Received: 1 May 2025 | Accepted: 5 January 2026

DOI: 10.1111/1365-2664.70307

Journal of Applied Ecology

RESEARCH ARTICLE

Implementing Bayesian network models using expert elicitation for instream barrier assessment

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Funding information
HORIZON EUROPE Marie Sklodowska-Curie Actions, Grant/Award Number: RISE-2015-690857-KEEPFISH; Royal Society Te Apārangi, Grant/Award Number: RIS-NIW1501; New Zealand Ministry for Business, Employment and Innovation Endeavour Fund, Grant/Award Number: C01X1615

Handling Editor: Paulo S. Pompeu

Abstract

1. Reducing river fragmentation is crucial for restoring freshwater biodiversity. Cost-effective methods of assessing the likelihood of fish passage at river infrastructure are required for spatial planning of barrier mitigation strategies. A paucity of empirical data on the swimming capabilities and movement behaviour of many fish species presents a challenge for evaluating barrier permeability.
2. We used a combination of expert knowledge and empirical data to define prior probabilities in Bayesian network (BN) models to estimate culvert, ford and weir permeability for multi-species fish assemblages in New Zealand. The models have been implemented as part of a national fish passage assessment tool. Model outputs are illustrated for a range of structures.
3. Uncertainty associated with incomplete knowledge was explicitly incorporated in the BN models. Experts were most confident in predicting barrier permeability under conditions where fish passage was expected to be poor. Estimates of fish passage success were more varied for conditions considered less likely to impede fish movements. This reflects experts' understanding of the varying swimming and climbing capabilities of different fish species and life stages and how this impacts barrier permeability.
4. The BN models form the basis of a new fish passage assessment tool that has been implemented in New Zealand. Users collect data using a mobile app, recording the key features of instream structures that have been determined to influence the likelihood of successful passage. The BN models are then used to objectively classify the risk to fish passage for each structure.
5. *Synthesis and applications.* We have demonstrated that BN modelling and expert knowledge can be used for assessing the likelihood of fish passage where empirical data are lacking or sparse. The probabilistic framework is consistent with the need to reflect that many structures are partial barriers to fish movement and cannot be represented accurately in a binary pass/fail classification. This facilitates risk-based decision-making, but also suggests that widely used connectivity indices should not ignore the uncertainty in barrier permeability by parameterising connectivity as a single value.

KEYWORDS
barrier, environmental management, fish migration, fish passage, passability

1 | INTRODUCTION

The impacts of river infrastructure on fish passage and diversity are well documented (Belletti et al., 2020; Thieme et al., 2024). Identification of complete physical barriers to fish movements (e.g. large dams) is often straightforward (Kemp & O'Hanley, 2010). However, rapid evaluation of permeability at partial barriers, that is those that may not be a complete physical barrier but create impediments to movement, remains challenging. Bayesian network models (BN; also called Bayesian Belief Networks) provide a means for integrating a range of empirical evidence and expert knowledge to facilitate the objective assessment of barrier permeability (Marcot et al., 2006).

Instream structures that obstruct the movement of fish between habitats impact the abundance, distribution and genetic diversity of freshwater fish species worldwide (Dudgeon et al., 2006; Thieme et al., 2024). Complete physical barriers to movement lead to dwindling populations, disruption of gene flow and ultimately extirpation of species (Pelicice et al., 2015; Wilkes, Webb, et al., 2018; Zarri et al., 2022). However, many of the more common structures found in waterways, such as culverts and weirs, act as partial barriers (Franklin & Gee, 2019; Januchowski-Hartley et al., 2013; Tummers et al., 2016). These structures may impede the movements of particular species or life stages, select for individuals with specific fitness traits (e.g. strong swimmers) or sizes, or may only be passable under a restricted range of conditions (e.g. low or high flows). The consequences of partial barriers for fish populations depend on factors such as the severity of the impediment, and the species, life stages or traits that are most affected.

Accurately locating, characterising and assessing the permeability of each barrier (natural and anthropogenic) on a stream network is an essential step for spatial planning of barrier mitigation efforts (Kemp & O'Hanley, 2010; McKay et al., 2017). Kemp and O'Hanley (2010) reviewed a range of strategies for evaluating barrier permeability. Direct empirical measurements of permeability, e.g. using biotelemetry to track fish movements, can be used to quantify passage rates at individual or multiple barriers, but are generally not financially or logistically feasible at a catchment-wide scale. Biotelemetry is also limited to larger fish or life stages (Birnie-Gauvin et al., 2018; Franklin & Gee, 2019). Indirect empirical measurements such as fish abundance or presence/absence surveys can be informative, but provide limited information on permeability at individual structures. A range of analytical methods are also utilised and are more widely applied for the rapid assessment of many structures at a catchment scale (Kemp & O'Hanley, 2010; McKay et al., 2017). These may include rule-based methods, statistical models or expert judgements (e.g. Goodrum et al., 2025; Januchowski-Hartley et al., 2014).

New Zealand's native freshwater fish communities are characterised by high levels of endemism. Many species are small-bodied (<150 mm total length) as adults and amphidromy is prevalent, meaning that the main upstream migrations occur as small (20–60 mm) juveniles. Their small size at migration means that seemingly small obstructions (e.g. drops of >100 mm) can be a significant impediment to upstream movements of these juveniles (Baker, 2003; Franklin & Gee, 2019), although several species have the ability to climb enabling them to surmount significant obstacles. The sparsity of empirical data suitable for developing models of fish passage success means that employing the body of knowledge held by freshwater fish experts offers a pragmatic way of delivering knowledge-based criteria for fish passage assessment.

BN models are increasingly being used to model environmental systems and inform decision-making (Chen & Pollino, 2012; Marcot, 2017; Uusitalo, 2007). Bayesian modelling techniques can integrate a range of evidence types in a probabilistic form that explicitly incorporates uncertainty. They can also be updated as new data or knowledge becomes available. A key benefit is the ability to incorporate expert knowledge as evidence in the model. This means that even when there is a paucity of empirical data, the knowledge and experience of qualified individuals can be utilised to support evidence-based decision-making (Choy et al., 2009; Kuhnert et al., 2010).

We adopted a BN modelling approach combined with formal expert elicitation as the basis for developing a new fish passage assessment methodology for New Zealand. Our goal was to demonstrate that, in the absence of sufficient empirical data, available expert knowledge could be used as the basis of an analytically robust decision support tool for environmental managers. A priority was ensuring that uncertainty in expert knowledge was explicitly accounted for in the model and could be reflected in decision-making. In this paper we describe the methodological framework used to elicit expert knowledge and incorporate it in the BN models. We also discuss limitations of the approach and propose refinements for future applications that will be relevant to researchers and practitioners in other jurisdictional areas and in the broader context of environmental decision-making.

2 | MATERIALS AND METHODS

2.1 | Bayesian networks

BNs consist of nodes representing causal and response variables, each with discrete or continuous states. The nodes are linked by arcs describing probabilistic dependency relations within the network. These relations are specified by populating conditional probability tables (CPTs) that describe the probability of each state of the child (response) node for each state of the parent (causal) node. CPTs may

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be populated from a range of sources, including empirical data and expert knowledge.

Marcot (2017) points to a number of potential problems that must be addressed to ensure that BN applications are robust, including several that are highly relevant to this application: (i) being unclear about BN objectives; (ii) including too many parent nodes, with insufficient consideration of combining causal variables for a more parsimonious BN; (iii) ignoring latent variables and not considering confounding variables; (iv) failing to incorporate peer-review into the network specification and CPT population process; (v) discounting or eliminating 'outlying' expert inputs'; (vi) conflating conditional probability with confidence; (vii) not mitigating for judgement biases (e.g. anchoring, bandwagoning) in expert elicitation; and (viii) failing to include specific tests of model calibration and validation. Below we describe how we developed BNs through a process that addressed these potential pitfalls, using the software package *Netica*.

2.1.1 | Objectives of the Bayesian networks

We used BNs with the basic objective of *predicting* the permeability of common barrier types (culverts, weirs, fords) for multi-species native fish assemblages, that is the proportion of upstream migrating individual fish able to pass the barrier. We constructed five separate BNs: one for fords and two for both weirs and culverts (one each for swimming species and for species that can also climb). Using separate BNs for each structure reduced the number of parent nodes required and prevented known difficulties in visualising and populating CPTs (Marcot, 2017). We considered it necessary to make culvert and weir permeability predictions for swimming and climbing species in separate BNs because the ability to climb meant that some of the causal nodes differed. The expert panel had insufficient confidence in their ability to distinguish differences in outcomes for swimming and climbing species to allow two separate models for fords.

2.1.2 | Constructing prototype networks

To mitigate the omission of latent and confounding variables in the BNs, and to check the validity of our CPTs, we incorporated peer review into every step of the BN construction process. First, prototype BNs were specified through three rounds of unstructured discussions with two New Zealand fish passage experts. In the first round, experts identified a short list of the causal and response variables and node states to be included in each BN. Further rounds of discussions then focused on refining the BN architecture with the explicit objective of including any potential latent and confounding variables and combining parent nodes into fewer, intermediate nodes where possible. Second, during the expert elicitation workshops (see below) each expert was given the opportunity to propose changes to the BN model structures by adding or removing nodes and node states. Finally, after the CPTs had been populated, the predictions from the final BNs were reviewed by the full expert panel to ensure they were logical and consistent with experts' expectations.

2.2 | Empirical probabilities

Few empirical data were available in the existing literature to build the BN model. The few published studies that were available at the time of the expert elicitation workshop (e.g. Doehring et al., 2011; Franklin & Bartels, 2012) were largely limited to studies of single species/life stages at only a single structure under a limited set of conditions. As such, they offered limited information on how passage performance systematically varied across the range of conditions that required evaluation for a nationally applicable fish passage assessment tool. Consequently, we relied on the familiarity of the expert panel with these studies and, hence, their incorporation into the BN models indirectly via the expert elicitation process, rather than trying to integrate them explicitly. For specific parts of the culvert BNs, we were able to use the data of Baker and Boubee (2006) and Baker (2014) to populate CPT entries concerning the accessibility of perched culverts with ramps constructed for fish passage. Both studies systematically quantified the passage of representative swimming (e.g. *Galaxias maculatus*) and climbing taxa (e.g. *Gobiomorphus huttoni*) over experimental ramps across a gradient of ramp slopes and lengths in the laboratory. *G. maculatus* is a weakly swimming species with a broad range in New Zealand and the temperate Southern Hemisphere that is commonly used as an indicator species for fish passage studies (e.g. Amtstaetter et al., 2024; Crawford et al., 2025; both undertaken after the tool was developed). To enable us to combine these experimental results we used data for adult *G. maculatus* and *G. huttoni* as these were the species and life stages that both studies had in common. The results of Baker and Boubee (2006) for *G. maculatus* were similar for adults and juveniles, indicating that our inclusion of adults only is not likely to have biased the CPTs. Predictions from the culvert BNs were later compared to the original data of Baker and Boubee (2006) and Baker (2014) (see Supporting Information S1).

2.3 | Expert elicitation

Expert knowledge is commonly used to make important environmental management decisions (Krueger et al., 2012) yet is rarely elicited using a formal protocol that considers variability in expert beliefs and confidence, and controls for common biases, such as anchoring (Hysenbelli et al., 2013) and bandwagoning (Friedkin et al., 2016). We chose to use the four-point elicitation protocol of Speirs-Bridge et al. (2010). This approach is based on rigorous cognitive psychological research and includes appropriate mathematical treatment of outputs to deal with uncertainty, described in detail in Wilkes, Baumgartner, et al. (2018).

In summary, for each combination of the states of causal nodes connected to a response node, experts were asked four questions: (i) what is the minimum permeability you would realistically expect?; (ii) what is the maximum permeability you would realistically expect?; (iii) what is your most likely estimate of permeability?; and (iv) how confident are you that this range includes the true permeability? Questions were asked in two rounds. In the first round, experts were asked to answer without conferring. To mitigate for anchoring bias, we took frequent breaks in which experts were distracted with numerical trivia. We also asked experts to write their answers on separate pages, handing each page to the workshop leader after each question to prevent looking back at previous answers. After the first round, experts' answers were tabulated and presented to the whole group. The second round then involved discussions between experts on the reasons for differences in responses to reach consensus. Experts were given the opportunity to change their answers at this time.

Two separate expert elicitation workshops were held, covering the culvert models in the first and the weir and ford models in the second. Separate workshops were held to reduce the potential impact of expert fatigue. Each workshop was held over 2 days with nine and eight experts for the culvert and weir/ford workshops, respectively, including the two initial experts involved in constructing the draft models. All eight experts that participated in the weir/ford workshop were also involved in the culvert workshop. Experts were invited to be involved in the elicitation process via email and confirmed their consent to participate by return email. The experts were all fish ecologists, representing both academic and applied sectors, with between five and 40 years' experience of working with freshwater fish in New Zealand.

2.4 | Deriving conditional probability tables

To derive CPTs for input into Netica, we transformed experts' answers from the four-point elicitation process into statistically representable distributions. As our response variables were all bound between zero and one, we represented probabilities as Beta distributions. The beta parameters were derived for each expert using the *betaExpert* function in the *Prevalence* package in R (Devleesschauwer et al., 2022). The *betaExpert* function fits a standard Beta distribution to expert opinion following the method of Branscum et al. (2005). Fitting Beta distributions to each expert's answers allowed us to translate their responses to standardised quantiles allowing for quantile aggregation of responses across experts. This was achieved by using the *qbeta* function in R to calculate expected permeability at set quantiles (0.05, 0.50 and 0.95 representing a 90% credible interval and the median) for each expert and then averaging expected permeability across experts at each quantile for each question. One strategy we employed to reduce expert fatigue during the elicitation workshops was to reduce the overall number of questions by choosing to interpolate intermediate states for some parent nodes. In these cases, we used the average of the expected permeability for the high and low states at each quantile. We then used the *fitdist* function in the *SHELF* package (Oakley, 2024) to fit a Beta distribution to the aggregated permeability scores. The CPTs for the child nodes in each BN were then populated in Netica using equations based on the derived Beta shape parameters (Supporting Information S2).

2.5 | Model outcomes

Netica case files were created for each BN model including all possible permutations of causal variables and their states. The case files were processed in Netica to generate the expected beliefs (i.e. posterior probabilities) for each state of the child nodes. The expected beliefs for each permutation were subsequently exported to R and Beta distributions fitted using the *fitdistr* function in the *MASS* package (Venables & Ripley, 2002). The resulting Beta distributions were used to allocate discrete fish passage risk classes to each model permutation. Area under the curve was calculated for each of five evenly sized classes (0.0–0.2, 0.2–0.4, 0.4–0.6, 0.6–0.8, 0.8–1.0) describing the proportion of fish expected to pass. A risk class based on a five-point ordinal scale (Very high, High, Medium, Low, Very low risk) was then allocated to each model permutation based on the interval with the highest area under the curve. These risk classes are used in the NZ Fish Passage Assessment Tool (https://niwa.co.nz/fish-passage/fish-passage-assessment-tool) to predict, for assessed structures, the likelihood of a structure presenting a barrier to fish passage.

2.6 | Model sensitivity

To quantify the relative importance of nodes and node states in determining outcome (e.g. overall permeability) and intermediate (e.g. accessibility) variables, an information theoretic approach was taken using Kulback–Leibler (KL) divergence. KL divergence quantifies the 'influence' of nodes and node states based on how much the associated beta distribution differs from a reference distribution, which was defined as the average distribution among all node states. KL divergence was calculated both for individual node states and as a mean across all node states within root nodes (e.g. ramp slope). For the culvert BNs (Figure 1a,b), this approach was applied separately to the case with a ramp and without a ramp.

3 | RESULTS

BN models were successfully developed for culverts and weirs (swimming and climbing fish) and fords. Model architecture varied between the three structure types, but common factors influencing permeability included fall height, surface roughness and water velocity. Because the objective was to develop models that could form the basis of a national fish passage assessment protocol, model variables and node states focused on structural characteristics that were practical to measure in the field and experts considered integral to barrier permeability. The need to

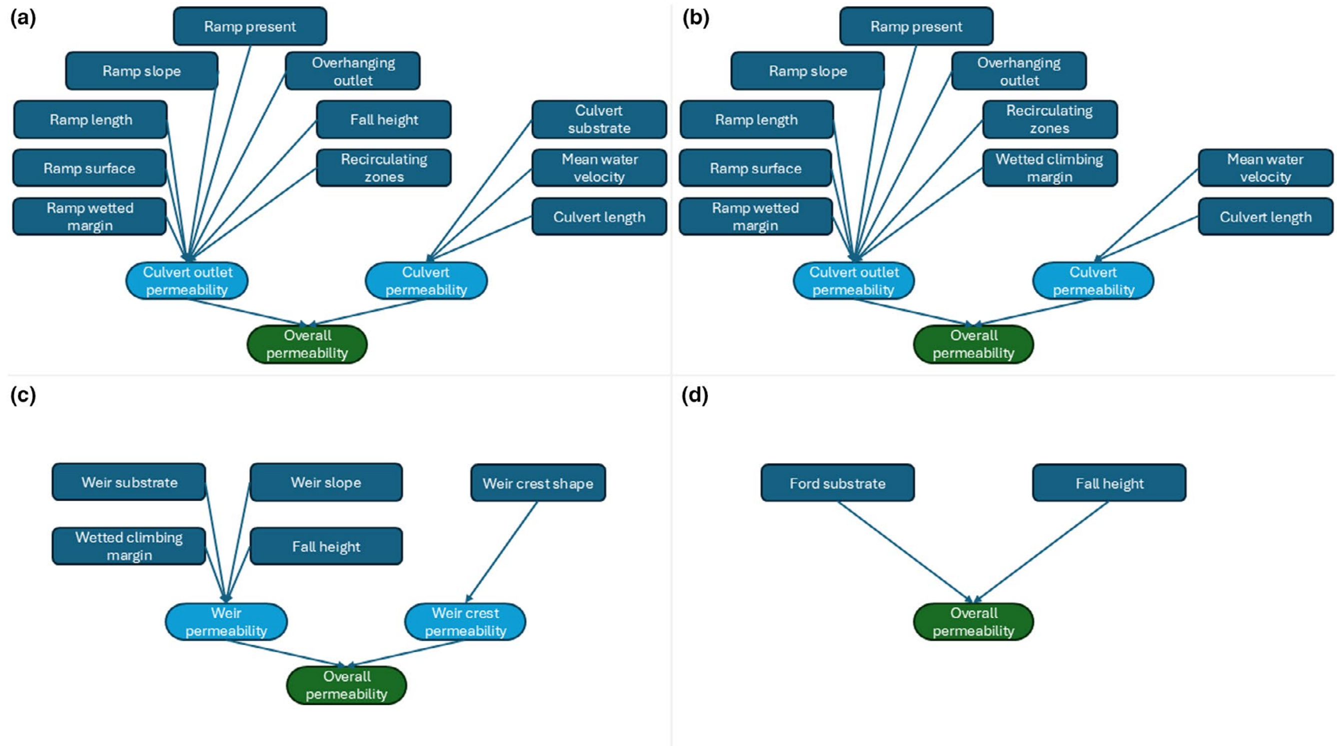

FIGURE 1 BN model architecture for (a) culverts for swimming fish species; (b) culverts for climbing fish species; (c) weirs (note the wetted margin node was only utilised for climbing species); and (d) fords.

constrain model architecture to ensure that the expert elicitation process was manageable resulted in the introduction of intermediate nodes in the culvert and weir models. This limited the number of interacting parameters that the experts had to consider to no more than four at once.

3.1 | Model architecture

The architecture of the culvert models (Figure 1a,b) was more complex than those for weirs (Figure 1c) and fords (Figure 1d). This reflects the greater number of factors identified as being important for influencing successful fish passage at culverts.

The architecture of the culvert BN models incorporated two intermediate nodes; the first (Culvert outlet permeability) describes the factors influencing the likelihood of fish being able to enter the culvert, while the second (Culvert permeability) describes the factors controlling the likelihood of a fish being able to successfully pass through the culvert once it has entered. The product of these two intermediate nodes defined the overall probability of a fish passing. The primary differences between the swimming (Figure 1a) and climbing (Figure 1b) model structures were the inclusion of 'Wetted margins' and removal of 'Fall height' as parents to the Outlet permeability node and the removal of 'Culvert substrate' as a parent for Culvert permeability for the climbing fish model. For both weirs (Figure 1c) and fords (Figure 1d), the model architecture was simpler than that for culverts and the same structure was used for both swimming and climbing species (with the exception of the inclusion of a wetted climbing margin node for climbing species in the weir model).

3.2 | Expert elicitation

No modifications were made to the BN model structures by the panel of experts as they collectively considered the models a fair reflection of the current state of knowledge regarding the key factors influencing fish passage success at these structure types. In subsequent sections we present only the results of the swimming versions of the BN models because these were the models ultimately implemented as part of the NZ Fish Passage Assessment Tool. The outcomes for the climbing models are presented in Supporting Information (S3).

3.2.1 | Culverts

The experts considered that culvert access was strongly influenced by both the presence of an overhang and drop height at the culvert outlet (Figure 2 and Figure S2). There was a strong consensus that the combination of an overhanging outlet and high (>0.10 m) drop height would severely impede fish access to culverts (Figure S2). Notably, even under optimal outlet conditions (no overhang, low drop height, recirculation zones present), some experts predicted a relatively broad range of potential passage success.

Culvert water velocity, length and substrate all exerted a relatively strong influence on the experts' predictions of fish passage

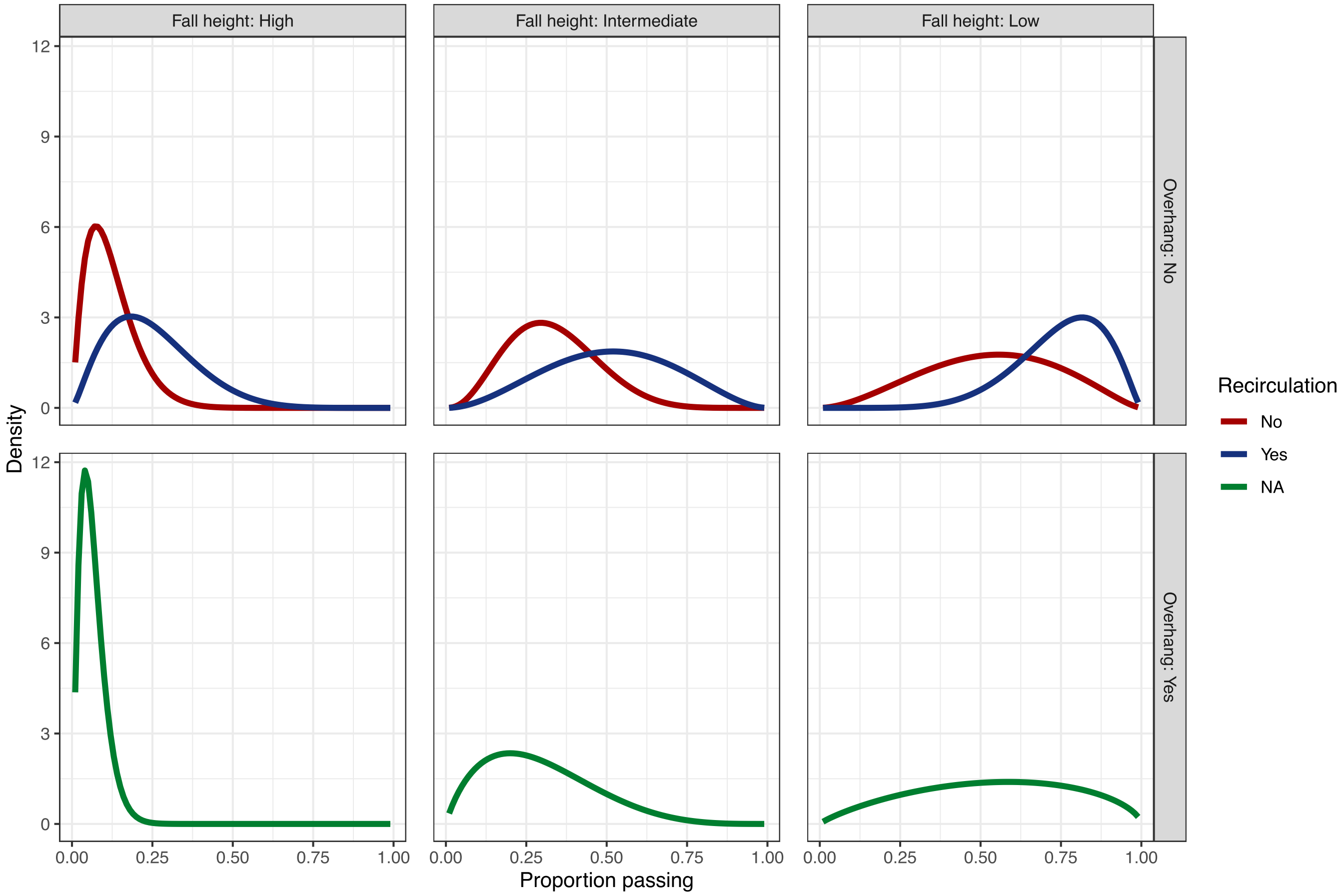

FIGURE 2 Mean estimated culvert entrance permeability for swimming fishes where no ramp is present. Note that the influence of recirculation zones at the culvert entrance was considered redundant where an overhang was present.

success through the culvert barrel (Figure 3 and Figure S3). A strong consensus between experts was the prediction that the combination of fast water velocities (>1 m s^{-1}), long culverts (>50 m), and a smooth substrate (i.e. bare concrete), would have the lowest passage rates (Figure 3 and Figure S3). In contrast, the optimum combination for passage success was predicted to be slow water velocities (<0.5 m s^{-1}), short culverts (<50 m) and a rough substrate (e.g. natural gravels). Culvert length generally had a stronger influence on predicted passage success when culvert water velocities were slow, likely reflecting the trade-off between swimming endurance and water velocity. The presence of substrate in the culvert increased experts' confidence in fish being able to pass when compared to the 'smooth' substrate setting. Substrate generally had a greater influence on predicted outcomes at fast water velocities, when compared to slow water velocities. For most scenarios there was relatively good consistency between experts' predictions (Figure S3).

3.2.2 | Weirs

Weir height, slope and substrate all influenced the experts' predictions of weir face passage success (Figure 4 and Figure S4). Weir face passage success rates were predicted to be lowest when weir height and slope were high (>1 m and >45°, respectively), and the weir substrate was smooth (Figure 4). As weir height and slope reduced, experts predicted passage rates to increase. Consensus between experts was comparatively lower for weirs when compared to culverts (Figure S4).

Experts' estimates of passage success at the weir crest were strongly influenced by crest shape (Figure 5 and Figure S5). There was a strong consensus between experts regarding the negative effects of an overhanging crest design, with predicted passage rates very low (<5%). A rounded crest shape was considered to offer the best passage rates by experts.

3.2.3 | Fords

Experts' predictions of passage success for swimming fishes at fords were most strongly aligned under the conditions where passage rates were expected to be poorest (Figure S6). Particularly under intermediate conditions, there was a high level of uncertainty in the experts' answers (indicated by broad, flat distributions; Figure 6) and lower consensus between experts.

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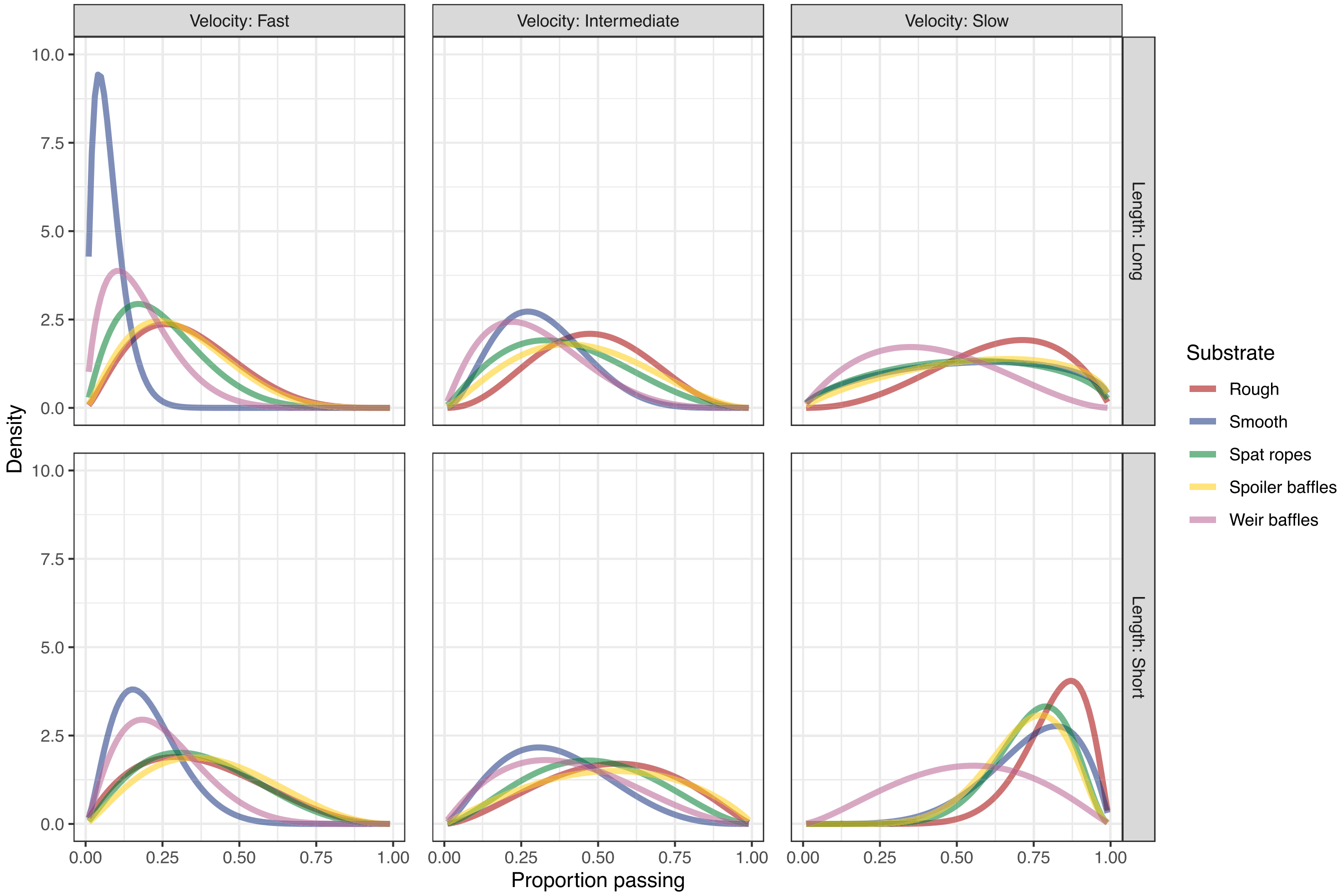

FIGURE 3 Mean estimated culvert barrel permeability for swimming fishes. A rough substrate was defined as representing natural gravel/cobble and a smooth substrate was defined as plain concrete.

3.3 | Model outcomes

3.3.1 | Culverts

There are 39,240 potential permutations of the culvert BN model. Most permutations (86%) were predicted to result in a Very High risk to fish passage (0%–20% passage), with 13% classified as High risk (20%–40% passage), 1% as Medium risk (40%–60% passage) and 0.5% as Low risk (60%–80% passage). No combination of characteristics resulted in a Very Low risk class (80%–100% passage).

In the absence of a ramp at the culvert entrance, the culvert accessibility model was most sensitive to fall height (Figure S10). All scenarios where the fall height at the culvert entrance was high resulted in a Very High risk to fish passage; reflecting experts' expectations and confidence that this characteristic is a major impediment to the upstream movement of fishes. The only scenario where risk was predicted to be low was where fall height was low, with low water velocities and a rough substrate inside a short culvert.

Where a ramp was present at the culvert outlet, the culvert accessibility model was most sensitive to ramp slope followed by ramp length (Figure S11). Ramp slope, length and substrate have all been shown to influence passage efficiency of ramps for native fishes in New Zealand and act as important controls on culvert accessibility when a ramp is present (e.g. Franklin & Bartels, 2012). The optimum ramp design (low slope, short, with rough substrate) increases the number of scenarios where overall passage risk is classified as Low. Culvert permeability is most sensitive to water velocity, with culvert length and substrate similarly influential (Figure S12).

3.3.2 | Weirs

Almost all (29 of 32) weir permutations resulted in a Very High risk classification for swimming fishes. This reflects the combined effect of the relatively low predicted passage success at both intermediary nodes (weir face and crest) under most scenarios. The weir accessibility model is sensitive to both weir height and slope (Figure S13). Crest shape (Figure S15) has a strong impact on the shape of the overall probability distribution and, hence, the risk class.

3.3.3 | Fords

Predicted fish passage risk classes for fords without culverts ranged from Low to High across the six possible scenarios. No scenarios fall into the Very High or Very Low risk categories. The ford model

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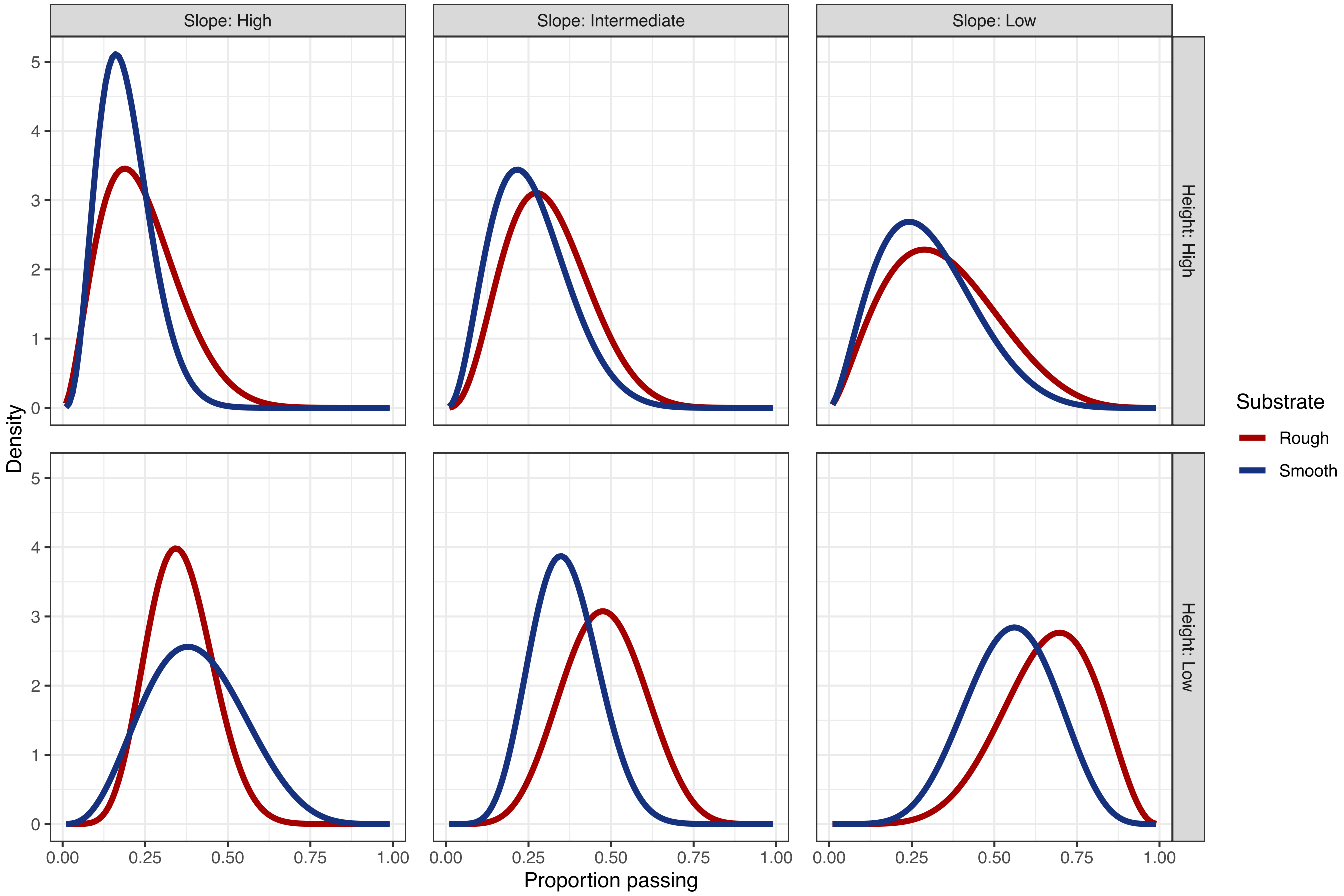

FIGURE 4 Mean estimated weir face permeability for swimming fishes.

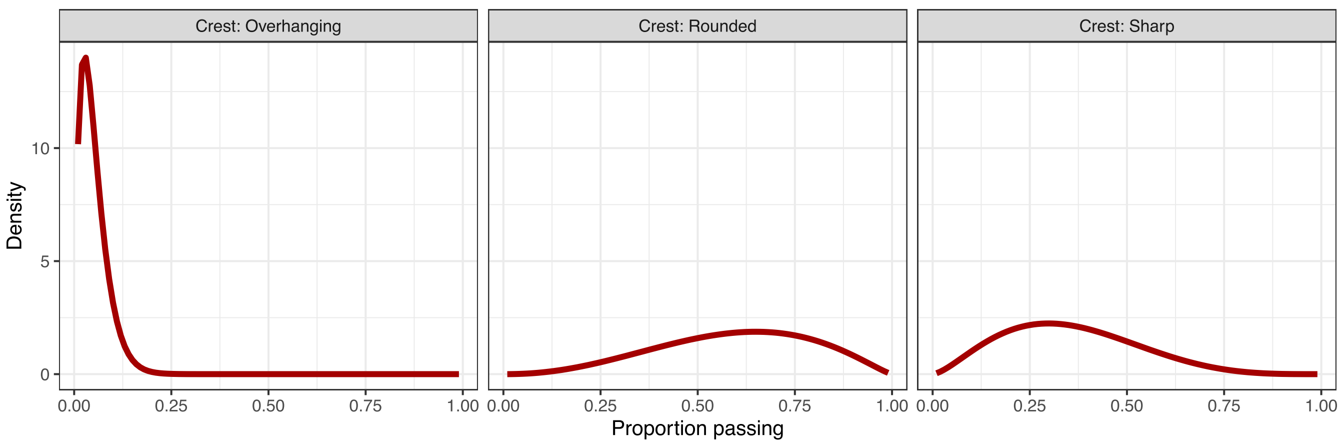

FIGURE 5 Mean estimated weir crest permeability for swimming fishes.

is most sensitive to fall height (Figure S14). In the real world, the experts' predicted probability distributions spanned the full range of risk classes. However, the degree of uncertainty in the experts' predictions of passage success across the different ford scenarios means that there is currently insufficient confidence to definitively distinguish Very High or Very Low risk structures. In part this reflects knowledge gaps, but it also likely reflects a relatively simple model structure (compared to the culvert and weir models) that doesn't provide sufficient granularity to differentiate the scenarios at the extremes of the distribution.

3.4 | Model deployment

The culvert, weir and ford BN models have been implemented as a component of the New Zealand Fish Passage Assessment Tool

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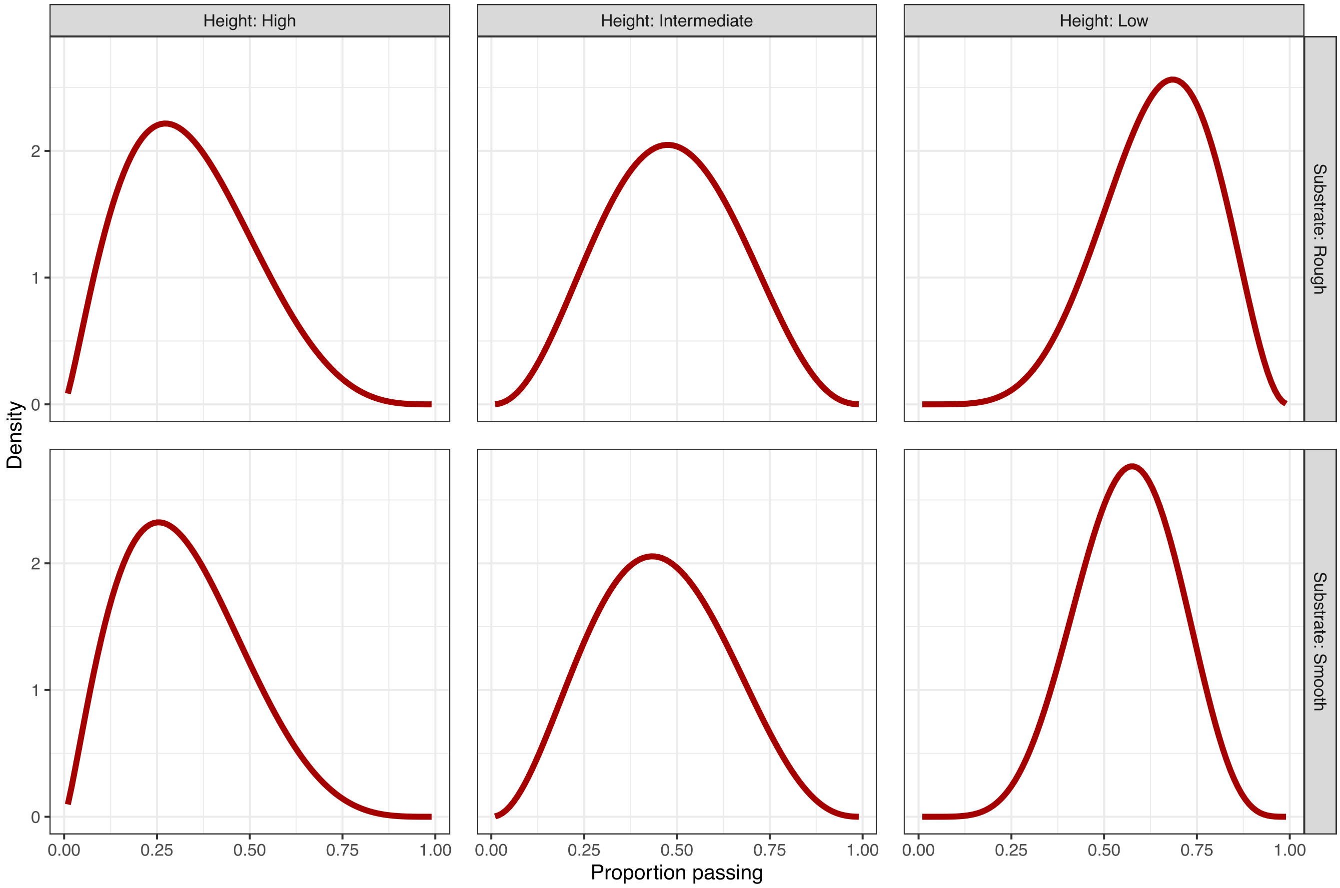

FIGURE 6 Mean estimated ford permeability for swimming fishes.

(FPAT). The FPAT comprises a mobile app for field data collection, a database, and a web tool and Application Programming Interface (API) for data visualisation and access (https://fishpassage.niwa.co.nz/). The BN models are applied to the data collected using the FPAT app and used to allocate a fish passage risk class to each structure on a five-point ordinal scale from Very Low risk to Very High risk. The tool is now used by a wide range of organisations to capture information on fish passage barriers to fulfil national policy requirements.

4 | DISCUSSION

Identifying, documenting, assessing and prioritising instream barriers for remediation is critical for addressing the impacts of river fragmentation on freshwater biodiversity (Belletti et al., 2020; Franklin et al., 2022; Januchowski-Hartley et al., 2013; O'Hanley, 2011). Given the large number of barriers present on global waterways, there is a need for practical, evidence-based tools to enable river managers and infrastructure owners to collect and use the information required to inform investment decisions and guide conservation planning (Thieme et al., 2024). Here, we have leveraged the collective knowledge and experience of multiple experts to underpin the development of a national fish passage assessment methodology for New Zealand. At the time of publication, the New Zealand Fish Passage Assessment Tool has been used to assess >18,500 structures, supporting implementation of national freshwater policy. While the specific model architecture and conditional probabilities may not be directly transferable to fish communities outside of New Zealand, the model development framework described can be adopted for other fish communities, structure types, stream environments and other freshwater management problems globally.

Environmental decision-makers are regularly faced with balancing a desire for knowledge to support evidence-based decisions with a need to act despite uncertainty (Ascough et al., 2008; Cook et al., 2013). The impact of small-scale, partial barriers on aquatic species has received increasing recognition in recent years (Frankiewicz et al., 2021; Januchowski-Hartley et al., 2020). Investigation of these small-scale impediments is beginning to improve the picture of how characteristics of these structures impede the movement of fish under various conditions (e.g. Amtstaetter et al., 2017; Goerig et al., 2017; Jones et al., 2021). However, in most cases quantitative evidence remains sparse, site specific and restricted to a limited range of species and life stages. This limited availability of empirical evidence presents a challenge for policy makers and practitioners when tasked with defining design standards for new structures and planning actions to restore river connectivity.

Expert knowledge can play a valuable role in supporting environmental decision-making, particularly where there is a paucity of empirical evidence or where problems are complex (Drescher et al., 2013; Elsmore & Congreve, 2022; Martin et al., 2012). Experts often hold a wealth of knowledge and experience and there is a long history of using expert knowledge in environmental decision-making (Krueger et al., 2012; Morgan, 2014; Sutherland & Burgman, 2015). However, experience has shown that uncertainty is often not explicitly considered, and there is the potential for significant biases (Drescher et al., 2013; Kuhnert et al., 2010). Formal expert elicitation processes can help overcome some of these issues and improve the utilisation of this valuable resource, which can be indispensable in circumstances with sparse empirical data (Drescher et al., 2013; Kuhnert et al., 2010; Martin et al., 2012).

Probabilistic Bayesian methods are well-suited to translating expert knowledge into useable frameworks for decision-making (Kuhnert et al., 2010). One of the benefits of Bayesian models is the ability to blend multiple information sources and the facility to update the conditional probabilities as knowledge increases. We have demonstrated an approach to formally incorporate expert knowledge in a BN modelling framework suitable for application to a practical ecological management problem—the need to consistently determine the risk of fish passage being impeded at instream structures. The model results are informative in two ways: (1) they help decision-makers and practitioners to understand which instream structures present the greatest risk and the characteristics of those structures that likely have the greatest impact on risk, and (2) they identify gaps and uncertainties in current knowledge that can be addressed to increase confidence in decision-making.

Vertical drops, whether at the outlet of culverts or at a weir or ford, are highlighted in the models as having a significant negative impact on the passability of structures. This is consistent with evidence documented for a wide range of species globally (e.g. Adams et al., 2025; Januchowski-Hartley et al., 2019). Avoiding vertical drops in the design of new structures and finding effective interventions enabling fish to overcome vertical drops at existing structures (e.g. fishways) must be a high priority for managers and practitioners seeking to preserve and restore river connectivity and ecosystems. In common with global studies (e.g., Mahlum et al., 2014; Zubick et al., 2025), high water velocities within culverts are also identified as a significant impediment to successful passage. Stream simulation culvert designs (Barnard et al., 2015; Cenderelli et al., 2011) are intended to overcome this issue or, where the structure cannot in the short-term be replaced, installation of baffles can mitigate the impacts (Enders et al., 2017; Franklin & Baker, 2025).

We made a conscious effort to capture and incorporate uncertainty in our model through use of the four-point elicitation method. The explicit incorporation of uncertainty into the BN models improves the credibility and legitimacy of the tool among decision-makers (Cook et al., 2013). It acknowledges the limitations of current knowledge and highlights where greater scrutiny may be required to support decision-making. For example, in our case it became apparent that there is a bias in the experts' knowledge towards having greater confidence in the features of a structure that makes it a barrier, rather than what is not a barrier. The requirement to consider passage of the whole fish community was one of the factors that contributed to our experts' inability to effectively discriminate very low risk structures; experts' confidence in whether all, or even most, species or life stages would be unimpeded was relatively low. To some extent this uncertainty reflects a lack of species-specific knowledge, but it is also reflective of the experts' understanding of natural variation in different organisms' locomotive capabilities and motivations (e.g. Crawford et al., 2024; Radinger & Wolter, 2014). These uncertainties make predictions of 'good' passage within the BN model conservative, but gives river managers confidence that structures identified as being a very high risk to fish passage are very likely in need of management intervention. However, mirroring global calls for improved outcome monitoring to improve the effectiveness of fish passage solutions (e.g. Bunt et al., 2016; Franklin et al., 2024; O'Connor et al., 2022), they also highlight the need for increased efforts to capture empirical data that can help discriminate likely outcomes across different species, life stages, environmental conditions and structure characteristics.

5 | SYNTHESIS AND APPLICATIONS

Fragmentation of river networks has caused reductions in freshwater biodiversity worldwide (Fuller et al., 2015; Grill et al., 2019; Thieme et al., 2024). Mitigating the impacts of river infrastructure requires effective methods for assessing barrier permeability for multiple fish species and life stages (Bourne et al., 2011; Garcia de Leaniz & O'Hanley, 2022; Sun et al., 2025). Empirical data on fish locomotive capabilities and behaviour are lacking for many species, presenting a challenge for deriving the necessary assessment methodologies. We showed that BN models offer an effective way of building expert knowledge and uncertainty into environmental management tools. The models are now being used as part of a nationally consistent fish passage assessment tool and prioritisation framework (https://shiny.niwa.co.nz/barrier-assessment/) to support implementation of national fish passage policy in New Zealand. By explicitly incorporating estimates of uncertainty in the model, river managers can make risk-based prioritisation and investment decisions. A future priority will be to utilise empirical data as they become available to update the Bayesian models to reflect best available evidence.

Formal methods of incorporating expert knowledge in ecological modelling and management are important where empirical data are scarce. In the past, expert elicitation was often ad hoc, lacked transparency and failed to effectively account for biases in knowledge (Drescher et al., 2013). However, the increasing formalisation of expert elicitation in the conservation and wider environmental sciences (Drescher et al., 2013; Kuhnert et al., 2010; Martin et al., 2012), alongside efforts to recognise and incorporate a greater diversity of knowledge types and ways of knowing (e.g. Reid et al., 2020), offers researchers, decision-makers and practitioners alike the opportunity to access complex understanding

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and inference that may not be reflected in empirical data sources. An advantage of the BN approach is the ability to incorporate multiple lines of evidence in one model. This enables managers and researchers across diverse fields to take advantage of the full range of evidence available to reach better-informed conclusions. We have demonstrated that the BN approach can achieve this by integrating it into a national decision-support system for fish passage assessment. However, we acknowledge the challenges faced in mitigating for bias and epistemological uncertainty in developing these models. Consequently, we encourage researchers to make use of existing guidance on how best to elicit expert knowledge for conservation science and environmental decision-making (e.g. Drescher et al., 2013; Kuhnert et al., 2010) and to explore approaches for achieving this and to undertake work to validate these models.

AUTHOR CONTRIBUTIONS

Paul Franklin and Martin Wilkes conceived the ideas and designed the methodology. Paul Franklin, Martin Wilkes, Cindy Baker and Eleanor Gee developed the conceptual models for the Bayesian networks. Paul Franklin, Martin Wilkes and Cindy Baker contributed to data collection. Paul Franklin and Martin Wilkes analysed the data and led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

ACKNOWLEDGEMENTS

We gratefully recognise the contribution the expert panel members Richard Allibone, Jacques Boubée, Bruno David, Brendan Hicks, Don Jellyman, Alton Perrie and Dave West made to the completion of this project. Valuable comments on early drafts of this manuscript were provided by Peter Hairsine, Neale Hudson and James Shelley. We also acknowledge the valuable insights provided by Angus Webb on approaches to aggregating the experts' probability distributions. This work was funded by the European Commission through the Marie Sklodowska-Curie action, 'Knowledge Exchange for Efficient Passage of Fish in the Southern Hemisphere' (RISE-2015-690857-KEEPFISH), the Royal Society of New Zealand (contract RIS-NIW1501) and the New Zealand Ministry for Business, Employment and Innovation Endeavour Fund (contract C01X1615). Open access publishing facilitated by Earth Sciences New Zealand, as part of the Wiley - Earth Sciences New Zealand agreement via the Council of Australasian University Librarians

CONFLICT OF INTEREST STATEMENT

Paul Franklin is an Associate Editor of Journal of Applied Ecology, but took no part in the peer review and decision-making processes for this paper. Otherwise, the authors have no conflict of interest to declare.

DATA AVAILABILITY STATEMENT

Data available from figshare https://doi.org/10.6084/m9.figshare.28915874 (Franklin & Wilkes, 2026).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Appendix S1. Empirical probabilities.

Appendix S2. Netica equations used to generate the CPTs for each BN model for swimming fishes.

Appendix S3. Expert elicitation results.

Appendix S4. Model sensitivity Kulback–Leibler divergence plots.

Appendix S5. Weir crest types.

How to cite this article: Franklin, P., Baker, C., Gee, E., & Wilkes, M. (2026). Implementing Bayesian network models using expert elicitation for instream barrier assessment. *Journal of Applied Ecology*, *63*, e70307. https://doi.org/10.1111/1365-2664.70307