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A decision support system to predict mortality events in finfish aquaculture

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ABSTRACT: The aquaculture industry can be impacted by mortality events triggered by marine heatwaves, pathogens, and other environmental factors. Aquaculture managers would benefit from advanced warning of mortality events so they can make decisions to maximise production and profitability. To help monitor fish health and performance, finfish farms are often equipped with an array of cameras and environmental sensors. However, analysing and interpreting all this information can be difficult. Decision support systems (DSSs) can help by simplifying multiple data sources into a single output for quick interpretation and action. Here, we present a DSS capable of providing salmon farmers with 4 wk warning of an impending mortality event. This DSS was trained on a suite of data routinely collected by New Zealand salmon farmers and provides an alert if weekly mortality is predicted to exceed 0.5%. In the final model, present mortality, water temperature, and standardised feeding rate were all found to be significantly correlated with the probability of a future mortality event. The model performed well when tested on data not included in the model-building process, suggesting that the DSS could be useful to farm managers. This study shows that even limited information can be used to construct a DSS capable of providing some advanced warning of elevated mortality risk. Given the ease with which DSSs can be adapted to ingest and predict other parameters, we see strong potential for future development and adoption of these tools by the aquaculture industry and other sectors.

KEY WORDS: Models · Forecasts · Salmon · Management · Climate change · Disease

1. INTRODUCTION

Marine aquaculture is a highly productive and profitable industry. Each year, the finfish sector alone generates over 8.5 million t of seafood worldwide, worth an estimated US$36 billion (FAO 2024). However, the sustainability and growth of this industry faces many environmental challenges, including climate change, harmful algal blooms, pests, and diseases (Braña et al. 2021, Maulu et al. 2021). Consequently, aquaculture managers are frequently under pressure to make decisions that maintain production and profitability in the face of these challenges (Cobo et al. 2019, Stavrakidis-Zachou et al. 2021).

Although aquaculture managers have limited control over the external environment in open water systems, they can make decisions which maximise fish growth and survival. For example, they can adjust stocking densities, feeding regimes, and stocking and harvesting schedules. They can also choose to conduct on-site maintenance (e.g. net cleaning), artificially supplement oxygen levels, mitigate harmful algal blooms (e.g. by flocculation or water column mixing), and medicate, relocate, or cull some of their stock if necessary (Forsberg & Guttormsen 2006, Gallardo-Rodríguez et al. 2019, Brown et al. 2020, Burke et al. 2022, Wright et al. 2023). However, these decisions are complex and often require urgent action in response to emerging problems and with

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limited information (Georgiades et al. 2016, Reid et al. 2019).

To assist farm managers in making decisions, modern finfish farms are often equipped with an array of sensors and cameras for monitoring a suite of parameters, including water temperatures, dissolved oxygen levels, current speeds, wave heights, fish health, and fish behaviour. Additionally, managers frequently have access to forecasts and reports relating to events such as storms, harmful algal blooms, marine heatwaves, and outbreaks of infectious pathogens (Davidson et al. 2016, 2021, López-Cortés et al. 2017, Alaliyat et al. 2019, Fernandes-Salvador et al. 2021, de Burgh-Day et al. 2022). Analysing and interpreting this wide array of information can, however, be overwhelming and confusing. Therefore, the development of computerised analytical tools, capable of analysing, synthesising, and simplifying a large variety of data, could help facilitate decision-making in finfish aquaculture (Bolte et al. 2000, Mathisen et al. preprint doi: 10.48550/arXiv.1611.08374).

Decision support systems (DSSs) are interactive, computer-based models that can incorporate data from different sources and summarise information in a way that can be quickly interpreted by non-specialists (Shim et al. 2002). They can also be programmed to identify and evaluate different courses of action (Bolman et al. 2018). Correspondingly, DSSs have facilitated decision-making in a wide variety of fields, including stock market investments (Solares et al. 2022), disaster management (Rolland et al. 2010), and clinical diagnosis (Sutton et al. 2020). However, these tools remain underdeveloped and scarcely applied in the context of aquaculture (Mathisen et al. preprint doi:10.48550/arXiv.1611.08374), even though they have the potential to provide a significantly positive impact on the industry.

The aim of this study was to develop a new DSS capable of alerting finfish managers of an impending elevated mortality event, which is a priority concern worldwide (Singh et al. 2024). The prototype described in this paper was designed for, and is currently being used by, the finfish aquaculture industry in Aotearoa New Zealand. As DSSs can be trained on other datasets and redesigned to predict other parameters, the tools and approaches presented here can readily be adapted to other locations and sectors.

2. MATERIALS AND METHODS

2.1. Study area

2.1.1. The New Zealand salmon aquaculture industry

In New Zealand, farmed chinook/king salmon *Oncorhynchus tshawytscha* represents 15% of annual aquaculture production by weight but nearly half of the country's aquaculture-derived revenue (Brosnahan et al. 2019). As a result, the continued viability of this sector could contribute disproportionately towards economic growth. Despite driving significant revenues, salmon aquaculture in New Zealand has experienced high mortality rates in recent years, with annual mortality on farms increasing from around 17% to a peak of 42% between 2018 and 2022 (McClure 2022). Such mortality rates inevitably incur large financial costs; for example, a single mortality event in January 2022 resulted in an estimated loss of US$12.6 million (NZKS 2022). This prompted the industry to suspend production at several farms within the Pelorus Sound (Fig. 1) and to develop more resilient brood stocks and production cycles (NZKS 2024).

Although the exact mechanisms underlying these high mortality rates remain undetermined, thermal stress caused by marine heatwaves and high summer sea surface temperatures are a likely cause (Broekhuizen et al. 2021, Lane et al. 2022). Emerging infectious pathogens (Brosnahan et al. 2019, Kumanan et

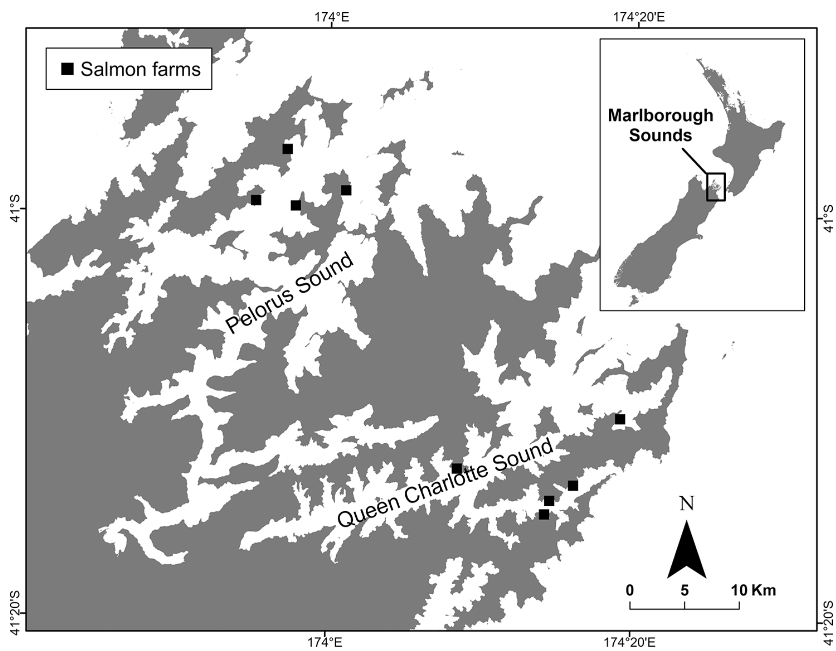

Fig. 1. Salmon farm locations within the Marlborough Sounds, New Zealand

al. 2022, 2023) and harmful algal blooms (MacKenzie et al. 2011, Hallegraeff et al. 2021, Rolton et al. 2022) may also be contributing factors. Worryingly, all these factors may be exacerbated by climate change.

2.1.2. Marlborough Sounds

The Marlborough Sounds in New Zealand produce over half of the world's cultured chinook salmon (Brosnahan et al. 2019). The largest water bodies in this region are the Pelorus Sound and Queen Charlotte Sound (Fig. 1). Marine farms in the Marlborough Sounds are categorised as being either low or high flow depending on whether mean mid-water current speeds are greater or less than 10 cm s^{-1}, respectively (Fletcher et al. 2022). Generally, low-flow sites have experienced the highest rates of mortality in recent years.

2.2. DSS development

2.2.1. General approach

The 4 main considerations when developing a DSS are: (1) end-users; (2) objectives; (3) data (i.e. quantity, quality, and inputs); and (4) outputs (Bolman et al. 2018). For the first and second considerations, it is highly recommended that developers consult end-users throughout planning and testing stages to ensure the DSS aligns with end-user objectives (e.g. Reed 2008, Allen et al. 2017, Bolman et al. 2018). In doing so, the DSS is more likely to be of benefit to end-users and, therefore, be integrated into their decision-making processes. Regarding the third consideration, it is critical to ensure there are sufficient quantity and quality of data to train and validate models prior to DSS development. Lastly, it is important that DSS outputs are useful and interpretable by end-users. It is for these reasons that farm managers and veterinarians were consulted throughout the development and testing of the DSS presented in this study. Fig. 2 provides a conceptual diagram of this development process.

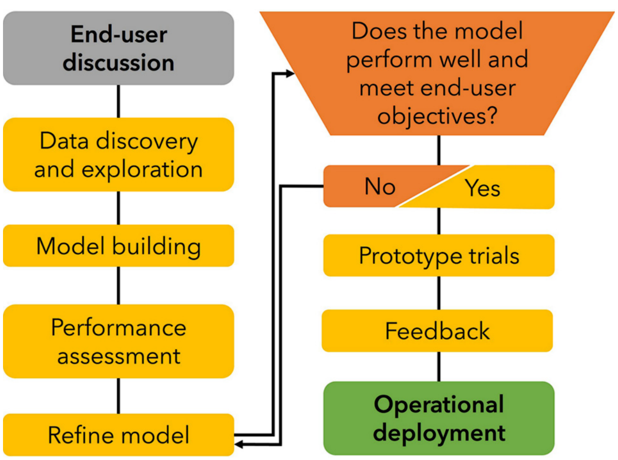

Fig. 2. The process taken to develop a decision support system capable of predicting mortality events to assist the New Zealand salmon aquaculture industry

2.2.2. Data sources

During consultations, end-users specified that the DSS should simplify a suite of data that are already routinely collected and monitored on New Zealand salmon farms. These data can be divided into:

1. Environmental data: oxygen saturation (%) and water temperature (°C) sampled once per day at approximately 5 m depth in a consistent location and time on each farm using a calibrated handheld sensor.

2. Stocking data: estimated number, total biomass (kg), mean weight (kg) and density (kg m^{-3}) of fish within each individual pen. Density was calculated by dividing the total biomass by the volume of the fish pen.

3. Feeding rates: 'standardised feed rate', calculated as the total weight of feed supplied to each pen as a percentage of its total fish biomass.

4. Mortality: the total number of dead fish counted per day in each pen or farm.

These data were provided by the New Zealand King Salmon Company Limited as a single value per day for high-flow chinook salmon farms within the Queen Charlotte Sound between 2017 and 2022.

2.2.3. Data exploration and preparation

All data analysis was conducted in R (v.4.4.0)(R Core Team 2024). Data exploration followed the approach described in Zuur et al. (2010). Mortality, temperature, and oxygen concentrations were logarithmically transformed with an added scalar ($\log_{10}(x + 1)$). While logarithmic transformation can potentially make interpreting results more challenging, it was considered an appropriate step to reduce skewness and the influence of outliers on the linear models created in this study.

Daily mortality rates were highly variable between and within pens. According to farm managers, some of this variability may be due to differences in estimation methods among staff, and difficulties in making consistent daily mortality measurements during adverse weather. Consequently, all mortality and other data were aggregated to weekly values at the farm scale. Temperature was aggregated as the weekly maxima, dissolved oxygen as the weekly minima, and all other variables as the weekly mean from daily values. Following these preparatory steps (including transformations on some variables), maximum weekly temperature was found to be strongly positively correlated with mortality (Pearson's $r = 0.5$, log-log relationship) and standardised feeding rate was the most negatively correlated (Pearson's $r = -0.446$, log-linear relationship).

2.2.4. Model building

To construct the model, elevated mortality was defined as 'true' or 'false' if weekly mortality rates were greater or less than 0.5%, respectively. This threshold was partly determined by farm managers and partly to ensure there were enough mortality events to provide a suitable sample size to build a model. To predict the binomial 'true' or 'false' threshold, logistic generalised linear models (GLMs) were constructed within R using a binomial error distribution and logit link function (R Core Team 2024). This linear modelling approach was selected, given the simplicity of its interpretation and widespread use in animal health investigations (Dohoo et al. 2014), and its use was confirmed through a comparative performance assessment against 5 other classification methods (see later in this section). The models were trained on a randomly selected 70% fraction of the dataset, referred to as the 'training dataset'. A 'testing dataset' was then constructed from the remaining 30% and was subsequently used to assess model performance.

To ensure a balanced above- and below-limit response variable, data were up-sampled using the 'Caret' package (Kuhn 2008). Categorical model performance was assessed using Cohen's inter-rater performance metric (Cohen 1960), often referred to as Cohen's kappa (κ). The κ metric will give a value of 0 for a worthless model, 1 for a perfect model, and is considered 'good' if it has a value >0.6 (Landis & Koch 1977). Iterative backward stepwise selection using the 'glmStepAIC' method from the 'Caret' package (Venables & Ripley 2002) was used to select the most performant model based on κ. Model selection was based on 3-times repeated 10-fold cross-validations of the training dataset, including interaction terms. If the final model included non-significant terms ($p > 0.05$), they were excluded and the model selection process was repeated until an optimal model containing just significant terms was generated.

For farm managers to formulate and execute a management response within a timely manner, end-users specified the DSS must be able to provide warning in advance of an event. Thus, to assess the potential to forecast mortality events up to 4 wk in advance, the model selection process was repeated on explanatory variables that were lagged by between 1 and 4 wk. Overall, the cross-validation machine learning approach used in this study was considered an appropriate way to build a robust model while setting aside some independent data to assess model performance (Bergmeir & Benítez 2012).

Performance of our selected logistic modelling approach was compared to alternative machine learning classification methods across all 4 lag periods, using κ as the performance metric. This comparison used the same 'Caret' model training approach, on the training dataset for the following 5 additional methods: random forest (Liaw & Wiener 2002), LogitBoost (Dettling & Bühlmann 2003), linear and quadratic discriminant analysis (Venables & Ripley 2002), and penalised discriminant analysis (Hastie et al 1995). The comparative performance of the logistic 'glmStepAIC' modelling approach used here showed the best performance on the testing data (i.e. data not used for training) (see Table S1 in the Supplement at www.int-res.com/articles/suppl/q017p033_supp.pdf). Training performance was better for some other methods (i.e. random forest and LogitBoost methods), but worse test data performance shows these methods were less able to predict mortality events on independent data. The reduced performance of these other methods on the test dataset was not investigated in detail, but may be due to overfitting of the other models on training data (e.g. Hawkins 2004).

Confirmatory analyses were performed on the final logistic models using the testing dataset. Receiver operating characteristic (ROC) analysis of area under the curve (AUC) was also conducted to provide management-specific performance measures on sensitivity and specificity (i.e. true positive and true negative rates) from the models (reviewed in Fawcett 2006). Model performance was considered better than 'good' when the AUC was >0.8 (e.g. Wikstrom et al. 2012) and when κ was >0.6 (Landis & Koch 1977). To determine an appropriate threshold for the model results, the maximum Youden's *J* statistic (Peirce 1884, Youden 1950, Fluss et al. 2005) was used to determine an optimal threshold for determination of a mortality event (referred to here as the 'Youden point').

As detailed in Section 3, the inclusion of mortality as a lagged dependent variable produced the best-performing model, indicating the importance of autocorrelation in the model (i.e. that past mortality affects future mortality). For example, a 4 wk model with lagged mortality included as a predictor produced a κ value of 0.68, compared to 0.55 when it was omitted. However, including a lagged dependent variable is potentially problematic, as the strong association of future mortality to historical mortality can reduce the influence of other influential explanatory factors (Keele & Kelly 2006, Wilkins 2018). Nevertheless, as past health is highly likely to influence future health, particularly if there are pathogenic drivers (e.g. May & Anderson 1979), and that the best-performing model included the lagged dependent variable, it was considered suitable for inclusion here.

2.2.5. DSS application

For user-friendly access to the DSS, a web-based application programming interface (API) was created using the 'PlumbeR' package (Schloerke & Allen 2022). A web-calling function was set up in Microsoft Excel to allow farm managers to manually input daily recordings of environmental, stocking, feeding, and mortality data, and then retrieve outputs indicating the risk of an impending elevated mortality event. While a manual data entry system is not advisable in the long-term, because of workload and potential for human error, it was considered a useful temporary solution for development and testing of the prototype DSS.

3. RESULTS

3.1. Model performance

All models performed better than 'good' on the testing dataset (Table 1). Although model performance decreased the further into the future mortality events were forecasted (i.e. κ and AUC decreased with increased lag), the DSS was deemed suitable for detecting mortality events up to 4 wk in advance (i.e. κ > 0.6 and AUC > 0.9 for the testing dataset). As the end-user was interested in having as much early warning as possible, the remainder of this paper focuses solely on the 4 wk forecasting model, referred to as the 'final model' from herein.

Table 1. Estimates of model performance on the training and testing datasets across varying lags of explanatory variables. AUC: area under receiver operating characteristic curve; κ: Cohen's kappa; N: sample size. Note that up-sampling of rare mortality events applied to training data, so N is artificially inflated

Lag	κ		**AUC**		**N**	
(wk)	Training	Testing	Training	Testing	Training	Testing
1	0.884	0.793	0.974	0.964	472	134
2	0.817	0.605	0.957	0.912	468	133
3	0.669	0.667	0.927	0.863	466	133
4	0.574	0.657	0.874	0.905	464	132

In the final model, lagged mortality was significantly ($p < 0.05$) positively correlated with the probability of a future elevated mortality event, and lagged feeding rate was significantly negatively correlated (Table 2). Therefore, reduced feeding and high present mortality were associated with a greater probability of a future mortality event. There was also a significant positive interaction between temperature and feeding rate, indicating that higher temperature (for a given feeding rate) was also associated with higher mortality.

The final model performed better than 'good' on the testing dataset, yielding a Cohen's κ of 0.66 (Table 1) at the optimal Youden point threshold value of 0.56 (Fig. 3). If the model returned values greater than this threshold, the model would be predicting an 82% chance of an elevated mortality event within the next 4 wk (Table 3). At this threshold, there is also a low probability (12%) the model would fail to predict an elevated mortality event (i.e. a false negative), but a similar probability (18%) that the model could raise a false alarm (i.e. a false positive) (Table 3). The model was likely able to predict true negative events better than true positive events

Table 2. Coefficient estimates for 4 wk lagged variables in the final logistic regression model of future weekly mortality threshold exceedance, where the mortality threshold was set at 0.5% wk^{-1}. SE: standard error; z: z-value at which coefficient changes sign; p (>|z|): probability of coefficient changing to positive or negative; *statistical significance ($p < 0.05$)

Coefficients	Estimate	SE	z	p (>|z|)
Intercept	−0.7572	0.4653	−2.76	0.104
Log_{10}(Mortality+1)	9.7949	1.5179	6.63	<0.001*
Feeding	−25.1263	4.7326	−5.61	<0.001*
Log_{10}(Temperature+1): Feeding	20.1618	3.7972	5.64	<0.001*

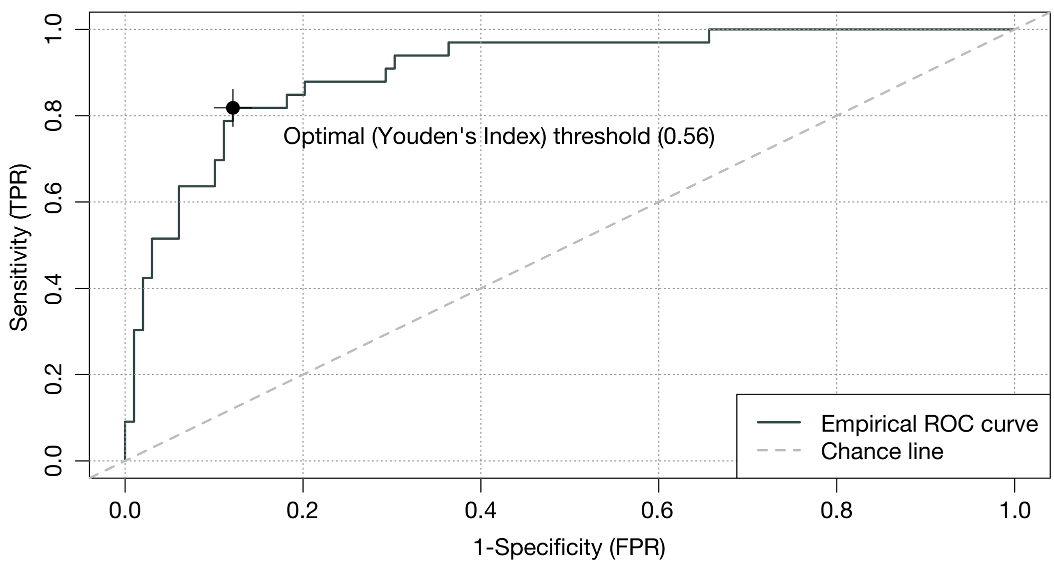

Fig. 3. Receiver operating characteristic (ROC) curve for the model on the test dataset (n = 132). The optimal (Youden point) value was 0.56 and the area under the curve was 0.91. TPR: true positive rate; FPR: false positive rate; and 'chance line': the theoretical performance of a random choice

because elevated mortality events were comparatively scarce in the data.

It is also possible for farm managers to adjust the DSS without changing the underlying model. For example, lowering the logistic threshold would make the model more likely to predict mortality events (true positives), but will also raise a greater number of false alarms (false positives). Alternatively, raising the logistic threshold could cause the model to miss some elevated mortality events (false negatives), but would raise fewer false alarms. Therefore, farm managers can choose to raise or lower the logistic threshold if the consequences of missing a mortality event are high, or raise the threshold if false alarms are too costly. Such trade-offs may be reduced in the future, if new data, or training methods, further improve model accuracy.

Table 3. Confusion matrices of model performance applied to the testing and industry trial datasets. Count values are provided, with percentage performance in brackets: true negative (TNR), false negative (FNR), false positive (FPR), and true positive rate (TPR). The same optimal training threshold value (0.56) was applied to both the testing dataset from the training period, and the industry trial

Test scenario	Predicted values	Actual values Negative	Positive
Testing dataset (N = 132)	Negative	87 (88% TNR)	12 (12% FNR)
	Positive	6 (18% FPR)	27 (82% TPR)
Industry trial (N = 175)	Negative	100 (79% TNR)	26 (21% FNR)
	Positive	13 (27% FPR)	36 (73% TPR)

3.2. Industry trial

To further assess model performance, the DSS was independently tested by inputting data collected during the summer of 2022/2023 from 3 high-flow chinook salmon farms in Queen Charlotte Sound. Overall, this industry trial of the 4 wk forecasting DSS did not perform as well as the model did on the testing dataset using the optimal testing threshold for classification. An AUC value of 0.84 (Fig. 4) and a Cohen's κ of 0.47 were recorded for the industry trial. Similarly, there was a reduced true positive rate of 79% and increased false positive rate of 27%, indicating the industry trial led to a higher rate of false alarms and a lower rate of true positives.

Given this situation, a shorter forecasting could be used to improve performance. For example, the 2 wk lag model meets the 'good' performance criteria based on Cohen's κ metric (κ = 0.62). However, given that the 4 wk model still appears to support prediction of most events, it may still be useful for the New Zealand chinook salmon aquaculture industry operating within Queen Charlotte Sound. In addition, the optimal Youden point for the industry trial was a lower value than the optimal training threshold (Fig. 4), so this performance could be improved through selection of a different threshold.

A visual summary of the results of the trial are provided in Fig. 5. All the farms experienced different intensities and timing of mortality events. Clay Point experienced the highest rates of weekly mortality

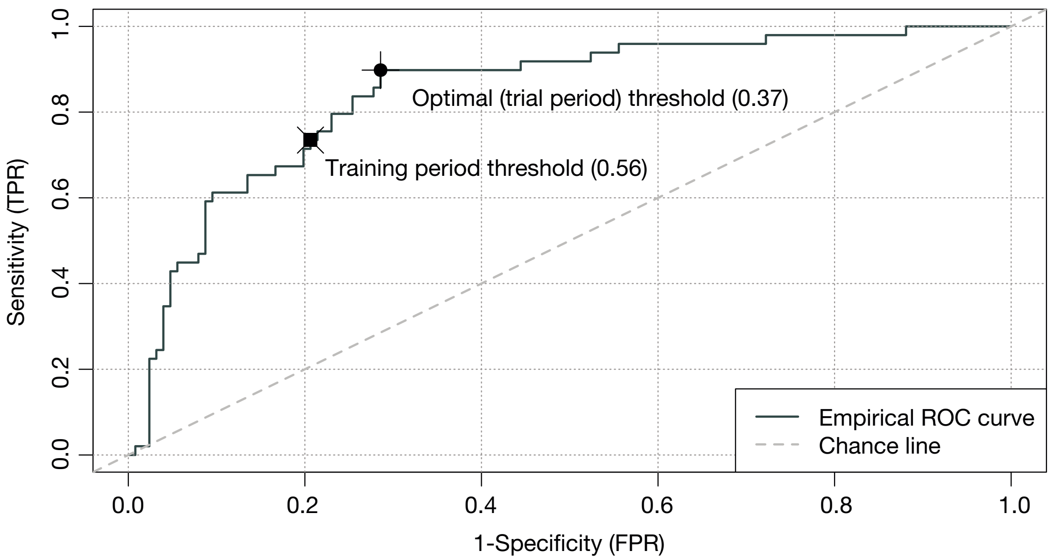

Fig. 4. Receiver operating characteristic (ROC) curve for the model on the industry trial dataset (n = 174). The optimal (Youden point) threshold point value for the industry trial was 0.37 and the area under the curve was 0.84. The optimal threshold value for the training period (0.56) is also shown to demonstrate how the choice of threshold affects the sensitivity and specificity of the model. TPR: true positive rate; FPR: false positive rate; and 'chance line': the theoretical performance of a random choice

(about 1.5% wk^{-1}), which peaked in June–July 2023. Ngamahau exhibited elevated mortality only in March 2023, while Te Pangu experienced elevated mortality in January and April 2023. Overall, the model appears to be 'reactive', as it only seems to predict an impending mortality event after an initial spike in mortality is recorded. Ideally, the underlying drivers of the initial spike in mortality would be better identified, or have a stronger influence, in future iterations of this DSS. While reactivity is likely an artifact of including a lagged mortality response variable in the model, the model's reasonable performance suggests that the inclusion of lagged mortality is still valuable for the purposes of supporting decision-making. It is also apparent that applying the higher decision threshold obtained from the training dataset fails to predict some high mortality events in the trial dataset (i.e. too many false negative predictions). Consequently, while the model undoubtedly has value for predicting elevated mortality, further training and refinement of the models underlying this prototype DSS would be beneficial.

4. DISCUSSION

DSSs can facilitate decision-making by analysing complex data and simplifying it into outputs which can be quickly interpreted and acted upon by non-specialists. This study aimed to develop a DSS capable of providing finfish aquaculture managers in New Zealand with 4 wk warning of an impending mortality event. With adequate warning, farm managers could then implement decisions to reduce mortality, such as increasing surveillance during periods of high risk, reducing feed inputs (thereby reducing metabolic demand), supplementing oxygen levels, or harvesting the stock earlier than planned. As chinook salmon farms in New Zealand have suffered high mortality rates in recent years, such a tool could prove invaluable and help the industry reduce losses while promoting production and profitability. Furthermore, the DSS approach presented here could easily be adapted to suit a wide range of different sectors and industries.

Finfish farmers in New Zealand routinely collect and monitor a suite of biophysical data. When lagged, several of these variables (i.e. temperature, mortality, fish weight, and feeding rate) were found to significantly influence future mortality. By inputting these data into a DSS, the model was able to predict 56% of the true elevated mortality events up to 4 wk into the future on a completely independent dataset. Although a higher percentage should be aimed for in the future, end-user feedback has been positive, with farm managers and veterinarians stating the tool is already helping them simplify decision-making and prioritise additional fish health surveillance when the elevated risk of mortality has been predicted. Consequently, the use of DSSs in finfish aquaculture has potential to improve fish welfare and farm profitability, with little need for additional investment, as suit-

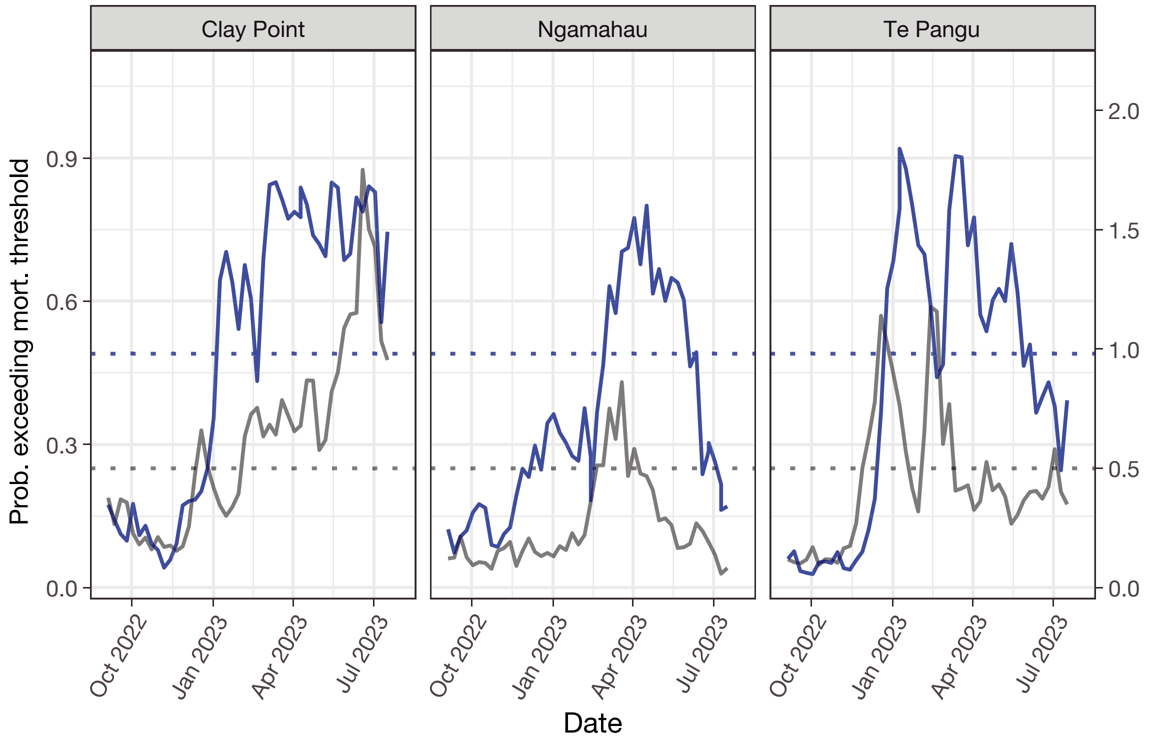

Fig. 5. Visual comparisons of the modelled probability of a future mortality event exceeding the mortality threshold (blue solid line) across the 3 salmon farm sites (Clay Point, Ngamahau, and Te Pangu) compared with future (4 wk) mortality rates (grey solid line) observed over the summer of 2022–2023. Also displayed (blue dotted line) is the probability (Youden point) threshold for estimating future mortality exceedance (obtained from the training dataset), and the weekly elevated mortality threshold of 0.5% (grey dotted line). Note that the model probabilities have been shifted forward by 4 wk to facilitate comparisons with future mortality

able data already exist and are routinely collected by the industry.

The positive correlation with temperature and mortality was expected, as high summer temperatures are a driver of elevated mortality in this region (Broekhuizen et al. 2021, Lane et al. 2022, McClure 2022). Likewise, correlation between lagged and future mortality suggests that elevated mortality results is associated with future mortality risk. This is intuitive, as high baseline mortality would suggest an existing stressor is already starting to have a negative impact on fish health. In contrast, feeding rates were negatively correlated with mortality, which suggests that fish appetite may be reduced preceding a mortality event, and is a common trend in fish suffering from disease or environmental stress (reviewed in McClure 2022). Interestingly, while low dissolved oxygen concentrations can contribute towards aquaculture mortality, especially during warm summer months (Oldham 2018, Sajid et al. 2024), the model did not find oxygen to have a significant relationship with mortality. Industry discussions suggested this is because oxygen levels typically remain above 80% saturation in the region studied (Broekhuizen & Plew 2018).

Although the prototype DSS presented here is already proving useful to the New Zealand finfish aquaculture industry, there are several aspects that could be improved. Firstly, the prototype only predicts mortality at the farm scale. However, farm managers would prefer the DSS to operate at a pen scale so they can make more focused decisions, such as early harvesting a single pen, rather than an entire farm. To achieve this, it is likely some trade-offs would be required based on current data inputs, such as reducing the forecasting period to less than 4 wk. Potential improvements could also be made by adopting a different modelling approach, such as incorporating bioenergetic approaches to better model thermal stress (e.g. Stavrakidis-Zachou et al. 2023). Predictive power could also potentially be improved by sourcing additional information (e.g. weather) or greater-resolution environmental data (e.g. more frequent sampling of oxygen and temperature within pens), in addition to data on fish health (e.g. lesion prevalence) and behaviour (e.g. feeding and swimming).

The model could be further improved by sourcing new cost-effective, and potentially valuable, information from emerging technologies, such as the combined use of underwater video systems and artificial intelligence, which can better inform changes in fish health and behaviour (e.g. Pinkiewicz et al. 2011, Gupta et al. 2022). Additionally, seasonal forecasting tools could provide predictions of key environmental parameters, such as water temperatures and wind, for up to 6 mo in advance (e.g. Jacox et al. 2022). Likewise, farm management forecasting tools could provide estimates of future fish weight and density (Thyholdt 2014, Føre et al. 2016), which could enable longer projections. Another improvement could be made by automating model improvements to enable the DSS to retrain itself as additional data become available. This has the potential to create a feedback loop, whereby the model used by farmers helps to reduce mortality rates and improve farming practices, but in turn, hinders future predictions of increasingly rarer mortality events.

Independent of DSSs and this study, more research into the drivers of elevated mortality is needed to ensure farming practices and locations are appropriately tailored to sustaining healthy stocks and reducing their exposure to environmentally driven mortality. In New Zealand, there has been recent focus on compromised fish health caused by higher ocean temperatures and pathogen outbreaks (e.g. Brosnahan et al. 2019, Johnston et al. 2021). Future DSSs should take advantage of any new insights to the causal factors of elevated mortality in finfish aquaculture to generate DSSs with greater predictive power and warning time.

5. CONCLUSIONS

Global finfish aquaculture production has increased dramatically in recent decades (FAO 2024). However, maintaining consistent production and profitability is being hindered by a variety of environmental challenges (e.g. marine heatwaves, harmful algal blooms, extreme weather, and pathogens) that are increasing in frequency, scale, and duration (Samsing et al. 2017, Sajid et al. 2024, Singh et al. 2024). As these events can negatively impact fish health and survival, they pose serious animal welfare concerns and can have strong negative impacts on local economies and coastal communities.

The aquaculture industry often collects extensive data on stock health and behaviour, as well as environmental conditions such as temperature and dissolved oxygen. This provides untapped potential to explore drivers of fish health and mortality. As indicated by the DSS presented here, even relatively small amounts of information can provide advanced warning of elevated mortality risk, and can be used to help inform aquaculture management decisions. Given the ease with which DSSs can be adapted to other sectors and used to predict other parameters, we see strong potential for future development and adoption of DSSs by the aquaculture industry.

Data availability. All computer code used to undertake these analyses is available upon request. Data used in this study is privately owned and can be requested by application to the New Zealand King Salmon Company.

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