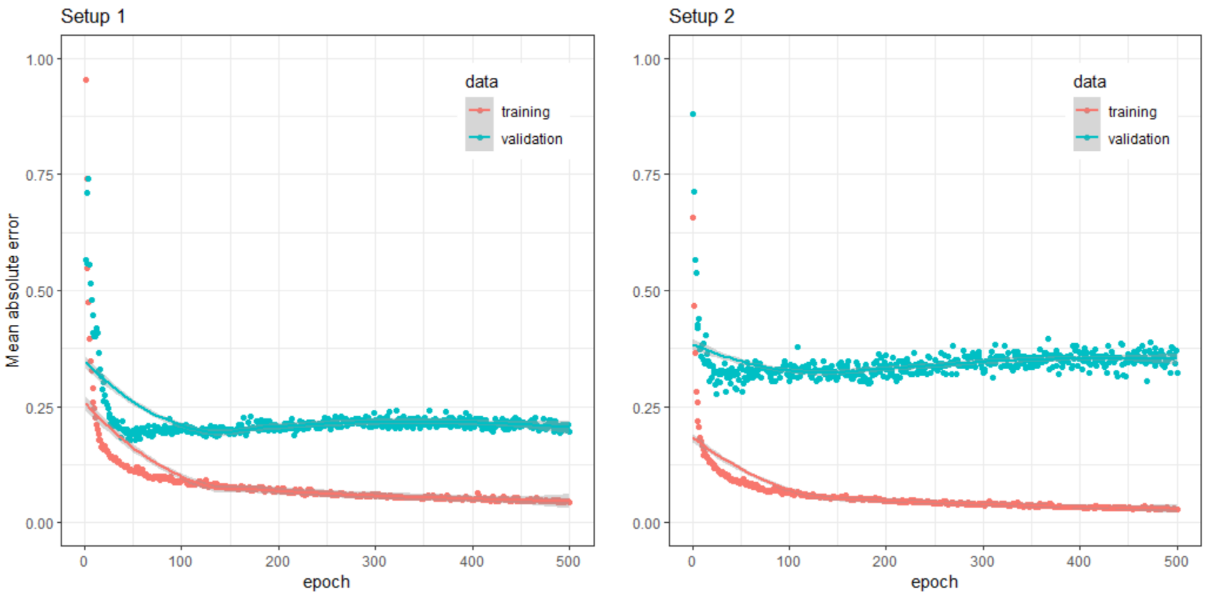

Figure 3-1: Mean absolute error (units are transformed streamflow) against epoch number for training and validation periods for Setup 1 and Setup 2.

The modelling results for Setup 1 and Setup 2 are shown in Figure 3-1, Figure 3-2, Figure 3-3 and Table 3-1. Figure 3-1 indicates for both Setup 1 and Setup 2, models perform better in the training period than validation period, which generally occurs in hydrologic modelling. Although these two models perform similarly (MAEs are around 0.03) in the training period, the model with Setup 1 (MAE is around 0.19) performs better than that with Setup 2 (MAE of 0.28). This can be corroborated by Figure 3-2 (simulation results at 3-hour time step) and Figure 3-3 (simulation results are daily averaged). Generally, both LSTM models perform similarly well in the training period (with NSE and NSlog 0.99 in Table 3-1). However, in the validation period, Setup 1 model performs better than Setup 2 with NSE and NSlog greater than 0.85 and around 0.5, respectively. Visual inspection indicates that the LSTM model with Setup 1 (red line) matches observations well, and Setup 2 tends to underestimate the flows for simulations at both 3-hour time step (Figure 3-2) and daily average (Figure 3-3). According to the criteria in Moriasi et al. (2015), Setup 1 model is classified as “Very good” while model with Setup 2 is classified as “Satisfactory” (based on NSE) or “not satisfactory” (NSlog) in the validation period. Therefore, we used the LSTM model with Setup 1 to undertake further analysis.

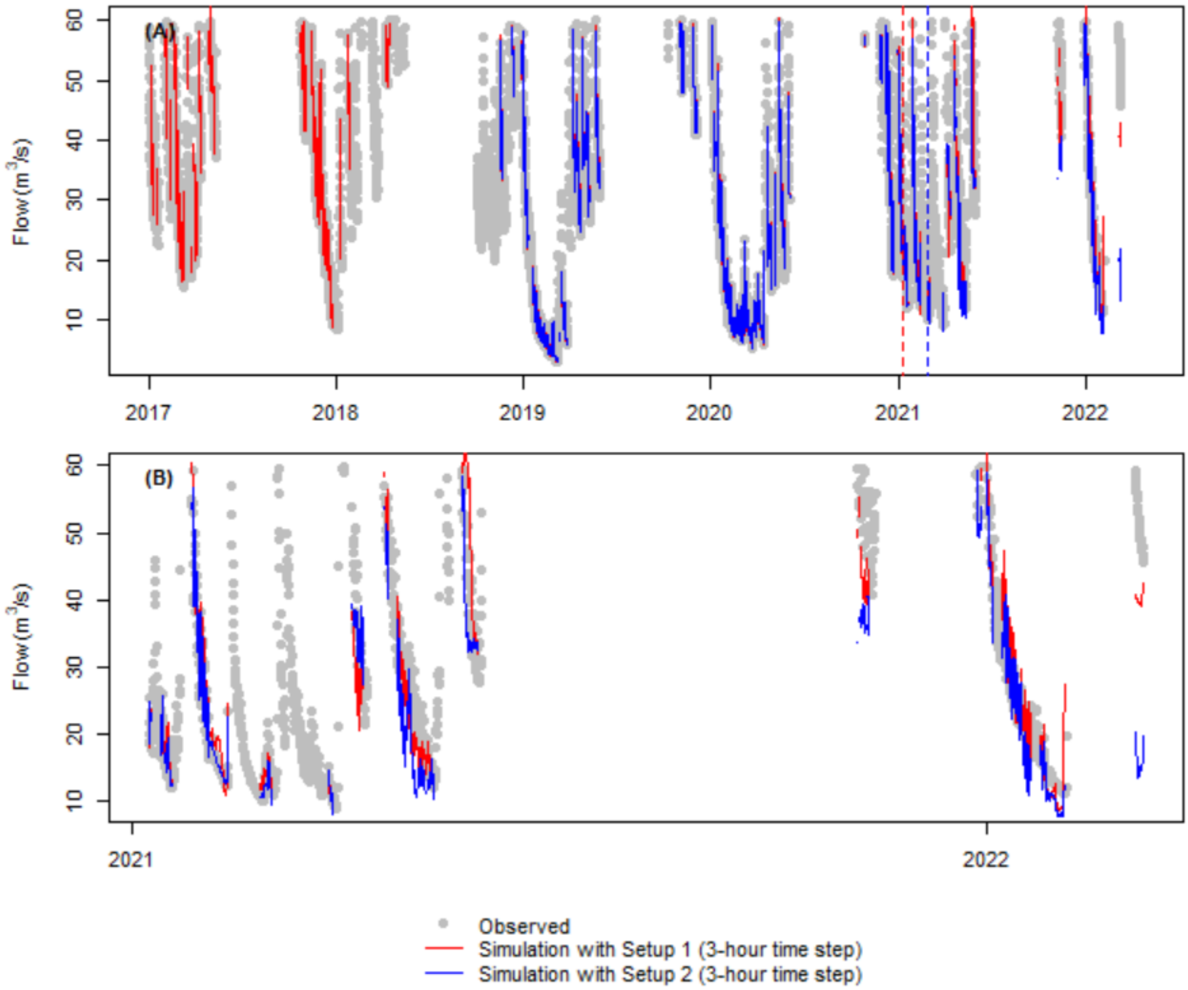

Figure 3-2: Comparison of model simulations at 3-hour time step with observed flow at "Wairau at Barnetts Bank" for two setups. (A) Model simulation for both training and validation periods; (B) Zoomed model simulation from 2021 to 2022. Dashed lines in (A) indicate the separation between training and validation periods for the two setups (red line: Setup 1; blue line: Setup 2).

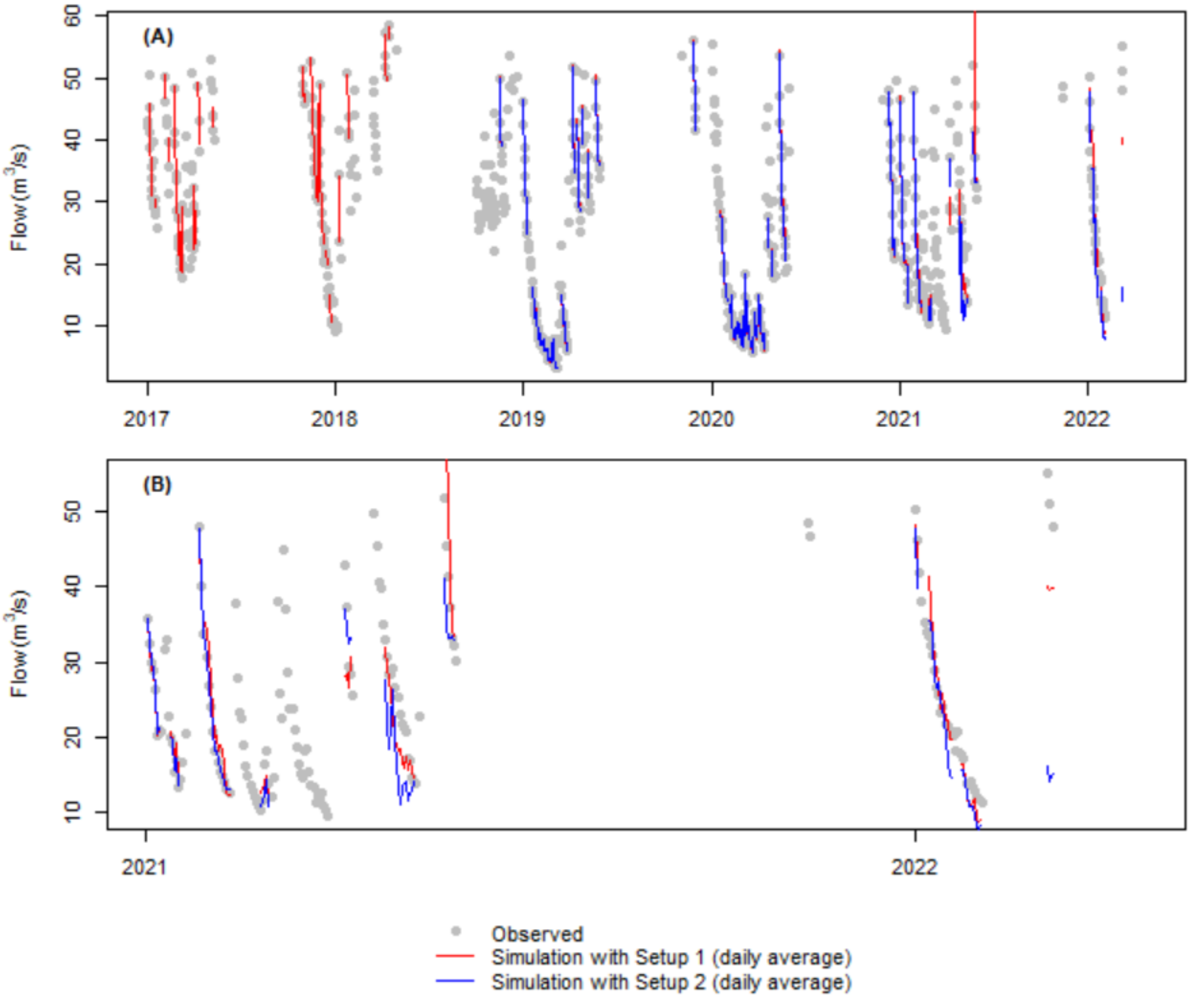

Figure 3-3: Comparison of simulated flows with observations at “Wairau at Barnetts Bank” at 3-hour time step (red: Setup 1; blue: Setup 2). (A) Model simulation for both training and validation periods for entire record; (B) Model simulation from 2021 to 2022.

Table 3-1: Model performances for difference model setups.

Setup	Training		Validation	
	NS	NSlog	NS	NSlog
Setup 1	0.99	0.99	0.85	0.87
Setup 2	0.99	0.99	0.52	0.48
Setup 3	0.83	0.94	-3.56	0.54
Setup 4	0.91	0.96	0.49	0.68

3.2 Linear regression model

Performance of the linear regression models (Setup 3 and Setup 4 in Table 2-2) are summarised in Table 3-1.

Table 3-1 indicates the linear regression models performed less satisfactorily than the LSTM models. Linear regression model with Setup 3 was worse than its corresponding LSTM model (Setup 1) in both training and validation periods, especially in the validation period where it is classified as “not satisfactory”. Linear regression model with Setup 4 performs slightly worse than its corresponding LSTM model (Setup 2) in the training period, and similarly in the validation period.

Given that the LSTM models perform better than the linear regression models, the influence of hydro dam operations on low flows was carried out using the LSTM model with Setup 1.

3.3 Influence of irrigation dataset for pasture and vines

From results of Sections 3.1, it is interesting to observe that the model that does not include water take data for pasture and viticulture (Setup 1) performed better than the model with water take data (Setup 2). However, this does not mean that irrigation for pasture and viticulture in Wairau valley has no effect on the flow at “Wairau at Barnetts Bank”. Whilst the exact reasons for this model behaviour needs to be investigated, the following are provided as possible reasons:

1. The LSTM model, which is a machine learning or black-box model, implicitly accounts for the impact of different water takes (including for pasture and viticulture), through other variables (i.e., rainfall and temperature), because irrigation is typically a function of weather.
2. This modelling was undertaken using two representative water use datasets for pasture and viticulture irrigation (see Section 2.1). However, the actual patterns of water use in other farms/water uses may be different to the data used.
3. The water use data for pasture and viticulture are not long enough to construct a robust LSTM model.
4. Most of the takes are from groundwater galleries, so there will be buffering of the stream depletion effect due to the separation distance from the river.

In summary, the quantity and quality of data are essential to machine learning based modelling. This exercise indicated that the water take data that were recently collected are not adequate to construct a data model that meets MDC’s accuracy requirements.

3.4 Influence of hydro dam on low flow

To study the impact of hydro dam operation on low flow, we developed a simple scenario that assumes that there are no hydro dams within the Wairau catchment. We compared the river flow outputs for this scenario at “Wairau at Barnetts Bank” using LSTM model in Section 3.1 (“Simulation without hydro dam”) against the baseline, i.e., simulated flows (“Simulation with current hydro dam operation”) that include the influence of dams (given in Section 3.1).

The comparison of modelled flow time series with and without a hydro dam is given in Figure 3-4 and Figure 3-5, for the 3-hour and daily average comparisons, respectively. Without hydro dams, the flow at site “Wairau at Barnetts Bank” will decrease at more time steps modelled than increase (bottom plots in Figure 3-4 and Figure 3-5).

Statistically, the change in the river flow is small at low flows and increases as the flow increases (Figure 3-6), and the change at the 3-hour time step is larger than the change observed using daily average flows because daily averaging tends to reduce the influence of extreme low and high values. Table 3-2 and Figure 3-7 summarises the percentage of flow decrease and average flow change for each period if the hydro dam is removed. If the hydro dam is removed, there is a decreasing trend in the river flow over the past several years. This seems to indicate that the Branch HEPS increased the low flow. However, this might be biased due to the missing values in the model prediction and short period for year 2017 (it started from 1/1/2017).

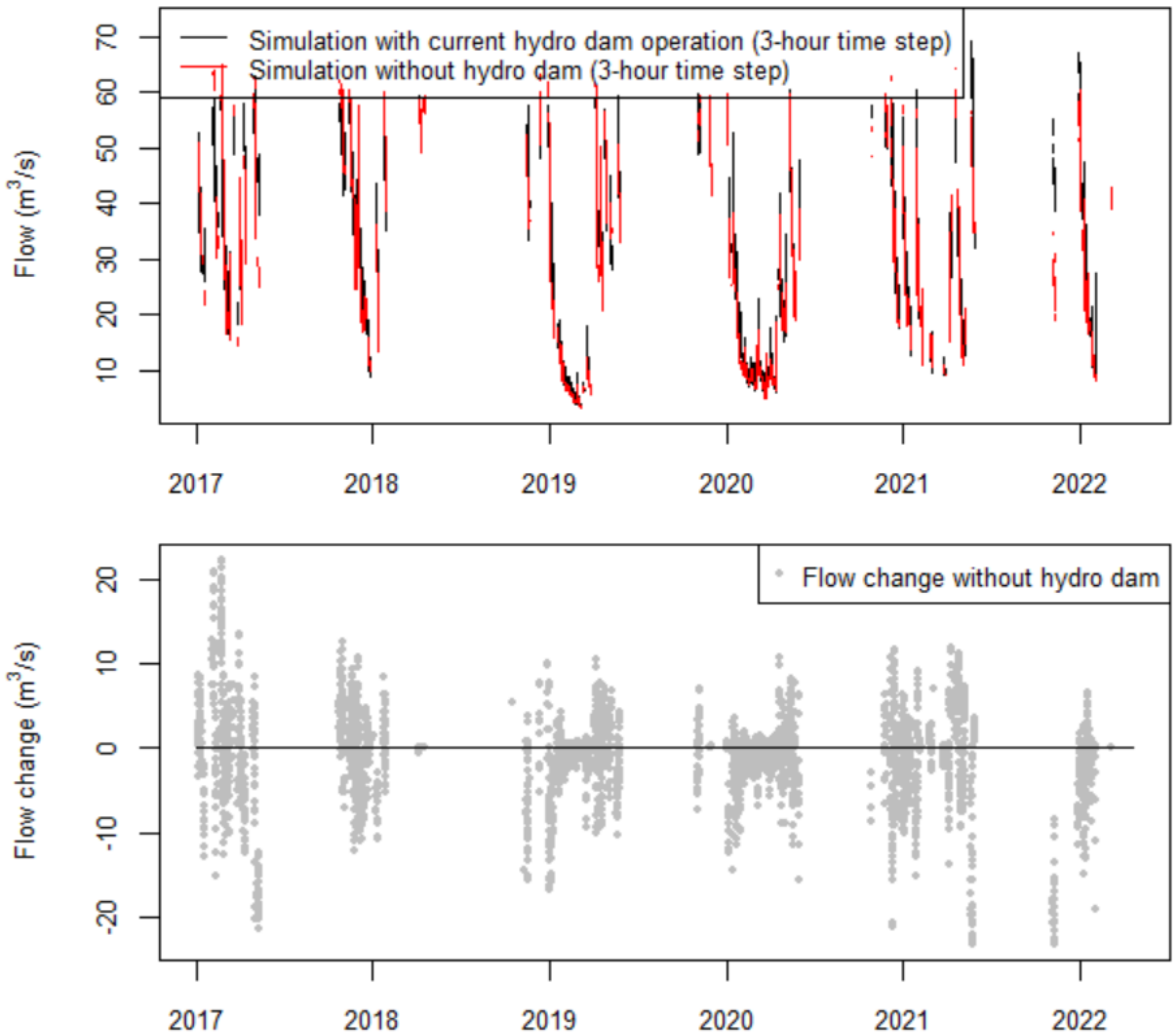

Figure 3-4: Top: Comparison of flow simulations at 3-hour time step at “Wairau at Barnetts Bank” with and without current hydro dam operation. Bottom: Flow change due to hydro dam removal.

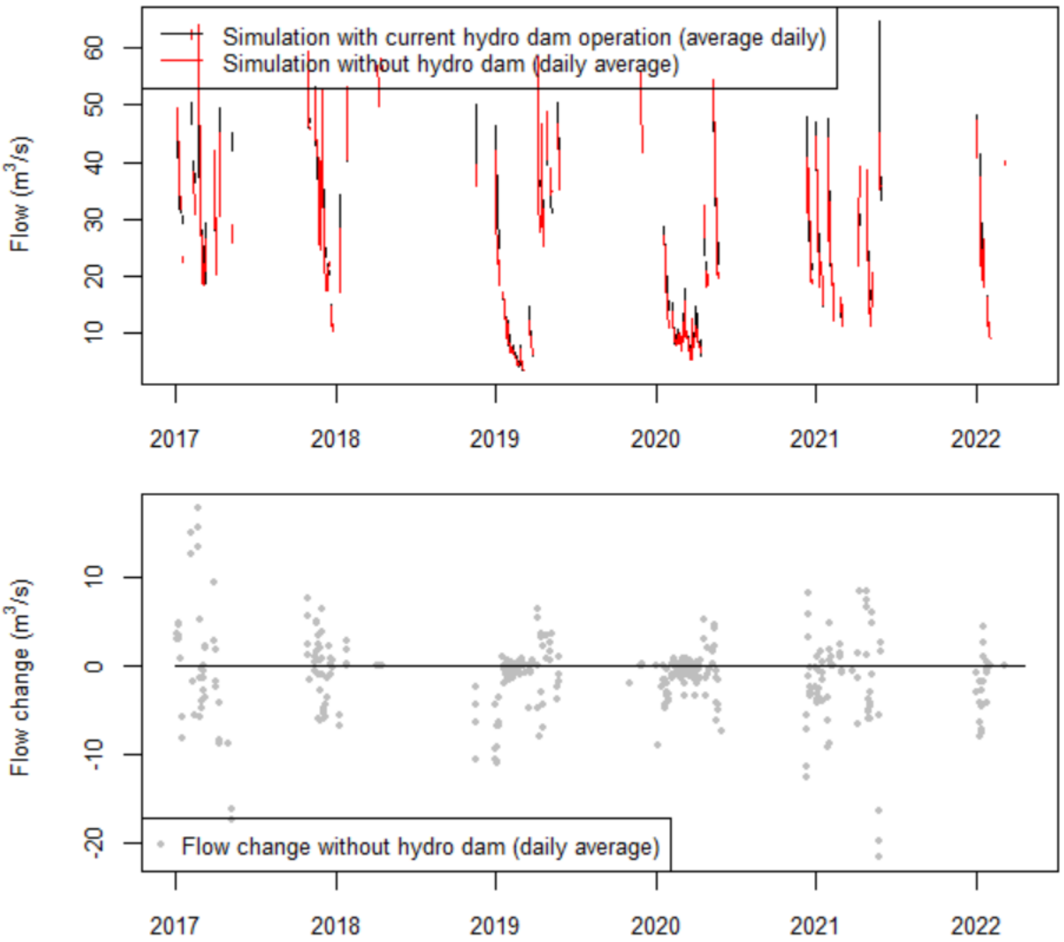

Figure 3-5: Top: Comparison of daily flow simulations at "Wairau at Barnetts Bank" with and without current hydro dam operation. Bottom: Flow change due to hydro dam removal.

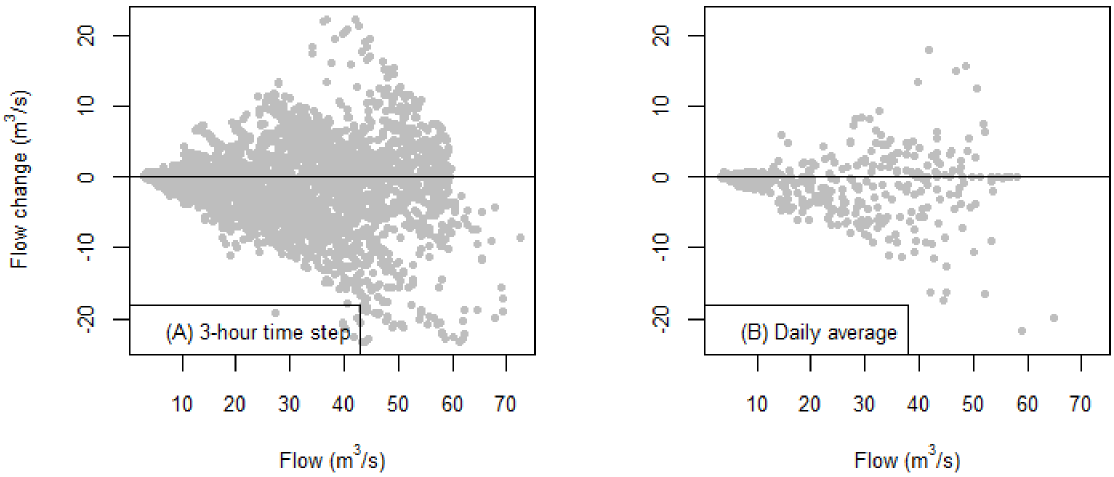

Figure 3-6: Flow change due to hydro dam removal versus simulated flow at "Wairau at Barnetts Bank" with current hydro dam operation.

(A) simulation based on 3-hour time step; (B) simulation summarised at daily time step.

Table 3-2: Flow change summarised for each year.

Year	Period	Percentage of time with decreasing flow	Average flow change (m^3/s)
2017	1/1/2017 - 31/5/2017	50%	-0.04
2018	1/10/2017 - 31/5/2018	47%	0.12
2019	1/10/2018 - 31/5/2019	60%	-1.29
2020	1/10/2019 - 31/5/2020	60%	-0.79
2021	1/10/2020 - 31/5/2021	67%	-1.50
2022	1/10/2021 - 1/4/2022	74%	-3.77

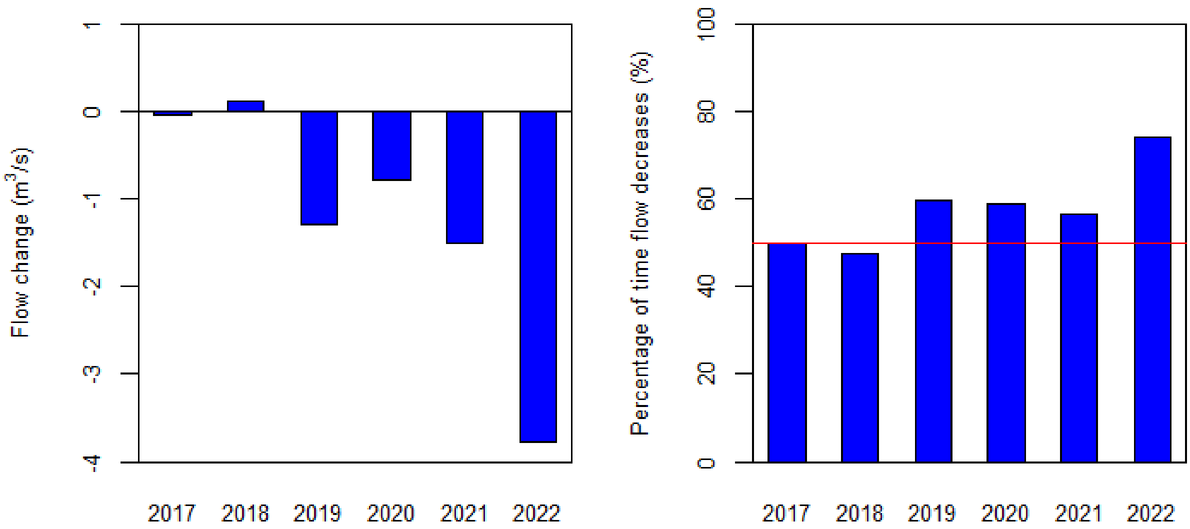

Figure 3-7: Flow change summarised for each year for the scenario with no hydro dam. The red line in the right plot is the 50% line, indicating the threshold between low flow increase or decrease.

In addition to allowing use of stored water for hydropower generation, hydro dams can also play a major role in managing the spatiotemporal distribution of water resources (i.e., enabling transfer of water from water abundant areas to water scarce areas, and enabling storage during periods of high flows and subsequent release during periods of low flows). When managed properly, water storage can be beneficial to the maintenance of the river aquatic ecosystem (Anderson et al., 2015; Tickner et al. 2017), sustaining social and economic development, reducing flood damage, and mitigating drought conditions. As a hydro dam, the operation of Branch HEPS can be influential on low flow in the Wairau River although it is a 'run of river' scheme with minor buffering storage. As indicated in the results above (i.e., through scenario analysis), current management of the hydroelectric power scheme appears to generally increase low flow values, as well as the proportion of time during which low flows occur (as indicated in Figure 3-8), but also increases and decrease the low flows at different time.

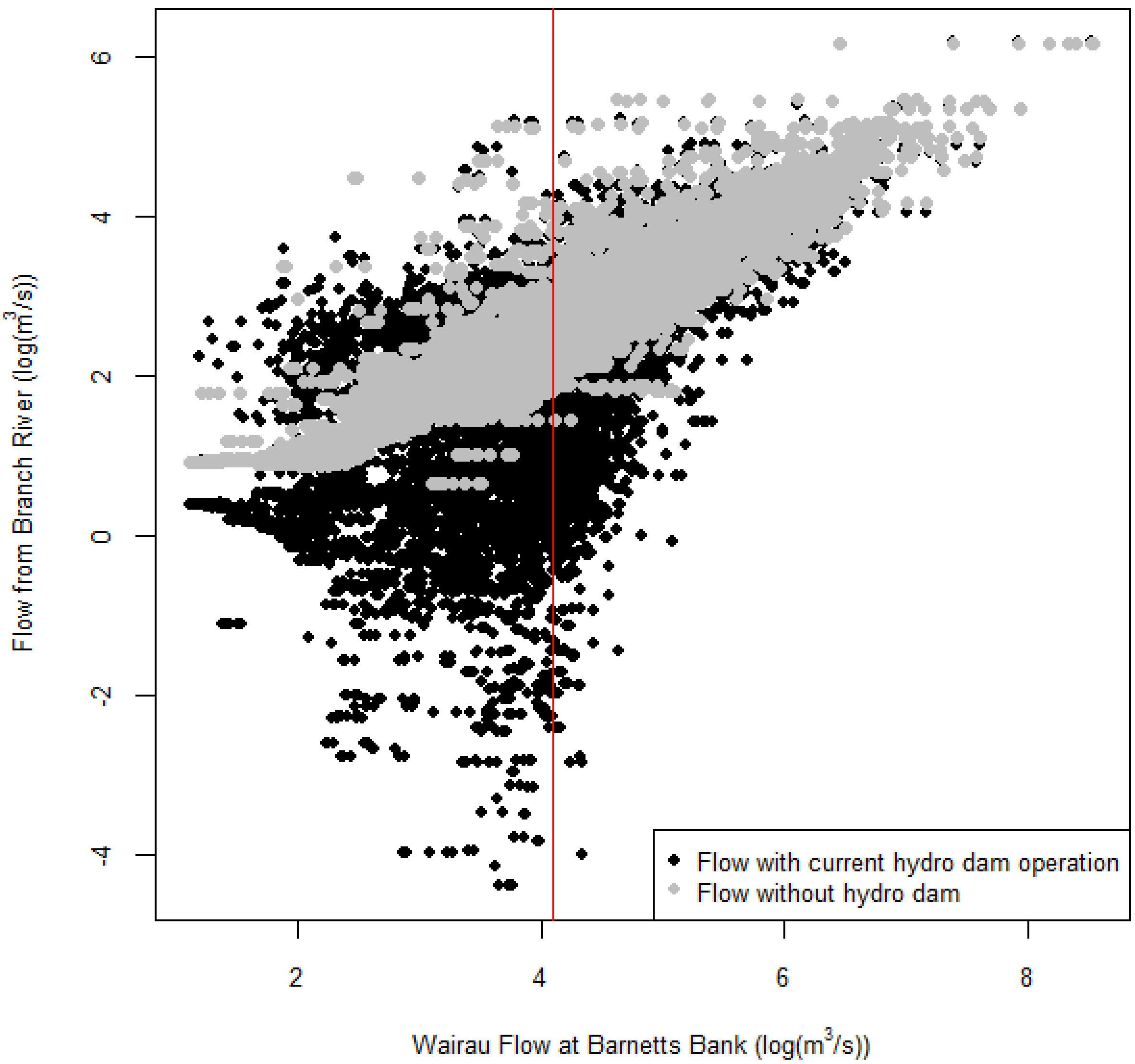

Figure 3-8: Flow from Branch River with and without hydro dam operation versus observed flow at "Wairau at Barnetts Bank". Vertical red line is the flow at 60 m^3/s. The flow from the Branch River is calculated as the flow at "Branch at Weir Intake" by minus the flow at "Branch Hydro Intake" and plus the flow at "Branch Hydro Discharge"

4 Conclusion

In this study, we applied LSTM model to simulate the low flow in the Wairau River and study the impact of hydro dam on the low flow (river flow at “Wairau at Barnetts Bank” lower than 60 m^3/s from October to May) at a 3-hour time step.

Compared to the linear regression model, the best performing LSTM model achieved better model performance when simulating low flow at “Wairau at Barnetts Bank” with a Nash-Sutcliffe coefficient close to 1 in the training period and over 0.85 in the validation period. This LSTM model is classified as “very good” and suitable to simulate the low flow.

Performances of the LSTM models indicate that available irrigation data for pasture and viticulture are not adequate to represent abstractive water takes.

Compared to the current hydro dam operation, removing the effects of the hydro dam will generally result in decrease in the extent and duration of low flows. Although current operation of the hydro scheme seems to have a positive impact on low flow conditions at more incidences (decreasing the extent and severity of low flows). Optimal hydro dam operation could consider both hydropower generation and downstream flow conditions to further optimise the benefit of this hydro dam operation for multiple uses. The constructed LSTM model can be adapted or further developed and refined (particularly if available data are improved) to improve analysis of these dynamic, complex relationships and provide guidance.

The performance of the LSTM models could be improved if irrigation data and other types of water use data (e.g., stock water, food processing) were collected over longer time periods. The impact of hydro dam on low flow in the Wairau River could be further studied if the operational rules of hydro dam operation could be provided.

In addition to low flow modelling and supporting the assessment of hydro dam operation, LSTM models can also be used to simulate and manage flood risk.

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6 Glossary of abbreviations and terms

Epoch	The period in which each training sample is used once for updating model parameters
LSTM	Long-short-term memory algorithm in artificial neural network
MAE	Mean absolute error between observation and simulation when optimising LSTM parameters
RNN	Recurrent neural network

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