Predicting impacts of agricultural land use on stream and river biota: method review, evaluation and guidance

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Abstract

Predicting land use and land management effects on stream and river biota is an important aspect of land-water management, yet there are no collations of what methods are available to carry out those assessments nor guidance on which methods to use. This paper summarises a range of methods with examples of their applications, comments on their strengths and weaknesses, evaluates them against a set of criteria, and provides guidance on method selection. Assessment methods include empirical statistical and mechanistic models, Bayesian Networks, likelihood-consequence risk assessments, scoring methods, and hybrid methods, some of which can be informed by expert elicitation. An evaluation matrix for methods indicated that no single method is ideal, and selection of methods needs to carefully consider factors such as the physico-chemical stressor or biotic impact of interest, the intended stakeholders, and the scales of assessment. One emergent principle is the separation of relationships between land use and stressors from assessments of stressors and biota, for which alternative methods could be used. A tiered approach is recommended, whereby simple methods with low resource and time requirements are applied first, followed by more sophisticated methods for selected aspects if needed. There is a need for more ready-made methods at the screening level, as well as development of new methods to address remaining gaps such as multiple stressors.

Keywords: stream, biota, river, impact assessment

1. Introduction

Land use and land management have a strong influence on the health of biota (plants, algae, invertebrates, and fish) in rivers and streams (Allan 2004 ; Larned et al. 2020; Schürings et al. 2022). Accordingly, freshwater management legislation in many jurisdictions calls for assessment of ways to avoid or reduce such impacts by modifying land use (changing the primary class of land use such as forestry or dairy farming) or land management (practices that modify land use, such as fertiliser use or irrigation)(Kallis and Butler 2001; New Zealand Government 2023). For brevity, in this paper we refer the influence of land use and land management on biota in rivers and streams as land-use/biota impacts. Despite the rich literature on land-use/biota impacts, it is unclear whether there are sufficient methods available for predicting such impacts or how to choose among methods.

To our knowledge, there are no existing guides or papers that survey and assess a wide range of methods for predicting land-use/biota impacts. This paper aims to fill this gap by surveying a range of methods for predicting land-use/biota impacts, evaluating them, and providing guidance for their selection. The paper does not aim to provide specific relationships between land use and biota, nor quantify limits or thresholds. The primary audience of the paper is land-water 'practitioners' (such as land and water managers, consultants, and policy analysts) who do not have specialist modelling or ecological expertise and who which to obtain an overview of the range of methods and their application, to assist with guiding and interpreting assessments undertaken by specialists. A second audience is scientists who are familiar with some methods (for example, a catchment modeler for water quality) but is less familiar with other methods (for example, statistical methods for biota). A third audience is scientists who are familiar with many methods, but who have not considered how the methods are related and their relative role and land-use/biota assessments. The paper does not address monitoring methods to evaluate current state or trends, but rather focuses on methods (typically, models) for predicting changes associated with potential future changes to land use or land management.

This paper focusses on agricultural (e.g. pasture, cropping, forest plantations) rather than urban land-use. Urban land use certainly does impact stream biota (e.g., Petsch et al. 2021), and many of the principles and methods in this paper could be applied to urban land use. The scope of the paper is restricted to agricultural land as the impacts of agricultural land are extensive (Larned et al. 2020) and because stressors on urban streams are different in type or nature compared with agricultural streams (for example, piped stormwater drainage, and urban contaminants such as metals associated with impervious areas). Examples in the paper focus on New Zealand, which has a range of land uses and a rich record of freshwater science and management. The scope is also restricted to streams and wetlands (lotic systems) rather than lakes or estuaries. Despite the restriction of scope to agriculture and stream/river biota, many of the principles and methods in this paper will be applicable to other land uses, locations and receiving environments.

The paper first provides a brief introduction to land-use/biota impacts. Additional material on freshwater ecology principles is included in supplementary material for readers less familiar with these concepts. The paper then presents a range of predictive methods for land-use/biota impact assessment. Each method is described, and examples of applications are given where available. Commentary on the methods is then provided, methods are compared and evaluated against criteria, and guidance is provided as to what stages and scale of assessment the methods can be used in. Readers already familiar with ecological impacts of land use and methods for evaluating those impacts may wish to focus on the synthesis and evaluation sections of the paper.

2. Overview of ecological impacts of land use

Agricultural land use impacts freshwater biota in a multitude of ways and at different scales and levels of ecological complexity (Allan 2004 ; Larned et al. 2020; Schürings et al. 2022), as depicted in the simple overview diagram in Figure 1. The figure hides many underlying complexities, such as interactions between items within the boxes and across boxes. For example, different species interact in complex food webs, macrophytes alter river hydraulic habitat, and decreased flow rates interact with primary production and respiration to exacerbate dissolved oxygen deficits. The figure indicates the direction of responses, but in reality the direction (and strength) of responses can vary depending on the environmental setting, the specific land use, intensity of land use (Schürings et al. 2024a) and the biotic indicator used in an assessment (Schürings et al. 2022). For example, the effect of land use on stream biota in Europe depended on crop type, amount of pesticide used, and the class of biota (Schürings et al. 2024a; Schürings et al. 2024b).

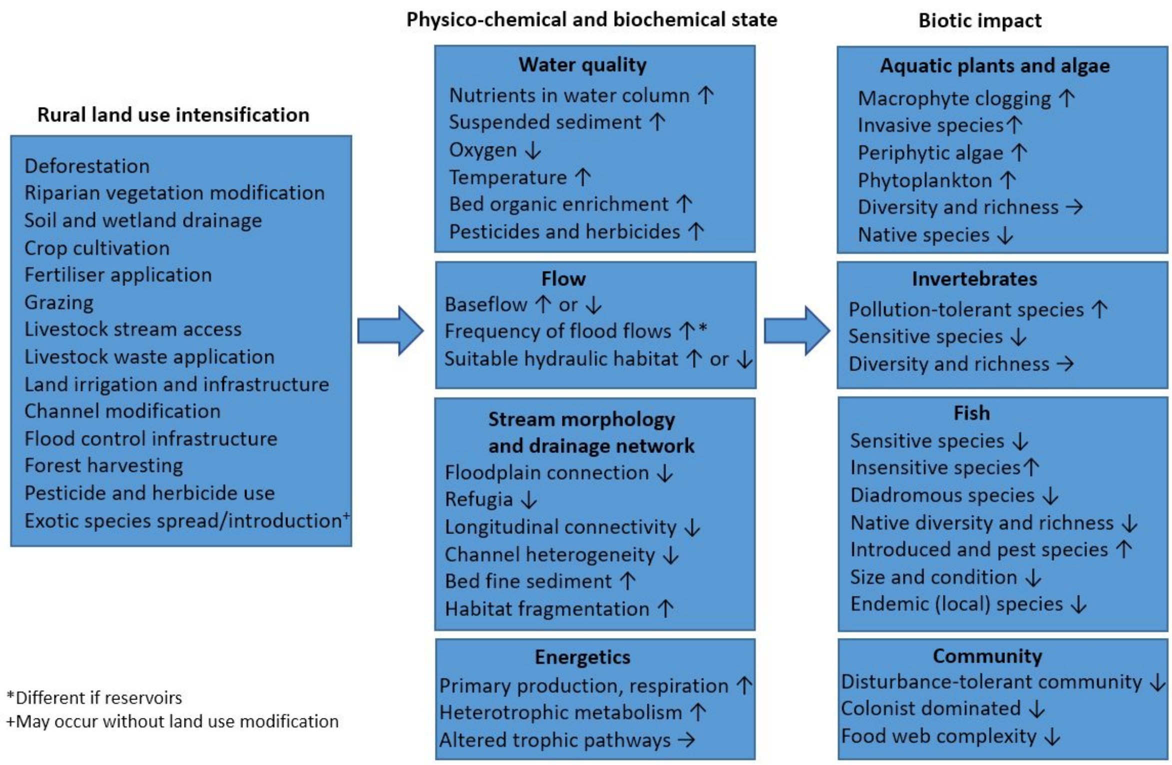

Figure 1. Schematic overview of effects of activities associated with agricultural land use on physico-chemical state and lotic biotic impact. An upward arrow indicates an increase in the state, downward a decrease, and horizontal no change anticipated or variable direction of response.

The collective effects of multiple changes in physico-chemical state may result in 'multiple stressor' impacts on biota (Ormerod et al. 2010; Birk et al. 2020). Here we define stressors as aspects of physico-chemical state such as flow, water temperature and contaminant concentration that are influenced by human activities and that can cause adverse biotic impacts. Effects may also be cumulative over time and space.

The influence of land use within a catchment of a stream location depends on the extent of the land use in the catchment, location in relation to landscape factors, and the intensity of the land use. The extent and location are typically expressed in terms of the area proportions of land use, location of the land use in relation to landscape factor and proximity to biotic receptors, while intensity relates to factors such as stocking rate, type and number of crop rotations, and amount of fertiliser, pesticide and irrigation used.

Biotic responses can also depend on the spatial scale of the land use modifications, ranging from local (reach, local riparian) to catchment scales. At local scale, streams can be influenced by conditions in adjacent riparian zones, through alterations in organic matter input, primary production, shading and water temperature (Rutherford et al. 2004; Burrell et al. 2014). Channel modifications such as straightening and weed removal to improve flood conveyance influence water quality and habitat locally, but may also affect water quality downstream (Greer et al. 2017). Land use in a headwater catchment may influence water quality conditions well downstream of the land parcel (Snelder et al. 2022b). It is also possible for a local stream modification such as a diversion dam to affect the biota in an entire stream network by restricting fish migration (Thieme et al. 2023).

One framework for considering biotic effects of land use is through the Driver-Pressure-State-Impact-Response concept (DPSIR) which, in broader use, is a causal framework for evaluating interactions between society and the environment (Maxim et al. 2009). In the DPSIR context, drivers are socio-economic factors that give rise to pressures, and responses are actions that are taken in the system to counter undesirable impacts and may alter DPSIR items. In Figure 2 we present a modified and narrower view related to land use and freshwater ecology, where impact includes effect on biota and human values, and state is primarily considered as physico-chemical state. A confusion of terminology is that the term 'stressor-response relationship' is also used to denote the relationship between a stressor and a biotic response, and we retain the use of that term in this paper because it is familiar to ecologists.

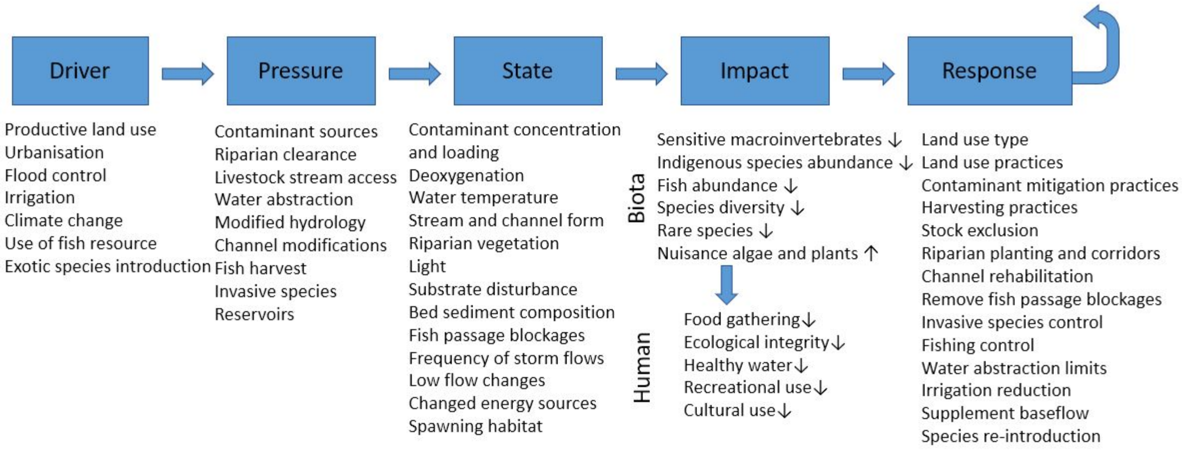

Figure 2. DPSIR model in the context of land-use and freshwater ecology impacts.

Stream ecologists use some organising concepts to structure their thinking about how stream ecosystems operate, and to guide restoration efforts. Some of these concepts and their relevance to effects of land use on freshwater biota, are summarised in the Supplementary Material. Key concepts are that biological communities are shaped by the physical and chemical habitat, disturbance events, resources (light, nutrients, external energy inputs), lateral and longitudinal connectivity, and complex nonlinear interactions with other biota at multiple spatial and temporal scales of influence.

3. Models and predictive methods for relating land use to biotic impacts

3.1. Overview

Numerous models and predictive methods are available for assessing land-use/biota impacts. Sections 3.2 to 3.7 provide a basic description of these models and examples of previous applications. The methods are summarised in Table 1.

In this study, literature was found using a combination of Google Scholar (primarily for journal literature) and internet searches (primarily for technical reports), using forward (citation) and backward (reference list) methodologies. Since the review was not intended as a quantitative systematic review, search terms and databases were not defined or used formally, evolved during the process of searching for and evaluating literature, and included existing domain knowledge of the authors.

Effects of land-use on biota can be assessed without reference to the mediating physico-chemical state (for example, by relating land use proportions to biotic responses without considering the mechanisms and their interactions). Alternatively, effects of land use on biota can be assessed by first considering how land use affects the physico-chemical state of the freshwater environment, and in turn how changes in physico-chemical state affect biota. Hence presentations of some of the methods and models (in Sections 3.2 and 3.3) are structured by whether the method is for predicting physico-chemical-state from land use, stressor-response relationships, or to relate land use to biotic impact directly.

Table 1. List of key broad classes of methods.

Class of predictive model or method	Description
Empirical relationships	Data-based methods for relating predictors to responses. Usually statistical. Many statistical methods are available including regression, random forest, and structural equation modelling.
Mechanistic model	Models based on systems of mathematical equations that represent causal process-based relationships between environmental components.
Bayesian Network (BN)	Probabilistic method to relate a set of system inputs (e.g., climate and land-use) to system outputs (e.g. fish abundance) through network of nodes and linkages.
Expert Elicitation	Use of experts to provide information based on their knowledge and judgement without modelling. Can be applied to a range of information needs and as part of other methods.
Likelihood-consequence risk assessment (LC)	Assessment of risk of impacts by assessing likelihood of events occurring and the resulting consequences if the event occurs.
Evaluation matrix and scoring	Scoring systems are often used to evaluate environmental management options against sets of criteria
Expert system	A system for encoding knowledge about causal relationships in logic rules and inference, fuzzy logic, or neural networks.
Causal diagrams	Network depicting components of a system, their interaction, and direction or strength of interaction, typically assessed in a subjective or qualitative way.
Compound and hybrid methods	Combination of different model types or methods which each address part of the land-use/biota assessment.

Land-use/biota impacts assessments can take place at different spatial scales, and with different levels of complexity applied to the physico-chemical and biotic components (Figure 3). The example pathway in the diagram is for a catchment-scale assessment which considers the effect of land use on multiple physico-chemical variables separately (for example, concentrations of different non-interacting contaminants) which are then combined to assess impacts on a single species or biotic index (for example, a sensitive fish species).

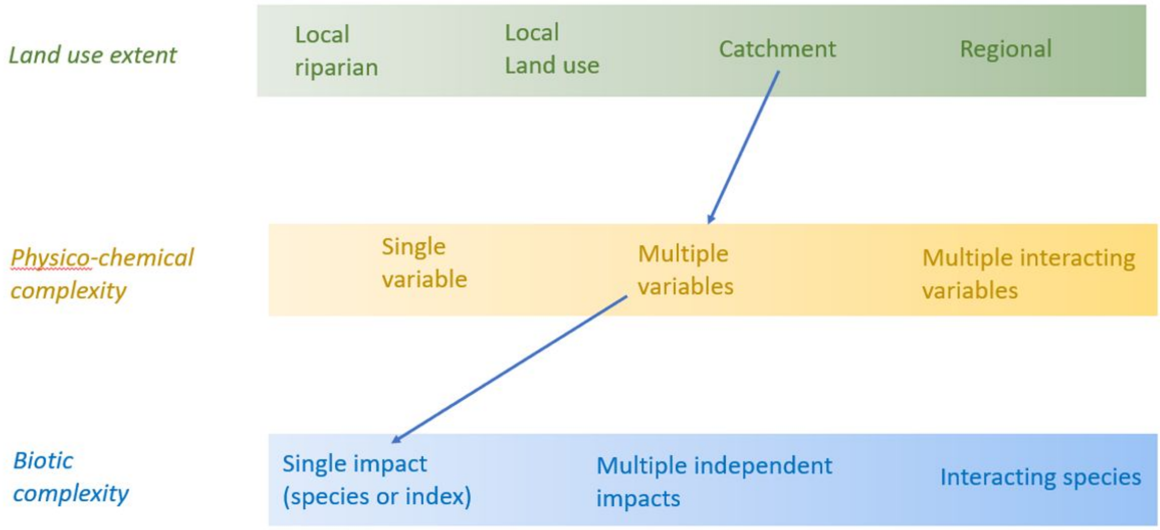

Figure 3. Pathways for assessing land use effects on biota, differentiated by extent, complexity of physico-chemical state assessment, and biotic impact assessment. The arrows indicate an example of a pathway, but many different pathways are possible.

Stressor limits are often used as a bridge between land use and biotic impacts, as depicted in Figure 4. Stressor-response relationships, usually between a single stressor and a single biotic impact, are used in conjunction with the desired state of the biota to define limits for stressor variables. These limits are linked to land use through other models, to assess whether the physico-chemical state associated with a stressor falls below the limit level, or to define levels of contaminant emissions or water takes corresponding to the limit. The land-use/stressor and stressor-response relationships can be specific to the landscape factors. Landscape factors are attributes of the catchment and river setting (such as climate, geology, soil, proximity to the coast, and stream size) that affect or constrain the relationships between physico-chemical state or biota.

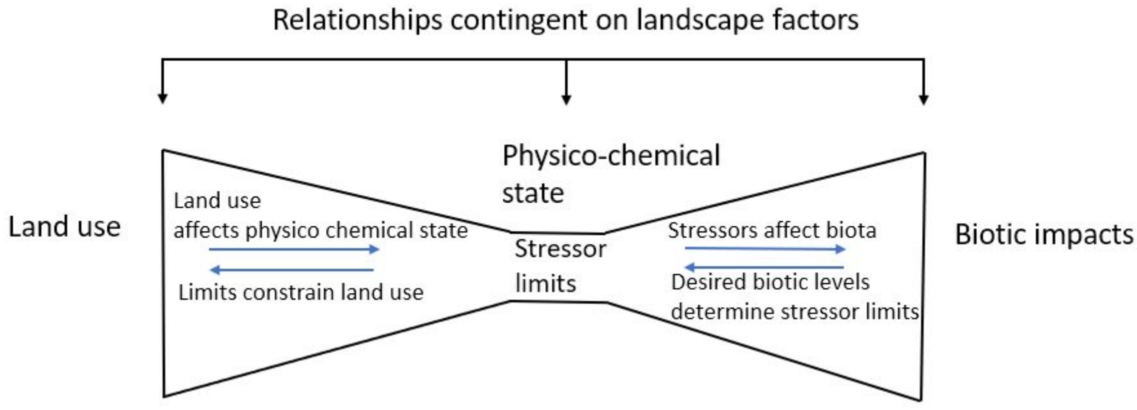

Figure 4. Depiction of the use of stressor limits to link between land use and biotic impacts.

3.2. Empirical relationships

Description of the models

Empirical models can be used to quantify relationships between predictor variables (for example, the proportions of land-use in a catchment) and responses (for example, water quality variables or a macroinvertebrate index). The models can be used for making predictions of responses for different values of predictor variables (within the range of data used to establish the model) or to derive levels of predictor variables that would be associated with desired levels of response variables. A critical caveat is that empirical models are correlative and do not prove causality.

There are many empirical modelling methods. At the simplest level, a single response variable is related to a single predictor variable (a bivariate model), expressed as a correlation or a curve. More generally, a single response variable can be predicted from multiple predictor variables. Common methods include multiple linear or nonlinear regression, generalised linear models (GLM, Zuur et al. 2009), quantile regression (Baas et al. 2003), generalised additive models (GAM, Zuur et al. 2009), and machine-learning methods such as random forests (RF, Pichler and Hartig 2023) and boosted regression trees (BRT, Pichler and Hartig 2023). Multivariate statistical models analyse multiple response variables together (RDA, Borcard et al. 2018).

Empirical models can allow for the dependence on landscape setting by including landscape variables as explanatory variables, or by using different land use-biota relationships for different classes of landscape variables. This has the advantage of reducing the effects of correlation between land use and landscape variables, and focussing on the influence of land-use or a stressor apart from the landscape variables.

Land use is commonly represented in empirical models by land cover variables such as proportions of land area comprised of native or pastoral land cover or specific classes of land use such a dairy pasture. A smaller number of models have also included land use intensity variables, such as density of stock units in the catchment (e.g., Whitehead et al. 2022b). Widely used landscape variables include rainfall, catchment area, elevation, slope, and distance to sea.

Empirical models can be applied to make predictions across a river network provided that the predictors are available for the relevant reaches. This approach has been used commonly across the national digital stream network in New Zealand (Unwin et al. 2010).

Path analysis and structural equation modelling (SEM) is a group statistical tools that can be used to evaluate and elucidate networks of predictor-response relationships (Grace et al. 2010; Fan et al. 2016). The networks can reflect chains of interactions such as land use affecting water quality and then biota, and effects of multiple stressors on biota (see Section 2). The methods can incorporate indirect relationships, in which the effects of predictor variables are mediated by intermediary variables, which in turn have direct effects on system response variables. The form of relationships between variables is described by a path diagram (a network, without feedback loops), and each direct relationship is represented with a linear model. SEM extends path analysis by including latent variables, which are derived from indicator variables using methods such as factor analysis, and can represent conceptual variables such as habitat quality that are not measured directly but can be understood by stakeholders (e.g., Riseng et al. 2011; Bizzi et al. 2013; Feist et al. 2017).

Examples of empirical relationships

A review by Larned et al. (2020) summarised New Zealand studies that related land use or land cover and land management practices to biotic responses. Of the 17 studies addressing biotic responses, seven compared biota in streams with contrasting catchment land use classes; such results can inform decisions regarding future land use in a general way, but do not quantify responses, and they are often limited to coarse land use classes. Ten studies examined biota across land use gradients. Some of the results were expressed in terms of direction or strength of correlation between land use and the biotic response, while others provided more information that can be used to evaluate land-use thresholds. For example, Quinn and Hickey (1990) found that macrofauna remained typical of forested conditions as the percent of pasture in the catchment increased, up to a threshold of 30% pasture cover, above which more tolerant taxa were prevalent. Other more recent studies relating land use and land cover to biotic responses include Whitehead et al. (2022b) and Graham et al. (2018b). Some spatial RF and BRT models of species distributions that include land use variables have provided information about the influence of land use on biota. For example, Crow et al. (2014) found from a RF model that the proportion of indigenous forest in the upstream catchment had a low importance for fish presence in New Zealand. Unwin and Larned (2013) found from RF analysis that land cover was a high-importance predictor for macroinvertebrate community indices. Clapcott et al. (2013) also found from RF that land use was an important predictor for macroinvertebrate species, and used partial dependence plots to show the variation of the indices with land cover.

The review by Larned et al. (2020) also summarised 18 New Zealand studies that related rural land use and land cover to water quality, primarily nutrients. Some of the results simply contrasted water quality between land use classes, while others evaluated water quality variation over gradients of land use. Percent native forest cover, percent agricultural cover, and percent impervious cover were frequently identified as top contributors to variation in nutrient concentrations and sediment. RF models have been used to assess national-scale variation in water quality (e.g., Whitehead et al. 2022a). The primary purpose of such models was to predict current water quality, rather than to attribute water quality to landscape or land use factors, but partial dependence plots gave some indication of the influence of land-use factors. Stoffels et al. (2021) related land use to turbidity for different classes of stream using classification analysis and linear regression. Empirical modelling has been used to relate stream flow regimes to land use and landscape variables (Booker et al. 2015).

Various empirical methods have been used in New Zealand to relate stressors to biota, as summarised in Table 2. Several of these have been used to determine contaminant limits for regulation New Zealand Government (2023).

Table 2. Additional examples of empirical relationships between stressors and biota.

Study	Method	Application
Franklin et al. (2019)	Multiple methods. BRT for invertebrate metrics and breakpoints in response; Quantile regression and departure from reference index value; GLM with multiple classes of landscape variables; Extirpation analysis (Cormier et al. 2018) with species probability models. Departure of probability of finding fish	Derivation of visual clarity and deposited fine sediment limits based on fish and invertebrate responses to sediment.

	compared with reference probability, averaged across fish species.	
Snelder et al. (2022a)	Inversion of least-squares regression between periphyton biomass and nutrients, varied by river class and shading	Derivation of nutrient concentrations required to meet periphyton biomass targets.
Haddadchi et al. (2020)	Bivariate relationships between periphyton and hydraulic conditions	Prediction of periphyton abundance based on hydraulic conditions.
Snelder et al. (2013)	Inversion of regression relationships between periphyton (considered as a stressor) and macroinvertebrate community indices.	Establishment of periphyton biomass thresholds and grading bands corresponding to specified macroinvertebrate community states.
Canning (2020)	Regressions between nutrients and periphyton, macroinvertebrate indices, fish indices, and respiration and cotton degradation process rates. Inversion of relationships for given levels of biotic response.	Recommendation of nutrient criteria to provide for specific states of periphyton, macroinvertebrates, fish and ecosystem processes.
Matheson et al. (2012)	Quantile regression between shade and macrophyte abundance, and nutrients and macrophyte abundance.	Prediction of shade and nutrient levels that would lead to undesirably high levels of macrophytes

Path analysis and SEM have been used to develop combined land-use/stressor/biota relationships. Clapcott and Goodwin (2014) used SEM to relate MCI scores (a macroinvertebrate community index used in New Zealand, Stark and Maxted 2007) to land use using a national dataset for New Zealand. The analysis identified that the degree of pasture use was strongly related to nitrate concentrations, but there were weaker pathways through to MCI; stream habitat variables (such as substrate composition and flow variables) were more strongly related to MCI. A simplified model found different influence strengths, suggesting that the inferences regarding influences of factors depends on the construction of the SEM. They concluded that MCI is related to land use through a complex chain of causality, which make identifying the role of specific variables difficult. Internationally, path analysis and SEM studies of the effects of land use on freshwater biota have shown that the proportions of catchment area in agricultural and urban land use generally have indirect, negative effects on metrics of biotic health, and proportions of riparian cover generally have indirect, positive effects (e.g., Fernandes et al. 2019). The effects of land use are mediated by a range of intermediary variables, including water quality and channel conditions (e.g., sediment stability and grain size) and additional exogenous variables such as soil type and geomorphic context.

Empirical relationships between stressors and biotic impact have in some cases been developed through experiments under controlled laboratory conditions, rather than from statistical relationships. Examples are nitrate toxicity (Hickey 2013) and water temperature (e.g., Cox and

Rutherford 2000) thresholds determined from experiments. These attempt to establish causal mechanistic empirical relationships, rather than statistical associations.

Agricultural land use can affect flow rates in streams, especially as a result of abstraction for irrigation. As part of the Instream Flow Incremental Method (IFIM, Milhous and Waddle 2012), empirical relationships between flow metrics such as depth of flow and fish prevalence are used in conjunction with observations or predictions of the flow metrics to predict the available lotic habitat at a given flow. Flows can also be related to dissolved oxygen empirically to predict minimum flow requirements required to avoid levels of dissolved oxygen that would be harmful to aquatic life (e.g., Wilding et al. 2012; Graham et al. 2018a). Dissolved oxygen is not actually a biotic response, but is mentioned here because it is closely related to a biotic response and the relationship between flow and oxygen (two stressors) does not fit in neatly elsewhere.

3.3. Mechanistic models

Mechanistic models relate model inputs (such as land use and climate) to outputs (such as periphyton abundance) through systems of mathematical equations that represent causal process-based relationships between environmental components (e.g. a species of chemical or a class of invertebrate), often based on mass balance and transport relationships for water, energy, chemicals, biomass and populations. A wide array of models is available, differing spatial discretisation, time-step, number and type of environmental compartments, and the number and complexity of processes and equations. Mechanistic models can be used to relate land use to physico-chemical state, physico-chemical state to biota, or a combination of these. In this section, examples are interwoven with presentation of the types of models.

Mechanistic models relating land-use to physicochemical state

Predictive models of physico-chemical state are usually developed at the spatial extent of the stream system, so that the effects of land use throughout the catchment can be assessed. That is, catchment models are applied. Exceptions include modelling the effect of riparian shade on stream temperature at reach scales (Rutherford et al. 2004).

Stream flow and hydraulics

Many mechanistic hydrological models and software packages are available to predict stream flow at catchment scales (see overviews in Singh and Woolhiser 2002). These models generally apply a time series of rainfall and other climate variables to land elements (grid cells, land-soil units, or subcatchments), and represent water mass balance processes through various flow storages (e.g., soil, shallow groundwater) and pathways (e.g., near-surface runoff, drain flow, or groundwater) to the stream, with subsequent flow accumulation and passage through the stream system. While early hydrological models tended to focus on surface water and flood flows, there is increased emphasis of coupled surface-groundwater models (Ntona et al. 2022) and modelling of low flows.

There is also a range of well-established mechanistic hydraulic models that can be used to represent flow passage down the stream network, and to predict variables such as flow depth, velocity, and bed shear stress with a range of resolution. Examples of these models are HEC-RAS (Hydraulic Engineering Center River Analysis System, US Army Corps of Engineers 2016) and TELEMAC (opentelemac.org 2022).

Land-use effects on stream flows are represented in hydrological models through the influence of land cover on evapotranspiration and aspects of hydrology associated with land use such as water abstraction for irrigation and stock watering. Land management is reflected through modifications to irrigation, pond and reservoir storage, and water abstraction restrictions.

There has been little application of mechanistic hydrologic models in New Zealand in the context of evaluating land use impacts biota. This is partly because mechanistic models (such as a national hydrological model TopNet , Clark et al. 2008) have typically been targeted primarily at predicting high flows rather than baseflow or low flow that could be more relevant to hydraulic habitat, and partly because historically there has been little irrigation development. Internationally, hydrological models such as SWAT have been coupled to habitat suitability models (e.g., Kim et al. 2023)

Water quality

A range of models is available for assessing land use effects on stream water quality at catchment scale (Yuan et al. 2020; Bai et al. 2022). Such models generally build on hydrology models by adding processes related to chemical storage and movement in vegetation, soil, subsurface groundwater and streams.

The simplest models use steady-state nutrient budgets to calculate contaminant flux (e.g., Greene et al. 2015; Elliott et al. 2016; Elliott et al. 2020). In this class of model, the contaminant source per unit area (the source coefficient) can vary by land use and characteristics such as soil and rainfall. The source coefficients can be derived from other point-scale mechanistic models, summaries of experimental data, or calibration to measured loads, so budget models are best considered as a mixture of mechanistic (mass conservation) and empirical modelling. Reduction in loading due to land management can be represented with empirical load adjustment factors. A limitation of such models is that they generally predict contaminant loads rather than concentrations, and additional steps may be needed to relate loads to concentrations (Oehler and Elliott 2011).

Dynamic catchment models simulate the temporal progression of environmental storage compartments and mass exchanges, and can include components for chemical transformations within the drainage network, temperature (Dugdale et al. 2017) and indirect effects on water quality such as dissolved oxygen and algal growth (Yuan et al. 2020). Examples in New Zealand include application of SWAT (Hoang 2019; Ayele et al. 2023), MODFLOW-MT3D (Hemmings et al. 2022), eWater Source (Blyth and Clay 2018). Dynamic models have the potential to represent not only land use, but land management practices such as fertiliser application and mitigation measures such as constructed wetlands. Some dynamic models can also account for the effect of riparian vegetation on stream temperature and dissolved oxygen.

Several river simulation models are available to dynamically simulate dissolved oxygen, temperature, and suspended algae in river networks, in response to catchment inputs of nutrients. Examples are QUAL2E (Pelletier et al. 2006) and its related unsteady model Qual2KW (Pelletier and Chapra 2005), D-Water Quality (DeltaRes Systems 2017) and the stream component of HSPF (Hydrologic Simulation Program in Fortran) (Bicknell et al. 2001). Algae can be considered as a water quality variable or a biotic response variable.

Mechanistic models relating stream physicochemical state to biota

Flow and hydraulic impacts on biota

One commonly-used partially-mechanistic approach is to establish hydraulic habitat suitability for a species as a function of flow rate, using mechanistic models of the spatial and temporal distribution of velocity and depth in conjunction with empirical habitat preference curves for the species of interest, combined with (RHYHABSIM and PHABSIM, Jowett 1989; Milhous and Waddle 2012). Such models have received criticism for failing to account for fine-scaled hydraulic variability or variation in flow timing, flow regime or organism populations, (Railsback 2016). Such criticism is commonly acknowledged, but the approach persists because it is quantitative, relatively easily applied and has stood up to scrutiny in legal proceedings.

Individual Based Models (Breckling 2002) simulate the responses of individual organisms (or sub-populations) to stream conditions and were used to relate flow conditions to population dynamics of flow-sensitive invertebrates in South Australia (Sultana et al. 2020). Such models can be complex and it can be difficult to represent animal movement and behaviour at the individual level mechanistically. Suitable data are lacking for most lotic species. Bioenergetics habitat suitability models (Hayes et al. 2019) relate flow conditions and food concentrations to the energy demands of fish.

Fully mechanistic models have been used to relate stream flow rates to dissolved oxygen using stream biogeochemical simulation models (Kumar et al. 2022).

Water quality (including combined quality-quantity) impacts on biota

Some mechanistic models are available to relate water quality to impacts on biota, either with or without consideration of river flow or feedbacks between biota and water quality, as described below.

Some mechanistic models are available to predict algae attached to the bed (loosely referred to 'periphyton') in stream reaches or networks (Chapra et al. 2014) including applications to the Tukituki River in New Zealand (Rutherford 2011). Some river models such as HSPF, QUAL2E and D-Water Quality also include periphyton components, although not with the same process representation as Rutherford's Tukituki River model (e.g., they do not account for periphyton sloughing in relation to increased flow). The Tukituki River application showed that despite effort in setting up and applying a detailed periphyton model, there was large uncertainty, which made it difficult to use the model for nutrient limit-setting.

There are no well-established mechanistic models to predict macrophyte abundance and growth in stream networks in response to physico-chemical conditions. A macrophyte component for Delwaq has been developed, but it was experimental and has not been published.

Rutherford et al. (2000) developed a stream model for diatoms that grow on rocks. The model included invertebrate grazers (mayflies) and responses to flow and temperature fluctuations (the latter influenced by stream shade), with an application to a hill-country stream reach in the Waikato Region. The model involved simplifications of the biota into representative lumped 'functional groups', yet demonstrated complex temporal system dynamics.

IBM can potentially represent water quality impacts and multiple life-stages. For example, Dudley (2019) included turbidity and other physico-chemical factors in IBM for salmon. There are some mechanistic models for relating stream temperature to freshwater biota. For example, Railsback et al. (2021) and (Ayllón et al. 2019) developed models for fish population response to temperature and flow.

Mechanistic coupled land-use/physico-chemical state/biota

Some integrated mechanistic models are available to couple physico-chemical processes and limited biotic components. Typically, a catchment model is used to predict flow and chemical inputs to rivers, models of the lotic system are then used to determine flow rates and concentrations and subsequent impacts on biota. For example, HSPF includes a catchment model and river models. The lotic component may include feedbacks from the biota to physio-chemical state (full coupling) or only the response of biota to physico-chemical state (chained models). Mechanistic coupled models are generally limited in the number of biotic components - very few models include macrophytes, zooplankton, invertebrates, or fish.

3.4. Bayesian networks

Description of the method

A Bayesian Network (BN, or Bayesian Belief Network) is a probabilistic method to relate a set of system inputs (e.g., climate and land-use) to system outputs (e.g. fish abundance) using a network of nodes and linkages. The relationship between inputs to a node and the outputs from a node are represented in terms of conditional probabilities, most commonly as 'contingency tables' relating discrete states of the inputs (which can be quantitative or qualitative variables) to discrete output states. The contingency tables can be obtained from a variety of methods including expert elicitation and training of the tables to observations. The probabilities of system outputs are then related to the probabilities of system inputs by propagating probabilities through the network using calculations based on Bayes' Theorem.

A range of software is available for developing and applying BNs, including integrated packages, GIS (geographic information system) add-ins, packages in general software such as R and Python, and API's (application programming interfaces) (Pérez-Miñana 2016). Popular software such as Netica (Norsys Software) and HUGIN (HUGIN EXPERT A/S) include user interfaces to enable drawing of the network and visualisation of results. They typically include methods to learn or update the conditional probabilities given observations, and can include aspects related to decision-making such as decision nodes and utility or value nodes. The networks can be used to predict the outputs in response to changes in inputs or to identifying the probability of inputs to achieve a specific output.

BNs have been used in a range of environmental modelling applications (Aguilera et al. 2011) including environmental and ecological risk analyses (McDonald et al. 2015; Kaikkonen et al. 2021), ecosystem services analyses (Pérez-Miñana 2016) water allocation (Hart and Pollino 2009) and broader water resources management (Phan et al. 2019). Good-practice guidelines have been developed for using BNs (McDonald et al. 2015).

BNs are often aspatial, static temporally, and do not allow for cycles/feedbacks in the system, but these limitations are being overcome with more recent developments. Spatial BNs, whereby a BN is applied to each grid cell or polygon in a map, are becoming more common and are available in packages such as a QGIS plug-in for HUGIN, gBay (Anon 2023) and as an R package (bnspatial). While these spatial methods have been used for land and marine spatial planning and risk assessment (e.g., Guo et al. 2020), they have not been used to assess the effects of land-use on lotic biota, perhaps because the methods are not designed for dendritic spatial structures associated with catchments and drainage networks; spatial interactions are then not addressed or are introduced through coarse splitting of the catchment or river (e.g., upland versus lowland areas). Dynamic BNs have also become available (e.g., gbay, Anon 2023), although they are still novel. Dynamic BNs are also seen as a way to introduce feedbacks in the system, although such applications are uncommon.

Example applications

Several applications of BNs from New Zealand and internationally illustrate how BNs can be used to link catchment conditions to lotic impacts.

Quinn et al. (2013) developed a BN to relate land use, irrigation, and land management practices to stream habitat and water quality variables and then to biotic, water quality, and economic values for the Hurunui River in New Zealand. Some of the contingency tables were based on a numerical scoring approach, while others were based on simplified nutrient leaching and economics models. The BN was used to predict the consequences of several scenarios and these scenario predictions were used to develop a management plan for activities in the catchment.

BNs were used to relate catchment and reach attributes and water chemistry to an index of sensitive invertebrate species in New Zealand (Death et al. 2015). A feature of this application was the use of model training for parameterising the conditional probability tables, and model testing against a separate dataset. The approach gave management-relevant predictions, for example that improving river habitat would be as effective as reducing nutrients for improving the health of invertebrate species.

Other examples in New Zealand include BNs used to predict the effects of land and water management activities on various ecological aspects of gravel bed rivers (Storey 2015), predictions of nuisance periphyton and macrophyte biomass from physico-chemical variables such as flow, shade and nutrients (Matheson et al. 2012).

BNs have been used in many land-use/biota studies internationally. For example, Allan et al. (2012) demonstrated how BNs can be used to investigate relationships between land use and stream condition, and between sedimentation and benthic invertebrates. Scenarios of land and riparian management were applied as inputs to the BN, the outputs of which were used to guide land use and riparian management choices.

3.5. Expert elicitation

Description of the method

Expert elicitation uses experts to provide information based on their knowledge and judgement without modelling, typically when there is a scarcity of empirical data and high uncertainty (typical in ecology), and when urgent answers are needed to complex questions to inform policy and management decisions (Krueger et al. 2012; Martin et al. 2012). The information could be identification of the outcomes from land management scenarios, responses to stressors, evaluation of uncertainties, identification of causal linkages, evaluation of model parameter values, or preferred management actions. The knowledge and judgements are usually based on a sound conceptual understanding of the processes operating within an environmental system.

Expert elicitation processes can be either informal or structured. In informal approaches, a loosely-defined and unstructured approach is taken – for example, assembling a group and obtaining opinions based on discussion – whereas structured approaches follow a stricter process. While informal processes prevail (Krueger et al. 2012), the use of structured approaches has grown as a means of managing the biases of experts and the lack of transparency and reproducibility that jeopardises the credibility and legitimacy of the outcomes of informal approaches.

A range of structured expert elicitation techniques is available and they have been reviewed elsewhere (e.g., Colson and Cooke 2018). Common features of these structured protocols include the use of repeatable and transparent methods for each step of the elicitation process, identification and recruitment of experts, the framing of questions, the elicitation of expert knowledge or judgements including uncertainty, and the aggregation of responses from individual experts (Gosling 2018).

Example applications of expert elicitation to land-use/biota assessment

Semi-structured expert elicitation has recently been used by the Bay of Plenty Regional Council in New Zealand to support regional implementation of the NPS-FM and development of planning documents. Expert panels evaluated the impact of land and water management scenarios on freshwater attributes including water quantity, water quality and biotic response (Zygadlo et al. 2023). Individuals assessed the degree and associated confidence of the likely relative change in selected attributes, expressed as descriptive classes (e.g., moderate effect, high confidence), which was followed by a consensus process. The process helped to identify which biotic response variables were most sensitive to different land management actions.

Structured expert elicitation has rarely been deployed in the context of New Zealand freshwater management to date, but has been widely adopted in Australia and elsewhere. For example structured expert elicitation was used by Pollino et al. (2007) to help parameterise a BN for stressors on native fish, and by Mantyka-Pringle et al. (2014) to parameterise a BN of land use and climate change on freshwater macroinvertebrates and fish.

3.6. Other methods

In this section we survey some methods that have little or limited track-record in the land-use/biota assessment, yet could be useful methods if they were applied.

Likelihood-consequence risk assessment

Ecological risk assessment encompasses a range of methods to evaluate the risks of ecological harm resulting from pressures or stressors. Risk assessment tools for marine ecosystems in New Zealand have been surveyed recently and evaluated against suitability criteria (Clark et al. 2022). The authors noted limitations of the methods, such as accounting for multiple stressors and feedbacks and incorporating cultural values.

One of the simplest risk assessment methods is likelihood-consequence (LC) assessment, which is used widely for risk assessment (Clark et al. 2022). LC assessments are based on the likelihood of an event occurring and the consequences if the event occurs. The results may be displayed as a LC table, with high risks associated with combinations of high likelihood and high consequence. An example is assessment of risks to high-value areas from introduced marine species. There are many applications of LC in the area of natural hazards, environmental toxicology, and contaminant spill analysis. LC methods could be applied to assess land-use/biota impacts, but there are few documented examples of such applications.

Evaluation matrix and scoring methods

Multi-criteria evaluation matrices and scoring systems are often used to evaluate environmental management options against sets of criteria, but we could not find examples of scoring systems dedicated to linking land use to lotic biota. McDowell et al. (2018) presented a scoring method (at a conceptual level) to evaluate land management actions for reducing contaminant loads in relation to water quality, without addressing biotic impacts. Some of the conditional probability tables in the BN network of Quinn et al. (2013) were underpinned by a scoring system. Ecosystem services methodologies employ scoring methods and scores can be mapped spatially (Burkhard et al. 2014), but existing applications do not highlight links between land use and freshwater biota. Despite the lack of existing applications to land-use/biota assessment, we have presented the concept because we envisage that if such methods were developed, they would be useful for screening-level assessments, as discussed in Section 4.3.

Expert systems

An expert system is a method for encoding knowledge about causal relations in a system with the aim of emulating human thinking and decisions. Early expert systems were based on formal logic rules and inferences (Liao 2005). They could hold some appeal for capturing information and decision rules on land-use/biota relationships, but are limited because they rely on knowledge engineers to elicit information from experts and to formulate logic rules. More modern expert systems are used in the artificial intelligence field, include fuzzy logic and neural expert systems. There are many applications of artificial neural networks in freshwater ecology (Goethals et al. 2007; Quetglas et al. 2011), but little use of neural expert systems in land-use/biota assessment.

Causal diagrams

Causal diagrams (sometimes referred to as cognitive maps) capture an individual or group's understanding of a problem and the way a system operates, potentially including the influence of human actors in the system. A causal diagram typically takes the form of networks with connecting arcs denoting causality or influences. The diagram may contain cycles, the analysis of which yields insights of leverage points to influence outcomes. Much of the knowledge captured in a causal diagram may be tacit, subjective and qualitative, and different individuals or groups may have different cognitive maps for the same system. Menshutkin et al. (2014) suggest these models are used when our knowledge is insufficient for formal quantitative modelling, or when working across disciplines with different knowledge bases. Such diagrams may form a first step in making formal quantitative model, such as a system dynamics simulation model. Fuzzy cognitive maps are a form of causal diagram with a continuous-variable rather than binary representation of linkages (Mourhir 2021). Causal diagrams have been applied to capturing complex social and ecological interactions and as a tool for stakeholder participation in complex settings. One example is assessing lake management alternatives (Hobbs et al. 2002). Despite the attraction of being able to capture complex causal interactions and to serve as the basis for bringing knowledge systems together, there have been few applications to the area of land-use/biota impact modelling. They may serve as a useful tool for initial stakeholder engagement prior to invoking other methods.

3.7. Combination of methods into compound and hybrid methods

Compound or hybrid models combine different model types or methods to arrive at an overall assessment of the impact of land use on biota. Each model or method addresses part of the overall assessment. For example, a mechanistic model could be used to predict flow and water quality, while empirical stressor-impact models could be used to predict biotic responses.

A sophisticated example is in the compound environmental flow analysis of Sultana et al. (2020) to find invertebrate species that were most sensitive to flow in a monitored catchment. A dynamic mechanistic hydrologic model was used to relate land use and climate change scenarios to flow. An empirical gradient forest model (Ellis et al. 2012) was then used to indicate how influential different predictors were across the range of taxa. Mechanistic population dynamics simulation models were used to relate flow to the population of each of the most sensitive species, with calibration to detailed invertebrate sampling, which was then combined with the results of the hydrologic model to predict population response to land use and climate change.

Bayesian Networks can also integrate results from different model types. Bruen et al. (2022) provided a hybrid framework whereby biophysical models were used to evaluate physico-chemical conditions, which were in turn used as input to a BN to establish ecosystem responses. In the

Ruamahanga River BN in New Zealand (Storey 2015), outputs of nutrient loss models were combined with expert knowledge to assess impacts of land use scenarios.

4. Synthesis and guidance

4.1. Commentary on strengths and weaknesses of methods

Empirical relationships

While empirical methods are attractive in the sense that they could potentially provide simple land-use/biota relationships based on observations, they have several flaws which erode confidence in their application. The complex nature of land-freshwater systems makes it difficult to reliably attribute biotic impacts to specific stressors associated with land use (Allan 2004; Birk et al. 2020) or to distinguish the effects of land use from other drivers such as invasive species or climate change (Dupas et al. 2016; Snelder et al. 2021). Empirical relationships are often limited to bivariate relationships that do not take multiple stressors or their interactions into account. (Larned et al. 2020). Collinearity is particularly problematic in land use impact studies, where predictor variables may be functionally related (e.g., fertiliser input is positively related to livestock density), land-cover class proportions are inter-correlated, and land use is correlated with landscape variables (e.g., native forest land use and elevation) and other anthropogenic drivers (King et al. 2005; Clapcott et al. 2012; Stoffels et al. 2022).

By providing relationships that are specific to different classes of landscape variables (using stratified or hierarchical approaches, for example), the influence of landscape variables can be accounted for to some degree. At least, when applying empirical relationships, there should be a check that the landscape conditions that were used for developing the relationships are comparable to the conditions for which the relationships will be applied.

More complex regression methods such as RF offer the prospect of accounting for non-linear relationships and multiple stressors. In reality, methods such as partial dependence to extract the influence of a particular predictor are still limited due to predictor correlation, which limits their ability to predict responses to future land use land management changes.

Path analysis and SEM are helpful in identifying relationships between land-use pressures on biotic responses through intermediate state variables in a causal chain consistent with pressure-state-impact concepts and general understanding of effects of land use. The path diagram and path coefficients of SEM make the model amenable to interpretation and visualisation. Even though the direct relationships and network structure are intended to reflect causality and mechanistic linkages, path analysis and SEM models are still correlative rather than causal. While SEM models are useful in terms of identifying broad patterns and relationships, they will have limitations in relation to land-use/biota impact assessment because: there are typically only broad land use and land management categories in the models; models developed for one area are unlikely to be transferable to other areas; they do not include spatial interactions or a temporal component; they are generally limited to linear interactions between nodes; exogenous predictor variables use in the model may not be available in general (for example, riparian state); and conclusions regarding land use effect may depend on the chosen network structure.

Mechanistic models

Mechanistic models are often used to predict physico-chemical parameters in response to land use change and land management measures. Dynamic models can involve considerable investment in time and resources for a single catchment, and the resulting model may be difficult for users such as planners to understand and manipulate. Simplified budget models are quicker to set up and run, but have limited capability for predicting concentrations and temporal metrics, and they require simplification of source types and mitigation efficacy, and typically are partly empirical.

Mechanistic models are less useful for predicting biotic impacts compared with predicting physico-chemical variables, due to difficulties in formulating and parameterising complex biological responses and biotic interactions using mechanistic equations. Mechanistic models that account for individual biotic components and multiple environmental compartments are rarely used, except for modelling mainstem rivers. There are no practical mechanistic models for predicting the growth of macrophytes and their interaction with nutrients and dissolved oxygen, or models that predict response of fish and macroinvertebrates to changes in macrophytes. While mechanistic models are available for predicting periphyton abundance, the methods are not yet sufficiently well-developed or robust to enable confident predictions of periphyton responses to land use or physico-chemical variables. There may still be a role for developing mechanistic biotic impact models in selected cases where there are sufficient data and modelling expertise (e.g., Sultana et al. 2020).

The effects of land use on river flows can be linked tentatively to impacts on freshwater biota using mechanistic models in conjunction with empirical habitat preference information. Elaborate models such as individual-based models can account for a broader range of flow (and chemical) conditions and their effects on the movement and density of biota, but they are specialist models and difficult to parameterise.

Bayesian Networks

The examples of BN provided in Section 3.3 illustrate the flexibility of BNs. Contingency tables can be determined from a variety of methods such as expert elicitation, model results, or empirical data, or combinations of these. Networks can be constructed in a way that aligns with concepts of pressure, state and impact, and also ecological concepts of effects of disturbances propagating through chains of interacting ecosystem components.

BN networks generally don't address other ecological concepts such as feedback loops, spatial interactions along the drainage networks and between the channel and floodplains, and temporal dynamics. Categorical variables are often used in BNs, leading to fairly low responsiveness to changes in land use or management (e.g., small shifts in the distribution of probabilities across broad classes of value).

Complex BNs are generally unwieldy to set up and communicate. If there are fine divisions of variables (as a means to represent continuous variables) then the computations can be slow. Similarly, dynamic BNs need to be kept simple for computational tractability. As the network becomes larger and more influences are included, the response of utility nodes to interventions can become very muted, reflected in small differences in probability distribution, which makes decision-making difficult.

Stakeholders can be involved with designing and setting up the network for a BN, which has proven to be useful for building engagement and ownership of the ensuing model, because stakeholders can help identify components, envisage interactions, and appreciate the complexity of land-freshwater systems. However, simplification of BN networks, variable categorisation, and contingency table construction are often undertaken separately from stakeholders, and it can be difficult for stakeholders to understand how contingency tables are developed, with the potential to lose trust and engagement.

Clark et al. (2022) concluded that relatively simple methods such as BN are likely to be most appropriate for use in marine ecosystem-based assessment in New Zealand, and many aspects of their assessment would be relevant to freshwater systems. In an earlier review Clark et al. (2021) recommended a hierarchical approach in which BN are used for initial levels of assessment, and more complex methods such as mechanistic models are used at higher levels.

Expert elicitation

Expert elicitation is often viewed as a low-cost, low-effort approach to characterising environmental stressor-response relationships. At the simplest level (i.e., informally running a query past an expert) this may be true, but deploying expert elicitation in a robust, transparent, and reproducible way that is suitable for underpinning evidence-based decision-making requires considerable time and effort. However, expert elicitation methods make use of the best available information for addressing complex questions where empirical data are limited or unavailable. Expert elicitation can also be used as an input to other methods.

Utilising expert elicitation to help parameterize land-use/biota response models for New Zealand freshwater species likely offers a practical and realistic avenue for making use of best available information. However, deployment of these methods is most effective when they are well targeted (to limit scope) and follow formal protocols for expert elicitation.

Other methods

Limitations of the likelihood-consequence risk assessment method include difficulties in evaluating interacting stressors and cumulative impacts, doing spatial assessments, representing causal chains from pressure to state to impact, and including formal uncertainty analysis. Freshwater Farm Plans under environmental planning regulations in New Zealand (Ministry for the Environment 2023) call for risk assessments of farm activities in relation to freshwater ecology, but do not promote particular methods such as likelihood-consequence risk assessment.

Evaluation matrices and scoring methods typically rely on expert opinion to evaluate the outcomes associated with each option and criterion. We did not find existing scoring methods to relate land use to biotic impacts. It would be desirable to develop a scoring method that has standard categories and guidance for making an assessment. One difficulty with scoring methods is incorporating interacting effects, because individual effects are usually aggregated by summing sub-scores relating to individual effects. This could be overcome by different aggregation methods (for example, minima of scores). While scores can be evaluated for each spatial unit to arrive at a spatial distribution of scores, such methods do not account for spatial interactions.

Compound and hybrid methods can make the best of the strengths of multiple methods. For example, using a mechanistic model to evaluate physico-chemical state, then empirical models to evaluate the subsequent biotic impacts, or using mechanistic models to evaluate contingency tables in BNs.

Traditional rules-based expert systems rely on elicitation of appropriate rules from experts, and translation of these rules into logic rules or grades. There has been little application of more modern expert systems such as deep learning in the context of land-use/biota assessment. A limitation of neural expert systems would be obtaining sufficient observational data to train the neural networks.

Causal diagrams and causal loop analysis could provide a basis for initial communication and identifying the structure of a system, including in a participatory context, and as a first step for constructing other models such as BNs. However, translating a causal diagram into useful quantitative information to make land use decisions would be difficult, and we could not find examples of such applications in the literature.

4.2. Evaluation of assessment methods against criteria

The various methods for predicting land-use/biota impacts are evaluated against a set of selected criteria in Table 3. General criteria for assessing environmental models have been proposed (e.g., Hamilton et al. 2022), but they are not specific to biotic effects or land use assessment. Hence we developed a set of criteria, reflecting attributes that we considered relevant to the selection of methods for land-use/biota assessments. Expert elicitation is not included as a separate method in the table because it is generally used as a part of other methods (e.g., scoring methods or BN). This evaluation is not intended to identify a single 'best' method, but to highlight strength and weakness of different methods. Also, the gradings are indicative rather than definitive. For example, BNs are given a moderate to unsuitable rating in relation to being spatially distributed, because spatial variations and interactions are not generally included in BNs, but acknowledging that spatial BNs are emerging.

No single method met all of the evaluation criteria in Table 3. However, some methods met more criteria than others. For example, BNs met many of the criteria to some degree, although they have limitations in terms of spatial representation and capturing spatial connectivity and feedbacks. Mechanistic models can be used at multiple levels and, but they are generally difficult to set up and use and are not generally well suited for predicting biotic impacts. Empirical models are relatively simple, but are not suitable for causal analysis or for representing species interactions.

There are some commonalities across methods. Most of the methods can in principle link land use to separate physico-chemical stressors, and individual stressors to biotic community indices or individual lotic species. Most of the methods do not account for interactions between physico-chemical stressors (for example, sorption and release of phosphorus from sediment under anoxic conditions or chemical interactions). Most of the methods can be applied at a range of scales as spatially-lumped methods, but do not represent spatially-distributed processes. Few assessment methods represent legacy effects, feedback loops, mitigation measures and rehabilitation, stream connectivity and climate change.

Table 3. Evaluation of selected methods against criteria. Green indicates the method meets the criteria well, red poorly, and orange to moderate degree or with some variants of the method.

Class of criterion	Criterion	Empirical relationships: Correlation and regression[c]	Empirical relationships: Random Forest	Mechanistic	Bayesian Network	Likelihood-consequence, risk assessment	Evaluation matrix and scoring
Link land use to physico-chemical stressors	Individual or separate multiple	i					
	Interacting physico-chemical variables		d	k			
Link stressor to biotic impact	Community Index	i					
	Individual species	i					
	Interacting stressor	e	d				
	Interacting species						
Link land use to biota in one model		i					
Scale	Local						
	Parcel						
	Lumped catchment						
	Spatially distributed						m
Usability	Easy to develop						
	Easy to parameterise	f	f				
	Easy to use once set up						
	Low data requirement	g	g				
	Low expertise to develop						
	Well-estabilished			a		b	b
	Flexible			l			
	Transparent						
	Explicit uncertainty					j	
	Suited to community participation						
Other	Causal						
	Discriminate land use from landscape	h				N/A	N/A
	Can represent legacy effects						
	Can represent feedbacks						
	Can reprsent mitigations						
	Can reprsent connectivity						
	Can represent climate change						

Notes

[a] Less for biota
[b] Well known for risk assessment but not well established for landuse-biota assessments
[c] Including Extirpation analysis
[d] Limited
[e] Could have interaction terms, but not usually done
[f] Requires data for parameterisation
[g] Need data to set up, but application has low data need
[h] Can have stratified based on landscape variables
[i] Difficulty with separating covarying predictors
[j] Represents probabilty, but usually not confidence
[k] Only for some models
[l] Difficult to change model assumptions and structure
[m] Could be applied on a spatial basis

4.3. Proposed approaches for selecting predictive methods

Is it clear from the evaluation matrix in the previous section that the choice of predictive method (or combination of methods) will depend on a range of factors such as the choice of output variables and available resources.

A tiered assessment approach is one strategy for managing the problem of high resource requirements associated with complex or intricate models, as shown in Figure 5. Tiered approaches are used in aquatic contaminant risk assessment (e.g., Wang et al. 2009), but have not been used in the land-use/biota impact assessment, to our knowledge. For each of the four tiers, appropriate types of models are suggested in the figure.

In this approach, a screening level assessment using relatively simple methods is applied first. This may include evaluating the context (for example, mapping local and downstream biotic resources), mapping local or downstream locations that do not meet concentration or flow thresholds (evaluated either through modelling or measurement), and application of simple scoring, risk evaluation, or BN methods. The screening assessment could be used assess the relative desirability of different land use or land management options. As an example, a simple scoring method could rate factors such as the scale of the change being considered, whether there are local rare or sensitive habitats or species, the order of magnitude of contaminant losses or hydrological changes, and the current physico-chemical state of the receiving environment in relation to threshold values. Each of these factors would be assigned a score, and a sum (potentially accounting for stressor interactions) developed. This would give an indication of what are the type and magnitude of individual and overall risks associated with current and future land use and land management. If this screening shows that a land use or land management option has acceptable impacts, taking into account uncertainty, then there is no need to proceed to Tier 2. On the other hand, if there are significant risks of impact, then more detailed analysis would be conducted at higher tiers.

There is a surprising paucity of tools such as standardised BNs or scoring tools for assessing land use effects on biota at the screening level of the tiered assessment system. Currently, BNs or scoring methods would have to be developed for each individual land-use assessment, with considerable effort, considering that the aim is to carry out a rapid assessment with minimal resource requirements. There is clearly a need for such tools. They could include standard scoring sheets for evaluating likelihood-consequence assessments, and default BNs with pre-populated contingency tables.

Some maps are available in New Zealand to use at the screening level of the tiered assessment system. For example, maps are available to identify catchments that have downstream segments exceeding contaminant concentration or cumulative water abstraction thresholds (Booker and Henderson 2019; Elliott et al. 2020; Snelder et al. 2020). Mapping could be extended to include maps of catchments with sensitive or high-value freshwater biota to inform risk assessments, and maps of cumulative land use. Maps of land use vulnerability to contaminant losses (e.g., steep erodible land) could inform risk assessments.

At Tier 2, more detailed analyses are conducted for stressors, land uses, biotic impacts or locations that have been identified using the screening methods, or for areas where there is uncertainty. Further tiers of increasingly sophisticated models could then be used if necessary. For example, dynamic eutrophication models would only be undertaken if the need is identified from screening and simpler mechanistic models. In some cases, the risks may be known sufficiently and resources available to enter the process at a higher tier, without the need for analyses at lower tiers.

Tiered approaches have been promoted in relation to land use impacts on coastal environments. Brown et al. (2019) noted that there is a disconnect between simplified models needed by planners and detailed process-based models and difficulties in assessing biotic impacts. They proposed using expert input to devise plans initially, and then evaluate biotic and socio-economic outcomes at later stages using other modelling tools.

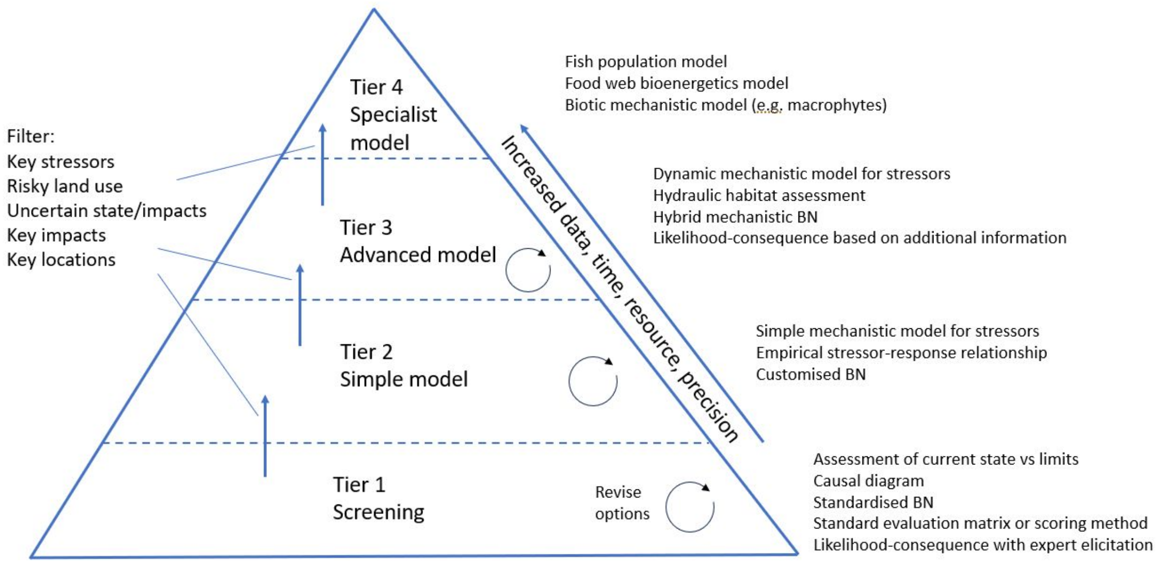

Figure 5. Tiered assessment approach. Vertical arrows indicate that a reduced set of factors is passed from lower tiers to upper tiers. The methods to the right indicated examples of methods that would be applicable at that level of assessment.

There are various factors that can be used to guide choices of assessment methods, which are discussed below. While the factors could be combined in a decision tree to lead to a set of methods most suited to a use case, that would be complicated, may provide an overly-narrow view of method suitability, and would not capture other approaches such as tiered or hybrid assessments, so we have not pursued that approach. The method evaluation matrix (Table 3) provides some information to assist with method selection. For example, the matrix indicates a small number of suitable methods if it is desired to represent interacting stressors.

Available resources (e.g., time, people, funding) for an assessment is an important factor in choosing a method for assessing land use effects. For example, it is unlikely that it would be appropriate to use a coupled mechanistic model for assessing the impact of a land use change on a single farm in a large catchment, whereas when considering land development associated with a large irrigation project, it could be appropriate to expend more resources to evaluate the impact, which means more elaborate methods could be used. The tiered approach proposed above can help match resources to the risks and vulnerabilities in a catchment, by proceeding to higher and more resource-intensive tiers only if there are risks of concern.

The intended use of an assessment of land-use/biota impacts will have a bearing on the choice of method. An assessment used to inform policy development may need less precision (detail and spatial resolution) than an assessment used to inform consenting of a large land-use change in a catchment. That is because policy development tends to deal with approximate assessment with coarse spatial resolution, whereas assessment for a large consent is likely to entail detailed consideration of impacts for a specific location. Accordingly, relatively simple methods could be used for regional policy development, whereas a tiered assessment methodology, potentially leading to detailed assessments, would be more appropriate for consenting a large land development or extensive intensification of land use. For assessment of land use choice or management options on a single property, relatively simple methods would be required because complex methods would be infeasible due to limited resources available for the assessment.

If the analysis is limited to physico-chemical stressors, then there are several modelling options. If biotic impacts are to be evaluated, then the biotic variables and models for relating stressors to biota will be needed, and there are fewer modelling options. Alternatively, at screening level, land use could be related directly to biota.

An associated choice is the selection of physico-chemical and biotic impact variables. This may be guided by preliminary screening analysis, but may also be guided by catchment values or regulatory requirements. For example, screening assessments may indicate that low flow and dissolved oxygen are key physico-chemical variables in some situations. The biotic variables are an important choice, because, as discussed earlier, some species or biotic indices are more sensitive than others to a land-use change or stressor, and it would be desirable to choose sensitive variables when evaluating land use options. A further choice is whether to include cumulative and interactive effects of stressors, and interactions of biotic components, in which case there are few methods available (see Section 4.2) and there would be large resource requirements.

The choice of method may also depend on the groups that will be the end users. If the end users are lay people in community participation, then it would be appropriate to use methods such a causal diagram to assist with communication, at least at initial stages. If more complex models are used, there should be effort put into visualisation and communication for lay users. Typically, planners tend to prefer simpler methods that can be understood and communicated fairly easily (Jones et al. 2020).

4.4. Limitations and gaps in assessment methods

Although there is a range of methods available for predicting land use impacts on aquatic biota, there are also gaps and limitations. As discussed earlier, methods are needed for rapid screening-level assessments. For example, templates for scoring the effects of land use options would be helpful. Different templates could be established for different landscape settings (for example, dry lowland catchments versus wet steep catchments).

There is a need to make modelling more efficient, at a range of levels of model complexity. This will enable assessments to be made more readily, in a more consistent fashion, by a wider range of users, at lower cost. Scoring templates and guidelines to enable rapid assessments without invoking expert elicitation for each application is one example. Providing default spatial setup, soil and climate data available for dynamic catchment models is another example, which would enable such models to be applied in a greater range of use cases.

Land management practices (including mitigation measures such as constructed wetlands) are important because they can ameliorate or exacerbate the effect of existing land use or future land use changes. It is the combination of land use and land management practices that results in changes in stressor levels, and hence biotic impacts, yet representing land management in models is more time-consuming and often lacks data, compared with land use.

Most of the methods do not incorporate stream restoration activities such as the removal of fish passage barriers, channel modifications, or removal of pest fish. Although such stream restoration was excluded from the scope of this paper, ultimately it would be desirable to include it in a broader consideration of methods for assessing freshwater biota protection, to identify opportunities to protect and enhance the health of biota, beyond what might be achieved through land-use or land management changes.

A difficult aspect of making choices about land use on a single property is that land use effects in a catchment can be spatially cumulative, local activities may influence the biota in distant but hydrologically connected freshwater systems, and local changes to land use may be constrained because physico-chemical or biotic state in downstream river locations might not meet desired levels. Cumulative effects can be accommodated in assessments of land use impacts on physico-chemical variables through contaminant source load limits and water abstraction limits for individual properties that are set in the context of overall catchment load and water limits, but it is more difficult to address cumulative impacts on biota from activities on a single property, because there is no biotic equivalent of cumulative load or abstraction limits. An associated difficulty is assessing stream connectivity considering impacts of a single property. As an example, local improvements to fish habitat will have limited influence on mobile fish species if fish passage is blocked (physically or through adverse water quality) downstream.

Ongoing elaboration of existing methods and development of novel methods could help address some of the limitations identified here. For example, while BNs are typically aspatial, non-cyclical, and atemporal, new methods are addressing these limitations. As further examples, spatial causal networks (Peeters et al. 2022) are intended to introduce more aspects of causality into network-based methods, and hybrid AI/mechanistic/Expert systems could be developed to fill some of these gaps.

5. Conclusions

A large range of methods was identified for predicting the effects of agricultural land use and land management on lotic (river and stream) biota, along with example applications. Some methods were from other environmental disciplines, where the methods have not yet been applied to predicting land-use/biota impacts, but where we saw potential to increase the range of methods. This collation and summary of methods should provide a valuable resource for land-water practitioners and scientists who wish to gain an appreciation of what methods are available or could be available for predicting land-use/biota impacts.

Evaluation of methods against criteria identified that different methods have different strengths and weaknesses. While empirical methods are relatively easy to develop and understand, they are limited by difficulties in capturing causality and complex interactions and underlying difficulties such as predictor correlation. At the other extreme, mechanistic models have the potential to capture complex interactions, but they are often difficult to parameterise and there are few mechanistic models for linking stressors to biotic impacts. Intermediate models such as Bayesian Networks can represent more complexity and causality than empirical models but tend to be simpler than mechanistic models, yet they also have limitations in representing spatial interactions and dynamic processes. Most of the methods have difficulties with representing complex biotic interactions, representing legacy effects and aspects of ecological systems such as feedbacks.

No one method met all the criteria. This points to the need to consider carefully the intended use, choice of physico-chemical and biotic impact variables and available when selecting a method or methods. Another general strategy is to consider separating assessment of physico-chemical stressors from the resulting assessment of biotic impact. Different classes of model could be used for each of these components.

A tiered approach was proposed to navigate the use of the range of methods, whereby simple methods are applied first at a screening level, and more complex and time-consuming methods are applied to critical or uncertain impacts that are identified by lower-tier analysis, targeting the use of the more sophisticated methods for times when they are needed, thereby rationalising the use of resources.

The proposed screening level of analysis includes the use of relatively simple methods such as scoring and likelihood-consequence risk assessment methods (potentially with expert elicitation). However, such methods have had little application to land-use/biota assessment. We therefore consider that future development and application of such methods, including standardising them and making them easy to use, is needed.

Although the analysis in this paper did not arrive at a definitive set of recommended methods for different situations, the information on individual methods, evaluation against criteria, and presentation of organising constructs should prove useful when selecting methods and designing strategies for applying them to predict impacts of agricultural land use and land management on lotic biota. Moreover, some of the principles could be extended to other land uses and receiving environments in the future.

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Data Availability Statement

This paper is a review that does not contain primary research data.

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