“Knowledge Strength”: maximising the reliability of evidence derived from environmental modelling in the face of uncertainty – the case of the salmon louse (*Lepeophtheirus salmonis*)

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Abstract

Policy developments for a sustainable Blue Economy require scientific advice. An important component of the Blue Economy is salmon (*Salmo salar*) aquaculture, the sustainability of which is limited by salmon louse (*Lepeophtheirus salmonis*) infection. This parasite impacts both farmed and wild salmonid fish. Modelling is a valuable source for advice, but inevitable uncertainties exist. Here we develop an approach we call “Knowledge Strength” to maximise our confidence in model results; this is aimed at reducing uncertainties in model outputs and understanding the remaining uncertainty in these outputs, to maximise our confidence in model results, so that we can give policy makers the best advice to support informed decision making. The approach consists of addressing five questions: (1) What is the objective addressed by the model? (2) What are the causes of uncertainty in model outputs? We describe uncertainties due to (a) limitations of computing, (b) model building and (c) parameters, and (d) forcing data. (3) What is the statistical nature of uncertainty? Noise and bias are qualitatively different. (4) How can knowledge strength be maximised given those uncertainties? Approaches of resourcing (“power”) and analysis (“wisdom”) are considered. (5) How can information, including uncertainties, be communicated to different audiences?

Policy makers/managers define and resource the objective for question 1, modellers address questions 2 to 4 - but their solutions are made transparent, and the communication question 5 is a two-way process with outputs transparent to immediate decision makers and external stakeholders. Examples of the policy environment behind salmon lice management are detailed in the Supplementary Material covering Scotland, Norway and the Faroe Islands.

Keywords

Aquaculture; decision making; Atlantic salmon farming; Blue Economy

1. Introduction: The challenge of applying environmental modelling advice to management for the Blue Economy

Sustainable development of a Blue Economy (the marine version of the Green Economy, Lee et al., 2020) involves balancing environmental, economic and social issues (Figure 1); this is similar to a one-health approach

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(Stentiford et al., 2020). Technically it is possible to weigh all the components in financial terms, but even this approach requires weightings that inevitably reflect policy positions and values for ecological and social benefits (Costanza, 2020). Therefore, the “optimal” state is a policy defined position and so ultimate decision making is undertaken by governments (ministers, policy makers or managers). However, advice as to how to achieve this optimum state is a technical issue requiring input from scientific experts. For this reason, decisions to support the Blue Economy require the input of both policy makers and scientists (HM Treasury, 2015; Rounsevell et al., 2021). All parties involved in decision making must have defined roles and responsibilities, and communications between scientists, decision makers and stakeholders need to be clear and unambiguous (Beck and Mahony, 2018; Vormedal, 2023). This process is an approach to the application of Good Modelling Practice (Jakeman et al. 2025).

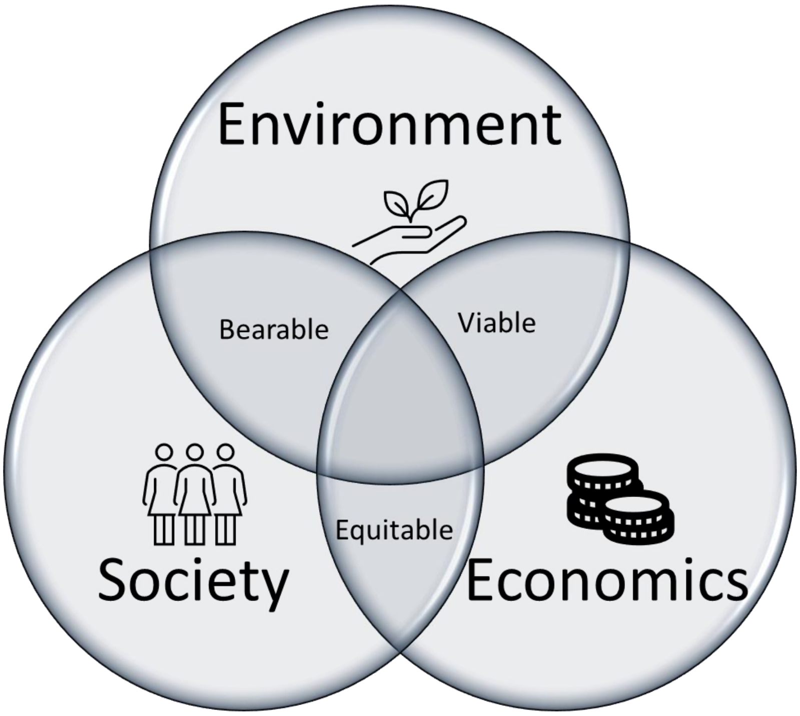

Figure 1: The Blue Economy seeks to balance environmental, economic and social values to identify an optimal sustainable policy position.

Here we use salmon aquaculture as a Blue Economy case study to demonstrate decision making advised by modellers working with various sources of uncertainty, focusing on the impact of salmon lice (*Lepeophtheirus salmonis*) on wild salmon. As background, salmon aquaculture is a major industry in several countries with cool temperate water, such as Norway, Chile, Scotland, the Faroe Islands and Canada, with worldwide production totalling 2.7M tonnes worth $15BN in 2020 (FAO, 2021). Salmon production is therefore a globally significant industry, with particular socio-economic importance in rural or remote areas, often with few alternative year-round employment opportunities. However, salmon aquaculture is associated with a range of risks to the marine environment (Taranger et al., 2015). The salmon louse is a key challenge to sustainability, both through direct impacts on farmed fish welfare and production and by impacts on wild salmonids (Vollset et al., 2016; Overton et al., 2019; Treasurer et al., 2022).

Salmon lice transmit as plankton in the marine environment while developing through two nauplii stages, before becoming infectious copepodids (Hamre et al., 2013). These plankton can be transported by currents over distances of several kilometres (Salama et al., 2016; Rabe et al., 2020), which creates interacting networks of farms (Adams et al., 2015; Kragesteen et al., 2019; Samsing et al., 2017; Husebråten and Johnsen, 2022) over considerable areas. This transport also leads to interaction between lice on farms and wild salmon (Moriarty et al., 2023). Because of this, salmon lice need to be managed not only for individual farms but over large areas, as well. This means area management and complex numerical modelling is needed as a key tool to assess boundaries and interactions of these management areas. The problem of salmon lice management is complex and different approaches have been adopted in different jurisdictions. Three examples of management are presented in Supplementary Material A, from Norway, Scotland and the Faroe Islands.

A key challenge for both decision makers and scientists is the inevitable uncertainties and limits to knowledge in any understanding of the marine environment because of the physical scale, biological complexity and literal fluidity of this environment. Understanding and communicating uncertainty, particularly between parties with different backgrounds (Karcher et al., 2022), requires clear and unambiguous language (EFSA, 2022) that does not downplay relevant uncertainties (Stirling, 2010), since the aim is to inform policy and stakeholders to make optimal decisions. This need for clear communication is emphasised in other fields, such as climate change (Beck and Mahony, 2018), where complex data must be presented to stakeholders. It is important to note that, while aquaculture producers seek to keep lice numbers low, this interest must be balanced against impacts of excessive treatments on farmed fish welfare (Overton et al., 2019). But conservationists' optimum is to avoid any salmon lice impact from aquaculture. Therefore, the interests of stakeholders can differ, making this a "wicked problem". It is the role of policy makers to find a balance of these stakeholders' interests (Figure 1).

In this paper, we assess how rigorous robust scientific advice can be generated and communicated, given the uncertainties in specific knowledge of the environment and of general limitations of modelling. We describe how to ensure robust information is generated, communicated and understood (we use the term "Knowledge Strength" to describe this robustness) to inform management of impacts from the interaction of salmon lice from farms with populations of wild salmonid fish. Policy makers use information generated through modelling to support decision making to manage salmon lice originating from salmon aquaculture as part of an overall Blue Economy problem (Figure 1) under which environmental, economic and society issues are balanced. This process is not perfect (Karcher et al., 2021), but the policy objectives are defined (Supplementary Material A) and here we try to find how the scientific contribution can be optimally targeted to support policy decision making and regulation, both for the specific salmon louse case and in other situations of decision making in uncertain environments.

2. Method: Breaking the problem into five questions

We aim to identify how to optimise advice from modelling to support decision making for salmon lice management, given the uncertainties in the system. To achieve this, the process is broken down into five specific questions (Table 1) with different defined roles and responsibilities of policy makers and modellers in this system (HM Treasury 2015; Maas et al., 2022).

Table 1. The five questions to address maximising Knowledge Strength given uncertainty in models.

Question	Method	Responsibility
Q1. What is the objective addressed by the model?	Clear objective defined when model is commissioned	Policy/managers
Q2. What are the causes of uncertainty in model outputs?	Model implementation, building, parameterisation and forcing – the art of modelling	Modellers/Oceanographers/Field and Lab Biologists
Q3. What is the statistical nature of uncertainty?	Issues of noise and bias in understanding uncertainty to be addressed in Q4	Modellers/Statisticians
Q4. How can "Knowledge Strength" be maximised given uncertainties?	Power – more resources applied to reduce noise Wisdom – assessing the extent of noise and reducing bias	Modellers
Q5. How can limits of "Knowledge Strength" be explained to stakeholders?	Unambiguous communication. Clear narratives but relevant uncertainties also presented	Two way communication between modellers and users in policy and management. Clarity for external stakeholders

3. Results and Discussion: Answering the questions

3.1 Question 1: What is the objective addressed by the model?

The purpose of a model depends on the applied objective that decision makers seek to address as part of a wider Blue Economy (Fig. 1). The specific objective should be defined when the model is commissioned (HM Treasury, 2015) and should be clearly understood by scientists and users of the model's outputs. Based on this, policy/management decides the question of interest, although modellers can advise on and discuss its scope and practicality as part of an iterative process. Scientists then assess levels of impact on the ecosystem of specific activities based on their model results. Policy mandates for lice management objectives are derived from parliaments and governments, as shown in Supplementary Material A for Scotland, Norway and the Faroe Islands.

Should circumstances change during model development (such as management objectives, new scientific advice, resource issues) then the decision to change the objectives must be made by policy/management in discussion with modellers. All parties should be clear as to any changes in the modelling objectives, which should be documented.

For example, the objectives of the Sea Lice Risk Assessment Framework (SRAF) in Scotland (described in Supplementary Material A.2) call for the modelling to provide assessments of salmon lice impacts (Figure A.3). Three different types of model fulfil different complementary purposes of (a) screening licence applications, (b) detailed management decision support and (c) scientific research. Modellers and policy makers working on or using these different models must understand that different criteria and aims are being addressed:

a. **Screening models** – these models provide a rapid assessment of whether salmon lice from a proposed new or expanded farm are likely to have an unacceptable impact on wild salmonids. These models must be simple to apply, with minimal local forcing data, so that a decision can be made quickly as to whether increased production will have acceptable, unacceptable or uncertain impacts. If the predicted impact is uncertain, more detailed management models need to be applied to provide additional information. The more discriminating the screening model the smaller the number of sites that will require more detailed further modelling. But there should not be a requirement for excessive effort in modelling or data collection at this screening stage.
b. **Management models** – these models assess the interaction between lice from farms and wild salmonids in more detail (Murray et al., 2022a), where this is ambiguous in the simpler screening models. Such modelling requires local forcing and validation data to assess the impacts of specific farms. These models are used to give more detailed assessments as to whether impacts are acceptable to regulators, and may also be used to consider how predicted impacts can be reduced, for example, by enhanced limitation on permitted lice counts or semi-enclosed farms. When screening indicates potentially unacceptable impact for regulators more detailed management models are created. However, collecting the data to support these models takes more time and money.
c. **Scientific models** – these models are used to advance scientific knowledge and understanding of the system, but also to explore processes that may be relevant for policy and management (e.g. questions of lice biology and lice transport). Scientific models must be developed outside the regulatory process because the way these models are advanced and operated is more complex. Specific scientific modelling is carried out to explore processes that might be relevant and can then be incorporated into management models, for example, whether inclusion of diurnal vertical migration is important for dispersal (Garnier et al., 2024) (now included in various management models).

The model cases here are examples of the application to suit a specific set of purposes. Other models might have entirely different purposes, for example modelling emergence of resistance of sea lice to treatment over years (Coates et al., 2022). The aim here is to illustrate specific examples of different objectives that require different solutions and modellers should focus their models on addressing these objectives.

3.2 Question 2: What are the causes of uncertainty in model outputs?

This technical question of what to include in a model is basically the art of modelling (Jørgensen and Bendoricchio, 2001). As frequently cited, all models are wrong, but some are useful (Box and Lucefio, 1998). Therefore, all model predictions will contain uncertainties because of the underpinning data and knowledge imperfections driving the models - it should also be pointed out that observational data also have errors and uncertainties associated with them. However, it should also be noted that all management interventions in a system require a model, even if only a conceptual one, as without some expectation of a response to intervention (a model) any management is random. By making the modelling explicit we can understand the nature of uncertainties (Question 3) and seek to minimise them (see Question 4).

We identify uncertainties arising from four causes (a - d):

a. **Computational implementation** - Model implementation is limited by computing resources and the technical architecture of models. For example, space and time are continuous, but salmon lice distribution model equations must be solved in spatial grids and with discrete time steps. The use of variable grids allows the modelling effort to be focused on areas of interest to decision makers, but the specific grid selected is a judgement decision. On the biological side, a key limit is the number of particles released in the model, and hence the number of lice each virtual particle represents. The number of particles released must be sufficiently large to allow simulated dispersal to be independent of the number of particles used (Murray et al., 2022a), for the purpose of Question 1. Further issues include the treatment of model boundaries, i.e. how particles behave at open (wet area outside the model domain; are particles lost to the system?) and solid (land, seabed, sea surface) boundaries (i.e. do the particles bounce or stick). This is particularly important in coastal applications with complex coastlines and bathymetry (Garnier et al., 2025). These features have no “true” value in reality, but model implementations that simulate behaviours and features of interest to address Question 1 are what matter.

b. **Model structure** - This is the heart and art of modelling. Developing a model structure concerns decisions about what variables and processes should be included in the model and how they should be implemented as equations and coded in programs (Jørgensen and Bendoricchio, 2001). Some processes may be well understood, others are more uncertain and require further research. In the case of salmon lice, maturation time for larvae to become infectious copepodids is well defined, while vertical swimming behaviours are still debated (Murray et al., 2022a). Vertical swimming behaviour has substantial impacts on dispersal patterns (Garnier et al., 2024) so inclusion of appropriate behaviour is important. Identifying the best model components requires incorporation of the best scientific knowledge and data to allow the closest approach to the true values (Skogen et al., 2021). Key knowledge gaps are reviewed by Moriarty et al. (2024).

c. **Model parameterisation** - Once a model structure is established, the specific parameter values and distributions for processes within that structure are needed (Brooker et al., 2018). There is considerable overlap with defining the structure, but the parameterisation addresses more focused questions for specific evaluation of values, using lab or field data, or expert opinion within this model structure. So, the parameterisation may be considered more as implementing rather than building the model.

d. **Model forcing** - model forcing includes the specific set of local forcing values that are obtained from surveillance data (or other models) to drive model behaviours, for example, local river inputs (Asplin 2020), numbers of adult female salmon lice on farms in the area (Heuch et al., 2011) or tidal forcing at model boundaries. Good forcing data are required for the model to replicate a specific system, and these data may require a system of surveillance

3.3 Question 3: What is the statistical nature of uncertainty?

Before attempting to reduce model uncertainties, we must consider the causes of these uncertainties. Single observations vary from system true mean values (Skogen et al., 2021) for two reasons: noise (a) and bias (b) (Kahneman et al., 2021; Figure 2). Additionally, there can be a phase mismatch (c) between observations and models that makes predictions from models look worse than they are under naïve model fitting. These different uncertainties need to be addressed appropriately.

a. **Noise** is scatter around the true mean value, either due to actual variation within the system, Ontic, or random error due to inadequate measurements, Epistemic (Knol et al., 2009). Noise can be reduced by increasing the number and distribution (in time and space) of observations, thereby reducing the error in the observed mean value, for example, increased fish sample numbers for salmon lice counts on farms (Heuch et al., 2011). Noise does not exist in deterministic models, although it can be specifically included in stochastic models to replicate scatter in observations.

b. **Bias** occurs when measurements deviate systematically from true mean values. Bias implies a process error in either the model or the sampling, or both. This could occur if a measurement technique is of low sensitivity, for example if salmon lice larvae are being misidentified as other zooplankton. In this case the collection of more observations would not reduce bias and so would not increase accuracy of the estimate of the true mean. Instead, increased understanding of the system is required, for example, plankton sampling methods must be improved using species specific fluorescence (Thompson et al., 2022). Bias can also occur in models if parameter values are incorrect. Worse, biased observations might be reproduced by incorporating an equivalent bias into a model if the model is fitted without understanding how and why these observations deviate from a true value.

c. **Phase mismatch** can occur if temporal or spatial deviations in model results exist from observations. To take a meteorological example, consider two forecasts: A “rain at 11 AM” and B “there will be no rain”. In reality, it rains at 10 AM. A naïve interpretation is that model A is wrong at both times, while B is correct at 11 (even if it is wrong at 10 AM). However, as a description of what occurs in the system, A is more useful. In the case of salmon lice, highly transient patches of planktonic larvae might be well simulated in terms of density and duration of patches, but with slight mismatches in space. In this case, a simple correlation of model outputs with observations could be poor for a model that is good and well suited to its purpose.

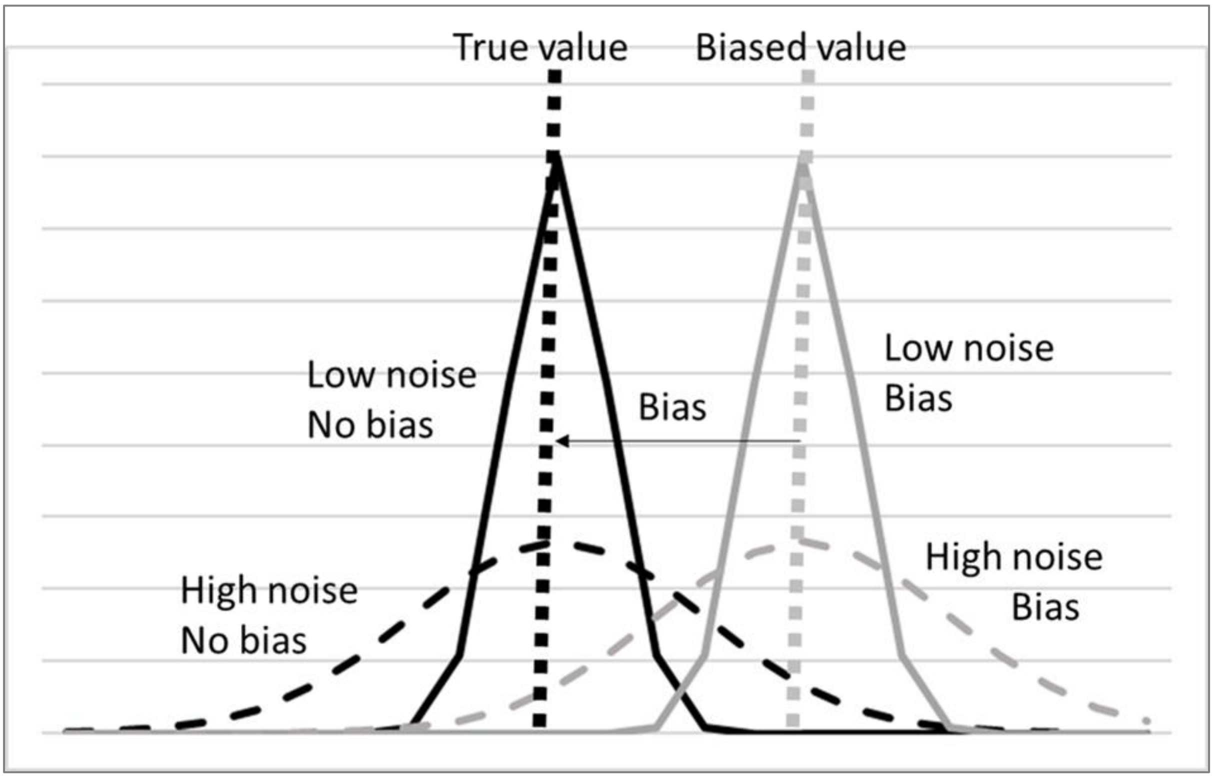

Figure 2: Noise and Bias effects on estimating mean value of a variable (Kahneman et al., 2021). Noise around the estimate of a true mean value is reduced by collection of more data. However, bias is not reduced simply by collecting more data, reduction of bias requires improved scientific understanding of the system measured and/or modelled.

3.4 Question 4: How can “Knowledge Strength” be maximized given the uncertainties in models?

“Knowledge Strength” is maximised when the model outputs provide the best information possible (for the purpose for which they are developed, i.e. Question 1) of the system. Two approaches exist to maximise this: (a) increased resources for computing or data collection that can be used to reduce model uncertainty (which we will call "Power") or (b) analysis of model uncertainty and how this affects outputs (which we will call "Wisdom"). These approaches have different applications dependent on resources, practicality and the type of uncertainty – noise or bias (Kahneman et al., 2021) – in observations.

a. Addressing Strength Through "Power"

The first approach to develop more highly resolved computing implementation of models, or, to collecting more information on the system ("power"). More fundamental scientific knowledge on salmon lice dispersal processes can be obtained to improve model structure (see Question 2.b), more data collection can improve estimates of specific parameters (Question 2.c), or, better surveillance data can more accurately force the model (Question 2.d). Gaps for sea lice models have been reviewed (Moriarty et al., 2024) and stakeholder opinions ranked for priority (Murphy et al., 2024) following an international workshop. Surveillance data (such as sea lice counts from farms) can be useful for model validation. However, data collected in association with management targets may become distorted by the process of meeting those targets (Manheim, 2023). These data (sea lice counts from farms) may be difficult to interpret without expert input due to an inherent population dynamic arising from the frequency of delousing (Sævik and Sandvik, 2023). Nevertheless, such surveillance data is a rich source of existing information and collecting more data, specifically for model validation, costs time and money and does not necessarily cope with sampling bias (Question 3). Multiple independent means of data collection are used in the Norwegian Traffic Light System (Supplementary Material A.1, Figure A.2) and this can allow potential biases to be addressed or at least identified (Stige et al., 2022).

b. Addressing Strength Through "Wisdom"

The second approach to improving model strength is to increase Wisdom, that is, to understand the nature of variation in model output associated with the uncertainties in the modelling: "To say you know something when you know it and to say you do not know something when you do not know it – that is true knowing" (Confucius, cited in Chin, 2014).

Understanding of the system, through application of basic science and from expert opinion (Murphy et al., 2024), allows causes of bias in observations to be identified and either addressed directly, by improved methods, or corrected for, if such improvement is not practicable.

A range of more formal methods for systematic analysis of factors generating uncertainty in model outputs has been developed (Bevan, 2022). For example, the NUSAP approach, used by EFSA in assessing food safety (e.g. Bouwknegt and Havelaar, 2015), uses a quantitative parameter assessment with N being numerical value, U units, S spread (e.g. 95% confidence intervals), together with expert assessment of the reliability of these estimates A. This is combined with a Pedigree matrix, a systematic assessment of the importance of specific parameter uncertainties in overall system uncertainty. The Pedigree matrix is evaluated by breaking down this uncertainty into multiple smaller assumptions such as plausibility of estimates and influence of uncertainties in these estimates on overall uncertainty in results. These assumptions are given a weight based on expert opinion and the product of these weights determines the importance of the factor to overall system uncertainty. This approach thereby combines both assessment of potential variation in parameter values and uncertainty in these assessments on overall confidence in predictions.

Understanding of the model through analysis gives the modeller a consideration of the uncertainties in the outputs and thus the Knowledge Strength – which must be transmitted to the decision makers. Uncertainty in a model can be explored by uncertainty and/or sensitivity analysis (Saltelli et al., 2019). OAT (one at a time) approaches, where only a single parameter is varied, are effective but obviously do not allow for systematic variation of multiple parameters (Saltelli and Annoni, 2010; Saltelli et al., 2019). The variation may be explored using different probability distributions (e.g. uniform, binomial, negative binomial) based on knowledge of the nature of the parameter. Unfortunately, the combined explosion of multiple parameters (Vn where V is the number of values tested for each parameter, e.g. 2 for maximum and minimum values only, and n is the number of parameters in the model) leads rapidly to a situation where systematic analysis becomes impossible. So, more sophisticated approaches must be used to explore a reasonable parameter space, such as simulated annealing (Coveney and Highfield, 1996). Scenario analysis can be used to assess situations where parameters are changed in groups to reflect a specific scenario, for example climate change scenarios where effects of higher temperatures, more freshwater inflow and stronger winds (Murray et al., 2022b) all occur together. The scenario approach has been used in Scottish agriculture to identify robust strategies for coping with an uncertain future environment (Boden et al., 2015). See also Elsawah et al. (2020) for a general review of scenario processes.

c. Ensemble Approaches to combine, Power and Wisdom

Ensemble approaches take multiple model runs with different parameter values or multiple different models to identify areas of agreement and disagreement and therefore give a measure of "Knowledge Strength". This approach is used in climate modelling (Semenov and Stratonovitch, 2010) and epidemiology (Lindström et al., 2015) and is being applied to salmon lice models (Marine Directorate, 2023). It is effectively done informally in the Norwegian Traffic Light system, where results from multiple models and field data sets are compared in the derivation of decisions (Supplementary Material A.1). This is a matter of both power (as multiple models and datasets take resourcing) and wisdom (in deciding how to compare and combine disparate sources of information.

3.5 Question 5: How can information, including uncertainty, be communicated to different audiences?

Model outputs must be communicated to decision makers and a range of other stakeholders if they are useful to inform understanding of those users (HM Treasury, 2015; EFSA, 2022). This knowledge exchange between model builders and model users is complex and often inadequate in practice (Karcher et al., 2021). Communication across boundaries of expertise has been a particular concern in areas such as climate change policy (Beck and Mahony, 2018). The data and models behind model outputs need to be transparent to ensure external stakeholder confidence in decisions (OSR, 2023). Outputs must be useful, understandable, assessable, and accessible (Figure 3), as described below.

- **a. Useful** – the outputs produced by the modellers must provide information that enable informed management decisions, as agreed when the model was commissioned (Question 1). This includes both the key narrative information to support decision making, but also description of relevant uncertainties to inform robust decision making (Stirling, 2010).
- **b. Understandable** – model output must be clearly understood by end users. This understanding must be discussed with the modellers to avoid ambiguity (EFSA, 2022; Speiglehalter, 2017). Publications should use clear and simple language, and assumptions of scientific knowledge should be avoided where possible (UK Government, 2023); summary reports may be valuable for stakeholders without the time to digest longer publications. Presentation of statistical evidence should be supported by clear and logical narratives. However, scientific outputs, such as technical reports or peer reviewed papers addressed to scientists, may require inclusion of technical details that are not readily understood by general audiences. Discussion of reasonable limits for the application of the models can be useful to confine their application to scenarios for which these models are appropriate.
- **c. Assessable** – managers and external stakeholders must not be required to treat the model as a "black box". The model should be transparent, so users are able to check where the outputs come from (EFSA, 2022). This might not be done by the model's output users per se, but the models should be available for assessment by independent experts. Transparency requires that the science and assumptions are specified explicitly and a chain of evidence provided that allows the source and quality of data behind models to be assessed in line with the concept of Intelligent Transparency (OSR, 2023). Sometimes these outputs must be in technical language because, for this assessability step, explicit detail is more important than clarity.
- **d. Accessible** – to be assessable, the output and models should be published, where possible, to allow scientists, managers, and independent stakeholders to access information behind decision making. This includes the clear understandable outputs for policy decision makers or general stakeholders as well as technical manuals and peer reviewed scientific publications to allow details to be assessable by independent experts. Publications should be openly available, preferably on-line, and in formats appropriate for users (https://marine.gov.scot/node/24311). Outputs can include games or toy models allowing stakeholders to explore scenarios (Rodela and Speelman, 2023).

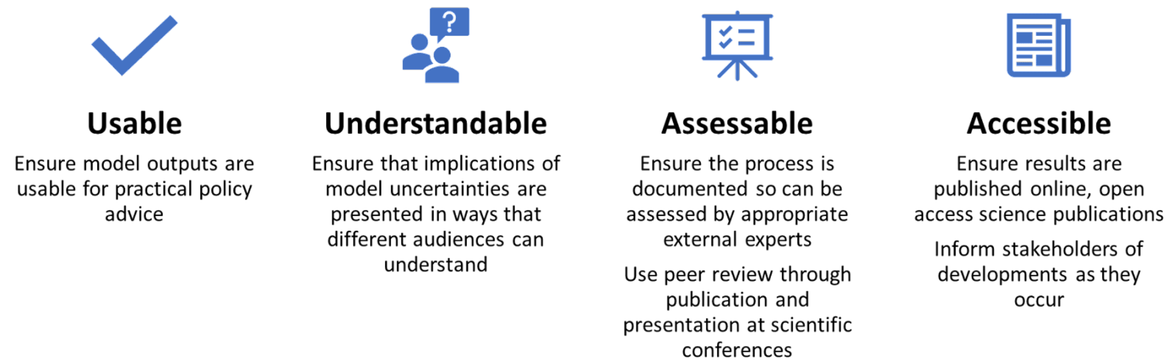

Figure 3: An illustration of the process of making model outputs with uncertainty as useful as achievable to stakeholders by clarifying "Knowledge Strength"

6. Conclusions

The Blue Economy requires decision making that balances economic, ecological, and social interests; the appropriate balance is a policy decision informed by experts. The case of managing impacts of salmon lice on wild salmonids requires coupled hydrodynamic – particle tracking models developed by oceanographers and biological modellers and supported with extensive field and laboratory data sets to formulate, parameterise, force and validate such models. This modelling informs on the impacts of management strategies to meet objectives defined by policy.

These models necessarily contain uncertainties (discussed under Question 2) because of the limitations of models as well as the availability and quality of data in a noisy environment (Box and Lucifio, 1998). Therefore, information derived from models will always have uncertainties. More detailed modelling and improved validation can be done to reduce (but not eliminate) these uncertainties but this is a decision for policy makers. These uncertainties in model outputs must be explained to users such as policy makers (Stirling 2010) without obscuring the narrative of most likely outcomes. This communication is a complex balance dependent on good dialogue and understanding between scientists and decision makers and other stakeholders. This information should be general enough for both parties to be able to decide when a model is good and when a model is "good enough".

When dealing with complex and wicked problems, uncertainties can be used by stakeholders to influence decision making. This can be legitimate, for example, decision on degree of precaution behind a policy, if the full uncertainty is presented, but not if uncertainty is used to present evidence on only the best or worst case estimates. This is a further value of transparency in uncertainties to decision making.

Predicting impacts of salmon lice from farms on wild salmonids, complicated as these are (Moriarty et al., 2023), does allow for a number of generalisations and simplifications that aid understanding. Firstly, there is no need for population modelling of adult lice, as these models can be driven by observational forcing data from farm lice counts (Heuch et al., 2011). This means the models are linear without the need to include feedback from previous infection events. Secondly, lice from farms account for the vast majority of lice in coastal waters (Dempster et al., 2021) and so other sources can be neglected in models. Thirdly, salmon lice do not affect hydrodynamics; this means in coupled modelling the computationally intensive hydrodynamics need be run only once to explore multiple biological assumptions (Murray et al., 2022a); that is, the particle tracking model can be run "offline" from the hydrodynamic forcing. In addition, larval lice do not feed (Hamre et al., 2013), which provides a fixed limit to their persistence in the environment. All of these factors allow modelling to be simplified, reducing sources of uncertainty and allowing more scenarios to be run.

Specific national salmon lice management policies are described in Supplementary Material A. These policies have been developed and implemented in parallel with the principles of "Knowledge Strength" laid out in this paper. The aims of salmon lice management are determined by the various governments and legislated in parliaments (Storting, Scottish Parliament, and Løgting). These aims are implemented in ways that seek stakeholder buy-in through processes such as the stakeholder consultation process initiated by SEPA (see Supplementary Material A) in Scotland to develop the Sea Lice Risk Assessment framework. Stakeholder buy-in to the modelling approach is important and for this reason clear guidelines as to requirements for models (Murray et al., 2022a) and gaps in information behind these models (Murphy et al., 2024) have been sought and obtained from scientists across a wide range of sectors. By formalising the Knowledge Strength approach in this paper we seek to further clarify the process and, by doing so, identify how to further improve salmon lice management.

The approach to increasing "Knowledge Strength" described here for the relatively simple case of salmon lice can be considered as illustrating decision making processes used in other uncertain environments, for example in climate change modelling (Beck and Mahony, 2018) or assessments of human health (Knol et al., 2009). These environments are often far more complex in terms of stakeholders, system scales and feedback mechanisms, and with greater costs and human impacts involved, so decision making is far more complex and so applied approaches need to take these complexities into account (de Pryck and Hulme, 2022). However, the basic principle is the same: policy makers identify the appropriate outputs, but modellers and other scientists make the decisions as to how models should be implemented. Modellers need to provide outputs that are clear to decision makers, but that do not smooth over valuable information on uncertainties. By providing clear outputs to clear questions "Knowledge Strength" is maximised.

Supplementary Material

The Supplementary Material for this article can be found online at https://sesmo.org/article/view/18750/18252.

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