An environmental modeling algorithm to predict naturalized hydrology and water allocation status at human-influenced gauged sites: case study, Otago New Zealand

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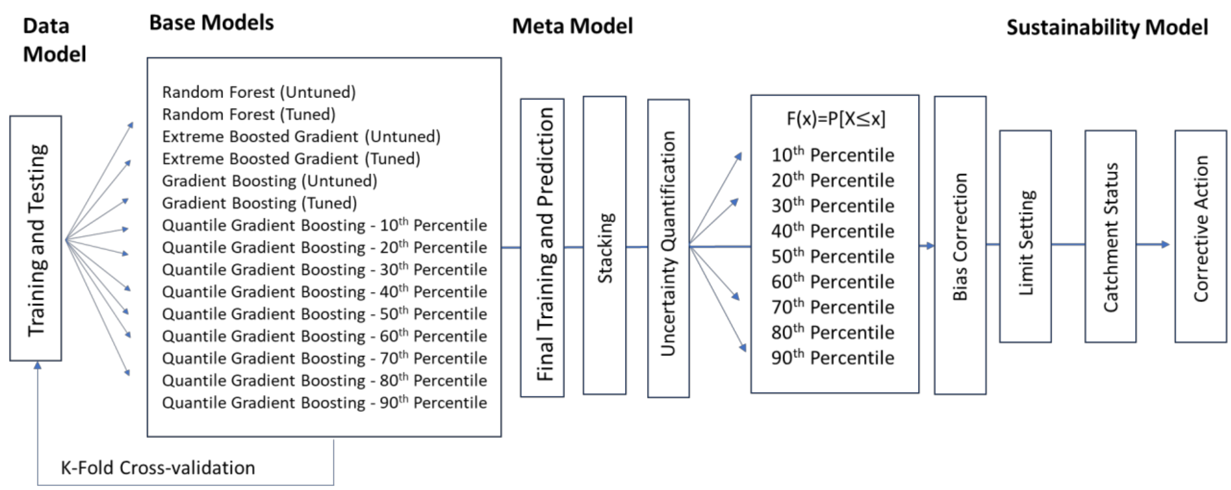
HIGHLIGHTS

- Base models are excellent predictors of naturalised Mean and Mean Annual Low Flow (MALF)
- Meta model predicts naturalised Mean and MALF at human-influenced gauged sites
- Meta predictions require stochastic correction for catchment areas < 4 km^2 and > 800 km^2
- Sustainability model converts predictions to minimum flows, allocation rates, and allocation status
- Meta predicts 54 overallocated catchments (50th percentile) of 317 human-influenced gauges

GRAPHICAL ABSTRACT



Abstract

Recent New Zealand legislation requires that regional councils set limits for water resource usage to manage the effects of abstractions in over-allocated catchments. Toward that end, an environmental modeling algorithm is proposed and demonstrated for applicability to sustainable stream management across the Otago Region of New Zealand. This four-layer algorithm includes a Data model, Base models, a Meta model, and a Sustainability model. The training and testing of Base models using limited natural catchment data (N=49) provided prediction accuracy equal to or better than very good ($R^2 > 0.9$) when predicting naturalised Mean flow (Mean) and 7-day Mean Annual Low Flow (MALF). Bias-corrected Meta modeling provided naturalised empirical cumulative distribution functions (ECDFs) for predictions at each gauged location. Naturalised predictions are independently validated using statistical, basin transfer and water balance methods. Application of the Sustainability model to naturalised Mean and MALF predictions provided naturalised default minimum flows and naturalised default allocation rates that when combined with consented abstractions determined the probable naturalised allocation status of human-influenced catchments (N=317) across catchment scales (1st to 7th order streams). The ECDFs of naturalised hydrology provide flexibility in selecting the level of risk to manage water-resource sustainability for over-allocated catchments; for example, at the respective 10th, 20th, 30th, 40th, 50th, average, 60th, 70th, 80th, and 90th percentiles the number of over-allocated catchments is determined to be 72 (over conservative), 68, 62, 57, 54, 50 (most likely), 45, 37, 31, and 26 (under conservative). In addition to the Otago Region, the proposed algorithm can be applied to inform sustainable stream management in regional catchments across New Zealand.

Keywords: Base models, Ensemble machine learning, Meta model, Sustainability model, Naturalised hydrology, Uncertainty quantification, Default abstraction limits, Default allocation rates, Catchment allocation status, Otago New Zealand

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1. Introduction

The current demand for freshwater resources is threatening sustainable management and security of regional catchments worldwide (McManamay et al., 2022). Focus on stream water allocation (process of distributing in-stream water for various sector needs) and environmental flows (ideal state of river flow regimes required to promote the sustainability of aquatic ecosystems; Booker et al., 2022) in regional catchments is of increasing interest among the international community (Jain and Kumar, 2014; Hoekstra, 2014; McManamay, 2014; Richter, 2013; Tharme, 2003). In New Zealand, the National Policy Statement for Freshwater Management (NPS-FM; Ministry for the Environment, 2020) gives direction to water resource reforms that include development of regional water management plans with freshwater objectives involving out-of-stream water allocation and in-stream environmental biodiversity outcomes. According to the NPS-FM, these freshwater objectives need to describe desired water-resource outcomes that will be achieved at the sub-regional scale, called a freshwater management unit (FMU).

Important NPS-FM objectives are to limit the streamflow below which all abstractions must cease (default minimum flow) and to limit the cumulative number of upstream abstractions above which the permitting of consented abstractions must cease (default allocation rate). Defining these limits on a catchment basis is considered important for quantifying the amount of freshwater resource that is available to out-of-stream users. In principle, comparing the difference between these limits provides a means for characterizing the catchment status as under-allocated or over-allocated. Knowledge of the catchment status is particularly important because the NPS-FM directs regional councils to reduce the allocation of water in over-allocated catchments. The NPS-FM further encourages councils to include desired water-resource outcomes in their regional plans, such as the use of predefined rules (allocation limits) for minimizing the potential cumulative effects of catchment abstraction on in-stream biodiversity through delivery of environmental flows while providing water for out-of-stream use (NPS-FM, 2020). In this way, the regional plans can better safeguard the water availability for public, industrial, and agricultural uses while ensuring a standard level of protection for cultural, social, and environmental values (Ministry for the Environment, 2015).

The NPS-FM provides impetus for councils to develop regional plans that manage the potential effects of in-stream abstractions as a freshwater objective, but there are challenges in defining freshwater resource use limits associated with environmental flows and therefore catchment allocation status (Booker et al., 2018). In principle, there is a tradeoff in defining the freshwater resource use limits and, at the time of this study, there are no published guidelines describing how these limits should be set. In 2021, Hayes et al. presented evidence to the Environment Court on guidelines to help inform the Otago Regional Water Plan. These sustainability guidelines describe a method for determining the default minimum flow and the default allocation rate as a percentage of the naturalised 7-day Mean Annual Low Flow (MALF) based on knowledge of the naturalised mean daily flow (Mean). In doing so, these two freshwater limits can be expressed in units of flow at any location where the naturalised Mean and naturalised MALF has been determined. Unfortunately, many of the observed flows originating upstream of gauging stations reflect a combination of natural and human activities (human-influenced). For this reason, the natural flows cannot always be directly measured and therefore must be determined using a naturalization method.

Streamflow naturalization methods typically involve the use of models (Terrier, et al. 2021). Most published models use the water balance approach (Fantin-Cruz, et al., 2015; Yuan et al., 2017). Other reconstitution methods use spatially explicit process-based hydrology models that are data and computationally intensive but when calibrated properly can predict streamflow at a daily time step (Barbarossa et al. 2017). In principle, these spatially explicit hydrological models can be developed and calibrated for regulated catchments and used to predict naturalised environmental streamflow following removal of the anthropogenic components (Gosain et al., 2005; Kim et al., 2012; Yin et al., 2017). In practice, these efforts are often challenged by uncertainty due to simplified process representation in the model structure, input data characterized by limited spatiotemporal measurements, and nonunique parameter estimates resulting from the calibration procedure (Ehlers et al., 2018; Gupta and Govindaraju, 2019; Jin et al., 2010; Moges et al., 2020; Setegn et al., 2009). As an alternative, recent applications include additional calibration constraints based on the regionalization of multiple hydrological models in data scarce and ungauged catchments (Garna et al., 2023; Golian et al., 2021; Mahapatra and Jha, 2022).

Regression based empirical models provide a practical alternative to the time-consuming, computationally intensive, and uncertain spatially explicit process-based hydrology models. In general, these models relate streamflow indices to explanatory catchment characteristics promoting scale-dependent understanding among hydrological processes and patterns in regional catchments (Farmer et al., 2015). These empirical models can be parametric with predictors based on equations (Barbarossa et al., 2017) or nonparametric with predictors based on information derived from data (Okkan and Serbes, 2012; Wu et al., 2009). Despite the number and type of empirical approaches available, few studies compute naturalised environmental flow indices. In one related study by Booker and Woods (2014), the nonparametric Random Forest regression (ensemble machine learning) method was found to outperform the process-based hydrological model when estimating environmental flow indices across ungauged catchments in New Zealand.

Despite the various approaches available for estimating naturalised streamflow, there is no approach for quantifying the naturalised allocation status across regional catchments. Possible reasons may be attributed to the challenges in computing naturalised hydrological indices across human influenced catchments, the tradeoff in computing catchment limits, and how to express management risk in terms catchment allocation with model uncertainty. The *aim* of this research is to develop a novel environmental modeling algorithm for predicting the naturalized water allocation status at human-influenced gauged catchments spanning multiple catchment scales. We hypothesize that the combination of natural hydrology and physical catchment characteristics can provide mutual information (Atienza, R., 2020) suitable to achieve this aim. Our *objective* is to test the environmental modeling algorithm for predicting the probable naturalised allocation status at human-influenced gage sites (N=317) spanning multiple Strahler stream orders (N=7) in the Otago region of New Zealand. Quantifying the naturalised water allocation status at human influenced sites and multiple catchment scales supports the Otago Regional Council's effort to develop a Land and Water Plan as required by the NPS-FM (Ministry for the Environment, 2020). This study extends the work of Booker et al (2014, 2018) whose studies on New Zealand stream catchments of Strahler stream order > 3 included using a random forest regressor to estimate deterministic indices of natural hydrology and using a weighting scheme to quantify the hydrological effect of permitted water abstractions.

2 Data and Methods

The proposed Environmental Modelling algorithm combines four elements: the Data model, Base Models, the Meta Model, and the Sustainability Model (Fig. 1). This algorithm is applied sequentially to determine the naturalized catchment hydrology and the water allocation status across a region. The four elements associated with the algorithm are briefly described next.

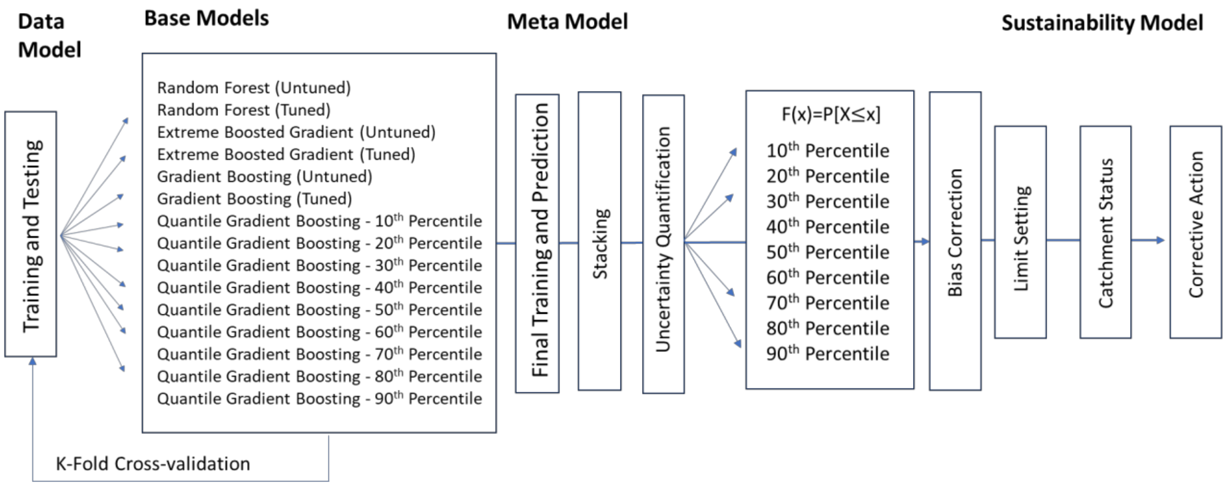


Fig. 1. Environmental modelling algorithm used to predict probable naturalised catchment hydrology and water allocation status at human influenced sites and stream reaches across multiple catchment scales.

2.1 Data model

The first element in the Environmental modelling algorithm is the Data model. The Data model is used to prepare regression response and predictor variables collectively called features. The *target* variables, also known as dependent or response variables, are hydrologic indices, namely the daily mean flow (Mean) and the 7-day mean annual low flow (MALF), computed from available daily streamflow time-series (Table 1). These target features are predicted based on the remaining features described as physical catchment properties. According to Rallo et al. (2002), one of the elements necessary for accurate model predictions is diversity of feature information. To achieve diversity, the hydrological indices and physical properties need to characterize mutually informative relations, i.e., be sourced from catchments spanning multiple scales (areas and stream orders) and environmental conditions (spatial and temporal sampling gradients).

Table 1. Hydrological Indices derived from observed mean daily flows.

Index	Description	Calculation
Mean	Mean flow over all time	Mean of all daily flows
MALF	Mean of minimum 7- day flow in each year	Mean of minimum flow for each water year after having applied a running 7-day mean to the daily flows

2.2 Base Models

The second element in the Environmental modelling algorithm are the Base models. The Base models rely on various ensemble machine learning algorithms (Pedregosa et al., 2011), namely Random Forest Regressor (RFR; Breiman, 2001), Gradient Boosting Regressor (GBR; De'ath, 2007), Extreme Gradient Boosting Regressor (XGB; Chen and Guestrin, 2016), and Quantile Gradient Boosting Regressor (QGBR; Zheng 2012), to predict hydrologic indices. These ensemble algorithms learn relationships among the response (one of the hydrologic indices) and predictor variables (catchment characteristics) without relying on statistical assumptions about the data (Dietterich, 2000). For a detailed review of these methods the reader is referred to the accompanying references. Important Base model tasks (standard practice) involve training and testing of the ensemble machine learning models (Dietterich, 2000).

Important Base model tasks involve (standard practice) training and testing of the ensemble machine learning models. Several decisions are required during the model *training* phase of Base models. First, a file with the naturalised catchment records is assigned. Second, a decision is made to assign either the natural Mean or the natural MALF as the response variable. Third, the number and type of physical catchment characteristics are assigned as independent predictor variables. Fourth, an arbitrary random seed (also referred to as the random state number) is assigned to initialize the random number generator for shuffling of the catchment records. Fifth, a decision is made on the relative proportion of records assigned to the training and testing phases. Sixth, a decision is made to use default (or base) ensemble model parameters or invoke a hyperparameter tuning method to optimize the ensemble model parameter values (Pedregosa et al., 2011).

In ensemble machine learning, hyperparameters refer to input parameters that influence the model structure and their predictions. The available parameters for tuning depend on the type of Base model and can determine how closely a model fits the training data. Fitting too closely tends to promote model learning from noise in the training dataset (overfitting). This situation typically results in poor prediction on the testing dataset. Conversely, fitting too loosely indicates that the model has not learned to represent patterns in the training data (underfitting). Even though there are many approaches to hyperparameter tuning, most studies use simple grid search and random grid search. In using the grid search, the number of values are defined for each parameter, creating a multi-dimensional grid space that includes every combination of hyperparameter values. Consequently, if there are many hyperparameters that require tuning, this approach can become time and computationally expensive. In a random search, the hyperparameter values are sampled from a pre-defined range of values. In both cases, each candidate model is formed on a unique set of hyperparameters, and the best model is chosen as the one that achieves the lowest mean square error on the test dataset.

Each ensemble machine learning algorithm employs a different number of model parameters that may be tuned. For instance, the *Random Forest* method optimizes three parameters during the tuning phase (Breiman, 2001). First, the number of variables parameter is randomly selected at each node and considered for splitting. Reducing this parameter increases the randomness of the tree-building process thereby creating trees that are more dissimilar to each other. Second, the number of trees parameter is used to build the forest. Model accuracy typically levels out after arriving at the number of trees required to build a credible model. Third, the tree depth is the point at which the tree stops growing. The larger the tree depth, the closer the model fits the training data increasing the risk of overfitting. In contrast to the Random Forest, the *Gradient Boosting* algorithm uses nine hyperparameters to facilitate convergence to an optimal solution (Malohlava and Candel, 2017). This method implements randomness in the modelling process to avoid overfitting. In addition to number of trees, maximum tree depth, and number of variables sampled for splitting, the number of variables sampled for each tree is also defined by the user. The number of variables sampled at each node is then calculated as the product of the variables sampled for the tree, multiplied by the variables sampled for splitting. The learning rate in this method is the factor by which the contribution of each consecutive tree is reduced compared to the previous tree. Another parameter defines the type of histogram used to speed up selection of the best splitting point at each node. The subsample rate determines the size of the random sample used at each iteration. Smaller samples give rise to lower testing errors whereas larger samples tend to improve the training accuracy. Lastly, there are two hyperparameters that determine the need for additional tree splitting: the minimum required relative improvement in squared error, and the minimum number of observations in a leaf node. Lastly, the *Extreme Gradient Boosting* represents another implementation of the boosting algorithm (Chen and Guestrin, 2016). The number of iterations, the subsample size, maximum tree depth, and fraction of explanatory variables sampled at each tree are also required hyperparameters. In addition, the shrinkage rate determines the learning rate of the algorithm in the training step, i.e. the amount by which the contribution of each consecutive tree is reduced compared to the previous tree. Additional parameters that need tuning when using this algorithm determine how conservative the algorithm is in terms of further partitioning at a leaf node.

The Base model *testing* phase is undertaken by presenting the independent split fraction to the trained models. This phase is important for assessing the ability of these models to generalize when presented with independent catchment records. The relative quality of trained regression models is based on the R-Squared coefficient of determination (Lewis-Beck, 2015) as follows: 60-70% poor, 70-80% good, 80-90% very good, >90% excellent. Scatterplots of the predicted to the observed values are often inspected to visually identify prediction bias, where values with a 1:1 correspondence reveals an (ideal) unbiased model. Feature importance scores (not used here) are sometimes reviewed to evaluate the relative influence that a feature may have on the model prediction process. However, the interpretation of these scores can be misleading because highly correlated features result in splitting their importance giving the false impression that they have less importance. Lastly, deviance plots are inspected to ensure the model is not overfitting the set of training records. Once the training and testing phases are satisfactorily completed, the next step is to create the Meta model.

2.3 Meta Model

The third element in the environmental modelling algorithm is the Meta model. The Meta model is developed with the aim of achieving greater predictive accuracy following the application of final training and predictions, stacking, uncertainty quantification, and bias correction briefly described in the following sections.

2.3.1 Final Training and Predictions

The final training phase is undertaken by retraining those Base models determined to be preferred predictors of hydrologic indices during the testing phase. These preferred Base models are then trained using the complete set of physical property data from natural catchment sites (training plus testing). The final predictions of natural hydrologic indices at human-influenced gauged sites are obtained by presenting independent physical catchment features to the preferred Base models. The relative quality of trained regression models is based on evaluating the prediction uncertainty of stacked models discussed next.

2.3.2 Stacking

Traditional stacking use a high-level (Meta) model that combines lower-level Base models to achieve greater predictive accuracy (Wolpert, 1992). The two common methods of stacking low-level Base models into a high-level Meta model include simple weighted average (Wolpert, 1992) or neural network model to learn the best combination based on residual errors (Ting and Whitten, 2011). In the former case, the weighted average does not consider the quality of models or provide a means for quantifying their predictive uncertainty. In the latter case, there are often issues achieving improvements relating to the machine learning problem being well represented by the training data, complex enough that there is more to learn by combining predictions, and choice of Base models that are sufficiently uncorrelated in their predictions (or errors). For these reasons, this study embraces simple statistical stacking in which the results of multiple random subsamples of the field observations are presented to the ensemble models to improve accuracy, quantify and reduce the prediction interval (Shrestha and Solomatine, 2006)**.** Advantages in using this approach are thought to prevent overfitting by providing a more robust estimate of the model performance on unseen data, and to compare different Base models and select those that perform the best. Disadvantages in using this approach include the increase in computational time for training when considering multiple folds (randomly shuffled split sets), the increase in computational time for cross-validation when multiple models need to be compared, and the bias-variance tradeoff, i.e., the choice in number of randomly shuffled split sets: too few folds may result in high variance, while too many folds may result in high bias.

2.3.3 Uncertainty Quantification

Statistical stacking of Base model results is used to quantify the prediction uncertainty at predefined percentiles, e.g., 10th (under conservative), average (most likely or expected value), 50th (median or 50% of values above and 50% of values below), and 90th (over conservative). Predictions of the Mean flow and the MALF at these percentiles describe empirical cumulative distributions functions (Shorack and Wellner, 1986) at each gauge site and stream reach segment. An empirical cumulative distribution function (ECDF) is a step function that reveals the association among corresponding data percentiles and observed values. The ECDF's value at a specific prediction value of the measured hydrologic variable is the fraction of observations that are less than or equal to that value. The step function increases by a percentage equal to 1/N for each observation in a dataset of N observations. The distribution of discrete Base model predictions characterize uncertainty that may be due, in part, to three sources. *First*, catchments are assumed to be in their natural state when calculating the hydrological indices used in training the Base models. *Second*, there is a limited number of randomly selected catchment records used for k-fold training of the Base models. The limited number of catchment records available for training and testing underscore the importance of identifying gauge stations reflective of natural conditions. *Third*, the upstream catchment characteristics are assumed to be optimal in type and number.

2.3.4 Bias Correction

Given limited resources available when collecting and preparing the Data model, the Base models might be trained with data that results in biased predictions. Bias refers to the presence of systematic errors in a model that leads consistently to making incorrect predictions. These errors may arise from different sources that include the selection of training data (sample bias), the choice of features used to build the model (feature bias), or the algorithm used to train the model (algorithmic bias). In the context of naturalised hydrology, the sample bias could be associated with poor-quality catchment features obtained from low order streams and/or limited number of catchment features from high order streams. In these instances, there may be the possibility to apply a linear bias correction based on the slope of log Mean (or log MALF) as a function of log catchment area (or Strahler stream order). Feature bias may be removed by reducing the model dimensionality to an optimal set of physical properties that satisfy the same hydrological index (response variable or target feature), e.g. using modern feature selection techniques involving learn heuristics, such as the filter (Buscema et al., 2013; Friedel et al., 2020) or wrapper (Calvet et al., 2017) methods. The algorithmic bias can be addressed through the stacking of Base model predictions. Completing the bias correction step results in a Meta Model suitable for predicting naturalised hydrologic indices at human-influenced gauge and stream reach sites of different stream orders. The ability to predict these naturalised probable hydrologic indices provides a basis for discerning likely departures from reference states (Vogel et al., 2007) in regional catchments. Comparisons of naturalised probable hydrologic indices to human influenced hydrologic indices can be used to quantify the probable rates of decline in flows from their reference state. In addition, the prediction of naturalised hydrologic indices can be used as direct input to the Sustainability model.

Sustainability Model

The fourth element in the environmental modelling algorithm is the Sustainability model. The Sustainability model involves limit setting and allocation status steps described next.

2.4.1. Limit setting

The application of limit setting in the Sustainability model is based on guidelines proposed and adopted in the Environment Court of New Zealand. According to Hayes et al. (2021), the proposed default limits (Table 2) serve two primary functions. First, these limits set the default minimum flows and default allocation rates to avoid more than minor in-stream ecological effects. Second, these default limits define a threshold for more than minor instream effects. In the event the default minimum flow is less than proposed and/or the default allocation rate is exceeded, the ecological effects are likely to exert pressures that are considered more than minor. The possibility exists for the proposed instream values and NPS-FM objectives to be adjusted with alternative allocation rates and alternative minimum flows, but the assessment of ecological effects supporting these outcomes require the collection and incorporation of additional information (e.g., hydraulic-habitat modelling and/or invertebrate drift versus flow relationship) to properly assess the ecological effects supporting that outcome (Beca, 2008).

The minimum flow and allocation limits set as proportions of historical flow statistics, such as the default limits proposed by Hayes et al. (2021), assume spatially consistent reductions in habitat and/or ecological responses with flow reduction. However, the flow related ecological flow and habitat relationships often respond nonlinearly to spatiotemporal flows resulting in default minimum flows and default allocation limits that may result in different ecological and habitat protection levels for different size rivers and aquatic species (Snelder et al. 2011; Booker et al. 2014). Application of the so-called Hayes guidelines are simpler to apply than the methods of assessing environmental flows and habitat setting limits, and some guidance already exists on percentage flow alteration limits likely to pose low risk of adverse ecological effects (Richter et al., 2012). According to Hayes et al., (2021), the default limits for perennial rivers will also provide protective limits for permanently flowing segments of intermittent rivers, and the proposed method to calculate the limits for such reaches, based on percentage of the MALF, is practical and environmentally conservative while allowing for modest levels of stream abstractions (also called takes). Lastly, the limits as proposed give effect to the NPS-FM directive of Te Mana o te Wai, whose translation means to put the health and wellbeing of waterbodies above other needs (Ministry for the Environment, 2023).

Table 2. Default limit setting guidelines expressed as a percentage of naturalised 7-day annual low flow (MALF) for maintaining flow regimes that present a low risk of more than minor effects on ecosystem health and wellbeing of Otago's streams and rivers, including their instream habitat, life-supporting capacity, and fisheries amenity (after Hayes et al., 2021).

Limiit	Surface water body with average Mean daily flow <= 5 m3/s	Surface water body with average Mean daily flow > 5 m3/s
Minimum flow	90% of naturalised 7-day MALF	80% of naturalised 7-day MALF
Allocation rate	20% of naturalised 7-day MALF	30% of naturalised 7-day MALF

2.4.2 Allocation status

To determine the naturalised allocation status for human-influenced gauged catchments, the current allocation rate (i.e., the sum of consented catchment takes upstream from the gauge station) is subtracted from the computed default allocation rate giving the default allocation rate available. If the default allocation rate available is positive, the catchment status is deemed to be under-allocated with additional water available for future consents. Conversely, if the default allocation rate is negative, then the catchment status is deemed to be over-allocated with a net deficit of catchment water available for future consenting. This process is repeated with default allocation rates computed at predetermined percentiles and expected value providing results that collectively describe a cumulative distribution function for every regional catchment of interest. This approach provides added information over deterministic solutions when selecting an appropriate level of risk to manage over-allocated catchments.

3 Case Study, Otago, New Zealand

In this section, efficacy of the proposed Environmental modeling algorithm is demonstrated by informing the Otago Regional Council's Land and Water Plan in support of the National Policy Statement for Freshwater Management (Ministry for the Environment, 2020, 2023). The objectives are to determine the default minimum flow, default allocation rate, and allocation status at human-influenced gauged catchments across the Otago region of New Zealand (Fig. 2). The practical aspects and findings when applying the Data model, the Base Models, the Meta Model, and the Sustainability Model are discussed next.

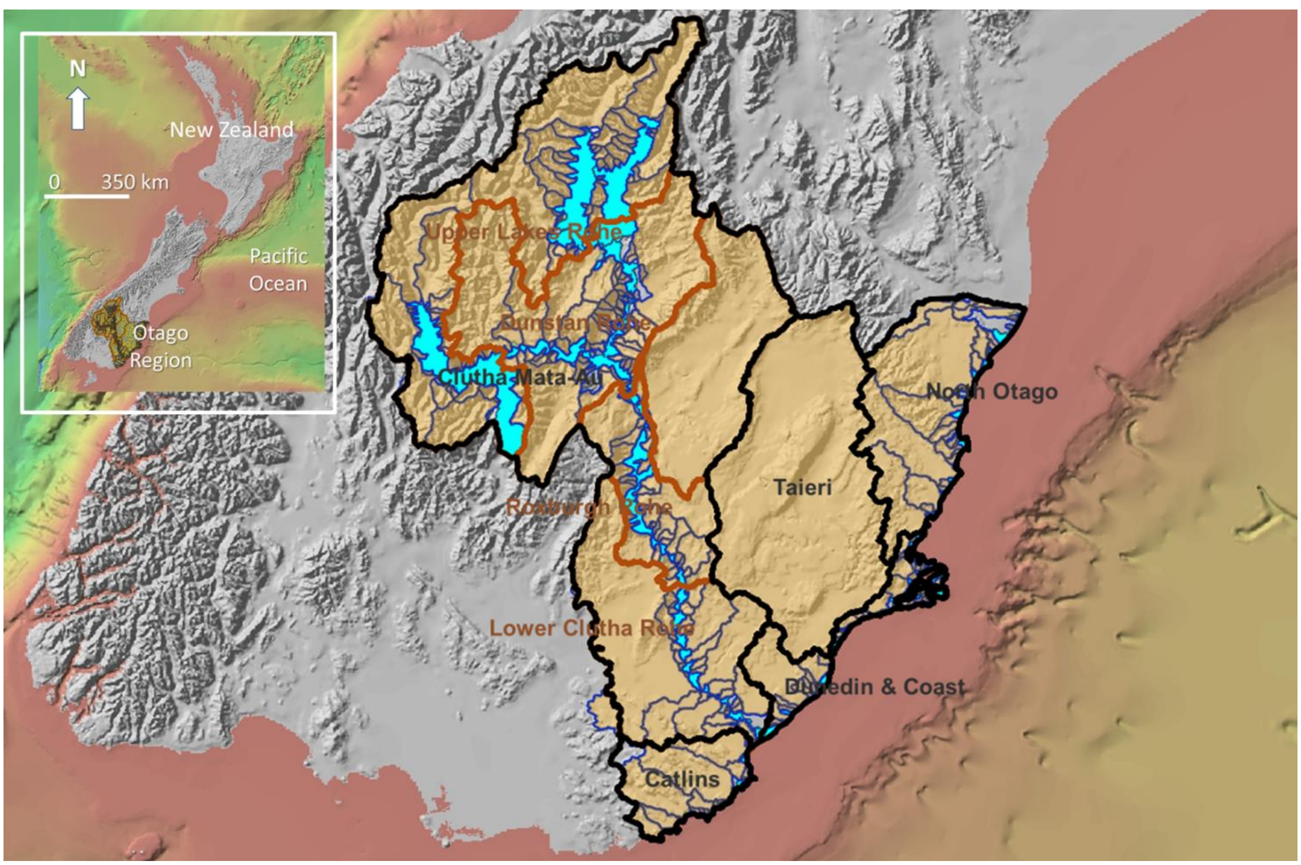


Fig. 2. Location map showing water management regions across the Otago Region, New Zealand. The region has 5 Freshwater Management Units (outlined and labeled in black) that include the Clutha (Mata-Au), Catlins, Dunedin & Coast, North Otago and Taieri. The Clutha comprises 5 smaller indigenous (iwi) management units (outlined and labeled in brown) called Rohe that include the Dunstan, Lower Clutha, Manuherekia, Roxburgh, and Upper Lakes.

3.1 Data Model

The Data model is used to compute naturalised hydrologic indices across the Otago Region (Fig. 2). The Otago Region (32000 km^2) includes human-influenced gauged catchments (N=317). These catchments span five freshwater management units (FMUs): Catlins, Clutha (Mata-Au), North Otago, Taieri, Dunedin & Coast. The Clutha (Mata-Au). These FMUs are further subdivided into five smaller water-management units called Rohe reflecting the specialized water-interests of different iwi tribes: Dunstan, Lower Clutha, Manuherekia, and Upper Lakes. The types of regression data sourced for this study include information in natural hydrological indices (response variables) and catchment characteristics (predictor variables) are associated with 1st to 7th order streams and catchment areas that range from 0.3 km^2 to 6000 km^2 (Fig. 3).

The natural hydrological indices, namely the Mean and the MALF, are computed from available daily streamflow time-series collated using the Hilltop software (Hill Laboratories, 2023) and Otago Regional Council hydrology database. From this database, a set of daily streamflow time-series are collected from gauging stations representing the range of hydrological conditions (natural to human-influenced) across the Otago region. Of these sites, only sites with at least five years of continuous (> 11 months per year) daily flow records are identified for possible use. Additional filtering of time-series records is undertaken to remove those gauge stations affected by upstream engineering projects, such as dams, diversions, or substantial abstractions. Lastly, selecting sites where the total consented upstream abstraction is less than 30% of the estimated median daily flow results in identifying flow sites (N=49) that approximate natural streamflow conditions for use in the Data model (Fig. 4). In using empirically based regression methods, the differences among sites in hydrological regimes is assumed to exceed any differences in hydrological regimes due to differences in observation periods, which are different for each observed time-series. The reader is referred to Booker and Woods (2014) for more details on gauge station selection.

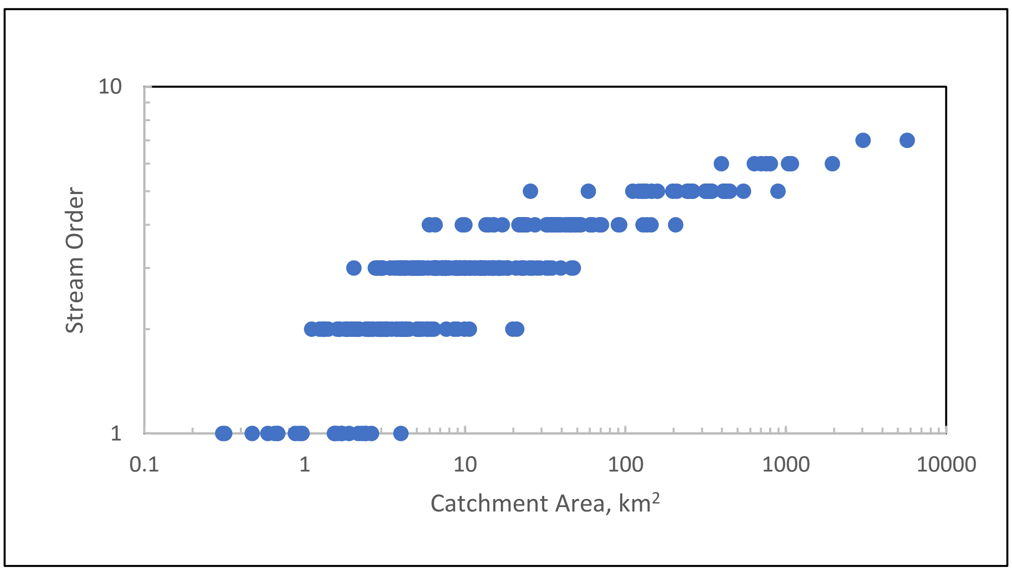


Fig. 3. Plot showing the distribution of natural streamflow gauging stations (blue dots) with respect to the Strahler stream order and catchment area in the Otago Region, New Zealand.

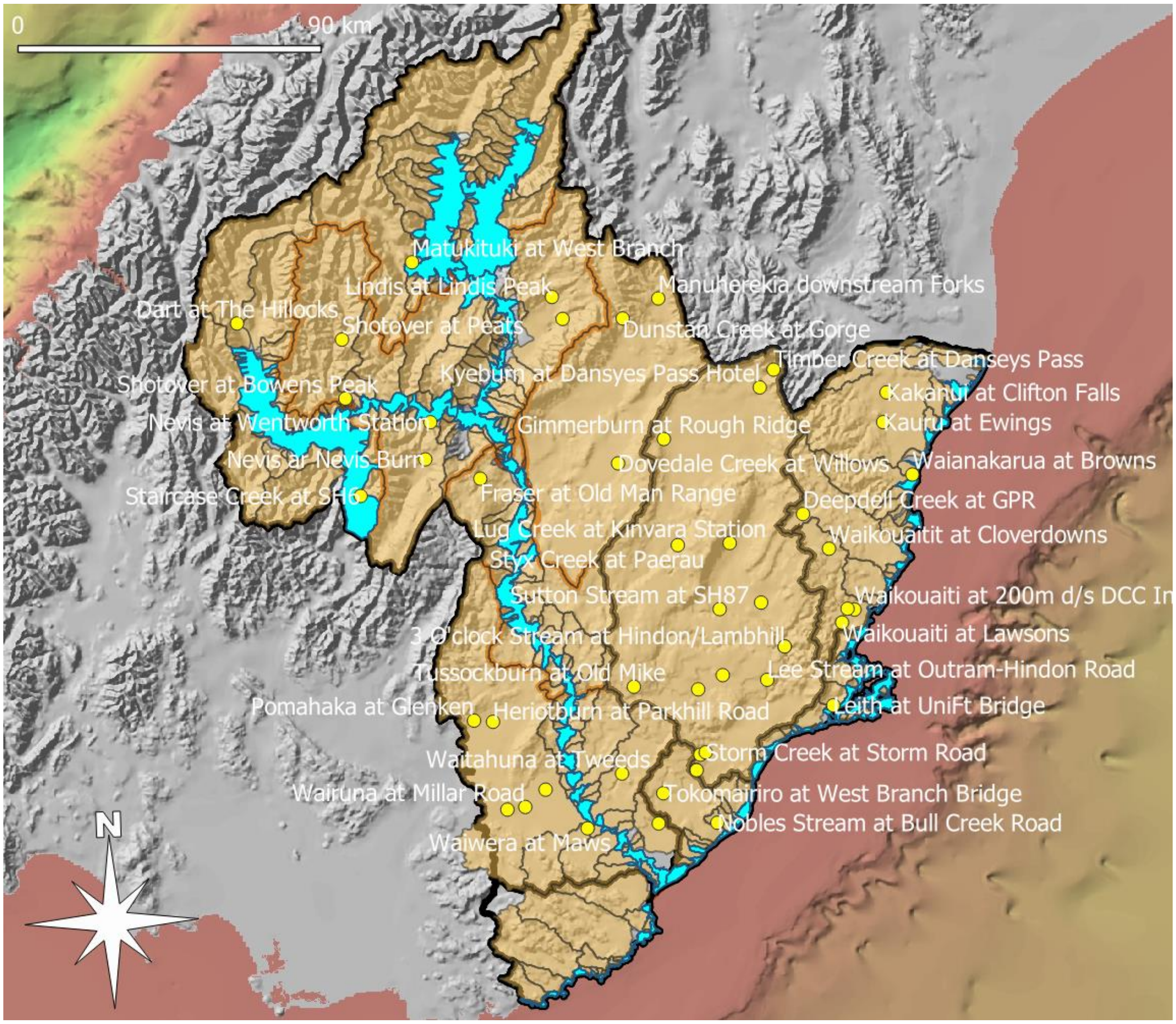


Fig. 4. Location map showing names (white text) of randomly distributed gauging stations (yellow dots) that recorded natural flows across Otago, New Zealand (N=49).

According to Booker and Snelder (2012), there is a set of catchment characteristics (features) considered suitable for explaining the variation in hydrological patterns across New Zealand (Table 3). The catchment features (N=8) include area, elevation, particle size, potential evapotranspiration (PET), rainfall variation, rain days, runoff volume. These physical characteristics represent average values obtained from the Freshwater Environments of New Zealand geo-database (Leathwick et al. 2011) sorted on reach numbers found in the River Environment Classification (Snelder and Biggs 2002). The catchment characteristics used in this study represent physical properties located upstream from gauge sites. For example, catchment characteristics acquired from the locations of natural stream flow sites (N=49) are presented in Fig. 4; the location of (named) human-influenced gauged sites (N=317) are presented in Fig. 5

Table 3. Summary of physical catchment features explaining hydrologic variation across New Zealand (Booker and Woods, 2014).

Feature	Description
Area	Log of catchment area (m2)
Elevation	Average elevation in the upstream catchment (m)
Particle size	Catchment average of particle size (mm)
Potential evapotranspiration (PET)	Annual potential evapotranspiration of catchment (mm)
Rainfall variation	Annual catchment rainfall coefficient of variation (mm)
Rain days	Catchment rain days, greater than 10 mm/month (days/year)
Runoff volume	Percentage annual runoff volume from catchment area with slope > 30° (%)
Slope	Average catchment slope (%)

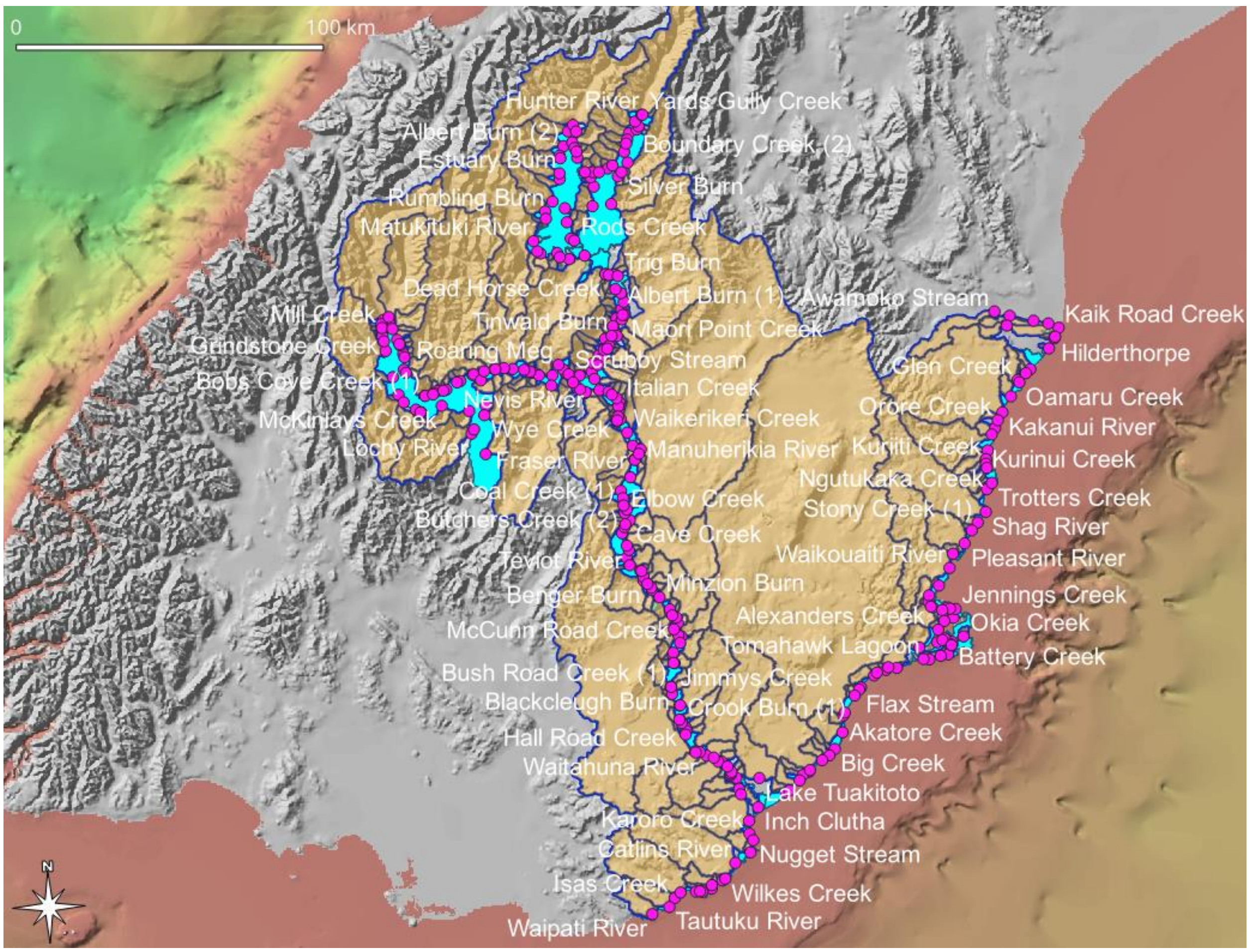


Fig. 5. Location map of 317 human-influenced gauged catchments where the naturalised annual mean flow and 7-day mean annual low flow, and catchment allocation status are predicted at 5th, 25th, 50th, 75th, and 95th percentiles across the Otago Region, New Zealand. The black outlines are the catchment boundaries and purple dots are the human-influenced streamflow gauge stations.

3.2 Base Model

3.2.1 Training and testing

In this section, the results are provided for model training and testing phases using catchment records (features) acquired at natural streamflow sites across Otago (Fig. 4). The set of catchment records comprises target hydrologic indices (Mean or MALF) and predictive features referred to as catchment characteristics (Table 3). A statistical summary of (dependent) hydrologic indices and (independent) catchment characteristics aggregated from natural streamflow sites is presented in Table 4. These catchment records are randomly shuffled and split multiple times during the training and testing phase. In this study, the ratio used in shuffling and splitting records is 80% (N=39) for training and 20% (N=10) for testing. This ratio is a matter of choice and alternative ratios could be adopted, e.g., such as 50% training and 50% testing, 90% training and 10% testing, as part of the testing phase. In this way, the shuffling process provides a means to evaluate the effect of different catchment characteristic subsets on the prediction bias and uncertainty of the Base models despite the limited number of records. One side benefit in using this procedure is that each random number seed produces a single reproducible (deterministic) outcome that can be repeated using the same python script for review and/or use in other related analyses at any time.

Table 4. Summary table of independent catchment characteristics and dependent hydrologic indices from the natural streamflow sites used in the base model training and testing phase across the Otago Region. PET = potential evapotranspiration (mm/unit time), Particle size = mm, Mean = mean of all daily flows, and MALF = Mean of minimum flow for each water year having applied a running 7day mean to the daily flows.

Model:									Mean	MALF
Statistic	Log Area (m^2)	Elevation (m)	Partilce Size (mm)	PET (mm/unit time)	Rainfall Variaton (mm)	Rain Days (days/yr)	Runoff Volume (%)	Slope (%)	Discharge (m3/s)	Discharge (m3/s)
count	49	49	49	49	49	49	49	49	49	49
mean	7.19	372	3.23	935	169	1.74	0.05	13.1	7.96	1.92
std	0.85	325	0.90	125	16	0.67	0.10	5.64	15.6	4.38
min	5.87	14.8	1.10	404	143	0.81	0.00	0.33	0.01	0.00
25%	6.57	126	2.57	885	155	1.44	0.01	9.66	0.58	0.10
50%	7.05	214	3.51	958	168	1.65	0.02	13.3	2.22	0.31
75%	7.53	569	3.90	995	179	1.87	0.04	15.3	5.63	1.05
max	9.50	1180	4.79	1166	203	5.35	0.48	28.4	80.2	20.8

In this study, there are different Base models (N=16) being evaluated as part of the training and testing phase. The total number of models reflects variations with and without hyperparameter tuning available as part of the scikit-learn toolbox (Pedregosa et al., 2011). Hyperparameter tuning includes random grid search and random grid search plus cross-validation methods available from this machine learning toolbox. Different feature subsets (called folds) are used to train and test the Base models. The process used in selecting a subset of the catchment records is controlled by assigning a random number that initiates record shuffling prior to splitting. For example, there are 10 random numbers (10-fold) used to split records for training and testing the Mean and the MALF models. A summary of relative prediction quality is presented as R^2 values for the Mean (Table 5a) and MALF (Table 6a) models *without* hyperparameter turning, e.g., Random Forest Regressor (RFR), Gradient Boosting Regressor (GBR), Extreme Gradient Boosting (XGB), and Quantile Gradient Boosting Regressor at the 10th (QGBR10), 50th (QGBR50), and 90th (QGBR90) percentiles, and predictions using models *with* hyperparameter tuning, e.g., Random Forest Regressor with random grid search (RFRgs), Random Forest Regressor with random grid search and cross-validation (RFRgscv), Gradient Boosting Regressor with random grid search and cross-validation (GBRgscv), and Extreme Gradient Boosting Regressor with random grid search and cross-validation (XGBgscv), and Quantile Gradient Boosting Regressor with grid search at 10th (QGBR10gs), 20th (QGBR20gs), 30th (QGBR30gs), 40th (QGBR40gs), 50th (QGBR50gs), 60th (QGBR60gs), 70th (QGBR70gs), 80th (QGBR80gs), and 90th (QGBR90gs) percentiles. Companion tables reveal the discarded (0 = $R^2 < 0.9$) and retained (1 = $R^2 \geq 0.9$) models (Table 5b and 6b). These preferred Base Mean (N=129) and Base MALF (N=127) models are used in the final training and predictions at human-influenced gauge sites.

Table 5. Statistical quality of naturalised Mean flow models evaluated as part of the training and testing phase: (a) R^2 between observed and predicted natural Mean flows, (b) binary indicator used as basis to discard (N=31) models ($0 = R^2 < 0.9$) or retain (N=129) models ($1 = R^2 \geq 0.9$) for stacking. The retrained Base models are used in the Meta model phase. Base models include: Random Forest Regressor (RFR), Gradient Boosting Regressor (GBR), Extreme Gradient Boosting (XGB), and Quantile Gradient Boosting Regressor at the 10th (QGBR10), 50th (QGBR50), and 90th (QGBR90) percentiles, and predictions using models *with* hyperparameter tuning, e.g., Random Forest Regressor with random grid search (RFRgs), Random Forest Regressor with random grid search and cross-validation (RFRgscv), Gradient Boosting Regressor with random grid search and cross-validation (GBRgscv), and Extreme Gradient Boosting Regressor with random grid search and cross-validation (XGBgscv), and Quantile Gradient Boosting Regressor with grid search at 10th (QGBR10gs), 20th (QGBR20gs), 30th (QGBR30gs), 40th (QGBR40gs), 50th (QGBR50gs), 60th (QGBR60gs), 70th (QGBR70gs), 80th (QGBR80gs), and 90th (QGBR90gs) percentiles.

K-fold: Model	1 R^2	2 R^2	3 R^2	4 R^2	5 R^2	6 R^2	7 R^2	8 R^2	9 R^2	10 R^2
RFRbm:	0.96	0.92	0.99	0.97	0.99	0.99	0.98	1.00	0.96	0.99
RFRgs:	0.94	0.96	0.96	0.99	1.00	0.99	0.98	1.00	0.93	1.00
RFRgscv:	0.92	0.95	0.96	0.97	0.97	0.93	0.92	0.96	0.91	0.90
XGBbm:	0.96	0.95	0.97	0.98	0.95	1.00	1.00	1.00	0.96	1.00
XGBrgs:	0.96	0.91	0.96	0.96	0.96	1.00	0.99	1.00	0.96	1.00
GBRbm:	0.96	0.88	0.97	0.94	0.98	1.00	1.00	1.00	0.96	1.00
GBRRgs:	0.96	0.98	0.96	1.00	0.99	0.08	1.00	0.95	0.95	1.00
QGBR10gs:	-0.22	-0.16	-0.20	-0.18	-0.16	-0.28	-0.39	-0.12	-0.21	-0.42
QGBR20gs:	-0.12	0.10	-0.02	0.07	0.07	-0.20	-0.21	0.11	0.05	-0.33
QGBR30gs:	0.76	0.99	0.41	0.86	0.45	0.70	0.14	0.89	0.73	0.35
QGBR40gs:	0.96	0.98	0.97	0.98	0.97	0.97	0.99	1.00	0.96	0.96
QGBR50gs:	0.97	0.95	0.97	0.99	0.99	1.00	0.98	0.99	0.96	0.91
QGBR60gs:	1.00	0.96	0.97	0.99	1.00	1.00	1.00	0.99	0.97	0.99
QGBR70gs:	0.96	0.96	0.98	0.97	0.97	0.99	0.99	0.99	0.98	1.00
QGBR80gs:	0.98	1.00	0.96	0.98	0.99	1.00	0.98	1.00	0.97	1.00
QGBR90gs:	0.96	0.95	0.96	0.99	0.98	0.99	1.00	0.99	0.95	1.00

(a)

K-fold: Model	1 $R^2 \geq 0.9$	2 $R^2 \geq 0.9$	3 $R^2 \geq 0.9$	4 $R^2 \geq 0.9$	5 $R^2 \geq 0.9$	6 $R^2 \geq 0.9$	7 $R^2 \geq 0.9$	8 $R^2 \geq 0.9$	9 $R^2 \geq 0.9$	10 $R^2 \geq 0.9$	Count $R^2 \geq 0.9$
RFRbm:	1	1	1	1	1	1	1	1	1	1	10
RFRgs:	1	1	1	1	1	1	1	1	1	1	10
RFRgscv:	1	1	1	1	1	1	1	1	1	1	10
XGBbm:	1	1	1	1	1	1	1	1	1	1	10
XGBrgs:	1	1	1	1	1	1	1	1	1	1	10
GBRbm:	1	0	1	1	1	1	1	1	1	1	9
GBRRgs:	1	1	1	1	1	0	1	1	1	1	9
QGBR10gs:	0	0	0	0	0	0	0	0	0	0	0
QGBR20gs:	0	0	0	0	0	0	0	0	0	0	0
QGBR30gs:	0	1	0	0	0	0	0	0	0	0	1
QGBR40gs:	1	1	1	1	1	1	1	1	1	1	10
QGBR50gs:	1	1	1	1	1	1	1	1	1	1	10
QGBR60gs:	1	1	1	1	1	1	1	1	1	1	10
QGBR70gs:	1	1	1	1	1	1	1	1	1	1	10
QGBR80gs:	1	1	1	1	1	1	1	1	1	1	10
QGBR90gs:	1	1	1	1	1	1	1	1	1	1	10
											129

(b)

Table 6. Statistical quality of naturalised 7-day Mean annual low flow (MALF) model predictions evaluated as part of the training and testing phase. (a) R^2 between observed and predicted natural Mean flows, (b) binary indicator used as basis to discard (N=33) models (0 = $R^2 < 0.9$) or retain (N=127) models (1 = $R^2 \geq 0.9$) for stacking. These retrained Base models are used in the Meta model phase. Base models include: Random Forest Regressor (RFR), Gradient Boosting Regressor (GBR), Extreme Gradient Boosting (XGB), and Quantile Gradient Boosting Regressor at the 10th (QGBR10), 50th (QGBR50), and 90th (QGBR90) percentiles, and predictions using models *with* hyperparameter tuning, e.g., Random Forest Regressor with random grid search (RFRgs), Random Forest Regressor with random grid search and cross-validation (RFRgscv), Gradient Boosting Regressor with random grid search and cross-validation (GBRgscv), and Extreme Gradient Boosting Regressor with random grid search and cross-validation (XGBgscv), and Quantile Gradient Boosting Regressor with grid search at 10th (QGBR10gs), 20th (QGBR20gs), 30th (QGBR30gs), 40th (QGBR40gs), 50th (QGBR50gs), 60th (QGBR60gs), 70th (QGBR70gs), 80th (QGBR80gs), and 90th (QGBR90gs) percentiles.

K-fold:	1	2	3	4	5	6	7	8	9	10
Model	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2	R^2
RFRbm:	0.99	0.97	0.94	0.96	0.97	0.97	0.97	0.99	0.99	0.99
RFRgs:	0.98	0.97	0.81	0.98	0.95	0.98	0.98	0.99	0.98	1.00
RFRgscv:	0.96	0.98	0.94	0.94	0.96	0.93	0.93	0.98	0.95	0.91
XGBbm:	0.99	0.99	0.95	1.00	0.97	0.99	1.00	1.00	0.99	1.00
XGBrgs:	0.99	0.97	0.95	0.98	0.98	0.99	0.99	1.00	0.99	1.00
GBRbm:	0.99	0.99	0.95	0.99	0.96	0.99	1.00	1.00	0.99	1.00
GBRRgs:	0.98	0.98	0.95	1.00	0.98	0.98	0.96	1.00	0.99	1.00
QGBR10gs:	-0.16	0.38	-0.30	-0.23	-0.15	-0.29	-0.19	-0.11	-0.17	-0.42
QGBR20gs:	0.02	0.13	0.14	0.18	0.17	-0.22	0.04	0.14	-0.11	-0.21
QGBR30gs:	0.78	0.94	0.65	0.85	0.80	0.89	0.59	0.60	0.76	0.43
QGBR40gs:	0.96	0.99	0.94	0.96	0.97	0.95	0.90	1.00	0.97	0.82
QGBR50gs:	0.96	0.98	0.95	1.00	0.99	0.98	0.99	1.00	0.98	0.96
QGBR60gs:	0.94	0.94	0.95	0.99	0.98	0.99	0.98	1.00	0.97	1.00
QGBR70gs:	0.98	0.94	0.94	0.95	0.99	0.98	0.98	1.00	0.97	0.98
QGBR80gs:	0.99	0.98	0.95	0.98	0.96	0.93	0.99	1.00	0.99	1.00
QGBR90gs:	0.97	-0.62	0.94	0.99	0.94	0.97	0.98	1.00	0.98	1.00

(a)

K-fold:	1	2	3	4	5	6	7	8	9	10	Count
Model	$R^2\geq0.9$	$R^2\geq0.9$	$R^2\geq0.9$	$R^2\geq0.9$	$R^2\geq0.9$	$R^2\geq0.9$	$R^2\geq0.9$	$R^2\geq0.9$	$R^2\geq0.9$	$R^2\geq0.9$	$R^2\geq0.9$
RFRbm:	1	1	1	1	1	1	1	1	1	1	10
RFRgs:	1	1	0	1	1	1	1	1	1	1	9
RFRgscv:	1	1	1	1	1	1	1	1	1	1	10
XGBbm:	1	1	1	1	1	1	1	1	1	1	10
XGBrgs:	1	1	1	1	1	1	1	1	1	1	10
GBRbm:	1	1	1	1	1	1	1	1	1	1	10
GBRRgs:	1	1	1	1	1	1	1	1	1	1	10
QGBR10gs:	0	0	0	0	0	0	0	0	0	0	0
QGBR20gs:	0	0	0	0	0	0	0	0	0	0	0
QGBR30gs:	0	1	0	0	0	0	0	0	0	0	1
QGBR40gs:	1	1	1	1	1	1	0	1	1	0	8
QGBR50gs:	1	1	1	1	1	1	1	1	1	1	10
QGBR60gs:	1	1	1	1	1	1	1	1	1	1	10
QGBR70gs:	1	1	1	1	1	1	1	1	1	1	10
QGBR80gs:	1	1	1	1	1	1	1	1	1	1	10
QGBR90gs:	1	0	1	1	1	1	1	1	1	1	9
										Total =	127

(b)

3.3 Meta Model

The steps used to develop a Meta model include final training and predictions, stacking, uncertainty quantification, bias correction, prediction uncertainty, independent validation, and regional predictions. These steps are discussed next.

3.3.1 Final Training and Predictions

Development of the Meta models begin by retraining those Base models determined to be the best predictors of hydrologic indices during the training and testing phase (e.g., models with $R^2 \geq 0.9$). These preferred Base models are retrained using the complete set of records (training plus testing) obtained at natural catchment sites (N=49). These retrained models are then used to provide final predictions of natural hydrologic indices at human-influenced gauged sites. This process requires presenting independent catchment characteristics (i.e., those not used in the training and testing processes) upstream from the human-influenced gauged sites to the retrained Base models (N=16). Statistical summaries of these two sets of independent catchment characteristics are presented in Tables 7 and 8. The reader can download these catchment characteristics as part of the complete New Zealand Freshwater Ecosystems geodatabase by requesting access from the Department of Conservation (Gay, B., 2013; Department of Conservation, 2023; Envirolink, 2023). Differences in the statistical summaries presented in these tables are attributed to spatial sampling bias of the human-influenced gauged catchments draining into the Clutha, Taieri, and Manuherekia Rivers and the Pacific Ocean randomly located across the entire Otago Region. Once the desired hydrologic index (target), e.g., Mean or MALF, is assigned then the relevant set of independent catchment characteristics (features) is presented to each Base model for simultaneous prediction of the chosen hydrologic index across the domain of interest, e.g., gauged catchments. The relative quality of trained regression models is based on evaluating the prediction uncertainty of stacked models discussed next.

Table 7.
Summary table of independent catchment characteristics used to predict naturalised mean daily flow and naturalised 7-day mean annual low flow at 317 regulated priority catchments across the Otago Region.

Statistic	Log Area (m^2)	Elevation (m)	Particle Size (mm)	PET (mm/unit time)	Rainfall variation (mm)	Log Rain days (days/yr)	Runoff volume (%)	Slope (%)
count	317	317	317	317	317	317	317	317
mean	7.12	477	3.17	952	172	1.83	0.08	14.3
std	0.74	345	1.02	115	20.5	0.76	0.13	6.57
min	5.49	11.1	0	400	141	0.68	0	0.23
25%	6.61	147	2.7	880	155	1.4	0	9.75
50%	7	453	3.55	960	171	1.7	0.02	14
75%	7.54	733	3.89	1019	183	2.08	0.1	18.2
max	9.76	1386	5	1221	218	6.63	0.59	30.7

3.3.2 Stacking and Uncertainty Quantification

In this section, statistical stacking is undertaken by computing empirical distribution functions across the final predictions of naturalised Mean (N=129) and naturalised MALF (N=127) at human influenced sites. Uncertainty in the stacked predictions is quantified at predefined percentiles (e.g., 10^{th}, 20^{th}, 30^{th}, 40^{th}, 50^{th}, 60^{th}, 70^{th}, 80^{th}, and 90^{th}) and average (expected or most likely) for the naturalised Mean and

MALF at the gauged human-influenced sites. Collectively, these percentiles describe empirical cumulative distribution functions (estimators of cumulative distribution functions quantifying the probability that the random variable X is less than or equal to x) at the gauged sites. In this way, the largest prediction values are associated with the largest percentile and are equal to or less than other predicted values at lessor percentiles, and smallest prediction values are associated with the smallest percentile that will be less than values at all other percentiles. In the interpretation of these results, the average prediction value is considered the most likely (expected) value when there are no outliers that skew the distribution. In cases where there are no outliers, the median and average prediction values will be the same (or very similar) when the underlying process is Gaussian. In cases where these values are skewed by outliers then the median value (representing 50% of the predicted values above and 50% of the predicted values below) is considered a more robust measure of the central tendency. For these reasons, both measures are presented for review and consideration as well as computing the traditional prediction intervals defined as the difference between two alterative percentiles of choice. The last step in building the Meta model requires an assessment of prediction bias in the stacked Base models.

To assess the presence of Meta model bias, the predictions of Mean (and MALF) at human-influence sites are plotted as a function of catchment area for selected percentiles. For example, prediction results are presented at the 10th, 20th, 30th, 40th, 50th, 60th, 70th, 80th, and 90th percentiles in Fig 6. Inspecting this figure reveals that catchments less than 4 km^2 are initially biased upward (over predicted) whereas catchments greater than 800 km^2 are initially biased downward (under predicted. This bias is present in the Mean (and MALF) scatterplots across all percentiles. The systematic errors in the model predictions are attributed to a combination of sources that include the selection of training data (sample bias; Fig. 5), the choice of features used to build the model (feature bias; Table 3), and/or the algorithms used to train the model (algorithmic bias; Table 5 and 6).

(a) (b)

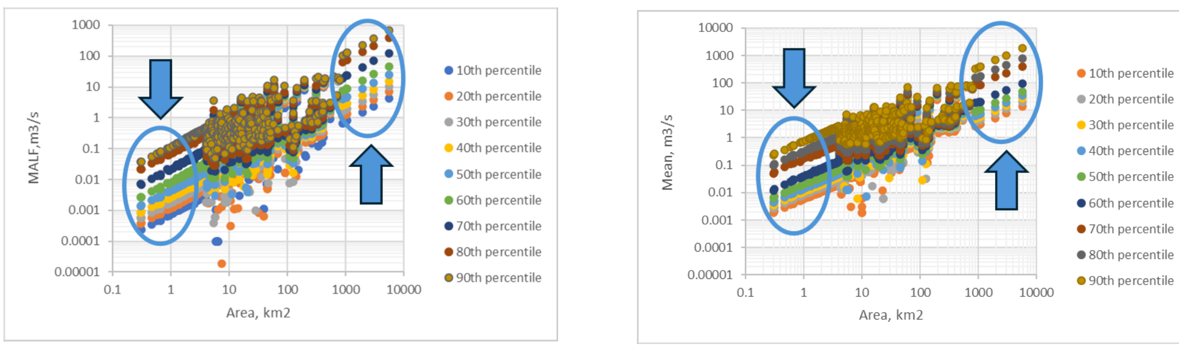
Fig. 6. Meta model predictions: (a) Biased 7-day Mean Annual Low Flow predictions. (b) Biased Mean flow predictions. The red circle and red arrows reveal catchment size and direction of Meta prediction bias.

3.3.4 Bias Correction

An algorithm is developed and applied to correct for bias in the Meta model predictions. The algorithm consists of the following steps: (1) Fit a regression equation to the unbiased Meta model predictions (catchment areas greater than or equal to 4 km^2 and less than or equal to 800km^2). (2) Compute an empirical cumulative distribution function (ECDF) characterizing the regional Meta predictions. (3) Assign triangular probability density functions (PDFs) to each catchment (domain of possible inputs), where the minimum value is set equal to 0, the likeliest value is set equal to the corresponding value obtained from the fitted equation, and the maximum value is set equal to 2x the likeliest value. (4) Perform random sampling (25,000 Monte Carlo trials) of the catchment PDFs multiplying each with the regional ECDF of

Meta prediction values. (5) Organize results into probability distributions conditioned by catchment area. (6) Combine the conditional predictions (< 4 km2 and > 800 km2) together with the original Meta predictions (> 4 km^2 and < 800 km^2). This process is repeated separately for each hydrologic index across the human-influenced gauge sites.

The naturalised Meta prediction results after application of the bias correction algorithm are presented for naturalised Mean and naturalised MALF at human-influenced gauge sites in Fig. 7. Application of the Stochastic bias correction algorithm results in conditionally reducing the naturalised Meta predictions at catchments less than 4 km^2 (Fig. 7a) and conditionally increasing the naturalised Meta predictions upward at catchments greater than 800 km^2 (Fig. 7b). In these panels, the blue circle and blue arrows reveal the location and direction of bias correction to the Meta predictions. Combining the bias corrected Meta model predictions with the original Meta predictions produces a continuous set of naturalised MALF and naturalised Mean predictions for use in the sustainability model. The similarity between the median and average values for Mean and MALF predictions for catchments implies that the bias corrections computed for the 10th to 90th percentiles are realistic and useful for computing prediction uncertainty.



(a) (b)

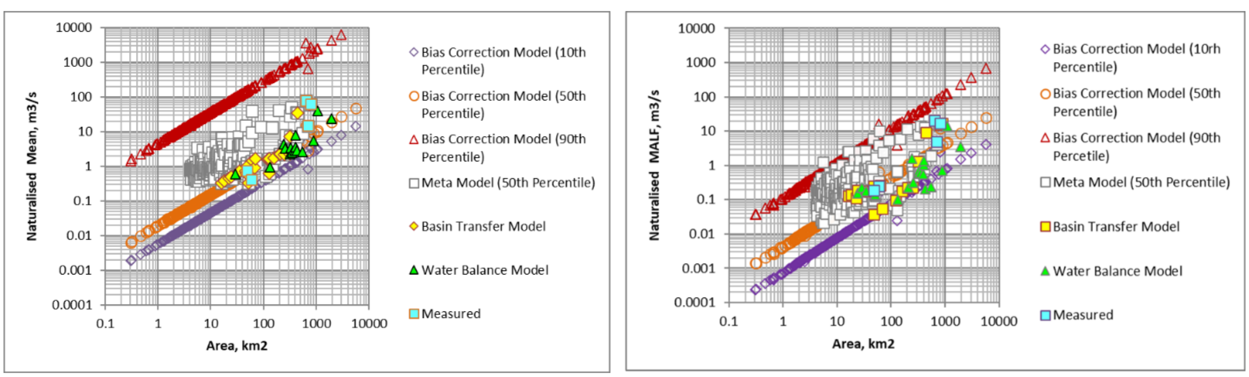
Fig. 7. Meta model predictions: (a) Bias corrected 7-day Mean Annual Low Flow predictions. (b) Bias corrected Mean flow predictions. Stochastic bias correction reduced the magnitude of Meta predictions for catchments < 4 km^2 and increased the magnitude of Meta predictions for catchments > 800 km^2. The red circle and red arrows reveal catchment size and direction of Meta prediction bias; blue circle and blue arrows reveal catchment size and direction of bias corrected Meta predictions.

3.3.6 Independent Validation

Validation of the naturalised prediction algorithm is undertaken to test the efficacy of using a Meta model for predicting naturalised hydrologic indices. To do so, three independent catchment methods are used to compare their predictions against those determined using the Meta model for catchments greater than 4 km^2. These independent methods used to estimate the naturalised Mean and the naturalised MALF for selected catchments include (1) Measured natural flow statistics, (2) Water Balance models (Lu et al., 2023a-f; Olsen, 2024), and (3) Basin Transfer models (D. Stewart, personal communication, October 3, 2024). In general, the Measured natural flow statistics reflect traditional calculations using natural streamflow time series at gauged sites, the Water balance method sums daily flows and water abstraction time series to approximate naturalised flows (Lu et al., 2023a-f; Olsen, 2024), and the Transfer method approximates the naturalised flow by multiplying the adjacent basin discharge (the hydrologic index divided by the catchment area) by the catchment area of interest (D. Stewart, 2024, personal communication). To fully understand the strengths and limitations in using these deterministic naturalization methods, the reader is referred to Fantin-Cruz, et al., (2015), Yuan et al., (2017), and Terrier, et al. (2021).

In this section, results of the deterministic models used to estimate hydrologic indices are presented together with results when using the stochastic Meta model to predict hydrologic indices. For example, the deterministic Measured, Water Balance and Basin Transfer model estimates of the naturalised Mean flows are presented together with the stochastic Meta model predictions of naturalised Mean flows as a function of percentile in Table 8. Similarly, the deterministic Measured, Water Balance and Basin Transfer model estimates of the naturalised MALF flows are presented together with the stochastic Meta model predictions of naturalised MALF flows as a function of percentile in Table 9. In these tables, the stochastic predictions associated with the Measured statistics are computed by supplying independent physical catchment features (not used in training the base models) to the final Meta model. Inspecting Tables 9 and 10 reveal that the independent deterministic model estimates of Mean and MALF compare favorably with the stochastic Meta model predictions. That is, the majority of independent deterministic estimates scatter on or close to the 50th percentile with the estimates confined between the 10th and the 90th percentiles of the Meta model predictions.

The use of Meta models for determining naturalised hydrologic indices is further supported by comparing plots of their predicted values with independent estimates and Bias correction model predictions (Fig. 8). The naturalised predictions at the 10th, 50th, and 90th percentiles while using the bias correction model are presented in plots for the Mean flow (Fig. 8a) and the MALF (Fig. 8b). Superimposed on these plots are Meta model predictions across the 317 human-influenced sites (> 4 km^2 and <800 km^2) at the 50th percentile (in white) together with independent Measurements (in blue) and independent predictions using the Basin Transfer naturalization method (in yellow) and the Water Balance naturalization method (in green). These plots reveal that the independent observations and independent predictions tend to scatter around the 50th percentile in the Mean panel (on the left) and between the 10th and 50th percentile in the MALF panel (on the right). These observations suggest that the independent methods predict unbiased Mean flows well but may be biased low when predicting the MALF. By contrast, the similar patterns in Meta model predictions across percentiles underscore the improved ability to predict flows when accounting for physical catchment properties.



(a) (b)

Fig. 8. Naturalised flow predictions at human-influenced gauge sites in the Otago region. Stochastic Meta model predictions of hydrologic indices for selected catchments at the 50th percentile are together with Measured and deterministic Water Balance and Basin Transfer method estimates at selected gauge sites. These values are plotted against the bias correction model predictions at 10th, 50th, and 90th percentiles. (a) Annual Mean flows and (b) 7-day Mean Annual Low Flows (MALF). The reader is referred to the complete list of independent estimates and stochastic predictions provided in Tables 8 and 9.

Table 8. Comparison of stochastic Meta model Mean daily flow predictions for selected catchments against Measured and deterministic Water Balance and Basin transfer method estimates. Red color denotes predictions using Bias correction model (comparison-indepedent-and-stochastic-predictions-mean-malf-at-gauged-sites).

Mean				Meta Model Stochastic Prediction								
Independent Method	Catchment	Area (km^2)	Independent Deterministic Prediction (m^3/s)	10th Percentile (m^3/s)	20th Percentile (m^3/s)	30th Percentile (m^3/s)	40th Percentile (m^3/s)	50th Percentile (m^3/s)	60th Percentile (m^3/s)	70th Percentile (m^3/s)	80th Percentile (m^3/s)	90th Percentile (m^3/s)
Measured	Water of Leith	48.68	0.747	0.522	0.684	0.707	0.784	0.892	1.158	1.955	2.653	3.369
Measured	Hayes Creek	58.67	0.413	0.362	0.557	0.667	0.758	0.858	1.104	1.492	1.746	2.447
Measured	Dart	635.2	80.20	69.17	78.88	80.02	80.19	80.20	80.20	80.20	80.20	80.20
Measured	Nevis	701.1	14.83	10.29	12.01	12.71	13.66	14.58	15.19	16.05	17.46	19.49
Measured	Matukituki	799.3	62.71	56.53	62.37	62.69	62.70	62.70	62.70	62.71	62.90	64.12
Water Balance	Amisfield Burn	29.2	0.603	0.000	0.000	0.034	0.122	0.226	0.306	0.575	0.901	1.123
Water Balance	Shingle Creek	34.8	0.718	0.531	0.643	0.839	1.059	1.269	1.492	2.085	2.749	3.301
Water Balance	Low Burn	51.4	0.331	0.120	0.263	0.344	0.473	0.554	0.669	0.818	1.110	1.506
Water Balance	Luggate Creek	127.7	1.595	0.600	0.937	1.202	1.380	1.577	1.884	2.379	2.833	4.096
Water Balance	Benger Burn	134.8	0.963	0.309	0.424	0.532	0.592	0.734	0.856	0.964	1.157	1.642
Water Balance	Waiwera	208.9	2.285	1.772	2.195	2.444	2.574	2.699	2.833	3.186	3.684	4.520
Water Balance	Arrow River	242.6	4.370	1.837	2.103	2.295	2.450	2.717	3.144	3.743	5.228	6.393
Water Balance	Waianakarua	260.7	3.257	2.138	2.260	2.433	2.542	2.608	2.693	2.894	3.412	4.629
Water Balance	Fraser River	315.0	2.332	1.618	2.194	2.311	2.416	2.510	2.661	2.805	3.259	4.012
Water Balance	Teviot	329.8	3.395	2.121	2.397	2.560	2.623	2.695	2.746	2.896	3.308	4.223
Water Balance	Cardrona	345.0	2.560	1.648	1.997	2.239	2.448	2.670	2.799	3.144	3.574	4.311
Water Balance	Tokomairiro	395.7	2.819	1.706	2.445	2.600	2.746	2.992	3.251	3.970	4.561	5.364
Water Balance	Waitahuna	406.5	3.545	1.970	2.486	2.761	3.009	3.322	3.676	4.107	4.709	5.806
Water Balance	Catlins River	408.6	7.813	4.546	4.939	5.172	5.572	6.424	7.081	7.971	9.266	11.368
Water Balance	Waikouaiti	426.4	2.855	2.338	2.519	3.748	4.789	5.850	6.762	8.881	11.74	13.50
Water Balance	Shag River	543.2	2.650	4.176	4.995	6.117	7.430	8.584	9.656	11.81	12.78	14.92
Water Balance	Kakanui River	893.7	5.650	2.591	3.802	4.891	6.303	9.229	18.61	91.09	132.0	293.4
Water Balance	Shotover River	1082	39.69	3.105	4.465	5.824	7.444	10.79	20.76	85.67	149.7	349.0
Water Balance	Pomahaka	1952	25.38	5.220	7.642	9.860	12.69	18.67	36.56	165.1	261.9	599.5
Basin Transfer	Park Burn	16.1	0.128	0.050	0.157	0.302	0.405	0.521	0.645	0.949	1.273	1.836
Basin Transfer	Tinwald Burn	18.2	0.376	0.172	0.322	0.456	0.608	0.791	1.083	1.424	2.283	3.593
Basin Transfer	Coal Creek (2)	22.4	0.464	0.173	0.345	0.462	0.566	0.758	0.940	1.364	1.818	2.539
Basin Transfer	Waitati	46.2	0.710	0.000	0.170	0.326	0.410	0.486	0.604	0.731	0.944	1.497
Basin Transfer	Minzion Burn	47.8	0.623	0.389	0.485	0.534	0.577	0.656	0.761	1.002	1.248	1.835
Basin Transfer	Coal Creek (1)	48.6	1.004	0.133	0.377	0.499	0.601	0.783	0.943	1.186	1.602	2.469
Basin Transfer	Tautuku River	62.6	1.463	1.581	2.145	3.071	4.325	5.377	6.546	8.135	9.779	12.890
Basin Transfer	Beaumont River	68.8	0.893	0.653	0.953	1.134	1.341	1.467	2.102	3.235	4.224	4.940
Basin Transfer	Fruid Burn	120.9	1.570	0.661	0.879	1.011	1.138	1.219	1.376	1.848	2.254	2.783
Basin Transfer	Kaihiku Stream	157.73	1.754	0.726	0.951	1.451	1.645	1.870	2.214	2.544	2.970	3.732
Basin Transfer	Puerua River	205.53	2.286	1.459	2.181	2.461	2.641	2.784	2.970	3.314	3.908	4.662
Basin Transfer	Tuapeka River	248.29	2.196	1.759	2.188	2.418	2.573	2.842	3.093	3.378	3.967	5.199
Basin Transfer	Tahakopa River	315.35	7.374	4.488	4.968	5.131	5.476	5.944	6.418	8.027	8.956	10.515
Basin Transfer	Hunter River	445.37	34.93	45.16	50.04	52.91	56.01	59.71	62.03	64.74	68.43	73.33

Table 9. Comparison of stochastic Meta model 7-day Mean Annual Low Flow predictions for selected catchments against Measured and deterministic Water Balance and Basin transfer method estimates. Red color denotes predictions using Bias correction model.

MALF				Meta Model Stochastic Prediction								
Independent Method	Catchment	Area (km^2)	Independent Deterministic Prediction (m^3/s)	10th Percentile (m^3/s)	20th Percentile (m^3/s)	30th Percentile (m^3/s)	40th Percentile (m^3/s)	50th Percentile (m^3/s)	60th Percentile (m^3/s)	70th Percentile (m^3/s)	80th Percentile (m^3/s)	90th Percentile (m^3/s)
Measured	Water of Leith	48.68	0.191	0.084	0.151	0.166	0.184	0.217	0.271	0.354	0.437	0.695
Measured	Hayes Creek	58.67	0.247	0.050	0.123	0.156	0.190	0.228	0.272	0.373	0.435	0.632
Measured	Dart	635.15	20.80	19.05	20.76	20.80	20.80	20.80	20.80	20.80	20.80	20.80
Measured	Nevis	701.11	4.570	2.418	2.906	3.314	3.779	4.089	4.344	4.681	5.069	5.318
Measured	Matukituki	799.26	16.75	16.10	16.74	16.75	16.75	16.75	16.75	16.75	16.78	17.25
Water Balance	Amisfield Burn	29.2	0.231	0.000	0.000	0.001	0.020	0.034	0.069	0.121	0.195	0.273
Water Balance	Shingle Creek	34.8	0.177	0.137	0.217	0.286	0.324	0.353	0.442	0.506	0.642	0.816
Water Balance	Low Burn	51.4	0.140	0.000	0.023	0.047	0.084	0.111	0.148	0.179	0.240	0.338
Water Balance	Luggate Creek	127.66	0.644	0.331	0.392	0.491	0.615	0.710	0.885	0.996	1.182	1.451
Water Balance	Benger Burn	134.79	0.102	0.036	0.049	0.062	0.073	0.086	0.098	0.130	0.159	0.201
Water Balance	Waiwera	208.94	0.231	0.056	0.158	0.213	0.242	0.279	0.333	0.400	0.561	0.793
Water Balance	Arrow River	242.63	1.560	0.280	0.349	0.419	0.543	0.641	0.791	0.907	1.084	1.577
Water Balance	Waianakarua	260.72	0.310	0.150	0.189	0.228	0.247	0.310	0.366	0.428	0.489	0.700
Water Balance	Fraser River	314.98	0.598	0.247	0.367	0.425	0.473	0.515	0.580	0.650	0.836	1.084
Water Balance	Teviot	329.77	0.703	0.251	0.371	0.423	0.478	0.518	0.570	0.621	0.673	0.749
Water Balance	Cardrona	345.03	0.606	0.121	0.242	0.354	0.435	0.508	0.611	0.713	0.863	1.345
Water Balance	Tokomairiro	395.7	0.562	0.155	0.265	0.350	0.452	0.549	0.636	0.802	0.983	1.421
Water Balance	Waitahuna	406.46	1.027	0.255	0.355	0.468	0.565	0.624	0.735	0.878	1.125	1.553
Water Balance	Catlins River	408.61	1.386	0.589	0.724	0.885	1.087	1.280	1.604	1.699	2.075	3.141
Water Balance	Waikouaiti	426.36	0.208	0.225	0.327	0.716	0.989	1.145	1.404	1.543	2.031	2.594
Water Balance	Shag River	543.19	0.235	0.931	1.310	1.485	1.544	1.670	1.892	2.097	2.339	3.033
Water Balance	Kakanui River	893.7	0.712	0.671	1.096	1.605	2.441	3.932	7.340	18.98	62.18	105.65
Water Balance	Shotover River	1082.4	13.90	0.809	1.317	1.941	2.903	4.681	8.687	23.26	74.99	126.80
Water Balance	Pomahaka	1952.3	3.521	1.482	2.391	3.503	5.362	8.621	16.24	42.73	137.7	229.70
Basin Transfer	Park Burn	16.1	0.128	0.000	0.014	0.043	0.084	0.119	0.153	0.213	0.286	0.393
Basin Transfer	Tinwald Burn	18.2	0.143	0.000	0.082	0.132	0.161	0.205	0.273	0.323	0.404	0.604
Basin Transfer	Coal Creek (2)	22.4	0.114	0.000	0.057	0.102	0.123	0.163	0.212	0.317	0.448	0.621
Basin Transfer	Waitati	46.2	0.182	0.000	0.027	0.055	0.084	0.119	0.147	0.171	0.223	0.321
Basin Transfer	Minzion Burn	47.8	0.038	0.027	0.042	0.054	0.067	0.077	0.097	0.129	0.172	0.256
Basin Transfer	Coal Creek (1)	48.6	0.238	0.000	0.055	0.103	0.128	0.159	0.207	0.286	0.364	0.537
Basin Transfer	Tautuku River	62.6	0.260	0.325	0.594	1.323	1.788	2.294	2.727	3.210	3.717	4.556
Basin Transfer	Beaumont River	68.8	0.055	0.113	0.192	0.255	0.323	0.456	0.590	0.807	0.973	1.177
Basin Transfer	Fruid Burn	120.9	0.097	0.049	0.107	0.143	0.170	0.202	0.255	0.369	0.458	0.554
Basin Transfer	Kaihiku Stream	157.73	0.177	0.021	0.085	0.120	0.181	0.228	0.290	0.336	0.465	0.570
Basin Transfer	Puerua River	205.53	0.231	0.061	0.179	0.252	0.342	0.402	0.458	0.550	0.753	0.835
Basin Transfer	Tuapeka River	248.29	0.231	0.176	0.244	0.298	0.368	0.418	0.473	0.528	0.615	0.831
Basin Transfer	Tahakopa River	315.35	1.312	0.670	0.780	0.880	1.019	1.330	1.607	2.170	2.597	3.367
Basin Transfer	Hunter River	445.37	9.330	12.417	13.726	14.315	14.939	16.005	16.709	17.273	17.847	19.034

3.3.7 Regional Predictions

In this section, the validated Meta model is used to predict naturalised hydrological indices at the human-influenced gauged sites. Given the relatively large number of naturalised Meta model predictions at gauged catchments the results in this section are sorted alphabetically. A partial set of these stochastic data are presented by percentiles for Mean and MALF in Appendix A. The reader can review the complete set of 317 naturalised stochastic prediction series together with coordinates, catchment area, Strahler stream order, FMU and Rohe available in the accompanying data file named *naturalised-bias-corrected-mean-malf-at-gauged-sites.csv*. In this file, some of the largest human-influenced rivers include the Taieri (5704.8 km^2), the Manuherikia (3033.6 km^2), the Pomahaka (1952 km^2), the Makaroa (752.9 km^2), and the Hunter (445.4 km^2); large natural rivers include the Matukituki (799.3 km^2), the Nevis River (701.1 km^2), and the Dart (635.1 km^2). The magnitude of hydrologic indices is not directly related to the catchment area, rather the values reflect a combination of physical catchment factors that control the Mean and the MALF. For this reason, the following descriptions are ordered according to the method used to model hydrologic indices.

Using the stochastic bias correction model, the Taieri River is determined to have a naturalised average value (expected and most likely) for *Mean* flow of about 91.0 m3/s and 50th percentile (median) of 46.6 m3/s with a probable range (describing uncertainty) from 14.3 m3/s at the 10th percentile to 398.2 m3/s at the 70th percentile; and a naturalised average value (expected and most likely) for *MALF* flow of about 32.6 m3/s and 50th percentile (median) of 24.9 m3/s with a probable range (describing uncertainty) from 4.16 m3/s at the 10th percentile to 120.7.2 m3/s at the 70th percentile (note that values for the 80th and 90th percentiles computed using the bias correction model produced artefacts and therefore are removed). There are no known calculations for validation of these results.

Using the Meta model, the Dart River is determined to have a naturalised average value (expected and most likely) for *Mean* flow of about 78.8 m3/s and 50th percentile (median) of 80.2 m3/s with a probable range (describing uncertainty) from 69.2 m3/s at the 10th percentile to 80.2 m3/s at the 90th percentile; and a naturalised average value (expected and most likely) for *MALF* flow of about 20.66 m3/s and 50th percentile (median) of 20.8 m3/s with a probable range (describing uncertainty) from 19.0 m3/s at the 10th percentile to 20.8 m3/s at the 90th percentile. For validation of the Mean and MALF, the respective average and median statistics based on Measured streamflow statistics at this natural site are 80.2 m3/s and are 20.8 m3/s.

Using the Meta model, the Makarora River is determined to have a naturalised average value (expected and most likely) for *Mean* flow of about 68.5 m3/s and 50th percentile (median) of 68.5 m3/s with a probable range (describing uncertainty) from 60.6 m3/s at the 10th percentile to 77.6 m3/s at the 90th percentile; and a naturalised average value (expected and most likely) for *MALF* flow of about 17.6 m3/s and 50th percentile (median) of 17.5 m3/s with a probable range (describing uncertainty) from 14.9 m3/s at the 10th percentile to 19.9 m3/s at the 90th percentile. There are no known calculations for validation of these results.

Using the Meta model, the Matukituki River is determined to have a naturalised average value (expected and most likely) for *Mean* flow of about 62.2 m3/s and 50th percentile (median) of 62.7 m3/s with a probable range (describing uncertainty) from 56.5 m3/s at the 10th percentile to 64.1 m3/s at the 90th percentile; and a naturalised average value (expected and most likely) for *MALF* flow of about 16.7 m3/s and 50th percentile (median) of 16.8 m3/s with a probable range (describing uncertainty) from 16.1 m3/s at the 10th percentile to 17.3 m3/s at the 90th percentile. For validation of Mean and MALF, the respective average and median statistics based on Measured streamflow statistics at this natural site are 62.7 m3/s and are 16.8 m3/s.

Using the Meta model, the Hunter River is determined to have a naturalised average value (expected and most likely) for *Mean* flow of about 59.2 m3/s and 50th percentile (median) of 59.7 m3/s with a probable range (describing uncertainty) from 45.2 m3/s at the 10th percentile to 73.3 m3/s at the 90th percentile; and a naturalised average value (expected and most likely) for *MALF* flow of about 15.8 m3/s and 50th percentile (median) of 16.0 m3/s with a probable range (describing uncertainty) from 12.4 m3/s at the 10th percentile to 19.0 m3/s at the 90th percentile. For validation of the Mean and the MALF, the respective Basin Transfer method estimates at this site are 34.9 m3/s and are 9.3 m3/s.

Using the Stochastic bias correction model, the Manuherikia River is determined to have a naturalised average value (expected and most likely) for *Mean* flow of about 52.5 m3/s and 50th percentile (median) of 27.9 m3/s with a probable range (describing uncertainty) from 8.0 m3/s at the 10th percentile to 232 m3/s at the 70th percentile for *MALF* flow of about 18.7 m3/s and 50th percentile (median) of 16.0 m3/s with a probable range (describing uncertainty) from 2.31 m3/s at the 10th percentile to 71.8 m3/s at the 70th percentile (note that values for the 80th and 90th percentiles computed using the bias correction model produced artefacts and therefore are removed). There are no known model calculations for validation of these results.

Using the Stochastic bias correction model, the Pomahaka River is determined to have a naturalised average value (expected and most likely) for *Mean* flow of about 22.3 m3/s and 50th percentile (median) of 18.7 m3/s with a probable range (describing uncertainty) from 5.2 m3/s at the 10th percentile to 65.1 m3/s at the 70th percentile; and a naturalised average value (expected and most likely) for *MALF* flow of about 11.5 m3/s and 50th percentile (median) of 8.6 m3/s with a probable range (describing uncertainty) from 1.48 m3/s at the 10th percentile to 47.7 m3/s at the 70th percentile (note that values for the 80th and 90th percentiles computed using the bias correction model produced artefacts and therefore are removed). For validation of Mean and MALF, the respective Water Balance method results at this human-influenced site are 25.4 m3/s and are 3.52 m3/s (Lu, 2023).

Using the Meta model, the Nevis River is determined to have a naturalised average value (expected and most likely) for *Mean* flow of about 14.6 m3/s and 50th percentile (median) of 14.6 m3/s with a probable range (describing uncertainty) from 10.3 m3/s at the 10th percentile to 19.5 m3/s at the 90th percentile; and a naturalised average value (expected and most likely) for *MALF* flow of about 3.99 m3/s and 50th percentile (median) of 4.1 m3/s with a probable range (describing uncertainty) from 2.42 m3/s at the 10th percentile to 5.32 m3/s at the 90th percentile. For validation of Mean and MALF, the respective Measured streamflow statistics at this natural flow site are 14.8 m3/s and are 4.57 m3/s (Lu, 2023).

In reviewing these results, one observation is that the average (expected) values for the majority of Meta predicted natural flow indices at the human-influenced gauged catchments are very similar to average values supporting the hypothesis that combining the predictions of many weak ensemble models (trained using a small number of catchment records) will (1) reduce the prediction bias at the expense of variance, and (2) reflect probability density functions that are normally distributed (expected value and median describe the same central tendency). That said, the expected smallest predicted natural flow indices differ from their median values for some catchments possibly related to greater uncertainty in describing the physical properties for the smallest catchments. This difference in central tendencies may become important should the regional council decide to provide consented abstractions in these small stream (order) catchments. In this case, the ensemble modelling could be refined using Learn Heuristics to define optimal catchment characteristics (number and type) for predictions with reduced uncertainty at these locations.

3.4 Sustainability Model

This section presents results following application of the sustainability model to Mean and MALF predictions that include limit setting and allocation status. The sustainability model, proposed by Hayes et al. (2021) and accepted in the Environment Court of NZ, provides rule-based guidance (shown in Table 2) for translating the naturalised catchment Mean and MALF predictions to default minimum flows, default allocation rates, and catchment allocation status.

3.4.1 Limit Setting

In this section, the application of default limit setting guidelines (Hayes et al., 2021) are used to transform the predicted naturalised hydrologic indices at human-influenced and independent natural gauged sites to their equivalent default minimum flows and default allocation rates for some of the largest rivers, namely the Taieri , Manuherikia (3033.6 km^2), Pomahaka River (1952 km^2), Makaroa (752.9 km^2), and Hunter (445.4 km^2); large natural rivers include the Matukituki (799.3 km^2), Nevis River (701.1 km^2), and Dart (635.1 km^2). A partial set of default minimum flows and default minimum allocation rates at the 317 human-influenced sites is presented for the set of human-influenced catchments across the Otago region in Appendix B. The reader can review the complete set of 317 default minimum flows and default allocation rates together with coordinates, catchment area, Strahler stream order, FMU and Rohe available in the accompanying csv file named *naturalised-default-minimum-flow-and-default-allocation-rate.csv*.

The relative magnitude in uncertainty at each site can be computed as the prediction interval between a pair of predictions at differing percentiles centered on the mean or median value.

In the first example, the hydrologic indices determined using the Stochastic bias correction model are transformed to default minimum flows and default minimum allocation rates for three of the largest human-influenced rivers, namely the Taieri, Manuherikia, Pomahaka Rivers. First, the Taieri River (5704.8 km^2) is determined to have a naturalised average value (expected and most likely) for *Default Minimum Flow* of about 115261 l/s (115.2 m^3/s) and 50th percentile (median) of 19966.7 l/s (19.6 m^3/s) with a probable range (describing uncertainty) from 3329.1 l/s (3.33 m^3/s) at the 10th percentile to 538264 (538 m^3/s) at the 90th percentile; and a naturalised average value (expected and most likely) for *Default Allocation Rate* of about 43223.2 l/s (43.2 m^3/s) and 50th percentile (median) of 24.9 m3/s with a probable range (describing uncertainty) from 1248.4 l/s (1.15 m^3/s) at the 10th percentile to 201849 l/s (201 m^3/s) at the 90th percentile. Second, the Manuherikia River (3033.6 km^2) is determined to have a naturalised average value (expected and most likely) for *Default Minimum Flow* of about 63126.9 l/s (63.1 m^3/s) and 50th percentile (median) of 10917.2 l/s (10.9 m^3/s) with a probable range (describing uncertainty) from 1850.4 l/s (1.85 m^3/s) at the 10th percentile to 289750.5 (289.7 m^3/s) at the 90th percentile; and a naturalised average value (expected and most likely) for *Default Allocation Rate* of about 23672.6 l/s (23.7 m^3/s) and 50th percentile (median) of 4093.9 (4,09 m3/s) with a probable range (describing uncertainty) from 693.9 l/s (0.693 m^3/s) at the 10th percentile to 108656.5 l/s (108.7 m^3/s) at the 90th percentile. Third, the Pomahaka River (1952 km^2) is determined to have a naturalised average value (expected and most likely) for *Default Minimum Flow* of about 39799.1 l/s (39.8 m^3/s) and 50th percentile (median) of 6897.1 l/s (6.9 m^3/s) with a probable range (describing uncertainty) from 1185.9 l/s (1.16 m^3/s) at the 10th percentile to 183760.6 (183.8 m^3/s) at the 90th percentile; and a naturalised average value (expected and most likely) for *Default Allocation Rate* of about 14924.7 l/s (14.9 m^3/s) and 50th percentile (median) of 2586.4 l/s (2.59 m3/s) with a probable range (describing uncertainty) from 444.4 l/s (0.44 m^3/s) at the 10th percentile to 68910.2 l/s (68.9 m^3/s) at the 90th percentile.

In the second example, the hydrologic indices determined using the Meta model are transformed to default minimum flows and default minimum allocation rates for two large human-influenced rivers, namely the Makaroa and Hunter. First, the Makarora River (752.9 km^2) is determined to have a naturalised average value (expected and most likely) for *Default Minimum Flow* of about 14065.2 l/s (14.1 m^3/s) and 50th percentile (median) of 14015.4 l/s (14.0 m^3/s) with a probable range (describing uncertainty) from 11911.8 l/s (11.9 m^3/s) at the 10th percentile to 15987 (16.0 m^3/s) at the 90th percentile; and a naturalised average value (expected and most likely) for *Default Allocation Rate* of about 5274.5 l/s (52.7 m^3/s) and 50th percentile (median) of 5255.8 l/s (52.6 m3/s) with a probable range (describing uncertainty) from 4466.9 l/s (44.7 m^3/s) at the 10th percentile to 5961.6 l/s (59.6 m^3/s) at the 90th percentile. Second, the Hunter River (445.4 km^2) is determined to have a naturalised average value (expected and most likely) for *Default Minimum Flow* of about 12645.7 l/s (12.6 m^3/s) and 50th percentile (median) of 12804.2 l/s (12.8 m^3/s) with a probable range (describing uncertainty) from 9933.6 l/s (9.93 m^3/s) at the 10th percentile to 15227.2 l/s (15.2 m^3/s) at the 90th percentile; and a naturalised average value (expected and most likely) for *Default Allocation Rate* of about 4742.2 l/s (4.72 m^3/s) and 50th percentile (median) of 4801.6 l/s (4.80 m3/s) with a probable range (describing uncertainty) from 3725.1 l/s (3.72 m^3/s) at the 10th percentile to 5710.2 l/s (5.71 m^3/s) at the 90th percentile.

In the third example, the hydrologic indices determined using the Meta model are transformed to default minimum flows and default minimum allocation rates for three large natural rivers, namely the Matukituki, Nevis, and Dart rivers. First, the Matukituki River (799.3 km^2) is determined to have a naturalised average value (expected and most likely) for *Default Minimum Flow* of about 13388.8 l/s (13.4 m^3/s) and 50th percentile (median) of 13400.1 l/s (13.4 m^3/s) with a probable range (describing uncertainty) from 12881.0 l/s (12.9 m^3/s) at the 10th percentile to 13800.8 (13.8 m^3/s) at the 90th percentile; and a naturalised average value (expected and most likely) for *Default Allocation Rate* of about

5020.8 l/s (50.2 m^3/s) and 50th percentile (median) of 5025.0 (50.2 m3/s) with a probable range (describing uncertainty) 4830 4. l/s (4.8 m^3/s) at the 10th percentile to 5175.2 l/s (51.7 m^3/s) at the 90th percentile. Second, the Nevis River (701.1 km^2) is determined to have a naturalised average value (expected and most likely) for *Default Minimum Flow* of about 115261 l/s (115.2 m^3/s) and 50th percentile (median) of 19966.7 l/s (19.6 m^3/s) with a probable range (describing uncertainty) from 3329.1 l/s (3.33 m^3/s) at the 10th percentile to 538264 (538 m^3/s) at the 90th percentile; and a naturalised average value (expected and most likely) for *Default Allocation Rate* of about 43223.2 l/s (43.2 m^3/s) and 50th percentile (median) of 24.9 m3/s with a probable range (describing uncertainty) from 1248.4 l/s (1.15 m^3/s) at the 10th percentile to 201849 l/s (201 m^3/s) at the 90th percentile. Third, the Dart River (635.1 km^2) is determined to have a naturalised average value (expected and most likely) for *Default Minimum Flow* of about 16480.4 l/s (16.5 m^3/s) and 50th percentile (median) of 166639.9 l/s (16.7 m^3/s) with a probable range (describing uncertainty) from 15236.1 l/s (15.2 m^3/s) at the 10th percentile to 16640.2 (16.6 m^3/s) at the 90th percentile; and a naturalised average value (expected and most likely) for *Default Allocation Rate* of about 6180.2 l/s (6.2 m^3/s) and 50th percentile (median) of 16639.9 (16.6 m^3/s) with a probable range (describing uncertainty) from 5714.4 l/s (5.7 m^3/s) at the 10th percentile to 6240.1 l/s (62.4 m^3/s) at the 90th percentile.

3.4.2 Allocation Status

This section provides results on the allocation status at the human-influenced gauged catchments across the Otago region. To arrive at the default catchment-allocation status, the total known allocation rate is subtracted from the default allocation rate resulting in the default allocation rate available. If this value is positive then the catchment status is deemed under-allocated with additional water available for consenting, and if the value is negative then the catchment status is deemed over-allocated with a net deficit of catchment water available. A summary table of probable allocation status for the first 75 of 317 gauged catchments across the Otago Region is provided in Appendix C, where catchment allocation status is indicated as follows: 1 = over-allocated and 0 = under-allocated. The reader can review the complete catchment status set together with coordinates, catchment area, Strahler stream order, FMU and Rohe available in the accompanying csv file named *naturalised-catchment-allocation-status.csv.*

Sustainability strategies required to manage catchment overallocation by the council policy team must assume some level of risk associated with limit setting. For this reason, a table indicating the number of over-allocated catchments is developed as a reverse empirical cumulative distribution function (Table 10). Inspecting this table provides insight into the likelihood and level of risk that might be adopted. For example, at the 10th percentile there is a 10% chance that the number of overallocated catchments will be 72 (over conservative) or greater and a 90% chance that the number of overallocated catchments will be 72 or less; at the 20th percentile there is a 20% chance that that the number of overallocated catchments will be 68 or greater and a 80% chance that the number of overallocated catchments will be 68 or less; at the 30th percentile there is a 30% chance that that the number of overallocated catchments will be 62 or greater and a 70% chance that the number of overallocated catchments will be 62 or less; at the 40th percentile there is a 40% chance that that the number of overallocated catchments will be 57 or greater and a 60% chance that the number of overallocated catchments will be 57 or less; at the 50th percentile there is a 50% chance that that the number of overallocated catchments will be 54 or greater and a 50% chance that the number of overallocated catchments will be 54 or less; at the 60th percentile there is a 60% chance that that the number of overallocated catchments will be 45 or greater and a 40% chance that the number of overallocated catchments will be 45 or less; at the 70th percentile there is a 70% chance that that the number of overallocated catchments will be 37 or greater and a 30% chance that the number of overallocated catchments will be 37 or less; at the 80th percentile there is a 80% chance that that the number of overallocated catchments will be 31 or greater and a 20% chance that the number of overallocated catchments will be 31 or less; at the 90th percentile there is a 90% chance that that the number of overallocated catchments will be 26 (under conservative) or greater and a 10% chance that the number of overallocated catchments will be 26 or less.

Table 10. Summary table of probable catchment status for human-influenced gauged catchments across the Otago region.

	Reverse Empirical Cumulative Distribution Function									
Catchment status	10th Percentile	20th Percentile	30th Percentile	40th Percentile	50th Percentile	60th Percentile	70th Percentile	80th Percentile	90th Percentile	Average
Over allocated	72	68	62	57	54	45	37	31	26	50
Under Allocated	245	249	255	260	263	272	280	286	291	267
Percent over allocated	23%	21%	20%	18%	17%	14%	12%	10%	8%	16%
Percent under allocated	77%	79%	80%	82%	83%	86%	88%	90%	92%	92%
Total catchments	317	317	317	317	317	317	317	317	317	317

Inspecting the partial list of overallocated catchments at the *90th percentile* reflects those names listed with a 90% chance of being overallocated (N=26) include: Albert Burn (1), Arrow River, Awamoa Creek, Bannock Burn, Basin Burn, Bendigo Creek, Benger Burn, Butchers Creek (1), Cardrona River, Coal Creek (1), Coal Creek (2), Fraser River, Hayes Creek, Low Burn (2), Luggate Creek, Pleasant River, Poison Creek, Roaring Meg, Shingle Creek, Teviot River, Tima Burn, Tinwald Burn, Waianakarua River, Waitati River, Water of Leith, and Welcome Creek.

The 80th *percentile* includes those catchments listed with a 80% chance of being overallocated (N=31) include: Albert Burn (1), Arrow River, Awamoa Creek, Bannock Burn, Basin Burn, Bendigo Creek, Benger Burn, Butchers Creek (1), Butchers Creek (2), Cardrona River, Coal Creek (1), Coal Creek (2), Elbow Creek, Fraser River, Hayes Creek, Long Gully Creek (1), Low Burn (2), Luggate Creek, Pleasant River, Poison Creek, Roaring Meg, Shingle Creek, Teviot River, Tima Burn, Tinwald Burn, Toms Creek, Waianakarua River, Waitati River, Waiwera River, Water of Leith, and Welcome Creek.

The 70th *percentile* includes those catchments listed with a 70% chance of being overallocated (N=37) include: Albert Burn (1), Arrow River, Awamoa Creek, Bannock Burn, Basin Burn, Bendigo Creek, Benger Burn, Bow Alley Creek, Butchers Creek (1), Butchers Creek (2), Cardrona River, Coal Creek (1), Coal Creek (2), Elbow Creek, Fraser River, Hayes Creek, John Bull Creek, Long Gully Creek (1), Low Burn (2), Luggate Creek, Manuherikia River, Mt Pisa Creek, Pleasant River, Poison Creek, Quartz Reef Creek, Roaring Meg, Shingle Creek, Teviot River, Thomson Creek, Tima Burn, Tinwald Burn, Toms Creek, Waianakarua River, Waitati River, Waiwera River, Water of Leith, and Welcome Creek.

The 60th *percentile* includes those catchments listed with a 60% chance of being overallocated (N=45) include: Albert Burn (1), Arrow River, Awamoa Creek, Awamoko Stream, Bannock Burn, Basin Burn, Bendigo Creek, Benger Burn, Bow Alley Creek, Butchers Creek (1), Butchers Creek (2), Cardrona River, Coal Creek (1), Coal Creek (2), Elbow Creek, Franks Creek, Fraser River, Hayes Creek, John Bull Creek, Lindis River, Long Gully Creek (1), Low Burn (2), Luggate Creek, Manuherikia River, Mt Pisa Creek, Pipeclay Gully Creek, Pleasant River, Poison Creek, Quartz Reef Creek, Rastus Burn, Roaring Meg, Roys Peak Creek, Scrubby Stream, Shingle Creek, Taieri River, Teviot River, Thomson Creek, Tima Burn, Tinwald Burn, Toms Creek, Waianakarua River, Waitati River, Waiwera River, Water of Leith, and Welcome Creek.

The 50th *percentile* includes those catchments listed with a 50% chance of being overallocated (N=54) include: Albert Burn (1), Amisfield Burn, Arrow River, Awamoa Creek, Awamoko Stream, Bannock Burn, Basin Burn, Bendigo Creek, Benger Burn, Bow Alley Creek, Burn Cottage Creek, Butchers Creek (1), Butchers Creek (2), Camp Creek (1), Cardrona River, Coal Creek (1), Coal Creek (2), Elbow Creek, Franks Creek, Fraser River, Gentle Annie Creek, Hayes Creek, John Bull Creek, Kakanui River, Lindis River, Long Gully Creek (1), Low Burn (2), Luggate Creek, Manuherikia River, Mt Pisa Creek, Pipeclay Gully Creek, Pleasant River, Poison Creek, Quartz Reef Creek, Rastus Burn, Roaring Meg, Roys Peak Creek, School Creek, Schoolhouse Creek, Scrubby Stream, Shingle Creek, Taieri River, Teviot River, Thomson Creek, Tima Burn, Tinwald Burn, Tokomairiro River, Toms Creek, Waianakarua River, Waitahuna River, Waitati River, Waiwera River, Water of Leith, and Welcome Creek.

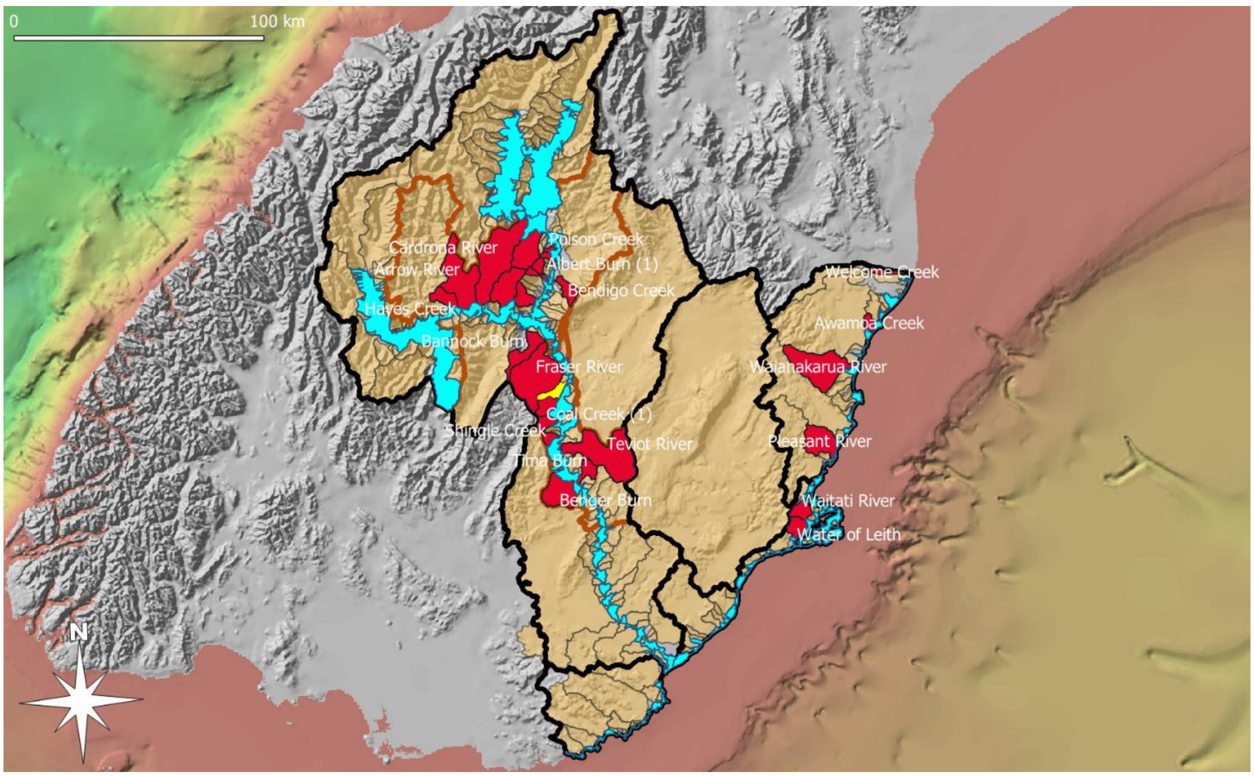
The 40th *percentile* includes those catchments listed with a 40% chance of being overallocated (N=57) include: Albert Burn (1), Amisfield Burn, Arrow River, Awamoa Creek, Awamoko Stream, Bannock Burn, Basin Burn, Bendigo Creek, Benger Burn, Bow Alley Creek, Burn Cottage Creek, Butchers Creek (1), Butchers Creek (2), Camp Creek (1), Cardrona River, Coal Creek (1), Coal Creek (2), Elbow Creek, Franks Creek, Fraser River, Gentle Annie Creek, Hayes Creek, John Bull Creek, Kakanui River, Landon Creek, Lindis River, Locharburn, Long Gully Creek (1), Low Burn (2), Luggate Creek, Manuherikia River, Mt Pisa Creek, Pipeclay Gully Creek, Pleasant River, Poison Creek, Quartz Reef Creek, Rastus Burn, Roaring Meg, Roys Peak Creek, School Creek, Schoolhouse Creek, Scrubby Stream, Shingle Creek, Taieri River, Teviot River, Thomson Creek, Tima Burn, Tinwald Burn, Tokomairiro River, Toms Creek, Waianakarua River, Waikerikeri Creek, Waitahuna River, Waitati River, Waiwera River, Water of Leith, and Welcome Creek.

The 30th *percentile* includes those catchments listed with a 30% chance of being overallocated (N=62) include: Albert Burn (1), Alpha Burn, Amisfield Burn, Arrow River, Awamoa Creek, Awamoko Stream, Bannock Burn, Basin Burn, Bendigo Creek, Benger Burn, Bow Alley Creek, Burn Cottage Creek, Butchers Creek (1), Butchers Creek (2), Camp Creek (1), Cardrona River, Coal Creek (1), Coal Creek (2), Elbow Creek, Franks Creek, Fraser River, Gentle Annie Creek, Hayes Creek, John Bull Creek, Kakanui River, Landon Creek, Lindis River, Locharburn, Long Gully Creek (1), Low Burn (2), Luggate Creek, Manuherikia River, Mt Pisa Creek, Pipeclay Gully Creek, Pleasant River, Poison Creek, Pomahaka River, Puerua River, Quartz Reef Creek, Rastus Burn, Roaring Meg, Roys Peak Creek, School Creek, Schoolhouse Creek, Scrubby Stream, Shingle Creek, Taieri River, Teviot River, Thomson Creek, Tima Burn, Tinwald Burn, Tokomairiro River, Toms Creek, Trotters Creek, Waianakarua River, Waikerikeri Creek, Waikouaiti River, Waitahuna River, Waitati River, Waiwera River, Water of Leith, and Welcome Creek.

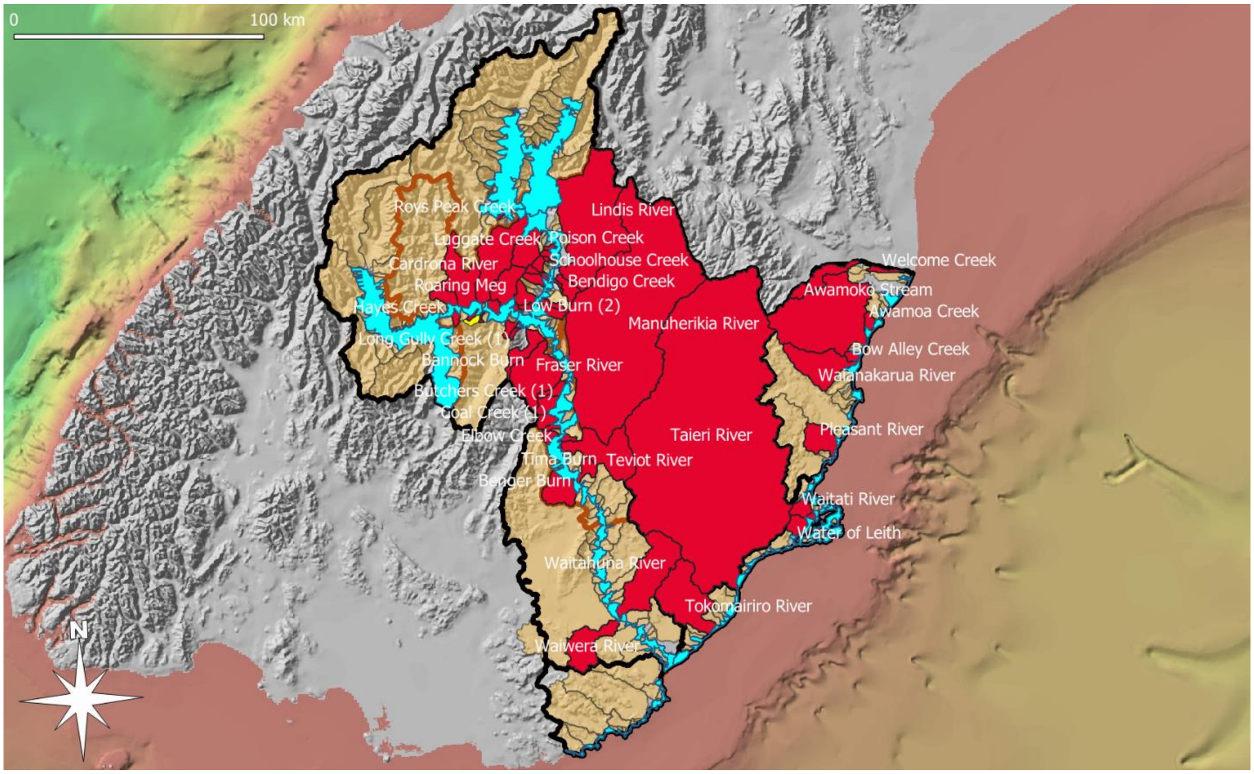
The 20th *percentile* includes those catchments listed with a 20% chance of being overallocated (N=68) include: Albert Burn (1), Alpha Burn, Amisfield Burn, Arrow River, Awamoa Creek, Awamoko Stream, Bannock Burn, Basin Burn, Bendigo Creek, Benger Burn, Bow Alley Creek, Burn Cottage Creek, Butchers Creek (1), Butchers Creek (2), Camp Creek (1), Campbells Creek, Cardrona River, Coal Creek (1), Coal Creek (2), Dead Horse Creek, Dinner Creek, Elbow Creek, Franks Creek, Fraser River, Gentle Annie Creek, Hayes Creek, John Bull Creek, Kakanui River, Landon Creek, Lindis River, Locharburn, Long Gully Creek (1), Low Burn (2), Luggate Creek, Manuherikia River, Mt Pisa Creek, Orokonui Creek, Pipeclay Gully Creek, Pleasant River, Poison Creek, Pomahaka River, Puerua River, Quartz Reef Creek, Rastus Burn, Roaring Meg, Roys Peak Creek, School Creek, Schoolhouse Creek, Scrubby Stream, Shag River, Shingle Creek, Shotover River, Taieri River, Teviot River, Thomson Creek, Tima Burn, Tinwald Burn, Tokomairiro River, Toms Creek, Trotters Creek, Waianakarua River, Waikerikeri Creek, Waikouaiti River, Waitahuna River, Waitati River, Waiwera River, Water of Leith, and Welcome Creek

The 10th *percentile* includes those catchments listed with a 10% chance of being overallocated (N=72) include: Albert Burn (1), Alpha Burn, Amisfield Burn, Arrow River, Awamoa Creek, Awamoko Stream, Bannock Burn, Basin Burn, Bendigo Creek, Benger Burn, Bow Alley Creek, Burn Cottage Creek, Butchers Creek (1), Butchers Creek (2), Camp Creek (1), Campbells Creek, Cardrona River, Coal Creek (1), Coal Creek (2), Dead Horse Creek, Dinner Creek, Elbow Creek, Five Mile Creek (2), Franks Creek, Fraser River, Gentle Annie Creek, Hayes Creek, John Bull Creek, Kaihiku Stream, Kakanui River, Landon Creek, Lindis River, Locharburn, Long Gully Creek (1), Low Burn (2), Luggate Creek, Manuherikia River, Mt Pisa Creek, Orokonui Creek, Pipeclay Gully Creek, Pleasant River, Poison Creek, Pomahaka River, Puerua River, Quartz Reef Creek, Rastus Burn, Roaring Meg, Roys Peak Creek, School Creek, Schoolhouse Creek, Scrubby Stream, Seven Mile Creek, Shag River, Shingle Creek, Shotover River, Taieri River, Teviot River, Thomson Creek, Tima Burn, Tinwald Burn, Tokomairiro River, Toms Creek, Trotters Creek, Waianakarua River, Waikerikeri Creek, Waikouaiti River, Waitahuna River, Waitati River, Waiwera River, Water of Leith, Waterfall Creek (1), and Welcome Creek.

The probable location of overallocated human-influenced catchments in the Otago region can be spatially visualized as a series of maps. In these maps, the overallocated catchments are colored red and their corresponding names colored white. Specifically, the probable location of 26 overallocated catchments (8% of the 317 catchments) at the 90th percentile (under conservative) are presented in Fig. 15a; the probable location of 54 overallocated catchments (17% of the 317 catchments) at the 50th percentile (median same as average; expected value) are presented in Fig. 15b, and the probable location of 72 overallocated catchments (23% of the 317 catchments) at the 10th percentile (over conservative) are presented I Fig. 15c. The average (expected value) number of overallocated catchments is 50 (Fig. 15b) with the probable range from 26 to 72. Given that the average number of overallocated catchments is (17% of the total number of catchments) the same as the median number of overallocated catchments (16% of the total number of catchments), one conclusion is that the underlying hydrologic process is Gaussian in nature.



(a)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Long Gully Creek (1)
Bannock Burn
Fraser River
Butchers Creek (1)
Coal Creek (1)
Elbow Creek
Taieri River
Tima Burn
Teviot River
Benger Burn
Waitahuna River
Tokomairiro River
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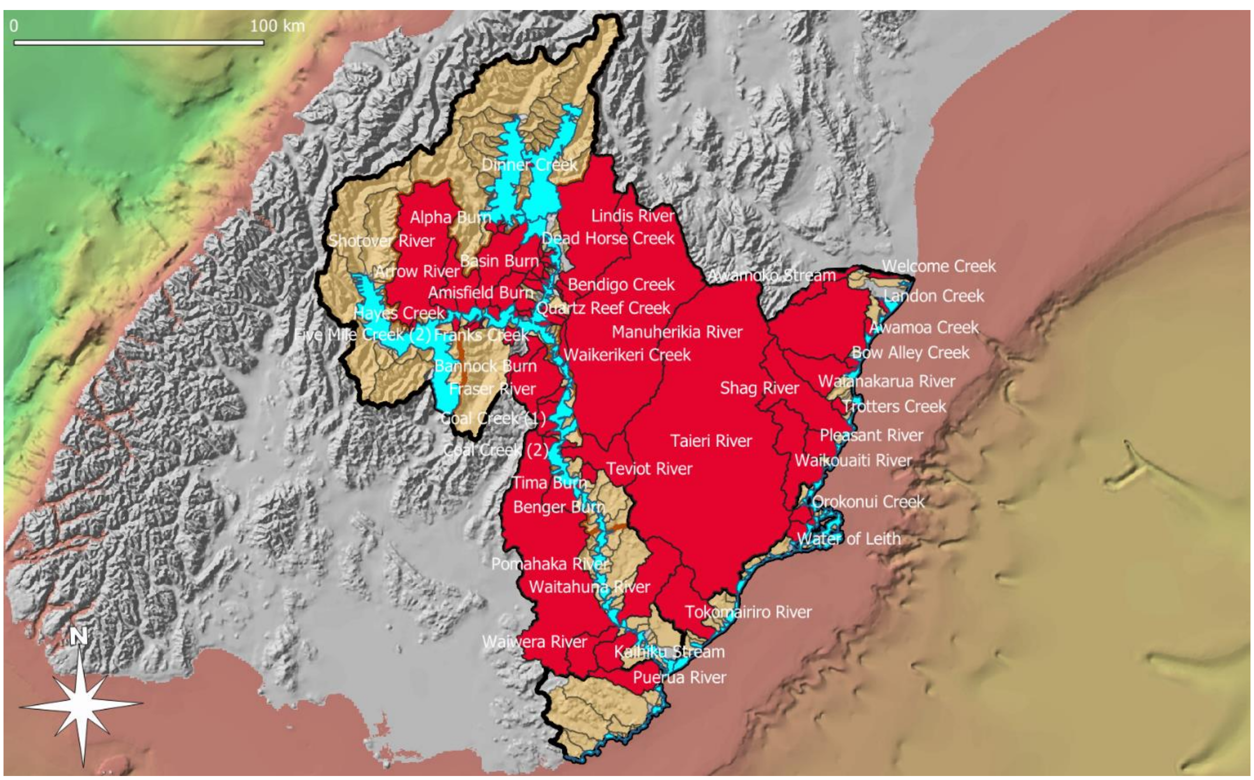
Bow Alley Creek
Waianakarua River
Pleasant River
Waitati River
Water of Leith

(b)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Arrow River
Basin Burn
Amisfield Burn
Bendigo Creek
Hayes Creek
Quartz Reef Creek
Five Mile Creek (2)
Franks Creek
Manuherikia River
Waikerikeri Creek
Bannock Burn
Fraser River
Shag River
Coal Creek (1)
Taieri River
Coal Creek (2)
Teviot River
Tima Burn
Benger Burn
Pomahaka River
Waitahuna River
Tokomairiro River
Waiwera River
Kaihiku Stream
Puerua River
Awamoko Stream
Welcome Creek
Landon Creek
Awamoa Creek
Bow Alley Creek
Waianakarua River
Trotters Creek
Pleasant River
Waikouaiti River
Orokonui Creek
Water of Leith

(c)

Fig. 15. Catchment-status predicted across the Otago Region. (a) Probable location of 26 overallocated catchments (8% of the 317 catchments) at the 90th percentile (under conservative). (b) Probable location of 54 overallocated catchments (17% of the 317 catchments) at the 50th percentile (median same as average; expected value), (c) Probable location of 72 overallocated catchments (23% of the 317 catchments) at the 10th percentile (over conservative).

4 Conclusions and suggestions for future work

A new environmental modelling algorithm is developed and validated to inform sustainable stream management across NZ catchments. Application of the proposed algorithm successfully predicted the probable naturalised Mean flow (Mean), probable 7-day Mean annual low flow (MALF), probable minimum flows, probable allocation rates, and probable allocation status at human-influenced gage sites (N=317) spanning multiple Strahler stream orders (N=7) in the Otago region. The Mean and MALF predictions are independently validated at natural sites using statistics of Measured daily streamflow, and at human-influenced sites using Water Balance and Basin transfer models. In Otago, the environmental modelling algorithm identified 54 as the median number of over-allocated catchments with 50 as the most likely number of over-allocated catchments. Quantifying the naturalised water allocation status at human-influenced sites and multiple catchment scales supports the Otago Regional Council's effort to develop a Land and Water Plan as required by the NPS-FM (Ministry for the Environment, 2020).

Credit authorship contribution statement

Michael J Friedel: Conceptualization, Methodology, Software, Visualization, Formal analysis, Writing – original draft. Dave Stewart: Data curation, Formal analysis, Investigation, Validation – review & editing. Xaio Feng Lu: Data curation, Formal analysis, Software, Validation, Visualization – review & editing. Pete Stevenson: Data curation, Formal analysis – review & editing. Helen Manly: Resources, Supervision – review & editing; Tom Dyer: Resources, Supervision – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available in a series of files in comma-separated values (csv) format: (1) appendix a-naturalised-bias-corrected-mean-malf-at-gauged-sites, (2) appendix-b-naturalised-default-minimum-flow-and-default-allocation-rate.csv, (3) appendix-c-naturalised-catchment-allocation-status.csv, (4) naturalised-gauged-mean-malf-bias-corrected.

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Appendix A. Summary table of naturalised Meta model predictions for the mean daily flow (Mean) and 7-day mean annual low flow (MALF) at various percentiles for the first 25 flows and last 25 flows across the Otago Region (other sites not shown here are presented along with coordinates, area, stream order, freshwater management unit, and Rohe are available in the *naturalised-bias-corrected-mean-malf-at-gauged-sites.csv*). Note: The red text is associated with flows predicted using the Bias correction model.

N	Hydrologic Index: Empirical Cumulative Distribution Function: Catchment	Mean 10th Percentile (m^3/s)	Mean 20th Percentile (m^3/s)	Mean 30th Percentile (m^3/s)	Mean 40th Percentile (m^3/s)	Mean 50th Percentile (m^3/s)	Mean 60th Percentile (m^3/s)	Mean 70th Percentile (m^3/s)	Mean 80th Percentile (m^3/s)	Mean 90th Percentile (m^3/s)	Mean Average (m^3/s)
1	Abernethys Creek	0.0036	0.0052	0.0067	0.0087	0.0127	0.0250	0.1134	0.2034	0.4573	0.0929
2	Afton Burn	1.7278	2.0227	3.0448	3.5514	3.9916	5.0854	6.0079	7.2380	9.7615	4.7146
3	Aitchison Road Creek	0.0145	0.0211	0.0274	0.0352	0.0511	0.0976	0.4070	0.7737	1.8813	0.3676
4	Akatore Creek	0.4037	0.5779	0.6386	0.7524	0.8351	0.9829	1.3959	1.7620	2.3421	1.0767
5	Albert Burn (1)	0.0000	0.1757	0.3106	0.4360	0.5548	0.6594	0.9617	1.3997	1.8258	0.7026
6	Albert Burn (2)	0.1264	0.4030	0.5342	0.6138	0.7123	0.8386	1.0035	1.2407	1.5671	0.7822
7	Alexanders Creek	0.0152	0.0219	0.0282	0.0361	0.0531	0.1068	0.4642	0.8481	1.9525	0.3918
8	Allangrange (N)	0.0722	0.1858	0.2370	0.2866	0.3349	0.4635	0.5729	0.8911	1.3481	0.4880
9	Allangrange (S)	0.0031	0.0475	0.1207	0.1977	0.2804	0.3784	0.4814	0.8455	1.3568	0.4124
10	Alpha Burn	0.6065	0.7770	1.0349	1.4278	1.9857	2.4854	3.3366	4.3257	5.4062	2.3762
11	Amisfield Burn	0.0000	0.0000	0.0335	0.1218	0.2261	0.3056	0.5748	0.9010	1.1235	0.3651
12	Arrow River	1.8368	2.1025	2.2949	2.4498	2.7168	3.1443	3.7429	5.2281	6.3926	3.3232
13	Awamoa Creek	0.0000	0.0000	0.0000	0.0683	0.1672	0.2706	0.3998	0.6906	1.1257	0.3025
14	Awamoko Stream	0.0000	0.0000	0.0283	0.1437	0.2520	0.3547	0.5277	0.6270	0.9447	0.3198
15	Back Creek	0.0000	0.0000	0.0000	0.0000	0.1075	0.1991	0.2715	0.5449	0.7294	0.2058
16	Balmoral Stream	0.1014	0.2356	0.3452	0.4188	0.6001	0.7493	0.9839	1.1569	1.7801	0.7079
17	Bannock Burn	0.0000	0.2905	0.3776	0.4886	0.5700	0.7227	1.0195	1.3871	2.4063	0.8069
18	Barnego Creek	0.0782	0.2254	0.3057	0.3995	0.5694	0.7424	0.9638	1.1580	1.7801	0.6914
19	Basin Burn	0.0000	0.1484	0.2646	0.4176	0.5145	0.6327	0.9075	1.2701	1.9876	0.6826
20	Battery Creek	0.0041	0.0059	0.0076	0.0099	0.0149	0.0303	0.1501	0.2291	0.5278	0.1088
21	Bay Burn	0.1658	0.3383	0.4465	0.6134	0.8127	1.0959	1.7114	2.3406	3.5929	1.2353
22	Baynes Creek	0.0085	0.0123	0.0159	0.0206	0.0296	0.0580	0.2453	0.4847	1.1033	0.2198
23	Beaumont River	0.6530	0.9526	1.1338	1.3412	1.4667	2.1017	3.2349	4.2243	4.9397	2.2275
24	Bee Burn	0.0591	0.2378	0.3218	0.4480	0.5025	0.5915	0.7244	1.0920	1.5049	0.6091
25	Beethams Creek	0.0000	0.0696	0.1821	0.2810	0.4112	0.4894	0.7931	1.1251	1.6810	0.5592
...											
292	Waianakarua River	2.1383	2.2601	2.4326	2.5420	2.6085	2.6926	2.8941	3.4124	4.6291	2.8455
293	Waiheke Stream	0.0159	0.0231	0.0294	0.0378	0.0543	0.1063	0.4492	0.8416	1.9951	0.3948
294	Waikerikeri Creek	0.0924	0.1958	0.3114	0.4105	0.5565	0.6552	1.0358	1.3838	1.8612	0.7225
295	Waikouaiti River	2.3377	2.5189	3.7477	4.7890	5.8495	6.7624	8.8807	11.7360	13.5030	6.6805
296	Waikoura Creek	0.0000	0.0000	0.0000	0.0000	0.1557	0.2151	0.3302	0.5566	0.9747	0.2480
297	Waipati River	1.7629	2.3102	3.3687	4.7561	5.4746	7.1260	8.5337	10.0576	13.4391	6.3143
298	Waitahuna River	1.9703	2.4858	2.7606	3.0087	3.3219	3.6758	4.1068	4.7089	5.8059	3.5383
299	Waitangi Stream	0.0156	0.0225	0.0292	0.0373	0.0536	0.1030	0.4429	0.8735	1.9885	0.3962
300	Waitati River	0.0000	0.1699	0.3257	0.4103	0.4861	0.6036	0.7311	0.9436	1.4970	0.5741
301	Waitepeka River	0.1027	0.2119	0.3396	0.4560	0.5801	0.7407	0.9493	1.1464	1.7801	0.7008
302	Waiwera River	1.7716	2.1946	2.4436	2.5735	2.6987	2.8328	3.1864	3.6843	4.5202	2.8784
303	Waiwherowhero Creek	0.0000	0.0000	0.0000	0.0000	0.1070	0.1892	0.3192	0.5312	0.7954	0.2158
304	Walkers Creek	0.0000	0.2071	0.3892	0.5259	0.6331	0.8947	1.4253	1.8225	2.4315	0.9255
305	Wangaloa Creek	0.2442	0.3554	0.4548	0.5566	0.7301	0.9190	1.3446	1.7007	2.2223	0.9475
306	Washpool Creek	0.1554	0.3211	0.4424	0.5564	0.6372	0.8185	1.1798	1.4187	2.2223	0.8613
307	Water of Leith	0.5223	0.6838	0.7075	0.7841	0.8924	1.1577	1.9545	2.6531	3.3687	1.4138
308	Waterfall Creek (1)	0.5971	0.7517	1.0174	1.2799	2.1713	2.7212	3.3867	3.9613	5.2378	2.3472
309	Waterfall Creek (2)	0.0666	0.2167	0.3573	0.4647	0.5984	0.7896	1.0540	1.5690	2.1775	0.8104
310	Weatherall Creek	0.0095	0.0136	0.0174	0.0222	0.0317	0.0616	0.2499	0.4900	1.1528	0.2276
311	Weipers Creek	0.0056	0.0081	0.0104	0.0134	0.0193	0.0377	0.1684	0.3057	0.7179	0.1429
312	Welcome Creek	0.0000	0.0000	0.0000	0.0000	0.0909	0.1676	0.2400	0.3701	0.7315	0.1778
313	Wharf Creek	0.0175	0.0254	0.0329	0.0422	0.0606	0.1163	0.5081	0.9377	2.2021	0.4381
314	Whiskey Gully Creek	0.0102	0.0147	0.0190	0.0245	0.0354	0.0709	0.3326	0.5725	1.2934	0.2637
315	Wilkes Creek	0.0153	0.0223	0.0288	0.0371	0.0539	0.1070	0.4439	0.8401	1.9960	0.3938
316	Wye Creek	0.2253	0.4249	0.6458	0.7924	0.9433	1.2093	1.6776	2.2223	2.8658	1.2230
317	Yards Gully Creek	0.0482	0.2165	0.3106	0.4025	0.4711	0.5898	0.7774	1.0102	1.5431	0.5966

N	Hydrologic Index: Empirical Cumulative Distribution Function: Catchment	MALF 10th Percentile (m^3/s)	MALF 20th Percentile (m^3/s)	MALF 30th Percentile (m^3/s)	MALF 40th Percentile (m^3/s)	MALF 50th Percentile (m^3/s)	MALF 60th Percentile (m^3/s)	MALF 70th Percentile (m^3/s)	MALF 80th Percentile (m^3/s)	MALF 90th Percentile (m^3/s)	MALF Average (m^3/s)
1	Abernethys Creek	0.0004	0.0007	0.0010	0.0016	0.0026	0.005	0.013	0.042	0.070	0.015
2	Afton Burn	0.424	0.491	0.575	0.722	1.013	1.350	1.610	2.201	3.595	1.331
3	Aitchison Road Creek	0.0022	0.0035	0.0051	0.0078	0.0127	0.024	0.064	0.201	0.338	0.073
4	Akatore Creek	0.022	0.067	0.095	0.118	0.148	0.166	0.214	0.304	0.395	0.170
5	Albert Burn (1)	0.000	0.017	0.114	0.159	0.179	0.267	0.341	0.460	0.662	0.244
6	Albert Burn (2)	0.000	0.055	0.083	0.116	0.147	0.165	0.199	0.273	0.362	0.156
7	Alexanders Creek	0.0022	0.0035	0.0051	0.0079	0.0129	0.025	0.064	0.195	0.332	0.072
8	Allangrange (N)	0.000	0.000	0.000	0.010	0.018	0.035	0.047	0.074	0.117	0.033
9	Allangrange (S)	0.000	0.000	0.004	0.009	0.019	0.025	0.036	0.069	0.111	0.030
10	Alpha Burn	0.041	0.168	0.264	0.329	0.431	0.500	0.552	0.785	1.447	0.502
11	Amisfield Burn	0.000	0.000	0.001	0.020	0.034	0.069	0.121	0.195	0.273	0.079
12	Arrow River	0.280	0.349	0.419	0.543	0.641	0.791	0.907	1.084	1.577	0.732
13	Awamoa Creek	0.000	0.000	0.000	0.016	0.048	0.072	0.102	0.148	0.243	0.070
14	Awamoko Stream	0.000	0.000	0.008	0.028	0.041	0.059	0.091	0.126	0.201	0.062
15	Back Creek	0.000	0.000	0.000	0.000	0.010	0.031	0.063	0.112	0.171	0.043
16	Balmoral Stream	0.000	0.012	0.040	0.060	0.087	0.126	0.158	0.202	0.260	0.105
17	Bannock Burn	0.000	0.016	0.046	0.094	0.128	0.163	0.256	0.344	0.481	0.170
18	Barnego Creek	0.000	0.014	0.049	0.064	0.092	0.125	0.160	0.204	0.246	0.106
19	Basin Burn	0.000	0.083	0.152	0.181	0.238	0.307	0.356	0.455	0.668	0.271
20	Battery Creek	0.0005	0.0008	0.0012	0.0018	0.0030	0.006	0.015	0.048	0.082	0.018
21	Bay Burn	0.000	0.019	0.070	0.119	0.157	0.195	0.273	0.428	0.554	0.201
22	Baynes Creek	0.0011	0.0018	0.0026	0.0040	0.0066	0.012	0.033	0.105	0.172	0.038
23	Beaumont River	0.113	0.192	0.255	0.323	0.456	0.590	0.807	0.973	1.177	0.543
24	Bee Burn	0.000	0.016	0.047	0.072	0.107	0.140	0.161	0.220	0.310	0.119
25	Beethams Creek	0.000	0.000	0.002	0.009	0.025	0.040	0.057	0.099	0.140	0.041

292	Waianakarua River	0.150	0.189	0.228	0.247	0.310	0.366	0.428	0.489	0.700	0.345
293	Waiheke Stream	0.0023	0.0038	0.0055	0.0084	0.0136	0.026	0.070	0.217	0.359	0.078
294	Waikerikeri Creek	0.000	0.001	0.035	0.076	0.111	0.151	0.205	0.267	0.397	0.138
295	Waikouaiti River	0.225	0.327	0.716	0.989	1.145	1.404	1.543	2.031	2.594	1.219
296	Waikoura Creek	0.000	0.000	0.000	0.014	0.032	0.048	0.076	0.128	0.201	0.055
297	Waipati River	0.391	0.637	1.401	1.840	2.290	2.856	3.251	3.786	4.672	2.347
298	Waitahuna River	0.255	0.355	0.468	0.565	0.624	0.735	0.878	1.125	1.553	0.729
299	Waitangi Stream	0.0024	0.0038	0.0055	0.0082	0.0132	0.025	0.069	0.217	0.359	0.078
300	Waitati River	0.000	0.027	0.055	0.084	0.119	0.147	0.171	0.223	0.321	0.128
301	Waitepeka River	0.000	0.005	0.028	0.056	0.076	0.111	0.144	0.188	0.249	0.095
302	Waiwera River	0.056	0.158	0.213	0.242	0.279	0.333	0.400	0.561	0.793	0.337
303	Waiwherowhero Creek	0.000	0.000	0.000	0.000	0.006	0.023	0.040	0.054	0.091	0.024
304	Walkers Creek	0.000	0.000	0.078	0.145	0.191	0.292	0.439	0.539	0.822	0.278
305	Wangaloa Creek	0.000	0.049	0.083	0.133	0.167	0.202	0.259	0.300	0.429	0.180
306	Washpool Creek	0.000	0.024	0.067	0.091	0.118	0.165	0.208	0.255	0.349	0.142
307	Water of Leith	0.084	0.151	0.166	0.184	0.217	0.271	0.354	0.437	0.695	0.284
308	Waterfall Creek (1)	0.097	0.175	0.243	0.306	0.398	0.513	0.669	0.826	1.393	0.513
309	Waterfall Creek (2)	0.000	0.020	0.083	0.140	0.169	0.221	0.354	0.499	0.704	0.243
310	Weatherall Creek	0.0013	0.0021	0.0030	0.0046	0.0074	0.014	0.038	0.121	0.199	0.043
311	Weipers Creek	0.0007	0.0011	0.0016	0.0025	0.0041	0.008	0.020	0.064	0.105	0.023
312	Welcome Creek	0.000	0.000	0.000	0.000	0.006	0.019	0.032	0.047	0.097	0.022
313	Wharf Creek	0.0026	0.0042	0.0062	0.0093	0.0154	0.029	0.078	0.244	0.408	0.089
314	Whiskey Gully Creek	0.0014	0.0023	0.0033	0.0050	0.0081	0.015	0.041	0.128	0.218	0.047
315	Wilkes Creek	0.0022	0.0035	0.0052	0.0078	0.0127	0.024	0.066	0.207	0.342	0.074
316	Wye Creek	0.001	0.170	0.219	0.258	0.342	0.412	0.559	0.708	1.081	0.417
317	Yards Gully Creek	0.000	0.002	0.036	0.056	0.089	0.117	0.150	0.188	0.271	0.101

Appendix B. Summary table of probable default catchment minimum flows and default catchment allocation rates arranged in alphabetical order (first and last 25 of 317 catchments) across the Otago Region. Note that the respective black and red text is associated with flows predicted using the Meta model and Bias correction model. A complete listing of default minimum flow, default allocation rate, coordinates, area, stream order, freshwater management unit, and Rohe are available in *naturalised-default-minimum-flow-and-default-allocation-rate.csv*. The red text is associated with flows predicted using the Bias correction model.

	Default Hydrology:	Minimum Flow l/s									
ID	Empirical Cumulative Distribution Function: Catchment	10th Percentile	20th Percentile	30th Percentile	40th Percentile	50th Percentile	60th Percentile	70th Percentile	80th Percentile	90th Percentile	Average
1	Abernethys Creek	0.4	0.7	0.9	1.4	2.3	4.4	11.9	37.7	63.2	13.7
2	Afton Burn	381.7	442.1	517.1	649.5	911.5	1080.0	1288.1	1761.0	2876.3	1100.8
3	Aitchison Road Creek	1.9	3.1	4.6	7.0	11.5	21.5	57.2	180.5	304.4	65.8
4	Akatore Creek	19.4	60.5	85.3	106.5	133.3	149.8	192.9	273.9	355.2	153.0
5	Albert Burn (1)	0.0	15.2	102.8	142.7	161.4	240.3	307.2	414.3	596.0	220.0
6	Albert Burn (2)	0.0	49.7	74.9	104.1	132.0	148.5	178.7	246.1	325.7	140.0
7	Alexanders Creek	2.0	3.1	4.6	7.1	11.6	22.1	57.4	175.5	299.0	64.7
8	Allangrange (N)	0.0	0.0	0.0	8.9	16.3	31.1	42.5	66.2	104.9	30.0
9	Allangrange (S)	0.0	0.0	3.6	8.0	17.0	22.1	32.3	62.3	99.7	27.2
10	Alpha Burn	36.7	151.5	237.4	296.4	387.7	449.6	497.1	706.6	1157.5	435.6
11	Amisfield Burn	0.0	0.0	0.9	18.0	30.8	62.5	108.8	175.3	245.9	71.4
12	Arrow River	252.2	314.5	376.9	488.4	577.1	712.2	816.3	867.5	1261.6	629.7
13	Awamoa Creek	0.0	0.0	0.0	14.6	42.8	64.4	91.9	133.0	219.1	62.9
14	Awamoko Stream	0.0	0.0	6.8	25.6	36.8	53.3	82.1	113.2	181.0	55.4
15	Back Creek	0.0	0.0	0.0	0.0	9.4	28.0	56.5	101.2	154.3	38.8
16	Balmoral Stream	0.0	10.6	36.0	54.3	78.0	113.3	142.3	182.0	234.3	94.5
17	Bannock Burn	0.0	14.6	41.2	84.9	115.5	146.3	230.0	309.9	432.7	152.8
18	Barnego Creek	0.0	12.7	43.7	57.5	82.8	112.2	143.8	183.2	221.7	95.3
19	Basin Burn	0.0	74.6	136.8	162.7	214.4	276.6	320.7	409.9	600.9	244.1
20	Battery Creek	0.5	0.8	1.1	1.7	2.7	5.1	13.5	43.6	73.5	15.8
21	Bay Burn	0.0	17.1	62.7	106.7	140.9	175.2	245.6	385.3	498.7	181.3
22	Baynes Creek	1.0	1.6	2.3	3.6	5.9	11.2	29.5	94.4	155.0	33.8
23	Beaumont River	101.7	172.4	229.3	290.4	410.1	531.2	726.0	875.7	1059.2	488.5
24	Bee Burn	0.0	14.2	42.5	64.5	96.0	125.7	145.3	197.9	278.7	107.2
25	Beethams Creek	0.0	0.0	1.7	7.8	22.5	36.3	51.7	89.4	126.4	37.3
. ..											
292	Waianakarua River	134.9	170.0	205.5	222.7	279.0	329.4	385.3	440.3	629.8	310.8
293	Waiheke Stream	2.1	3.4	5.0	7.5	12.3	23.3	63.0	195.1	323.4	70.6
294	Waikerikeri Creek	0.0	0.6	31.4	68.7	99.6	136.0	184.8	240.5	357.4	124.3
295	Waikouaiti River	202.6	293.9	644.7	890.5	915.9	1123.1	1234.6	1624.6	2075.3	1000.6
296	Waikoura Creek	0.0	0.0	0.0	12.2	28.6	42.8	68.8	115.0	180.5	49.8
297	Waipati River	352.0	573.1	1261.3	1656.1	1831.6	2284.7	2600.9	3028.9	3737.6	1925.1
298	Waitahuna River	229.2	319.8	421.6	508.8	562.0	661.2	790.0	1012.9	1242.1	638.6
299	Waitangi Stream	2.1	3.4	5.0	7.4	11.9	22.7	62.1	195.1	323.3	70.3
300	Waitati River	0.0	24.7	49.9	75.9	107.1	132.0	153.9	200.6	289.0	114.8
301	Waitepeka River	0.0	4.3	25.3	50.1	68.7	100.3	129.3	168.9	223.8	85.6
302	Waiwera River	50.6	142.5	191.6	217.9	251.0	299.7	359.9	504.5	713.8	303.5
303	Waiwherowhero Creek	0.0	0.0	0.0	0.0	5.0	20.5	36.2	48.8	81.6	21.4
304	Walkers Creek	0.0	0.0	70.2	130.6	171.9	263.1	395.0	484.8	739.4	250.5
305	Wangaloa Creek	0.0	44.5	74.5	119.4	150.3	181.7	233.2	269.8	386.0	162.2
306	Washpool Creek	0.0	21.4	60.5	81.5	106.2	148.4	187.3	229.6	314.5	127.7
307	Water of Leith	75.2	136.1	149.8	165.9	194.9	244.2	318.8	393.4	625.5	256.0
308	Waterfall Creek (1)	87.3	157.7	218.6	275.8	357.8	462.1	602.3	743.4	1114.6	446.6
309	Waterfall Creek (2)	0.0	17.9	74.3	125.9	152.5	199.0	318.7	448.9	633.5	219.0
310	Weatherall Creek	1.1	1.8	2.7	4.1	6.7	12.5	34.3	108.7	179.3	39.0
311	Weipers Creek	0.6	1.0	1.5	2.2	3.7	6.9	17.9	57.7	94.5	20.6
312	Welcome Creek	0.0	0.0	0.0	0.0	5.0	16.7	29.0	42.6	87.0	20.0
313	Wharf Creek	2.4	3.8	5.6	8.4	13.9	26.1	70.2	219.4	367.3	79.7
314	Whiskey Gully Creek	1.3	2.0	3.0	4.5	7.3	13.8	36.6	115.4	196.4	42.3
315	Wilkes Creek	2.0	3.2	4.6	7.0	11.4	21.7	59.0	186.7	307.8	67.0
316	Wye Creek	1.0	153.1	197.3	232.6	308.0	370.9	503.1	637.0	972.5	375.1
317	Yards Gully Creek	0.0	1.5	32.7	50.5	80.1	105.7	134.8	168.8	243.6	90.9

	Default Hydrology:	Allocation Rate l/s									
ID	Empirical Cumulative Distribution Function: Catchment	10th Percentile	20th Percentile	30th Percentile	40th Percentile	50th Percentile	60th Percentile	70th Percentile	80th Percentile	90th Percentile	Average
1	Abernethys Creek	0.1	0.1	0.2	0.3	0.5	1.0	2.6	8.4	14.0	3.0
2	Afton Burn	84.8	98.2	114.9	144.3	202.6	405.0	483.0	660.4	1078.6	363.5
3	Aitchison Road Creek	0.4	0.7	1.0	1.6	2.5	4.8	12.7	40.1	67.6	14.6
4	Akatore Creek	4.3	13.4	19.0	23.7	29.6	33.3	42.9	60.9	78.9	34.0
5	Albert Burn (1)	0.0	3.4	22.9	31.7	35.9	53.4	68.3	92.1	132.5	48.9
6	Albert Burn (2)	0.0	11.0	16.6	23.1	29.3	33.0	39.7	54.7	72.4	31.1
7	Alexanders Creek	0.4	0.7	1.0	1.6	2.6	4.9	12.8	39.0	66.4	14.4
8	Allangrange (N)	0.0	0.0	0.0	2.0	3.6	6.9	9.5	14.7	23.3	6.7
9	Allangrange (S)	0.0	0.0	0.8	1.8	3.8	4.9	7.2	13.8	22.2	6.0
10	Alpha Burn	8.2	33.7	52.8	65.9	86.2	99.9	110.5	157.0	434.1	116.5
11	Amisfield Burn	0.0	0.0	0.2	4.0	6.8	13.9	24.2	39.0	54.6	15.9
12	Arrow River	56.1	69.9	83.8	108.5	128.3	158.3	181.4	325.3	473.1	176.1
13	Awamoa Creek	0.0	0.0	0.0	3.3	9.5	14.3	20.4	29.5	48.7	14.0
14	Awamoko Stream	0.0	0.0	1.5	5.7	8.2	11.8	18.2	25.2	40.2	12.3
15	Back Creek	0.0	0.0	0.0	0.0	2.1	6.2	12.6	22.5	34.3	8.6
16	Balmoral Stream	0.0	2.4	8.0	12.1	17.3	25.2	31.6	40.4	52.1	21.0
17	Bannock Burn	0.0	3.2	9.2	18.9	25.7	32.5	51.1	68.9	96.2	34.0
18	Barnego Creek	0.0	2.8	9.7	12.8	18.4	24.9	32.0	40.7	49.3	21.2
19	Basin Burn	0.0	16.6	30.4	36.2	47.6	61.5	71.3	91.1	133.5	54.2
20	Battery Creek	0.1	0.2	0.2	0.4	0.6	1.1	3.0	9.7	16.3	3.5
21	Bay Burn	0.0	3.8	13.9	23.7	31.3	38.9	54.6	85.6	110.8	40.3
22	Baynes Creek	0.2	0.4	0.5	0.8	1.3	2.5	6.5	21.0	34.5	7.5
23	Beaumont River	22.6	38.3	51.0	64.5	91.1	118.1	161.3	194.6	235.4	108.5
24	Bee Burn	0.0	3.2	9.4	14.3	21.3	27.9	32.3	44.0	61.9	23.8
25	Beethams Creek	0.0	0.0	0.4	1.7	5.0	8.1	11.5	19.9	28.1	8.3
...											
292	Waianakarua River	30.0	37.8	45.7	49.5	62.0	73.2	85.6	97.8	140.0	69.1
293	Waiheke Stream	0.5	0.8	1.1	1.7	2.7	5.2	14.0	43.4	71.9	15.7
294	Waikerikeri Creek	0.0	0.1	7.0	15.3	22.1	30.2	41.1	53.4	79.4	27.6
295	Waikouaiti River	45.0	65.3	143.3	197.9	343.5	421.2	463.0	609.2	778.2	340.7
296	Waikoura Creek	0.0	0.0	0.0	2.7	6.4	9.5	15.3	25.6	40.1	11.1
297	Waipati River	78.2	127.4	280.3	368.0	686.9	856.7	975.4	1135.8	1401.6	656.7
298	Waitahuna River	50.9	71.1	93.7	113.1	124.9	146.9	175.6	225.1	465.8	163.0
299	Waitangi Stream	0.5	0.8	1.1	1.6	2.6	5.0	13.8	43.3	71.8	15.6
300	Waitati River	0.0	5.5	11.1	16.9	23.8	29.3	34.2	44.6	64.2	25.5
301	Waitepeka River	0.0	1.0	5.6	11.1	15.3	22.3	28.7	37.5	49.7	19.0
302	Waiwera River	11.2	31.7	42.6	48.4	55.8	66.6	80.0	112.1	158.6	67.4
303	Waiwherowhero Creek	0.0	0.0	0.0	0.0	1.1	4.6	8.1	10.8	18.1	4.7
304	Walkers Creek	0.0	0.0	15.6	29.0	38.2	58.5	87.8	107.7	164.3	55.7
305	Wangaloa Creek	0.0	9.9	16.6	26.5	33.4	40.4	51.8	59.9	85.8	36.0
306	Washpool Creek	0.0	4.8	13.4	18.1	23.6	33.0	41.6	51.0	69.9	28.4
307	Water of Leith	16.7	30.2	33.3	36.9	43.3	54.3	70.8	87.4	139.0	56.9
308	Waterfall Creek (1)	19.4	35.0	48.6	61.3	79.5	102.7	133.8	165.2	418.0	118.2
309	Waterfall Creek (2)	0.0	4.0	16.5	28.0	33.9	44.2	70.8	99.8	140.8	48.7
310	Weatherall Creek	0.3	0.4	0.6	0.9	1.5	2.8	7.6	24.1	39.8	8.7
311	Weipers Creek	0.1	0.2	0.3	0.5	0.8	1.5	4.0	12.8	21.0	4.6
312	Welcome Creek	0.0	0.0	0.0	0.0	1.1	3.7	6.4	9.5	19.3	4.4
313	Wharf Creek	0.5	0.8	1.2	1.9	3.1	5.8	15.6	48.8	81.6	17.7
314	Whiskey Gully Creek	0.3	0.5	0.7	1.0	1.6	3.1	8.1	25.7	43.6	9.4
315	Wilkes Creek	0.4	0.7	1.0	1.6	2.5	4.8	13.1	41.5	68.4	14.9
316	Wye Creek	0.2	34.0	43.8	51.7	68.4	82.4	111.8	141.6	216.1	83.3
317	Yards Gully Creek	0.0	0.3	7.3	11.2	17.8	23.5	30.0	37.5	54.1	20.2

Appendix C. Summary table of probable allocation status for the first and last 25 of 317 gauged catchments across the Otago Region. Catchment allocation status: 1 = over-allocated and, 0 = under-allocated. Other sites not shown along with coordinates, area, stream order, freshwater management unit, and Rohe are available as *naturalised-catchment-allocation-status.csv*.

ID	Percentile: Catchment	10th Allocation Over	10th Allocation Under	20th Allocation Over	20th Allocation Under	30th Allocation Over	30th Allocation Under	40th Allocation Over	40th Allocation Under	50th Allocation Over	50th Allocation Under	60th Allocation Over	60th Allocation Under	70th Allocation Over	70th Allocation Under	80th Allocation Over	80th Allocation Under	90th Allocation Over	90th Allocation Under
1	Abernethys Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
2	Afton Burn	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
3	Aitchison Road Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
4	Akatore Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
5	Albert Burn (1)	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
6	Albert Burn (2)	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
7	Alexanders Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
8	Allangrange (N)	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
9	Allangrange (S)	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
10	Alpha Burn	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	1	0	1
11	Amisfield Burn	1	0	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1
12	Arrow River	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
13	Awamoa Creek	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
14	Awamoko Stream	1	0	1	0	1	0	1	0	1	0	1	0	0	1	0	1	0	1
15	Back Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
16	Balmoral Stream	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
17	Bannock Burn	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
18	Barnego Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
19	Basin Burn	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
20	Battery Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
21	Bay Burn	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
22	Baynes Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
23	Beaumont River	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
24	Bee Burn	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
25	Beethams Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
...																			
293	Waiheke Stream	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
294	Waikerikeri Creek	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	1
295	Waikouaiti River	1	0	1	0	1	0	0	1	0	1	0	1	0	1	0	1	0	1
296	Waikoura Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
297	Waipati River	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
298	Waitahuna River	1	0	1	0	1	0	1	0	1	0	0	1	0	1	0	1	0	1
299	Waitangi Stream	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
300	Waitati River	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
301	Waitepeka River	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
302	Waiwera River	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	0	1
303	Waiwherowhero Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
304	Walkers Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
305	Wangaloa Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
306	Washpool Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
307	Water of Leith	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
308	Waterfall Creek (1)	1	0	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
309	Waterfall Creek (2)	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
310	Weatherall Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
311	Weipers Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
312	Welcome Creek	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0
313	Wharf Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
314	Whiskey Gully Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
315	Wilkes Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
316	Wye Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
317	Yards Gully Creek	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1	0	1
		10th Default Allocation Over	10th Defualt Allocation Under	20th Default Allocation Over	20th Default Allocation Under	30th Default Allocation Over	30th Defualt Allocation Under	40th Default Allocation Over	40th Defualt Allocation Under	50th Default Allocation Over	50th Defualt Allocation Under	60th Default Allocation Over	60th Defualt Allocation Under	80th Default Allocation Over	80th Defualt Allocation Under	80th Default Allocation Over	80th Defualt Allocation Under	90th Default Allocation Over	90th Defualt Allocation Under
		72	245	68	249	62	255	57	260	54	263	45	272	37	280	31	286	26	291