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Modelling temperature and fish biomass data to predict annual Scottish farmed salmon, *Salmo salar* L., losses: Development of an early warning tool

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ABSTRACT

Losses due to mortality are a serious economic drain on Scottish salmon aquaculture and are a limitation to its sustainable growth. Understanding the changes in losses, and associated drivers, are required to identify risks to sustainable aquaculture. Data on losses were obtained from two open source data sets: monthly losses of biomass 2003 – 2018 and losses of salmon over production cycles (numbers input minus output harvest) 2002–2016. Monthly loss rates increased, accelerating after 2010, while losses per production cycle displayed no trend. Two modelling frameworks were investigated to produce an early warning tool for managers about potential increases in losses. Both linear regression and beta regression showed that monthly losses related to biomass and minimum winter air temperatures with high precision and low bias. These relationships apply at both the national and regional levels where the beta regression best fit model explain 82 % and 69 % of variation in mortality, some regional differences apply, particularly for the Northern Isles. The lack of trend in losses per production cycle may have been due to shorter production cycles as more salmon were harvested earlier, and possibly increasing losses of larger salmon (which affects biomass but not numbers lost). In the long-term, the models predict that milder winters and increased biomass will be associated with increased mortality, which will need to be managed. In the short-term, given relatively little year-to-year variation in biomass, minimum winter temperature is a powerful early warning of the likely extent of losses in the Scottish salmon farming industry.

1. Introduction

Atlantic salmon, *Salmo salar* L., aquaculture is an important contributor to the Scottish economy, with a 2018 production of 156,025 tonnes whole fish weight, which had a farm gate value of £878 million (Munro, 2019) to the Scottish economy. Salmon production grew rapidly in the 1980’s and 1990’s but in recent years this growth has slowed. It fell during 2015 and 2016, and although production rose to its highest ever tonnage in 2017, there was a subsequent decrease of 17.8 % in the 2018 production level (Munro, 2019). To support sustainable growth in the aquaculture industry it is necessary to identify the factors that could inhibit production potential.

A limiting factor in maximum production potential is mortality (Aunsmo et al., 2010). There are a number of contributors to losses such as management, environmental factors, predation and disease (Soares et al., 2011). Monitoring trends in mortality may be used as an operational welfare indicator, as high mortality may be an indication of poor welfare (Ellis et al., 2012). About one third of production losses are attributed to diseases (Soares et al., 2011), the significance of different diseases has changed over time with viral diseases and sea lice increasingly becoming the focuses of research (Murray et al., 2016). Loss levels of Scottish salmon production have been relatively consistent at 10–20 % per production cycle for many years (Salama et al., 2016; Murray and Munro, 2018), however, loss rates above 20 % have occurred in recent years (Munro, 2019) and the emergence of gill diseases is an increasingly serious problem (Oldham et al., 2016; Hall et al., 2017). Changes in climate, particularly water temperatures has been linked to emerging marine diseases (Harvell et al., 1999), and may be an associated factor in increasing mortality on salmon farms (Thyholdt, 2014). Coastal sea surface temperatures around Scotland were, on average, between 0.2 °C and 0.4 °C warmer in the 2006–2016 period when compared to the longer-term average from 1981 to 2010 (Hughes et al., 2018). These temperature rises have been associated with changes in ecology and wild fisheries including salmon growth (Beaugrand and Reid, 2003; Todd et al., 2008). Temperature changes are likely to be associated with changes in aquaculture; as warming temperatures have positive effects that includes increases in growth rate (Calloway et al., 2012; Collins et al., 2020). However, warming temperatures also have negative effects that include increased prevalence and severity in diseases and parasitic infestations such as

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bacterial diseases (Thompson et al., 2006), sea lice (Rittenhouse et al., 2016) and particularly gill diseases (Oldham et al., 2016; Benedicenti et al., 2019).

The transmission of pathogens in aquatic environments is also likely to be associated with increased biomass. Many pathogens ability to transmit is enhanced as population densities increase (Anderson and May, 1979; Murray, 2009). Pathogens are often exchanged between aquaculture sites, the risk of transmission between sites is attributed to water movements and the distances between sites, and is related to number of sites and biomasses on sites (Salama and Murray, 2011).

The potential role of increased mortality in limiting growth of production is investigated here, through an assessment of the recent mortality trends. We aim to establish if there is any statistical significance in changes in losses over time and, if these are significant, to identify factors associated with variation in these losses. In this paper we posit that mortality rates in farmed salmon have increased in recent years. Secondarily we test the hypothesis that mortality rates are related to temperatures (either summer maxima or winter minima) and area population (as a proxy for density) experienced by fish, in a broad scale regional analysis. Finally, we develop and evaluate a modelling framework to assess the potential risk of losses in the current production cycle, to better inform management decisions.

2. Methods

2.1. Data sources

Open source data made available from industry and/or government bodies and agencies make reproducible research possible. Here the authors have decided to use only open source data to demonstrate the applications of these resources, particularly for managing risk in the current production cycle and assessing the long term trends in industry practises. The spatial and temporal resolution of these data varies so must be rationalised prior to analysis. Data were obtained from three sources, Scotland's Aquaculture website, Marine Scotland and the UK Met office. The first two sources capture information on losses and production on marine salmon farms while the latter provides data on environmental temperatures. The losses data are analysed as functions of environmental temperature, year and region (Table 1). The distribution of farms and regions is shown in Fig. 1.

2.2. Biological datasets

2.2.1. Monthly biomass losses

Data for 2002–2018 collated by the Scottish Environment Protection Agency (SEPA) on the aquaculture industries behalf was downloaded from Scotland's Aquaculture website (http://aquaculture.scotland.gov.uk/. Monthly consented biomass of fish present on each site (tonnes) and associated losses of biomass (kilogrammes) was the information required. This open source data does not include information on; the species being farmed; time on site; size or numbers of the fish when consented biomass and associated losses were recorded. Assessing records held by Marine Scotland it was possible to identify the species being farmed and subset the farms which held Atlantic salmon. Marine production of sea trout, *Salmo trutta* L., and rainbow trout, *Oncorhynchus mykiss* (Walbaum), and other species (e.g. lumpsucker, *Cyclopterus lumpus* L.) amounting to around 2.5 % of the biomass per year was removed from the data. The number of records of sites reporting biomass and mortality in the first year of the dataset (2002) was considered inconsistent with the subsequent years, as such these data were excluded from the analysis. There can be issues with synchronising reporting of biomass and mortality in the first and last month of a production cycle. For example, a site may report zero biomass but finite mortality if it had been harvested by the end of the month. Thus for this analysis we use regional averages in which averaged losses were divided by average biomass over all active sites in the region, to correct for site-level discrepancies between biomass and mortality reporting dates.

Annual average regional loss in tonnes per month (m), is the sum of losses in all farms in a region (or nationally) for all months in a year, divided by twelve. Average monthly biomass (B), is the sum biomass in all farms in a region (or nationally) for all months in a year, again divided by twelve. Proportional loss rate $M = m/B$, is calculated nationally or regionally and for each year. Values for M and B are listed in Appendix A. The proportional losses are used to calculate the odds of mortality, $M/(1 + M)$, for use in the regression analysis.

2.2.2. Numbers of salmon lost per production cycle between input and harvest

Marine Scotland has collected data on aquaculture production at the regional and national levels for the Scottish fish farm production survey since 1979 (Murray and Munro, 2018; Munro, 2019). This includes data on the difference between the numbers of salmon input and harvested, which gives an alternative measure of survival through a production cycle that can be compared with the monthly biomass loss data. Data is also available on the year of harvest after the year of input (0, 1 or 2 years).

Survival and harvest can only be calculated after the records for a complete harvest of a production cycle are obtained, which will be up to two years after the input. Currently, 2016 is the most up-to-date input year class (Munro, 2019). Loss rates correspond most closely to the year after input, so the 2002–2016 inputs can be used to compare with the biomass loss data for 2003–2017. These data are thus inherently out of date with respect to current loss rate patterns and are less useful for investigating recent loss issues than the SEPA monthly losses data (biological dataset a).

Regional loss data can also be obscured by the movement of salmon between sites, which can include movement across regional boundaries. If part grown salmon are moved from region A to region B, this leads to reduced production in A, and therefore apparently increased losses, and the reverse in region B. In the Southwest region in 2009, proportional apparent loss was -0.09 (i.e. a net gain), so for our analysis this is set at 0.01. The proportions of numbers of salmon lost per production cycle are used to carry out an additional analysis that provide additional

Table 1
Modelled variables and parameters.

Name	Definition	Units	Source
m	Biomass loss	Tonnes month^{-1}	SEPA
M	Proportion biomass lost	Month^{-1}	Calculated (M = m/B)
μ	Proportion lost per production cycle		Marine Scotland
B	Mean total biomass in area by year	Tonnes	SEPA
β	Mean total biomass 2003 – 2018	Tonnes	Weight for regional analysis
Yr	Year		SEPA
R	Region		SEPA/Marine Scotland
A_w	Winter minimum air temperature	°C	Met Office
A_s	Summer maximum air temperature	°C	Met Office

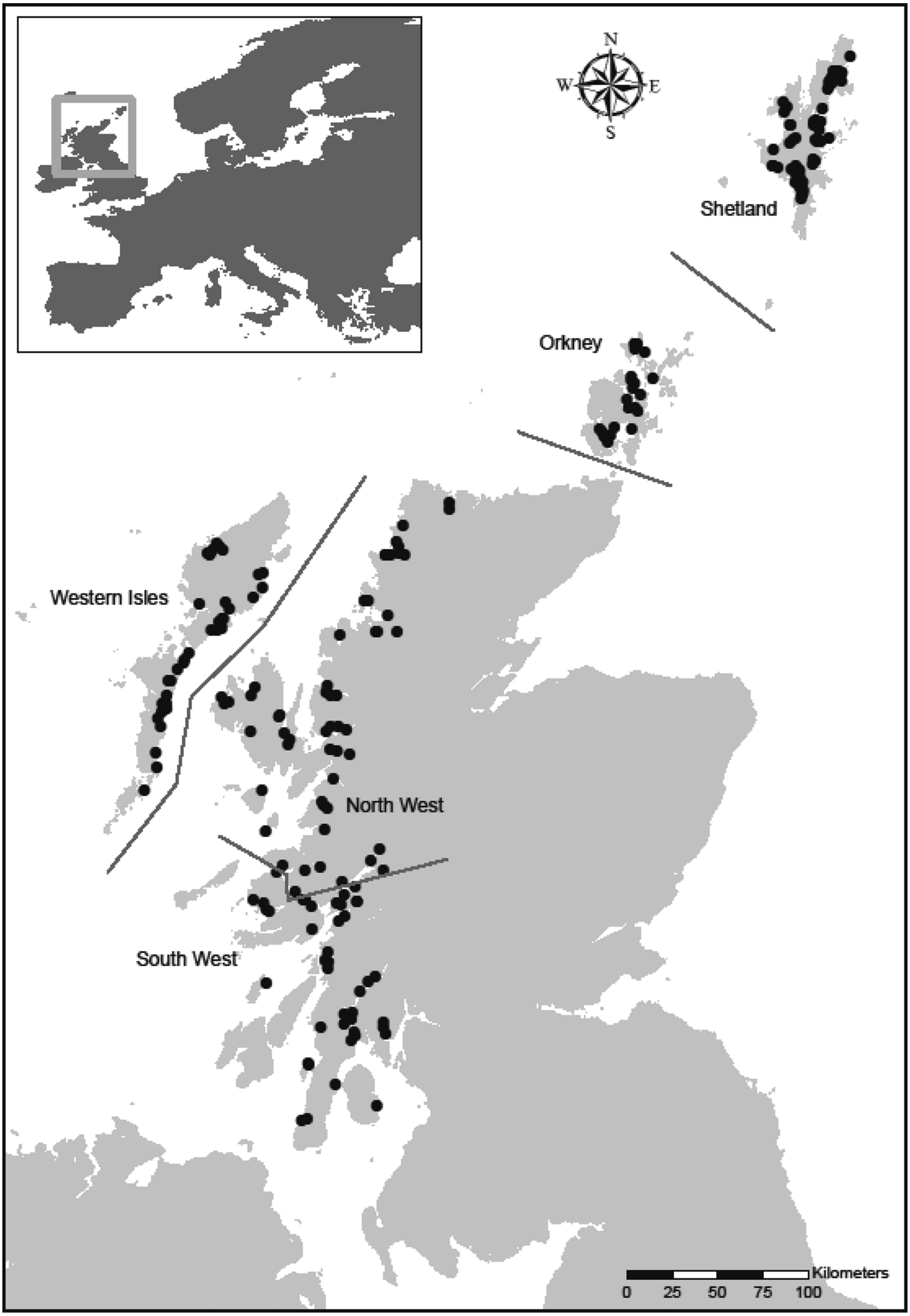

Fig. 1. Location of active salmon farms in Scotland in 2018 (Munro, 2019). These are divided between five regions of Shetland, Orkney, Western Isles (Eilean Siar) and Northwest and Southwest.

insight into patterns in losses; but as described above they are generally more difficult to interpret than monthly loss rates.

2.3. Temperature data

Water temperature experienced by fish and pathogens were expected to strongly influence mortality patterns. However, an initial model analysis including regional winter and summer sea surface temperatures (SST) from HadISST1.1 (Rayner et al., 2003) found these provided a less good fit than air temperatures and hence were discarded by the model fitting process. The water temperatures describe offshore temperatures and explicitly exclude coastal temperatures (Hughes et al., 2018). We therefore have used Met Office air temperatures to drive the modelling described in this paper.

Met Office data are available for air temperatures and long-term time-series exist for specific sites but also for conditions averaged over large areas; specifically Scotland and slightly more locally west Scotland and north Scotland. The west Scotland Met Office region covers the Southwest aquaculture region, the north Scotland region covers all the other aquaculture regions. Two Met Office temperature time series are selected for analysis, summer (June to August) mean daily maxima (A_s), and winter (December to February) mean daily minima (A_w), for Scotland and for the north and west Scotland regions. These two data sets were selected to give the range of conditions experienced in a given year. Air temperature data are obtained for 2003 – 2018. This data set is published on a quarterly basis, records of summer and particularly winter (December to February) are available before the complete annual temperature record is published, so air temperatures are available for the current winter temperatures, which are suspected to influence losses, thus may be a useful predictor of potential losses.

2.4. Data exploration and analysis

The data described above were used to assess variation and trends in annual average mortality at both the national and regional levels. In order to test our hypothesis, mortality rates on salmon farms may be related to increasing temperatures and biomass experienced on farms, we investigated the following questions:

1.) Are there significant increases in annual mortality of salmon on farms over time?
2.) Is there a significant relationship between proportion of losses in a region and the overall consented biomass and/or winter minima or summer maxima temperatures?
3.) If the relationship is significant, is there an interaction between losses, temperature and biomass, i.e. is there a higher risk of loss at higher temperatures and higher biomasses?

If there is a relationship then this leads us to two follow up questions:

4.) Can we predict potential biomass losses at a national or regional level based on air temperature and biomass?

And finally,

5.) Can these open source data be used as an early warning for potential losses, as a simple tool in a risk assessment framework? In this final question we are concerned with how much of the variance can be explained using the winter minima temperature. This data is available in March each year, thus may have an ability to provide an early warning of potential losses later in the season, allowing management decisions to be made considering this risk. All analyses were carried out using the R statistical environment version 3.6.1 (R Core Team, 2019).

2.5. Preliminarily data exploration

To explore our first three questions we visually assessed the patterns in mortality trends and temperature prior to performing rigorous statistical modelling. For a visual comparison of relative trends in losses per cycle (biological dataset b) and in annual average mortality (biological dataset a) the data sets were both normalised to their respective observed values for 2010 as the mid-point of the data series (this normalised data was not used for any other purpose). As increasing mortality is considered a relatively recent phenomena, the two trends were assessed using nonlinear regressions.

While it is not a direct question within the remit of this work, it is important to recognise there is a seasonality in the monthly loss rates. This was investigated by plotting mortality rate by month for all years and averaged across years. To allow comparison of the relative monthly mortality rates throughout the year, the monthly mortality was normalised to the annual average value to remove year-on-year variation, or trends, from the comparison of seasonality between years.

The correlation between air and water temperatures was tested at both national and regional level. At the regional level air and water temperatures are found to be correlated, therefore it was not appropriate to use both measures within the regression analysis. Thus we have made the decision to use air temperature and not water temperature given that the water temperature datasets are not well resolved in the coastal areas.

2.6. Developing modelling framework for early warning tool

The mortality analysed is as a proportion of biomass lost per month or a proportion of salmon numbers lost per production cycle and therefore vary from 0 to 1. To identify if temperature and biomass parameters play significant roles in explaining mortality patterns, two types of models may be appropriate:

1 A linear regression model, with logit transformed response data is a standard approach for proportion data, which is easily explained to a manager and has ample applied research examples.
2 A beta regression model, which is used extensively in theoretical modelling, but less so in applied research, so is a less intuitive option for a manager.

Thus, we felt it prudent to compare the inference from the linear model and the beta regression model and estimate the covariate effects on our response variable (proportion of biomass lost). The linear models were fit in the R statistical programming environment (R Core Team, 2019) following (Crawley, 2013). The full linear model for estimating the proportion of losses of salmon had the form:

$$\begin{aligned}\text{In}\,(M_i) = {} & b_0 + b_1 B_i + b_2 A_{wi} + b_3 A_{si} + b_4 R_i + b_5 R_i B_i + b_6 R_i A_{wi} \\ & + b_7 R_i A_{si} + b_8 B_i A_{wi} + b_9 B_i A_{si} + \varepsilon \end{aligned} \tag{1}$$

where b_0 represents the models intercept, and all other b terms represent the models fixed effect coefficients and ε represents the residual error term. All other modelled variables are listed in Table 1, for example M_i is the proportion of biomass lost, B_i is the mean total biomass in an area per year, etc. The full linear model at the national level had the same form except that region (R_i) is excluded as this is only applicable at regional level.

The beta regression model was fit in R using the "mgcv" package (Wood, 2017). The beta density, is given in terms of its two shape parameters $\{\alpha,\ \delta\}$, mean and precision:

$$f(y;\alpha,\delta) = \frac{\tau(\alpha+\delta)}{\tau(\alpha)\tau(\delta)} y^{\alpha-1}(1-y)^{\delta-1} \tag{2}$$

where we assume, $\alpha > 0,\ \delta > 0,\ 0 < y < 1$ and use $\tau(.)$ to denote the gamma function. The mean and variance of the random variable y are as follows:

$$E(y) = \frac{\alpha}{\alpha+\delta} \tag{3}$$

and

$$Var(y) = \frac{\alpha\delta}{(\alpha+\delta)^2(\alpha+\delta+1)} \tag{4}$$

$E(y)$ and $Var(y)$ denote the expectation and variance operators, with respect to the given beta distribution. In regression modelling it is more common to parameterize the density in terms of a mean (M) and dispersion parameter ($\varnothing$) instead of two shapes $\{\alpha,\ \delta\}$. In this parameterization we assume the following relationships

$$\mathrm{M} = \frac{\alpha}{\alpha+\delta} \tag{5}$$

$$\varnothing = \alpha+\delta \tag{6}$$

Which implies: $\alpha = \mathrm{M}\varnothing$ and $\delta = (1-\mathrm{M})\varnothing$, α and δ are estimated by maximum likelihood, and checked for bias using methods discussed in Grün et al. (2012). Using the parameterization of the beta distribution described above and the standard logit link the full beta regression model for the proportion of losses of salmon had the form:

$$\ln\left[E\left(\frac{p_i}{(1-p_i)}\right)\right] = b_0 + b_1B_i + b_2A_{wi} + b_3A_{si} + b_4R_i + b_5R_iB_i + b_6R_iA_{wi} + b_7R_iA_{si} + b_8B_iA_{wi} + b_9B_iA_{si} + \varepsilon \tag{7}$$

Where b_0 represents the models intercept, and all other b terms represent the models fixed effect coefficients and ε represents the residual error term. Our full models included the co-variates of the two air temperature sets outlined above (A_w) for winter and (A_s) for summer as outline in Table 1, biomass (B), and in the case of the regional model a categorical variable for regions (R). The most parsimonious or “best fit” model for the linear regression model and the beta regression model was selected using the Akaike Information Criterion (AIC) for each model type (Akaike, 1973). To fully assess the utility of these models as an early warning tool, we refit the model without the summer air temperature variable as this variable isn’t available at the beginning of the year when this tool could be applied to predict potential losses within the coming year. These models are referred to herein as the “reduced fit” model. To assess the importance of each variable in the model, the sum of model weights over all models including each explanatory variable was calculated, thus the importance metric is the cumulative Akaike weight for each explanatory variable.

The biomass loss models outlined above identified the probability a particular unit of weight will be lost per month; because we do not know the weight of individual fish, the relationship between biomass loss and weight loss rates are not defined. Regional regression models are weighted by the regional average biomass across years:

$$\beta_r = \sum \frac{\beta_{yr}}{16} \text{ for yr} = (2003 \text{ to } 2018) \tag{8}$$

Using a regional weight corrects for variation between regions and prevents regions with limited production unduly influencing the regional-level models’ overall results. Regional models are fitted both using mean trends across all regions and as multilevel models including interaction between each variable and region.

2.7. Model performance as early warning tool

We fit the best fit linear and beta regression models to the years 2003–2017, and then 2003–2018 and predicted the potential losses the best fit models for 2018 and 2019 respectively, based on the information made available in March of both years, which includes winter air temperatures for that year. For the 2018 prediction, biomass is known, whereas for the 2019 prediction biomass is estimated using the 2018 value as a baseline for production. For the 2019 prediction we examine inference of (i) no increase in production from 2018 (ii) a 10 % increase in production from 2018, given the mean winter air temperature in 2019. To critically assess each models performance we examined performance metrics of variance explained by the model, model accuracy and model bias. To assess the variance explained from each model we calculated the *pseudo* r^2, $(1 - \frac{\text{deviance explained by model}}{\text{deviance explained by null model}})$ · To assess model accuracy the relative mean absolute percentage error (MAPE) was calculated between the data and the modelled results using the following equation:

$$\text{MAPE} = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_t - \hat{y}_t}{A_t}\right| \tag{9}$$

Where A_t is the actual value and $\hat{y}_t$ is the modelled value, n is the number of data points.

To assess bias, we calculated the mean percentage error (MPE) between the data and the modelled data for both the full and the reduced models, using the equation:

$$\text{MPE} = \frac{100\%}{n}\sum_{t=1}^{n}\frac{A_t - \hat{y}_t}{A_t} \tag{10}$$

Where A_t is the actual value and $\hat{y}_t$ is the modelled value. Here we use actual rather than absolute values as this means it can be used as a measure of bias. This allows us to validate each model and investigate the utility of each model as an early warning tool for management decisions within a production cycle, thus addressing our final two questions.

3. Results

3.1. Preliminarily data exploration

Visually, biomass losses (M) do appear to have increased over the period 2003–2017, however losses per production cycle (μ) show no such trend (Fig. 2a). Values of both M and μ are normalised to 2009 values to make the trend lines visually comparable. Variation in the curves coincide best with smolt input in the preceding year, hence the 2002–2016 input year for a production cycle is lagged to compare best with the 2003–2017 proportion of the biomass loss rate data set.

Although analysis in this paper largely concerns inter-annual patterns, the data are available at the monthly level. This enables the pattern of seasonal variation in losses to be plotted (Fig. 2b), and this demonstrates a strong seasonal pattern in losses with most occurring in late summer or autumn. The biomass of salmon in the water increased fairly steadily through the period 2003 − 2018 (Fig. 2c) and in all regions (Appendix A, Table A2). Mean Scottish air temperatures were 0.37 °C for winter minima and 16.70 °C for summer maxima; inter-annual variation ranges were 4.35 °C and 2.47 °C respectively. Minimum winter air temperatures showed substantial inter-annual variation with very cold winters in 2009–2011, followed by a recovery, however, mild winters also occurred pre-2009 and post-2011, so the data lacks a trend but shows a shorter-term (but still several years) pattern of variation (Fig. 2d). The lack of change is consistent with general changes in Scotland, where a large warming of water occurred in the 1990s followed by stability or decline, but still leaving water temperatures 0.2 °C -0.4 °C warmer than the long-term average (Hughes et al., 2018). At the national level, summer (A_s) and winter (A_w) temperatures are not statistically significantly associated (p = 0.91). Loss rates for Scottish salmon aquaculture biomass increased over 2003 − 2018, this increase is best described using a quadratic equation, losses increased from 2010

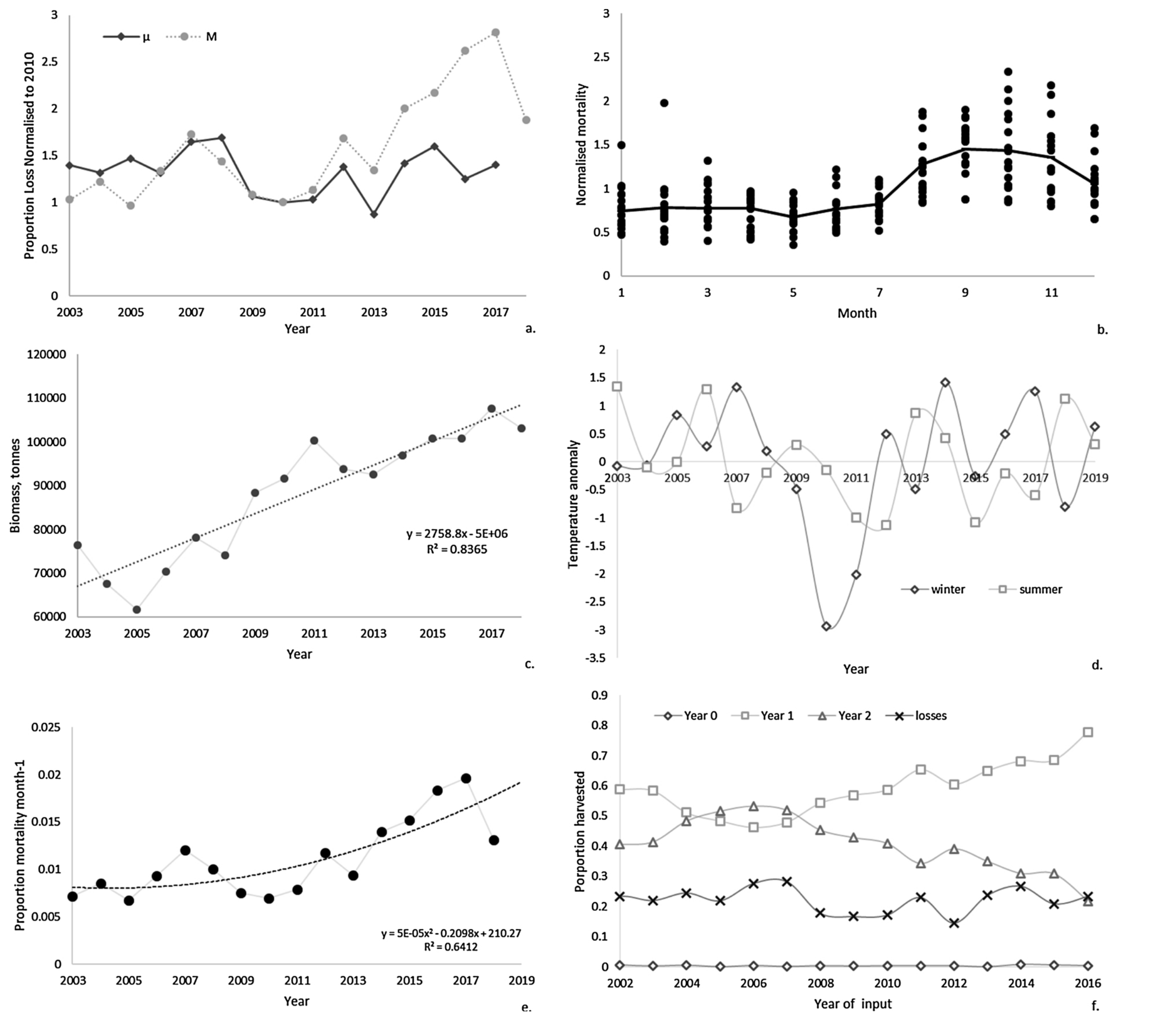

Fig. 2. Provides details about the preliminary data exploration undertaken. (a.) Losses as proportion of biomass per month (M) for 2003-2018 and per production cycle (μ) input in preceding year 2002-2017, normalised to 2010 values. (b.). Monthly losses as proportion of biomass lost per month at national level 2003 -2018, normalised to the average monthly mortality for the year, and mean loss (line). (c.) Average Scottish farmed salmon biomass by year (B) in tonnes for 2003-2018 and regression of 2759 tonnes per year increase. (d.) Temperature anomalies from mean air temperature 2003-2019 at the national level (e.) Proportion monthly biomass lost (M) by year 2003-2018, with a 2nd order polynomial fit (dash line). (f.) Proportion of salmon that are harvested in the year of input (year 0), a year later (year 1) or 2 years (year 2) after input, and proportion of salmon that are lost in the full production cycle (full production cycle: 2002-2016).

to 2017, decreasing again in 2018 (Fig. 2e). The proportion of salmon harvested in each year of a production cycle is shown in Fig. 2(f). There is a decrease in year 2 harvests and a corresponding rise in year 1 harvest, however the national losses associated with a production cycle are consistently around 22 %, regardless of production cycle length (Fig. 2f).

The annual monthly averaged proportion losses ranged from 0.68 %–2.01 % for Scotland as a whole, or from 0.34 %–2.81 % per month at regional levels. Increasing temporal trends of losses are apparent at both the national and most regional levels. Nationally the odds of mortality shows an increasing trend over time of:

$$Logit\ M_{yr} = -127.509 + 0.061(yr_i) + \hat{\varepsilon}_i \tag{11}$$

where $\varepsilon \sim N(0,\ 0.234^2)$ and $p = 0.0008,\ r^2 = 0.565$

The standard error associated with the year effect was ± 0.014. Increases in losses has not be constant, and varies between regions. Simple regional LOWESS (locally weighted scatterplot smoothing) curves fitted to observations of losses per year (M_{yr}) in each region indicates substantial difference in losses occurred around 2009, with an increase in loss rate beginning in most regions by 2011 (Fig. 3). There are substantial regional variations in loss rates over the 2003 − 2018 period. Mean losses for the mainland, 0.0095 m^{-1} (Northwest) and 0.0087 m^{-1} (Southwest), were approximately 1/3 less than those for the Western Isles (0.0138 m^{-1}) or Shetland (0.0135 m^{-1}), with Orkney intermediate at 0.011 m^{-1}. Regional variation, however, is less than the national inter-annual variation which nearly tripled from 0.067 m^{-1} in 2005, to 0.197 m^{-1} in 2017. Regional plots of loss rates show that there are indications of a change that occurs in the later part of the data set, with a change in most regions from a flat loss trend, i.e. no change from year to year, to a trend of increasing losses (Fig. 3). Multilevel modelling of regional trends identifies regional increases per year as:

$$Logit\ M_{yr} = R + 0.0007(yr) + \hat{\varepsilon}_i \text{ where } \varepsilon \sim N(0,\ 62.09^2) \text{ and } p = 1.211^{e-8},\ r^2 = 0.415 \tag{12}$$

Regions (R) are -1.3198 ± 0.2086 for the Northwest mainland, the

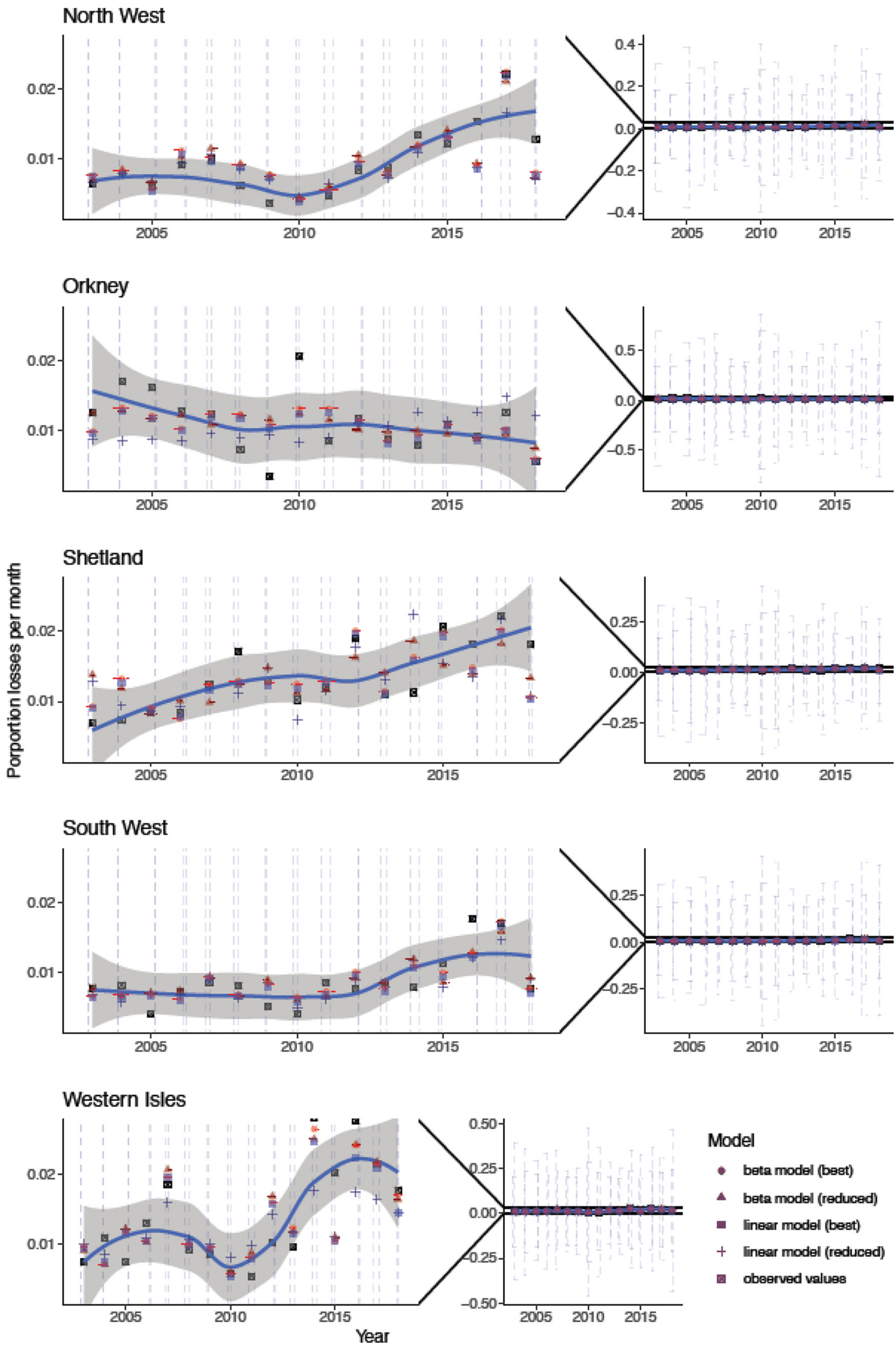

Fig. 3. Plots of regional LOWESS curves for losses with time 2003-2018 indicate an increase in average monthly proportion loss rate after 2010 for most regions. The predicted values from each model summarised in Table 2 are shown. LOWESS curve is based on observed data, error bars show the 95 % confidence intervals associated with each model.

Southwest mainland (-1.3206 ± 0.0014) and Orkney (-1.3183 ± 0.2133) are not significantly different from the Northwest. The Western Isles (-1.3156± 0.0014) and Shetland (-1.3158± 0.0013) differ significantly from the northwest with $p < 0.05$. The standard error associated with the year effect was ± 0.0001 ($p = 1.42^{e-8}$).

In the Scottish fish farm production survey, losses of salmon over a production cycle are calculated by comparing the reported smolt input with the number of salmon harvested. Losses included in this total are due to mortality and other factors, such as escapes. For yr = 2002–2016 the logistic regression model of this production cycle losses μ_{yr} showed no sign of increasing with time:

$$Logit\,\mu_{yr} = 16.526 - 0.0067(yr) + \hat{\varepsilon}_i \text{where } \varepsilon \sim N(0,\ 199^2) \text{ and } p = 0.5824,\ r^2 = -0.051 \tag{13}$$

The standard error associated with the year effect was ± 0.0119 ($p = 0.58$). There was no indication of a significant increase in μ with time for any region when analysed at that level (data not shown).

3.2. Developing modelling framework for early warning tool

The modelling of trend with time shows that there has been an increase in losses of biomass with time (although little evidence of increasing numbers lost per production cycle). Armed with this information we investigate if the increase in biomass losses can be explained by a few key factors. We explore how much variance can be explained by biomass increases, which may increase potential for pathogen transmission and by air temperatures in summer or winter, at both national and regional levels. The inference from the best fit linear regression model and the best fit beta regression model was similar at both national and regional levels. Here we present the outcomes from both the best fit models and the reduced models in order to appraise which one is most practical as an early warning tool for farm managers.

The best fitting linear and beta regression models at both national and regional levels for estimation of the proportion of losses of salmon in Scottish salmon farms suggested that air temperature and biomass were consistently significant factors in describing the variability seen in the data. Other fixed effect variables that were important in describing the proportion of losses of salmon in the regional models was region and the interaction between region and air temperatures. There was a significant interaction between the fixed effects of biomass and winter air temperature in both the linear and the beta models at both the national and regional levels (Table 2).

3.3. Model performance as early warning tool

Both the linear and beta regression models confirm that a substantial amount of the variance in the loss data can be explained by relatively few factors. Both models performed well in terms of the variance explained, MAPE and MPE. The beta regression model performed better, in terms of variance explained, by a small margin in both the national and regional models. The standard deviation and standard error around the mean is smaller in the beta regression than in the linear model. This indicates the beta regression model gives a more reliable and accurate reflection of the true mean in our response variable. Although the linear model provides the user with a computationally convenient framework, and preforms similarly to the beta regression in terms of the model performance metrics and predicted values, this is not the most appropriate model. The beta regression model has the benefit of being tailored for circumstances where the dependent variable is between 0 and 1, thus, is a more appropriate model. Details of model fit, coefficient values, and variable importance are given in Appendix B. Biomass and winter minimum air temperatures are critical factors associated with biomass loss rates across all models. Biomass is divided by the regional mean to correct for the different biomass variation between regions, and leave the trend apparent. The regional reduced fit models predict average regional 2019 losses of around 0.015. The Northwest (beta = 0.0108 ± 5.6e-8/ linear = 0.0099 ± 0.813) and Orkney (beta = 0.0088 ± 1.8e-7/ linear = 0.0142 ± 0.1821) are predicted to have the lowest losses. Shetland (beta = 0.0139 ± 6.6e-8/ linear = 0.0149 ± 0.0837) and the Southwest (beta = 0.0136 ± 1.3e-76/ linear = 0.0129 ± 0.1109) are predicted to have slightly more losses, whereas the Western Isles is predicted to have the highest loss (beta = 0.0325 ± 3.2e-7/ linear = 0.0203 ± 0.1211).

Given both the linear and beta regression national models preform similarly, both may be used to gain inference on the potential losses as a predictive tool. At the national level the best fit model is the same as the reduced fit model, where summer air temperature didn't add any explanatory power to the model, thus giving us an early warning tool that can be used to inform on potential losses later in the same year. Both of the models predict the 2019 losses to be around 0.016, (beta regression = 0.0163 ± 0.0009 /linear regression = 0.0161 ± 0.07) when given the same biomasses as 2018. An increase of 10 % biomass from

Table 2
Summary of explanatory variables tested and included (✓) or excluded (✗) in the best fitting and the reduced linear and beta regression models for estimating the factors that explain the variance in losses at national and regional levels in Scottish salmon farms. The use of (:) denotes the interaction between two explanatory variables. The final three rows in the table give the best fit model performance, the variance is explained by the r^2. Mean absolute percentage error (MAPE) is a measure of model accuracy and mean percentage error (MPE) is a measure of model bias.

	National Model				Regional Model			
	Linear Regression		Beta Regression		Linear Regression		Beta Regression	
	best fit	reduced fit	best fit	reduced fit	best fit	reduced fit	best fit	reduced fit
Explanatory variables								
B	✓	✓	✓	✓	✓	✓	✓	✓
A_w	✓	✓	✓	✓	✓	✓	✓	✓
A_s	✗	Not applicable	✗	Not applicable	✓	Not applicable	✓	Not applicable
R	Not applicable				✓	✓	✓	✓
R : B	Not applicable				✓	✓	✓	✓
R : A_w	Not applicable				✓	✗	✓	✓
R : A_s	Not applicable				✓	Not applicable	✓	Not applicable
B : A_w	✗	✗	✗	✗	✓	✓	✓	✓
B : A_s	✗	✗	✗	Not applicable	✗	Not applicable	✓	Not applicable
Model Performance								
r^2	80.7 %	80.7 %	81.8 %	81.8 %	65.3 %	51 %	68.9 %	61.4 %
MAPE	0.137 %	0.137 %	0.137 %	0.137 %	0.241 %	0.31 %	0.245 %	0.281 %
MPE	−0.011%	−0.011%	−0.025%	−0.025%	−0.049%	−0.071%	−0.091%	−0.11%

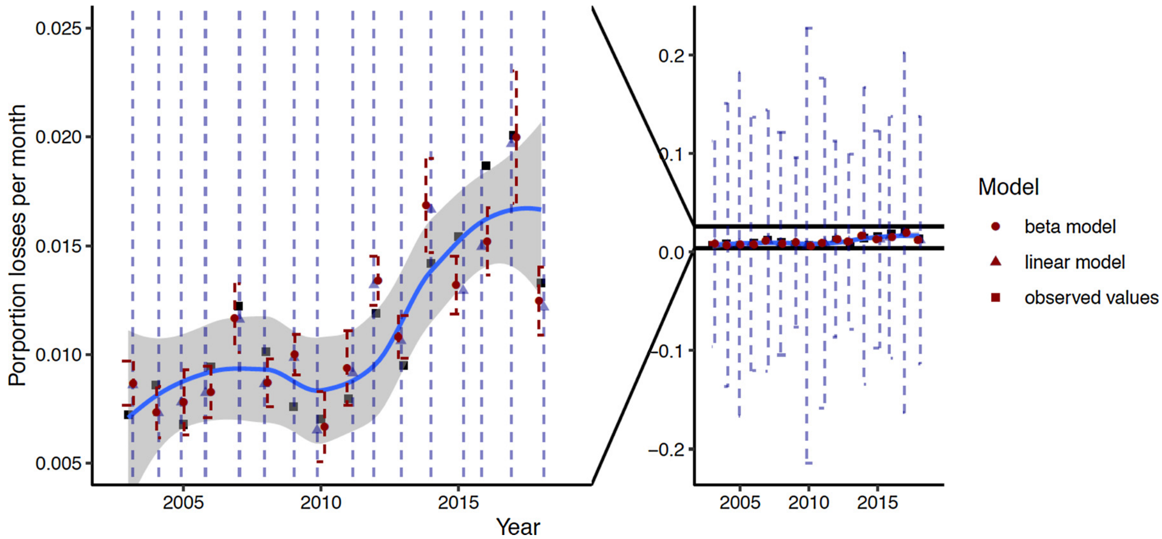

Fig. 4. Plot of national losses over time 2003-2018 indicate an increase in average monthly proportion loss rate after 2010. The predicted values from each model summarised in Table 2 are shown; LOWESS curve is based on observed data, error bars show the 95 % confidence intervals associated with each model.

Table A1
Monthly loss as proportion of biomass.

year	Scotland	North mainland	Orkney	Shetland	South mainland	Western Isles (EILEAN SIAR)
2003	0.007197	0.006466	0.012337	0.006811	0.007734	0.007277
2004	0.008527	0.007841	0.016649	0.007271	0.008135	0.010749
2005	0.006742	0.00613	0.015855	0.00829	0.004084	0.007329
2006	0.009339	0.009071	0.012545	0.008238	0.007282	0.012809
2007	0.012069	0.009865	0.012129	0.012209	0.008499	0.018105
2008	0.01003	0.006153	0.007246	0.016883	0.008068	0.009106
2009	0.007555	0.00374	0.003375	0.012721	0.00515	0.008313
2010	0.006987	0.004294	0.020127	0.010135	0.00405	0.005711
2011	0.007898	0.004684	0.008372	0.011955	0.008499	0.005334
2012	0.011753	0.008416	0.011493	0.018626	0.007656	0.010012
2013	0.009397	0.00866	0.008663	0.010921	0.008451	0.009421
2014	0.014001	0.013285	0.007849	0.011162	0.007802	0.02731
2015	0.015181	0.012015	0.01079	0.02022	0.011263	0.019701
2016	0.018343	0.015175	0.008953	0.017847	0.017363	0.026808
2017	0.019667	0.021658	0.012457	0.021681	0.016691	0.020905
2018	0.013120	0.012745	0.005562	0.017808	0.007594	0.017359

Table A2
Monthly mean biomass tonnes by year.

year	Scotland	North mainland	Orkney	Shetland	South mainland	Western Isles (EILEAN SIAR)
2003	76,471	20,401	2843	23,867	15,667	13,691
2004	67,529	23,554	2397	18,097	12,523	10,956
2005	61,664	17,759	1909	13,832	13,710	14,452
2006	70,427	24,192	2009	15,875	14,628	13,720
2007	78,112	23,062	3096	17,848	16,413	17,691
2008	74,022	23,985	2948	20,305	12,678	14,104
2009	88,334	22,118	4237	27,224	20,527	14,226
2010	91,687	24,884	4730	25,592	17,584	18,897
2011	100,370	27,023	5020	29,749	19,812	18,765
2012	93,843	24,834	6380	27,136	17,053	18,439
2013	92,490	23,375	6809	25,920	18,697	17,686
2014	96,968	23,630	7464	27,435	19,007	19,430
2015	100,795	32,624	7421	27,079	18,106	15,564
2016	100,791	23,926	8971	23,513	21,594	22,784
2017	107,675	30,004	9838	27,128	22,279	18,425
2018	103,194	24,141	10,127	23,199	22,220	23,505

the 2018 value in 2019 would suggest a higher mortality of around 0.19 (beta regression = 0.0198 ± 0.0016 / linear regression = 0.0194 ± 0.095). The national average winter minimum temperature was warmer in 2019 (1 °C) when compared to the 2018 value −0.43 °C), this increased winter temperatures is clearly linked to the increased mortality estimate in 2019. The reduced models were then refit without the 2018 data and used to predict the 2018 values of losses at the national level. The linear regression suggested potential losses of 0.01198 ± 0.0715 and the beta regression suggested potential losses of 0.01227 ± 0.0009; the 2018 losses were 0.0131. This is in line with the model performance which reports a bias of −0.025 % for both reduced national models and a precision estimate within 0.14 % for the beta regression and for the linear regression (Table 2, Fig. 4).

4. Discussion

Biomass loss rates for Scottish salmon aquaculture increased over 2003−2018, but this increase was not steady and losses increased from 2010 to 2017, decreasing again in 2018 (Fig. 2a/e). The decrease in 2018 is likely due to a reduction in biomass and a cooler winter. However, the increase in biomass fits a linear trajectory (Fig. 2c), thus it is possible that the association with mortality corresponds to an unknown factor that may have increased over the same time scale, such as an increase in pathogens in the marine environment over time. Conversely, the signal from cold winters is clear at both a national and regional level, thus we are confident that this likely to be a key environmental driver, that is easily measured, which is useful in prediction of losses. Losses in terms of the number of salmon per production cycle (μ) did not show an increase with biomass or time (Fig. 2a). A reason for the lack of a trend in μ could be due to aquaculture companies harvesting fish earlier, thus shortening the marine production cycles. The fact that salmon are in the sea for less time reduces the impact of increasing monthly losses on survival to harvest. In recent years, marine production cycle lengths have decreased, and although data on specific cycle lengths was not available, the proportion of salmon harvested in years 0, 1 or 2 after input is recorded in the Scottish fish farm production survey reports (Munro, 2019). These data show a recent strong decline in the proportion of salmon harvested in year 2 and a corresponding rise in year 1 harvest (Fig. 2f). This means farmed salmon have been spending less time in marine waters in recent years. A second explanation could be increasing mortality of larger salmon in association with gill diseases and cardiomyopathies. Mortality of larger salmon can result in an increased biomass loss, without necessarily increasing the numbers of salmon that die. Without explicit data on the size of the fish that are dying we cannot confirm that this has occurred, but it is a likely driver of the difference in trends in M and μ.

The data shows significant regional differences in patterns in losses (Fig. 3, Appendix B, Tables S2, S3, S5, S6). Losses were similar in the Northwest, the Southwest and the Western Isles, with increasing loss rates occurring after 2010 and reasonably stable losses before this. However, in the Northern Isles there were substantial differences from this pattern, Shetland displayed an increase through the pre-2010 period, although with a hiatus around 2010, whilst Orkney showed declining losses prior to 2009. The data on losses per production cycle is of limited value for regional analysis because movements of salmon between regions can distort apparent losses; however 90 % of movements between marine salmon sites are local, < 10 km (Wallace et al., 2016), restricting potential movement between areas.

This pattern in proportional biomass losses can be largely explained statistically by two factors, the biomass of farmed salmon and the minimum winter air temperature (Table 2, Appendix B). To a lesser extent, and apparently locally, associations also exist with summer maximum air temperature. Thus both climate and aquaculture intensification, at the regional level, appear to have roles in determining biomass loss.

4.1. The role of temperature

Only the associations with air temperature were tested. Water temperatures dropped out during the preliminary data analysis because fish farms were generally located in shallow coastal waters which are sensitive to the relatively large air temperature variations more than the relatively stable offshore water temperatures. Calculation of the water temperatures explicitly excluded coastal temperatures (Hughes et al., 2018), thus more highly resolved, or ideally farm-level water-temperature data would likely provide a better model fit (Thakur et al., 2018). Farm-level mortality modelling combined with more detailed data on production cycles and high resolution temperature data would likely provide a better insight into the exact role of water temperatures.

Summer air temperature was only an important factor in two models, the best fit linear and beta regression at regional levels (Table 2, See Appendix B: Table S2/S5 for additional details) which might appear surprising, since higher temperatures are likely to increase the severity of disease outbreaks. Mortality is highest in summer (Fig. 2b) and pathogens are more prevalent, for example, sea lice numbers tended to increase through the summer (Hall and Murray, 2018). However, the optimum water temperature for salmon growth is 15.9 °C with a maximum of 22.5 °C (Elliott and Elliott, 2010), and the highest summer air temperature was 18.11 °C in 2003. Therefore, even if water temperatures in hot summers occasionally exceeded optimum this would be associated with a longer period at near optimum for growth, particularly as water temperatures are likely to be lower than air temperatures (even if these drive the patterns in coastal waters). It is also the case that inter-annual variation for air temperatures was less for summer than winter and as a trend, summer maximum air temperatures declined over this studies time period (Fig. 2d). Therefore, the effects of summer temperatures' on disease appear to have been more than balanced by increased salmon growth rates and could be obscured by the trend of increasing mortality.

All models identified a strong association of winter minimum air temperature with mortality. The overall average effect of winter temperature on loss rate at the national level is 0.002 per degree from an average M = 0.01 month^{-1}, so the impact of the cold winters, nearly 3 °C colder than earlier years is a 60 % reduction in losses. This effect stood out because of a run of cold winters from 2009−2011. A recent cold winter in 2017/2018 (A_w = −0.43 °C, which was 0.80 °C below the 2003–2017 average) was followed by reduced mortality in 2018, and this was predicted by the model, although it had not been fitted using this 2018 data. This mortality reduction is unlikely to continue as A_w for the winter of 2018/19 was 1 °C which is 0.62 °C above the 2003–2017 average.

Cold winter temperatures can inhibit pathogens such as some bacterial diseases (Thompson et al., 2006), sea lice (Rittenhouse et al., 2016) and gill diseases (Benedicenti et al., 2019), although other diseases are most prevalent at cooler temperatures (Thompson et al., 2006). Gill diseases have emerged as a particular problem in recent years; initial invasion may be associated with warm summers but subsequent recurrence can follow mild winters. Winter was a time of lower mortality rates (Fig. 2 b), so the changes in annual average monthly mortality rate are likely occurring as a result of changes in summer or autumn mortality. This is likely due to the reduced winter survival of pathogens leading to a reduction in the occurrence and severity of disease outbreaks.

4.2. The role of biomass

The biomass of farmed salmon is the other key factor identified in the modelling of biomass losses. High biomass density is well known to be associated with the spread of pathogens (Anderson and May, 1979; Murray, 2009). Numbers of fish, as well as their biomass can affect transmission, however, such data were not available from the open source data described in the methods. Since the model was applied over large regional areas it is reasonable to assume these regional populations contained fish at all different stages of production from newly stocked smolts to large harvest sized fish; although size structure may have varied with time. The increase in mortality with increased biomass is supported by observations. In the case of sea lice it has been found that control becomes more difficult as regional biomass or temperature increases (Frazer et al., 2012) and sea lice treatment rates increase in association with total salmon biomass in a sea loch (Murray and Hall, 2014).

Geographical distribution of farms within regions may change and so the relationship of regional population with biomass density may also change. It may be possible to manage the distribution of regional biomasses into fewer but larger farms, which can reduce pathogen transmission between these farms if appropriate separation distances are achieved (Salama and Murray, 2011). Strategic spatial planning may be a useful tool for reducing mortality rate.

4.3. Implications for future mortality

Further changes in biomass and temperature are likely to occur, which may drive changes in future loss rates. Both of the modelling frameworks tested above can help to infer the potential welfare risks associated with changes in biomass or temperature. A 50 % increase in salmon production has been proposed for 2030 (Anon, 2017). Using the models developed here, and assuming increased salmon production is approximately proportional to increased biomass, the reduced fit linear model suggests the impact of a 50 % increase in biomass relative to the 2017 levels as predicted loss rates of 0.023 $\pm$ 0.231, 0.041 $\pm$ 0.226 or 0.054 $\pm$ 0.241 month^{-1} for the coldest (−2.57 °C), mean (0.37 °C) and mildest (1.78 °C) winter minima in the 2003–2019 observations. While the reduced fit beta regression model predicts the impact of a 50 % increase in biomass relative to the 2017 levels as loss rates of 0.025 $\pm$ 0.006, 0.042 $\pm$ 0.009 or 0.055 $\pm$ 0.012 month^{-1} for the coldest, mean and mildest winter minima in the 2003–2019 observations. These losses are proportions of biomass, so tonnage lost will increase with both increasing biomass and mortality rate. Increased mortality also creates increased problems for waste disposal (Anon, 2018). These projections must be treated with caution as they are outside the range of biomass values used to fit the models. Moreover, assuming biomass is increased it can still be possible to reduce its association with losses by developing better disease controls. This has occurred in the past with the introduction of antibacterial vaccines (Murray and Munro, 2018). More strategic management of farm locations (Salama and Murray, 2011) and area management can allow area-level biomass to be increased sustainably, by reducing interactions between farmed salmon populations. Simply using fewer but larger farms increases separation distance and although transmission on farms increases this is more than compensated by reduced transmission between farms (Salama and Murray, 2011), use of more detailed hydrodynamic models can allow identification of sites that do not interact (e.g. Adams et al., 2012). More data for more detailed modelling of losses including fish numbers as well as biomass data at the individual site level with site-level temperature data may also be used to improve the management of risk factors for specific sites (Falconer et al., 2020). Therefore, the existing association of loss rate with biomass should be a driver for developing improved disease control practices to weaken this relationship.

This early warning tool represents a first step towards supporting the industry in planned adaptation measures in aquaculture. Scotland's climate is trending towards milder winters, thus understanding this environmental pressure and putting measures in place to mitigate the risk is becoming increasingly important.

Author contribution statement

A.G.M conceived the presented idea M.M and A.G.M derived the models, analysed the data and co-wrote the manuscript. B.B provided temperature data. A.J.C provided losses data. L.A.M provided production losses data. I.S.W provided Fig. 1. All authors provided critical feedback to help shape the manuscript.

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Appendix A. Monthly losses and biomass (SEPA)

Table A1

Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.prevetmed.2020.104985.

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Appendix 1: Monthly losses and biomass (SEPA)

A. Monthly loss as proportion of biomass.

YEAR	SCOTLAND	NORTH MAINLAND	ORKNEY	SHETLAND	SOUTH MAINLAND	WESTERN ISLES (EILEAN SIAR)
2003	0.007197	0.006466	0.012337	0.006811	0.007734	0.007277
2004	0.008527	0.007841	0.016649	0.007271	0.008135	0.010749
2005	0.006742	0.00613	0.015855	0.00829	0.004084	0.007329
2006	0.009339	0.009071	0.012545	0.008238	0.007282	0.012809
2007	0.012069	0.009865	0.012129	0.012209	0.008499	0.018105
2008	0.01003	0.006153	0.007246	0.016883	0.008068	0.009106
2009	0.007555	0.00374	0.003375	0.012721	0.00515	0.008313
2010	0.006987	0.004294	0.020127	0.010135	0.00405	0.005711
2011	0.007898	0.004684	0.008372	0.011955	0.008499	0.005334
2012	0.011753	0.008416	0.011493	0.018626	0.007656	0.010012
2013	0.009397	0.00866	0.008663	0.010921	0.008451	0.009421
2014	0.014001	0.013285	0.007849	0.011162	0.007802	0.02731
2015	0.015181	0.012015	0.01079	0.02022	0.011263	0.019701
2016	0.018343	0.015175	0.008953	0.017847	0.017363	0.026808
2017	0.019667	0.021658	0.012457	0.021681	0.016691	0.020905
2018	0.013120	0.012745	0.005562	0.017808	0.007594	0.017359

B. Monthly mean biomass tonnes by year.

YEAR	SCOTLAND	NORTH MAINLAND	ORKNEY	SHETLAND	SOUTH MAINLAND	WESTERN ISLES (EILEAN SIAR)
2003	76471	20401	2843	23867	15667	13691
2004	67529	23554	2397	18097	12523	10956
2005	61664	17759	1909	13832	13710	14452
2006	70427	24192	2009	15875	14628	13720
2007	78112	23062	3096	17848	16413	17691
2008	74022	23985	2948	20305	12678	14104
2009	88334	22118	4237	27224	20527	14226
2010	91687	24884	4730	25592	17584	18897
2011	100370	27023	5020	29749	19812	18765
2012	93843	24834	6380	27136	17053	18439
2013	92490	23375	6809	25920	18697	17686
2014	96968	23630	7464	27435	19007	19430
2015	100795	32624	7421	27079	18106	15564
2016	100791	23926	8971	23513	21594	22784
2017	107675	30004	9838	27128	22279	18425
2018	103194	24141	10127	23199	22220	23505

Appendix 2: Summary of best fit models for predicting proportion of losses at both the national and regional levels.

Table S1. Summary of best fit linear model for predicting proportion of losses at a national level, the reduced model was identical to the best fit model in this case. During model selection all possible model combinations of fixed effects were tested. Biomass(I=1, N=9), A_w (I=1, N=8), A_s (I=0.39, N=8), A_w : Biomass (I=0.3, N=3), A_s : Biomass (I=0.11, N=3).

Best Fit Model (National)				
lm(formula = log(M) ~ Aw + biomass + 1, data = nat.dat, na.action = "na.fail")				
Explanatory variables	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-6.213e+00	2.693e-01	-23.066	6.24e-12 ***
Air temperature-winter (A_w)	1.934e-01	3.693e-02	5.236	0.000161 ***
Biomass (B)	1.524e-06	2.504e-07	6.087	3.86e-05 ***

Residuals:
Min 1Q Median 3Q Max
-0.25789 -0.13947 0.03461 0.14051 0.22281

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.1641 on 13 degrees of freedom
Multiple R-squared: 0.807, Adjusted R-squared: 0.7773
F-statistic: 27.17 on 2 and 13 DF, p-value: 2.273e-05

Table S2. Summary of best fit linear model for predicting proportion of losses at a regional level. During model selection all possible model combinations of fixed effects were tested. Importance was ranked from 0-1. Region (I=1, N=59), Biomass(I=1, N=59), A_w (I=1, N=54), A_w : Biomass (I=0.71, N=23), A_s (I=0.69, N=54), A_w : Region (I=0.66, N=23), A_s : Biomass (I=0.20, N=23), A_s : Region (I=0.32, N=23), Biomass : Region (I=0.46, N=25).

Best Fit Model (Regional)

lm(formula = log(M) ~ As + Aw + biomass + region + As:region + Aw:biomass + Aw:region + biomass:region + 1, data = dat, weights = bioR, ♠ na.action = "na.fail")

Weighted Residuals:
Min 1Q Median 3Q Max
-11468.0 -2448.5 336.5 2346.5 9728.6

Explanatory variables	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-7.73E+00	2.20E+00	-3.506	0.000877***
Air temperature - summer (A_s)	9.36E-02	1.08E-01	0.866	0.390008
Air temperature-winter (A_w)	-6.38E-01	4.04E-01	-1.579	0.119778
Biomass (B)	4.84E-06	2.38E-06	2.039	0.045916*
Region (R) - Orkney	6.08E+00	3.82E+00	1.592	0.1167
Region (R) - Shetland	7.38E+00	2.59E+00	2.848	0.006048**
Region (R) – Southwest	4.83E+00	2.92E+00	1.656	0.103091
Region (R) – Western Isles	1.61E+00	2.87E+00	0.561	0.576594
A_w : B	-2.52E-01	2.21E-01	-1.142	0.25788
R : A_s - Orkney	-3.53E-01	1.39E-01	-2.547	0.013503*
R : A_s - Shetland	-2.19E-01	1.56E-01	-1.4	0.166826
R : A_s - Southwest	-7.06E-02	1.54E-01	-0.46	0.647402
R : A_s - Western Isles	3.05E-06	1.32E-06	2.306	0.024634*
R : A_w - Orkney	4.31E-01	3.48E-01	1.236	0.221448
R : A_w - Shetland	-2.07E-01	9.56E-02	-2.17	0.034024*
R : A_w - Southwest	1.03E-01	1.39E-01	0.736	0.4644
R : A_w - Western Isles	2.88E-01	1.46E-01	1.976	0.052881.
B : R- Orkney	-1.12E-05	5.05E-06	-2.224	0.029967*
B : R - Shetland	-4.16E-06	2.49E-06	-1.675	0.099261.
B : R - Southwest	-4.16E-06	3.07E-06	-1.356	0.180207

B : R - Western Isles	1.41E-06	3.12E-06	0.451	0.653389

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 4708 on 59 degrees of freedom
Multiple R-squared: 0.6531, Adjusted R-squared: 0.5355
F-statistic: 5.554 on 20 and 59 DF, p-value: 1.295e-07

Table S3. Summary of best fit reduced linear model for predicting proportion of losses at a regional level. During model selection all possible model combinations of fixed effects were tested. Importance was ranked from 0-1. For Example: Winter air temperature (A_w) scored an importance (I) of 1 and was present in 13 models. A_w (I=1, N=13), Region (I=1, N=13), Biomass (I=1, N=13), A_w : Region (0.49=1, N=5), A_w : Biomass (I=0.57, N=5), Biomass : Region (0.26=1, N=5).

Reduced Fit Model (Regional)

Call:
lm(formula = log(M) ~ Aw + biomass + region + Aw:biomass + 1, data = dat, weights = bioR, na.action = "na.fail")
Weighted Residuals:

Min	1Q	Median	3Q	Max
-11415.0	-2653.0	-367.3	3516.5	10277.0

Explanatory variables	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	-6.12E+00	2.94E-01	-20.806	<0.0000000000000002***
Air temperature-winter (A_w)	1.30E-02	1.37E-01	0.095	0.925
Biomass (B)	4.42E-06	9.69E-07	4.561	0.0000204***
Region (R) - Orkney	1.22E+00	2.77E-01	4.415	0.0000349***
Region (R) - Shetland	4.64E-01	1.08E-01	4.304	0.000052***
Region (R) – Southwest	1.91E-01	1.38E-01	1.39	0.169
Region (R) – Western Isles	7.53E-01	1.43E-01	5.259	0.00000143***
A_w : B	7.26E-07	5.17E-07	1.404	0.165

Weighted Residuals:

Min	1Q	Median	3Q	Max
-11468.0	-2448.5	336.5	2346.5	9728.6

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 5066 on 72 degrees of freedom
Multiple R-squared: 0.5097, Adjusted R-squared: 0.4621
F-statistic: 10.69 on 7 and 72 DF, p-value: 3.737e-09

Table S4. Summary of best fit beta model for predicting proportion of losses at a national level , the reduced model was identical to the best fit model in this case. During model selection all possible model combinations of fixed effects were tested. Importance was ranked from 0-1. A_w (I=1, N=8), Biomass(I=1, N=9), A_s (I=0.35, N=8), A_w : Biomass (I=0.24, N=3), A_s : Biomass (I=0.08, N=3).

Best Fit Model (National)

Family: Beta regression(3393.598) Link function: logit
Formula: M ~ Aw + biomass + 1

Explanatory variables	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-6.241e+00	2.789e-01	-22.376	< 2e-16 ***
Air temperature-winter (A_w)	1.92e-01	3.789e-02	5.067	4.04e-07 ***
Biomass (B)	1.576e-06	2.516e-07	6.263	3.79e-10 ***

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
R-sq.(adj) = 0.798 Deviance explained = 81.8%
-REML = -61.362 Scale est. = 1 n = 16

Table S5. Summary of best fit beta model for predicting proportion of losses at a regional level. During model selection all possible model combinations of fixed effects were tested. Importance was ranked from 0-1. A_s (I=1, N=54), A_w (I=1, N=54), Biomass(I=1, N=59), Region (I=1, N=59), A_s : Biomass (I=1, N=23), A_s : Region (I=1, N=23), A_w : Biomass (I=1, N=23), A_w : Region (I=1, N=23), Biomass : Region (I=1, N=25).

Best Fit Model (Regional)

Family: Beta regression(1257.616) Link function: logit

Formula: M ~ As + Aw + biomass + region + As:biomass + As:region + Aw:biomass + Aw:region + biomass:region + 1

Explanatory variables	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-5.59E+00	3.64E-04	-15337.1	<2e-16***
Air temperature - summer (A_s)	-3.57E-02	2.28E-05	-1567.1	<2e-16***
Air temperature-winter (A_w)	-6.77E-01	2.28E-05	-29702.6	<2e-16***
Biomass (B)	-2.12E-06	1.18E-09	-1793.6	<2e-16***
Region (R) - Orkney	4.40E+00	3.50E-04	12590.8	<2e-16***
Region (R) - Shetland	7.51E+00	1.56E-04	48079.8	<2e-16***
Region (R) – Southwest	4.55E+00	1.92E-04	23768	<2e-16***
Region (R) – Western Isles	2.12E-01	1.85E-04	1141.4	<2e-16***
A_s :B	4.34E-07	7.59E-11	5713.8	<2e-16***
R : A_s - Orkney	-1.47E-01	2.17E-05	-6792.7	<2e-16***
R : A_s - Shetland	-3.62E-01	8.25E-06	-43894.3	<2e-16***
R : A_s - Southwest	-1.94E-01	1.12E-05	-17366.7	<2e-16***
R : A_s - Western Isles	2.79E-03	1.08E-05	259.3	<2e-16***
A_w :B	3.15E-06	7.27E-11	43419.1	<2e-16***
R : A_w - Orkney	4.58E-01	1.99E-05	23036.2	<2e-16***
R : A_w - Shetland	-2.06E-01	5.62E-06	-36680	<2e-16***
R : A_w - Southwest	1.05E-01	8.56E-06	12258.1	<2e-16***
R : A_w - Western Isles	3.04E-01	8.74E-06	34749.6	<2e-16***
B : R - Orkney	-1.14E-05	3.07E-10	-37060.6	<2e-16***
B : R - Shetland	-4.19E-06	1.45E-10	-28976.9	<2e-16***
B : R - Southwest	-4.58E-06	2.43E-10	-18850.1	<2e-16***
B : R - Western Isles	2.43E-06	1.82E-10	13373.5	<2e-16***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) = 0.617 Deviance explained = 68.9%
-REML = -7.3095e+10 Scale est. = 1 n = 80

Table S6. Summary of reduced fit beta regression model for predicting proportion of losses at a regional level. During model selection all possible model combinations of fixed effects were tested. Importance was ranked from 0-1. A_w (I=1, N=13), Region (I=1, N=13), Biomass(I=1, N=13), A_w : Region (I=1, N=5) A_w : Biomass (I=1, N=5), Biomass : Region (I=1, N=5).

Reduced Fit Model (Regional)

Family: Beta regression(1016.773)
Link function: logit
Formula: M ~ Aw + biomass + region + Aw:biomass + Aw:region + biomass:region + 1

Explanatory variables	Estimate	Std. Error	z value	Pr(>|z|)
Intercept	-5.98E+00	3.60E-05	-165803	<2e-16***
Air temperature-winter (A_w)	-4.13E-01	2.31E-05	-17902.5	<2e-16***
Biomass (B)	4.18E-06	1.19E-10	35299.3	<2e-16***
Region (R) - Orkney	1.80E+00	4.04E-05	44525.7	<2e-16***
Region (R) - Shetland	1.16E+00	4.03E-05	28741.7	<2e-16***
Region (R) – Southwest	6.56E-01	4.75E-05	13820.7	<2e-16***
Region (R) – Western Isles	3.06E-02	4.35E-05	703.2	<2e-16***
A_w : B	2.27E-06	7.40E-11	30714.8	<2e-16***
R : A_w - Orkney	2.44E-01	2.04E-05	11982.8	<2e-16***
R : A_w - Shetland	-1.92E-01	6.20E-06	-30907.8	<2e-16***
R : A_w - Southwest	5.12E-02	8.87E-06	5773.4	<2e-16***
R : A_w - Western Isles	2.26E-01	9.00E-06	25061.8	<2e-16***
B : R - Orkney	-9.57E-06	3.16E-10	-30286.6	<2e-16***
B : R - Shetland	-2.28E-06	1.34E-10	-17088.2	<2e-16***
B : R - Southwest	-2.02E-06	1.92E-10	-10519.8	<2e-16***
B : R - Western Isles	3.26E-06	1.65E-10	19774.5	<2e-16***

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

R-sq.(adj) = 0.56 Deviance explained = 61.4%
-REML = -7.1383e+10 Scale est. = 1 n = 80

Climate change and aquaculture

Marine Climate Change Impact Partnership (MCCIP) reports

Collins et al. 2020, Murray et al. 2022

Increase in diseases in shellfish

Increased in diseases in salmon

- especially complex gill disorder and sea lice

Increased growth, except in extreme conditions

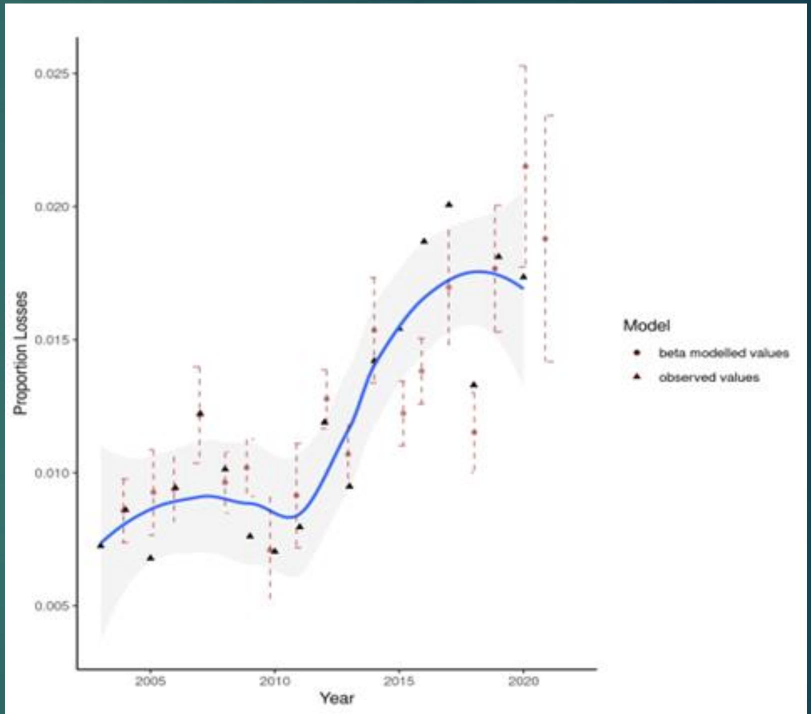
Modelling of salmon monthly mortality rates (% biomass)

Extensive data from Scotland's Aquaculture website

Good model only biomass minimum winter air temperature

Moriarty et al. 2020 Prev Vet Med 178, p.104985.

Although most mortality occurred in late summer/autumn this dropped out of the model



Marine Climate Change Programme

26 October 2023

Scottish Government
Riaghaltas na h-Alba
gov.scot

Changes in the ocean climate

- Scottish waters have warmed between 0.05 and 0.07 °C per decade, calculated across the period 1870 to 2016.
- The warming trend in the last 30 years has been higher.
- Scotland experienced a category 4 Marine Heatwave in June 2023.
- Mean sea level around the coast is increasing in all marine regions.
- Oxygen concentrations in the water are decreasing.
- pH is variable on seasonal and inter-annual time scales in coastal seas. There is currently insufficient data to detect a trend. Seeing hot spots of ocean acidification.

Biological impacts of climate change

- The impacts of climate change are seen in a wide range of species and habitats.
- These include changes in the spatial distribution, the timing of life events (hatching, spawning) and adult body size.
- Changes between the physical environment, individual organisms, populations and the foodweb are linked.
- Seeing changes to plankton community in Scotland.

Relevant to fish health:

- Warming conditions may lead to a rise in outbreaks including sea lice, fish diseases and shellfish pathogens, with subsequent increased mortality.
- The risk of mortality due to more frequent and intense heatwave events will increase in the future, highlighting the need for adaptive management.
- Offshore facilities may be more exposed to structural damage due to potential changes in storm events, with an increased risk of farmed species escaping.

Mitigation

Net Zero targets – 75% by 2030 and net zero by 2045.

→ Fisheries Sector

→ Aquaculture Sector

Nitrogen Balance Sheet

Requirement for aquaculture to report annually on nitrogen flows and the levels of nitrogen in coastal waters.

Adaptation

The Marine Directorate is a RISK OWNER and co-owner of a high priority risk.

Natural Environment and Assets

Risk or Opportunity	Receptor	Nature of risk/opportunity	Urgency Score	Risk Owner
RISKS	N14. Marine species, habitats, and fisheries	Changing climatic conditions, including ocean acidification and higher water temperatures	More action needed	Net Zero, Energy and Transport/ Rural Affairs and Islands

Natural Environment and Assets

Risk or Opportunity	Receptor	Nature of risk/opportunity	Urgency Score	Risk Owner
RISKS	N16. Marine species and habitats	Pests, pathogens, and invasive species	More action needed	Net Zero, Energy and Transport/ Rural Affairs and Islands

Natural Environment and Assets

Risk or Opportunity	Receptor	Nature of risk/opportunity	Urgency Score	Risk Owner
OPPORTUNITIES	N15. Marine species, habitats, and fisheries	Changing climatic conditions	Further investigation	Net Zero, Energy and Transport/ Rural Affairs and Islands

Just Transition

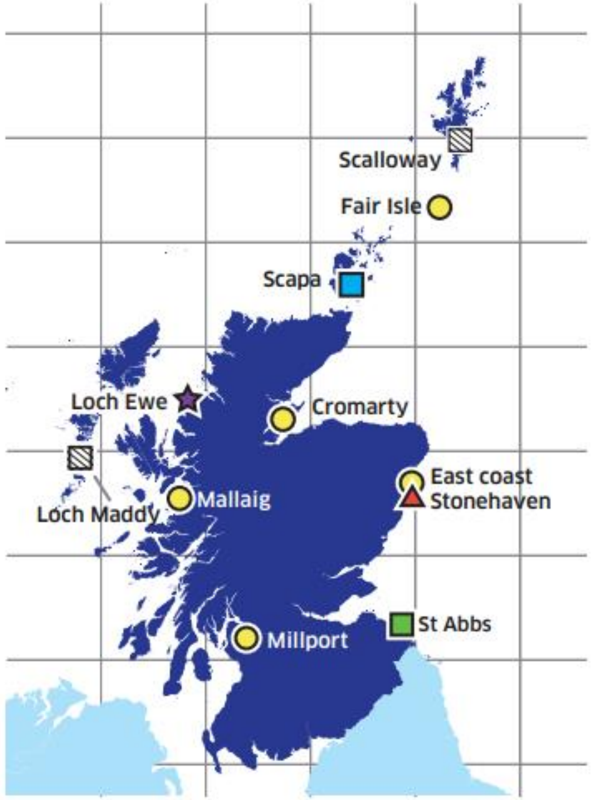
Climate Change Act (2019) embeds the principles of a just transition to give it a legislative basis.

Marine Directorate Agreed Climate Change Programme

Project	Timeline	Why needed
Marine Climate Change Programme Governance	Continuous alongside climate programme	To enable co-ordination across the directorate in line with target operating model and programme management approach.
Climate Change Plan Phase 1- **Development** Phase 2 **–Consultation and Delivery**	DECC Timeline	Statutory To deliver against requirement to progress toward net zero.
3. Scottish National Adaptation Programme 3 **WP 1 – Development of SNAP 3 policy package** **WP 2 – Delivery of Adaptation policy package** **WP 3 - To begin 2023 SNAP development.**	**Work package 1 up to publication in 2024.**	**Statutory requirement in climate change Act.** MS RISK Owner for 2 risks, co-owner of 1 high priory risk and owner of 1 opportunity. Synergies with a number of other risks across ENFOR.
4. Nitrogen Balance Sheet	Annual report - Report published in March each year looking for declining trend in overall nitrogen production and leakage.	**Statutory requirement in Climate Change Act**
5. Blue Carbon Programme **WP1 – Delivery of Blue Carbon Action Plan** **WP2 – Delivery of Blue Carbon Forum Review** **WP3 – Delivery of Blue Carbon Forum and cross forum co-ordination**	**WP1 – By March 2024** **WP2 – By August 2023** **WP3 – March 2023 with options analysis of what happens post March 2023.**	**Part Statutory & in policy prospectus and Cab Sec manifesto letter – Part of commitment to address Co-owned high priority risk on natural carbon stores on blue carbon.**
6. Climate Change in NMP2	In Line with NMP2 development by 2024.	Statutory requirement for CC to be included
7. Climate Change Projects **WP 1 – Fisheries** **WP2 – Aquaculture**	**Long term programmes**	**Delivery against statutory requirements for mitigation and adaptation.** **The project will set out the strategic direction of Scotland's fisheries and aquaculture sectors to meet Net Zero targets and adapt to the changes already locked in supporting a MD owned adaptation risk and mitigation actions.**
8. Marine Just Transition Plan	Statutory – but no specific timeframe associated as up to individual sector teams. Opportunity to link up with agriculture and Land use JT plan development including summer tour.	To support a just transition to net zero and nature positive marine economy.

Next Steps

- By December 2023 onboard 3 new staff – one will we working on supporting project 7 and begin recruitment for a climate science advice post to support science translation and co-ordination
- December 2023 MASTS workshop on setting out evidence needs across the marine space
- Scope project 7 – determine the key questions and scope of the project more strategic framework for climate change – fish health will be a component of the work.
- Aquaculture – New Updated MCCIP report card in 2024
- Updates to climate change forecasts UKPC -18 (sea levels) and updated modelling on temperature projections due in 2024.
- Scope the possibility of a Scottish Climate Vulnerability Assessment - Climate Vulnerability Assessments identify what species may be most vulnerable based on their exposure to projected changes in the environment (e.g., warming oceans) and their sensitivity or adaptability to handle those changes based on their life history characteristics (e.g., reproductive rates, diet etc).
- https://aquaculture.ec.europa.eu/knowledge-base/reports/recent-advances-climate-change-vulnerabilityrisk-assessments-fisheries-and
- Review of climate vulnerability assessment of Scotland’s marine environment and marine economy (ed.ac.uk)



TEMPERATURE, SALINITY, NUTRIENTS, OCEAN ACIDIFICATION, PIGMENTS, PHYTOPLANKTON, ZOOPLANKTON

TEMPERATURE, SALINITY, NUTRIENTS, PIGMENTS, PHYTOPLANKTON, ZOOPLANKTON,

TEMPERATURE, SALINITY, NUTRIENTS, PHYTOPLANKTON

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