

1 **Title:** Bias in self-reported parasite data from the salmon farming industry

2 **Running head:** Bias in parasite data from salmon farms

3

4 **Authors:** Sean C. Godwin^{1,2,*}, Martin Krkošek^{3,4}, John D. Reynolds¹, Andrew W. Bateman^{4,5}

5

6 **Author affiliations:**

7 ¹ Earth to Ocean Research Group, Department of Biological Sciences, Simon Fraser University,

8 8888 University Drive, Burnaby, British Columbia, Canada, V5A 1S6

9 ² Department of Biology, Dalhousie University, 1355 Oxford Street, Halifax, Nova Scotia,

10 Canada B3H 4R2

11 ³ Department of Ecology and Evolutionary Biology, University of Toronto, 25 Willcocks Street,

12 Toronto, Ontario, Canada, M5S 3B2

13 ⁴ Salmon Coast Field Station, General Delivery, Simoom Sound, British Columbia, Canada, V0P

14 1S0

15 ⁵ Department of Geography, University of Victoria, 3800 Finnerty Road, Victoria, British

16 Columbia, Canada, V8P 5C2

17

18 **Corresponding author:**

19 *Sean C. Godwin¹, 778-773-9706, sean.godwin@gmail.com*

20 **Abstract**

21 Many industries are required to monitor themselves in meeting regulatory policies intended to
22 protect the environment. Self-reporting of environmental performance can place the cost of
23 monitoring on companies rather than tax-payers, but there are obvious risks of bias, often
24 addressed through external audits or inspections. Surprisingly, there have been relatively few
25 empirical analyses of bias in industry self-reported data. Here, we test for bias in reporting of
26 environmental compliance data using a unique dataset from Canadian salmon farms, where
27 companies monitor the number of parasitic sea lice on fish in open sea-pens, in order to
28 minimize impacts on wild fish in surrounding waters. We fit a hierarchical population-dynamics
29 model to these sea-lice count data using a Bayesian approach. We found that the industry's
30 monthly counts of two sea-lice species – *Caligus clemensi* and *Lepeophtheirus salmonis* –
31 increased by a factor of 1.95 (95% credible interval: 1.57, 2.42) and 1.18 (1.06, 1.31),
32 respectively, in months when counts were audited by the federal fisheries department.
33 Consequently, industry sea-lice counts are less likely to trigger costly but mandated delousing
34 treatments intended to avoid sea-lice epidemics in wild juvenile salmon. These results highlight
35 the potential for combining external audits of industry self-reported data with analyses of their
36 reporting to maintain compliance with regulations, achieve intended conservation goals, and
37 build public confidence in the process.

38
39 **Key words:** environmental compliance; self-reported data; industry data; salmon farms; sea lice;
40 salmon lice; *Lepeophtheirus salmonis*; *Caligus clemensi*; environmental policy; environmental
41 management; Pacific salmon; policy implementation

42 **Introduction**

43 Environmental policies are intended to reduce human impacts on the natural world. The
44 scope and ‘teeth’ of an environmental policy can determine whether it meets its objectives, but
45 implementation, or lack thereof, can have equally strong impacts to on-the-ground success
46 (Howe 1993, Schwartz 2008, Wang et al. 2008). Analysis and evaluation of environmental-
47 policy implementation is critical for maximizing its efficacy (Potoski and Prakash 2013, Van
48 Den Hoek et al. 2014).

49 For numerous environmental issues, policy implementation relies on self-reported data
50 from industry to detect and mitigate problems (Livernois and McKenna 1999, Shimshack and
51 Ward 2005, Barla 2007). For example, national policies commonly rely on industry to self-
52 monitor pollution discharge or to self-report violations of pollution standards (Gamper-
53 Rabindran and Finger 2013, Russell et al. 2013). Industry self-reporting enables monitoring
54 programs that are otherwise infeasible due to costs or logistics (Gunningham and Rees 1997),
55 can shift monitoring costs from taxpayers to companies (Stoeckl 2004), and provides
56 opportunities for companies to demonstrate cooperation with regulatory authorities (Helland
57 1998). On the other hand, biased self-reporting can have significant environmental consequences
58 if inaccurate data generate management (in)actions and ecological responses that are misaligned
59 with policy intentions. Audits, inspections, and threats of legal action or financial penalty help
60 maintain the accuracy of industry self-reported data (Gray and Shimshack 2011), but accuracy
61 can be costly for industry if the data indicate violations to regulations (Gunningham and Rees
62 1997, Heyes 2000). Although these incentives for inaccurate self-reporting can be high, the
63 accuracy of self-reported data from industry is rarely investigated (but see references Li et al.
64 (2017) and De Marchi and Hamilton (2006), for example).

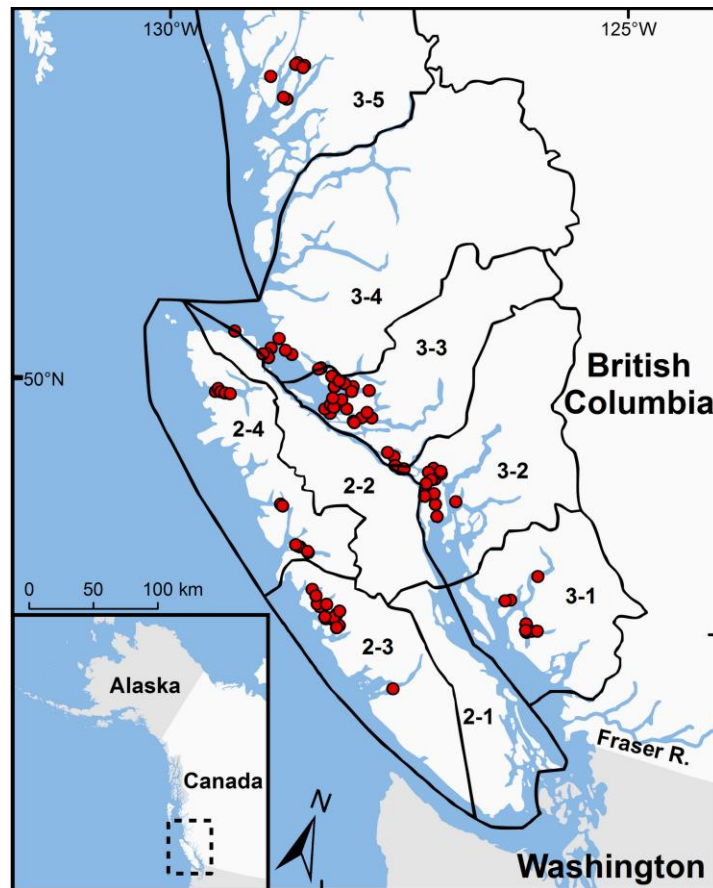
65 Recent decades have seen a surge in the number of policies designed to reduce the
66 environmental impacts of aquaculture, a set of industries whose rapid expansion, termed the blue
67 revolution, has resulted in an unprecedented rate of change in the relative contribution of farming
68 to overall production (Duarte et al. 2007). Although this shift might reduce fishing pressure in
69 some systems, it can also bring additional stressors in the form of emerging infectious diseases
70 (Daszak et al. 2000), as did terrestrial agriculture before it (Harwood 1990). Aquaculture
71 facilities can act as disease reservoirs that provide persistent sources of infection, even at low
72 densities of wild hosts, and may lead to elevated extinction risk for wildlife (De Castro and
73 Bolker 2005, Krkosek et al. 2013a). Effective policies are imperative to manage disease and
74 allow aquaculture and marine wildlife to coexist, while sustaining a productive seafood supply.

75 Of the many forms of aquaculture, salmon farming has raised the greatest concern in
76 terms of its impacts on wildlife. Salmon farms typically raise hundreds of thousands of Atlantic
77 salmon (*Salmo salar*) in open-net pens (Orr 2007) and operate in the same nearshore marine
78 waters through which wild salmon (*Oncorhynchus* spp. or *Salmo* spp.) migrate (Ford and Myers
79 2008). Consequently, pathogens and parasites are easily transmitted between farmed and wild
80 salmon (Krkosek 2017). The most studied example of this phenomenon is the spread of native
81 parasitic sea lice (primarily *Lepeophtheirus salmonis* and *Caligus* spp.) from wild adult salmon
82 to farmed salmon, leading to amplification of infections on farms and transmission to wild
83 juvenile salmon as they migrate past the net pens (Krkosek et al. 2007, Marty et al. 2010, Groner
84 et al. 2016). In the absence of salmon farms, juvenile salmon typically have low infestation rates
85 of sea lice (Costello 2009), but when they become infested they can suffer high levels of direct
86 (Morton and Routledge 2005, Jones et al. 2008) or indirect mortality (Peacock et al. 2015,
87 Godwin et al. 2017, Godwin et al. 2018), which is associated with reduced recruitment of wild

88 adult salmon in Europe (Krkosek et al. 2013b, Vollset et al. 2016) and North America (Krkosek
89 et al. 2011).

90 British Columbia (BC), Canada is the only region in the world that is a large global
91 producer of both farmed and wild salmon (Groner et al. 2016). In this important social-ecological
92 system, high sea-louse infestation rates on wild juvenile salmon in the early 2000s led to new
93 regulations designed to control sea-louse numbers on farms (Peacock et al. 2013). British
94 Columbia salmon farms are now required to self-monitor sea louse infestation rates on their fish
95 by performing sea lice counts every month, which distinguish between the two main species of
96 sea louse in BC: *L. salmonis* and *Caligus clemensi*. *Lepeophtheirus salmonis*, a salmonid
97 specialist, is the focus of sea louse regulations in BC (and most of the world) because until
98 recently (Godwin et al. 2015, Godwin et al. 2017, Godwin et al. 2018) there was no evidence of
99 harmful host effects from *C. clemensi*, a generalist that infects other nearshore marine fishes.
100 Prior to 2017, treatments to reduce sea-louse abundances on BC salmon farms were almost
101 exclusively conducted using an in-feed parasiticide called emamectin benzoate (trade name
102 SLICE®) (Saksida et al. 2010). Current policy requires salmon farms to either harvest or conduct
103 a delousing treatment when louse abundance exceeds three motile (i.e., adult or pre-adult) *L.*
104 *salmonis* per fish. This policy drastically reduced sea-louse epizootics on BC salmon farms and
105 seemed to halt the decline of local pink salmon populations in one region of the BC coast
106 (Peacock et al. 2013). The implementation of this policy requires salmon farms to collect and
107 report sea-louse count data themselves, in order to know when the three-louse threshold has been
108 exceeded. The Canadian federal Department of Fisheries and Oceans (DFO) occasionally
109 conducts scheduled audits of these industry counts (see the Appendix S1 for more local context).

110 Here, we assess whether industry self-reporting leads to underestimation bias in sea-louse
111 monitoring data from BC salmon farms. We address this question by analyzing time series of
112 self-reported, periodically audited parasite data from 91 farms (Fig. 1) over six years, using a
113 hierarchical model and Bayesian fitting methods. We use population-dynamic models to test for
114 potential differences between audited and unaudited counts.
115



116
117 Fig. 1. Locations of the 91 BC salmon farms in the industry sea lice dataset that were active (i.e.,
118 stocked with fish) for at least one month between 2011 and 2016. Solid black lines demarcate the
119 boundaries of DFO fish health surveillance zones, each of which is identified by number.

120
121 **Methods**

122 ***Data***

123 We used publicly available sea lice data collected by aquaculture industry staff on active
124 farms in BC from 2011 through 2016 (Fisheries and Oceans Canada 2017d). These data are
125 monthly averages of industry louse counts on individual salmon farms; data from individual
126 sampling events or individual fish are not publicly available. During each sea lice sampling
127 event, farm staff capture stocked fish by seine net in three net pens and collect at least 20 fish by
128 dip net from each seine (Fisheries and Oceans Canada 2016). One of the net pens is a reference
129 pen that is assessed in every sampling event, and the other two are selected randomly (Fisheries
130 and Oceans Canada 2016). The collected fish are then placed in an anaesthetic bath of tricaine
131 methanesulfonate (TMS, or MS-222) and assessed for lice by eye. The sea-lice counts
132 concentrate on the more pathogenic and mobile pre-adult and adult life stages (termed ‘motile’)
133 rather than the attached stages earlier in development. For each farm in the dataset, between 0
134 and 6 sea lice sampling events were conducted each month (mean = 1.64 events month⁻¹), and
135 99.1% of these months had 1 to 3 sampling events.

136 For every mean monthly motile louse count, the industry dataset includes the month and
137 year of the count, the number of sampling events contributing to the count, the age class of the
138 stocked fish, a farm facility identifier, the farm’s fish health surveillance zone (Fig. 1), and the
139 previous month’s mean louse count. The dataset also has comments denoting planned or recently
140 performed treatments, and from these we inferred the months in which treatments probably
141 occurred. We excluded mean monthly counts that were missing any of this information (n =
142 440). Our final dataset comprised 2,626 mean monthly louse counts over six years, from seven
143 health zones and 91 farms (Fig. 1). When visualizing the average monthly counts in a calendar
144 year, we bootstrapped 95% confidence intervals by sampling the monthly counts in each year

145 with replacement using the same sample size, combining the samples from all six years,
146 calculating the mean of the combined sample, repeating this process 10,000 times, and
147 calculating the 2.5th and 97.5th percentile of the 10,000 means for the confidence bounds.

148 In an attempt to ensure the quality of industry sea lice data, DFO performs intermittent,
149 pre-arranged audits of industry sea lice monitoring. The farm facilities to be audited are chosen
150 randomly each month, and the audits are then scheduled to coincide with one of those farms'
151 scheduled sampling events that month (Fisheries and Oceans Canada 2017c). During the audits,
152 fish are selected in the same manner as for non-audited sampling events and divided equally
153 between farm staff and DFO personnel for independent counting (Fisheries and Oceans Canada
154 2017c). Audit timing data are publicly available (Fisheries and Oceans Canada 2017b), and we
155 therefore knew whether or not an audit was associated with each of the mean monthly louse
156 counts. Audits occurred in 7.7% of the month-farm combinations in the dataset.

157

158 ***Model***

159 To assess the potential effect of DFO audits on industry-reported sea-louse counts, we fit
160 a hierarchical model to the mean monthly counts from the self-reported and publicly-available
161 industry dataset (Fisheries and Oceans Canada 2017d). While our primary goal was to clarify
162 whether sea-louse counts decrease in months when DFO audits are not conducted, our model
163 also accounted for the effects of month, year, and fish health surveillance zone – which
164 incorporate variation in environmental conditions – as well as farmed salmon age class and louse
165 density dependence. We fit the model using Markov chain Monte Carlo (MCMC) methods and
166 uniform priors. Our model was comprised of two identical parts – one for *L. salmonis* dynamics
167 and one for *C. clemensi* dynamics – but was fit to both species' count data simultaneously to

168 allow for the inclusion of an interspecific density dependence term in each part. For simplicity,
169 we present only the *L. salmonis*-focused components of our model.

170 The model had distinct population growth and colonization components. The
171 colonization component included covariates for year, health zone, and farmed salmon age class.
172 The population growth component included covariates for month, year, health zone, farmed
173 salmon age class, and inter- and intraspecific density dependence. Each component included a
174 varying-intercept term (i.e., a random-effect level) for each farm. The effects of delousing
175 treatment and DFO audit acted upon the entire model such that any effect would produce a
176 proportional change in louse counts. We fit our single model and interpreted its results rather
177 than performing model selection on smaller models because: 1) parsimony was not our objective,
178 2) the complexity of the model was justified by the size of the dataset, and 3) all the parameters
179 had strong biological justifications (see Gelman and Rubin (1995) and Neal (2012) for
180 discussion of this method of Bayesian model inference). Table 1 provides an overview of the
181 model notation, and Appendix S1 presents model diagnostics, posterior plots, and the full set of
182 parameter estimates.

183 In the industry dataset, the mean monthly counts are rounded to the nearest tenth and
184 include a high proportion of zeroes. Similar to Jansen et al. (2012), we model monthly louse
185 counts per ten fish (i.e., we multiplied the mean monthly counts by ten) and assume a negative
186 binomial error distribution:

$$187 \quad N_{L,t,f} \sim \text{negative binomial} (\mu_{L,t,f}, \rho_L), \quad (1)$$

188 where $N_{L,t,f}$ is the reported mean motile louse count per ten fish in month t on farm f , $\mu_{L,t,f}$ is the
189 predicted mean motile louse count per ten fish for that month and farm, and ρ_L is the negative
190 binomial shape parameter, fit as an additional free parameter. We allowed the shape parameter of

191 the negative binomial to vary between species because one key relationship that drives
192 overdispersion is the ratio of immigrants to births (Bolker 2008); the relative contributions of
193 colonization and on-farm population growth to counts are likely to be very different between *C.*
194 *clemensi* and *L. salmonis* due to the large difference in their mobility among hosts (Saksida et al.
195 2015, Atkinson et al. 2018). Using the negative binomial prevents complications associated with
196 zero counts because, unlike the gamma distribution, the negative binomial distribution allows for
197 zeros. A gamma hurdle model, for example, may better accommodate zero counts, but such a
198 model that included adequate complexity (i.e., terms for density dependence, delousing
199 treatments, temporal and spatial effects, and the necessary random effects) proved inordinately
200 complex and challenging to fit. In this case, the negative binomial is a natural choice for a single
201 distribution that accommodates zeros as well as extra-Poisson variability introduced by model
202 uncertainty. Also, parasites, including sea lice (Heuch et al. 2011), are typically overdispersed on
203 hosts (i.e., the variance is greater than the mean) and are commonly considered to be negative
204 binomially distributed (Crofton 1971, Anderson and May 1992, Shaw et al. 1998). We note that
205 the standard error (and therefore the distribution) of the mean monthly louse counts will, in fact,
206 be affected by the number of fish assessed on a farm in any given month, but this information is
207 not available. We use the negative binomial distribution as a good empirical approximation of
208 the true underlying distribution (see Appendix S1: Fig. S1 for diagnostics).

209 At their most basic, our models take the form:

$$210 \quad \mu_{L,t+1,f} = N_{L,t,f} \lambda_{L,t,f} + \gamma_{L,t,f} , \quad (2)$$

211 where the mean motile count in month t ($\mu_{L,t+1,f}$) is predicted by the sum of intrinsic on-farm
212 dynamics and external colonisation pressure. The on-farm dynamics are the product of the
213 previous month's count on that farm ($N_{L,t,f}$) and a per-capita population growth rate ($\lambda_{L,t,f}$)

214 affected by on-farm conditions, such as louse density and treatment status. The colonization rate
 215 ($\gamma_{L,t,f}$) is a function of extrinsic factors. Both the per-capita population growth rate and the
 216 colonization rate are modelled as transformed linear functions, where $\lambda_{L,t,f} = e^{\eta_{L,t,f}}$ and $\gamma_{L,t,f} =$
 217 $e^{\beta_{L,t,f}}$; thus $\eta_{L,t,f}$ and $\beta_{L,t,f}$ are analogous to linear predictors in generalized linear mixed models
 218 (GLMMs) with a logarithmic link function. Note that our model assumes key population
 219 processes can be captured by considering only motile lice, ignoring details of early
 220 developmental stages. But while our model does not explicitly consider larval lice, those that
 221 colonize as larvae and develop into motiles are still captured in the colonization-rate component
 222 of our model. We also implicitly model the influence of environmental conditions on
 223 development time between larval attachment and the motile stage (~27 days for *L. salmonis* at
 224 10°C (Johnson and Albright 1991) and unknown length for *C. clemensi*) in the growth-rate
 225 component. We do this by including spatial and temporal predictors (i.e., health zone, month,
 226 and year) that are strongly correlated with temperature and salinity (Pickard and McLeod 1953,
 227 Fisheries and Oceans Canada 2017a) – important drivers of development timing for sea lice
 228 (Johnson and Albright 1991). While it would be more direct to use actual temperature and
 229 salinity measurements from the farms, we were unable to obtain these data.

230 We allow delousing treatment to influence monthly louse counts, including the motiles
 231 that developed over the month, as:

$$232 \quad \mu_{L,t+1,f} = e^{\tau_{L,treat,t,f}} (N_{L,t,f} \lambda_{L,t,f} + \gamma_{L,t,f}), \quad (3)$$

233 where $e^{\tau_{L,treat,t,f}}$ is a proportional mortality term for farm f in month t that results from delousing
 234 treatment. The exponent takes one of three levels: zero if treatment last occurred more than one
 235 month before t , or one of two levels to describe louse decline when treatment occurred in month t
 236 or $t-1$, corresponding to the two-month effectiveness previously described for emamectin

237 benzoate (Lees et al. 2008, Saksida et al. 2010).

238 To account for the potential effects of DFO audits on industry louse counts, we extend
239 the model such that

$$240 \quad \mu_{L,t+1,f} = e^{\tau_{L,treat,t,f}} e^{\alpha_{L,t+1,f}} \left(\frac{N_{L,t,f,n}}{e^{\alpha_{L,t,f}}} \lambda_{L,t,f} + \gamma_{L,t,f} \right), \quad (4)$$

241 where $e^{\alpha_{L,t+1,f}}$ allows for a proportional change in a farm's counts in month t (or $t+1$, as
242 appropriate), if indeed they are influenced by whether the DFO audits a farm. The exponent,
243 $\alpha_{L,t,f}$, takes the value of 0, if no audit occurs, or a fitted estimate, if an audit occurs. When an
244 audit does occur in month t , that month's reported louse count ($N_{L,t,f,o}$) is rescaled by $e^{\alpha_{L,t,f}}$ to
245 account for any louse count observation error associated with audits.

246 The linear predictor for per-capita population growth rate in a given month and farm
247 ($\ln(\lambda_{L,t,f})$ from equation (2)) takes the form:

$$248 \quad \eta_{L,t,f} = \eta_{L,0} + \eta_{LL,class} N_{L,t,f} + \eta_{LC,class} N_{C,t,f} + \eta_{class,t,f} + \eta_{L,zone,f} + \eta_{L,year,t} + \eta_{L,month,t} + \\ 249 \quad \varphi_{L,f}, \quad (5)$$

250 The first term is an intercept ($\eta_{L,0}$) that defines growth rate at base factor levels ($class = < 1$ year
251 in sea, $zone = 2-3$, $year = 2011$, $month = \text{January}$) and louse counts of zero for *L. salmonis* and *C.*
252 *clemensi* abundance in the previous month. The next two terms represent the interspecific and
253 intraspecific density dependence on a farm's per capita louse count in month t ; they each
254 incorporate a farm's louse counts in month $t-1$ ($N_{L,t-1,f}$ and $N_{C,t-1,f}$) and a coefficient that
255 describes density dependence due to either *L. salmonis* ($\eta_{L,L,class}$) or *C. clemensi* ($\eta_{L,C,class}$).

256 These coefficients depend on the age class of the farm's stocked fish in month t (farm and month
257 subscripts not shown), which can take one of two levels: fish that have spent less than one year
258 in seawater, and fish that have spent greater than or equal to one year in seawater. Age class also
259 directly affects the per-capita growth rate of a farm in month t ($\eta_{class,t,f}$) because fish surface

260 area may influence louse survival (Tucker et al. 2002). There are three additional coefficients for
 261 categorical covariates: the age class of the fish for a given month and farm ($\eta_{class,t,f}$), the health
 262 zone of the farm ($\eta_{L,zone,f}$), and the year ($\eta_{L,year,t}$) and month ($\eta_{L,month,t}$) of the louse count.
 263 Among other things, these coefficients represent spatial and temporal variability in temperature
 264 and salinity. The last term in equation (5) is a varying coefficient (hereafter termed a ‘random
 265 effect’ to continue the parallel between our sub-models and GLMMs) describing how the
 266 intercept varies among farms.

267 We modelled the linear predictor for a farm’s colonization rate in month t such that

$$268 \quad \beta_{L,t,f} = \beta_{L,0} + \beta_{class,t,f} + \beta_{L,zone,f} + \beta_{L,year,t} + \psi_{L,f}, \quad (6)$$

269 where $\beta_{L,0}$ is an intercept term describing the colonization rate when counts were zero for L .
 270 *salmonis* and *C. clemensi* in the previous month, and at base factor levels ($class = <1$ year in sea,
 271 $zone = 2-3$ and $year = 2011$). The age class of the farm’s fish ($\beta_{class,t,f}$), the farm’s fish health
 272 surveillance zone ($\beta_{L,zone,f}$), and the year of the count ($\beta_{L,year}$) affect colonization rate in the
 273 same manner that they affected per-capita growth rate in equation (5). Finally, we include a
 274 random effect on the intercept of farm facility to account for the hierarchical nature of the data
 275 ($\psi_{L,f}$) while limiting the number of farm facility parameters in our model. We attempted to
 276 include colonization density dependence as we did for the population growth rate linear function
 277 (5), but that model did not converge.

278 The full equation for the predicted mean motile louse count is as follows:

$$279 \quad \mu_{L,t+1,f} = \overbrace{e^{\tau_{L,treat,t,f}}}^{\text{Treatment (3)}} \overbrace{e^{\alpha_{L,t+1,f}}}^{\text{Audit (4)}} \left(\overbrace{\frac{N_{L,t,f,n}}{e^{\alpha_{L,t,f}}}}^{\text{Rescale count (4)}} \overbrace{e^{\eta_{L,t,f}}}^{\text{Population growth rate (5)}} + \overbrace{e^{\beta_{L,t,f}}}^{\text{Colonization rate (6)}} \right), \quad (7)$$

280 where the overbraces reference the previously described equations and where the predicted mean
 281 motile louse count is the mean of the negative binomial probability density function in equation

282 (1).

283 We used uniform priors between -100 and 100 for all of our parameters except for a
284 single $\eta_{zone,C}$ coefficient. We constrained this parameter's uniform prior between -10 and 10
285 because the *C. clemensi* data for this particular fish health surveillance zone (zone 3-1) included
286 two drastic month-to-month declines in mean louse counts that caused fitting complications. This
287 constraint had little effect on the median parameter estimate for $\eta_{C,zone3-1}$, which was highly
288 uncertain regardless due to low sample size in that zone (Appendix S1: Fig. S2). The uniform
289 prior has the desirable property that the overall probability of either inflation or deflation is equal
290 – a necessary condition to avoid biasing the audit parameters, or indeed any of the parameters.
291 While this prior is not flat on the response scale (i.e., when exponentiated it is not distributed
292 uniformly), the audit result was unchanged when we used a prior that was “flatter” on the
293 response scale over the range of interest (but therefore assigned more prior weight to inflationary
294 audit effects; see Appendix S1). We fit separate variance parameters for the two farm-facility
295 random effects ($\varphi_{L,f}$ and $\psi_{L,f}$), in addition to a parameter describing the correlation between the
296 two; we used the same uniform priors for these random-effects parameters. The random effects
297 were each drawn from a multivariate normal distribution with a mean of zero and a covariance
298 matrix determined by an inverse-Wishart distribution, which was in turn informed by the three
299 random-effect parameters (Gelman and Hill 2007). The random effects were needed to account
300 for the hierarchical nature of the data while also avoiding fitting 180 separate fixed-effect
301 parameters.

302 When parameter estimates are given in the text, we report them as posterior medians
303 along with the lower and upper 95% credible intervals. Our analysis was performed using R
304 3.2.1 (R Core Team 2019) and JAGS 4.3.0 (Plummer 2017) with the R package R2jags 0.5-7

305 (Yu-Sung Su and Yajima 2015).

306

307 **Results**

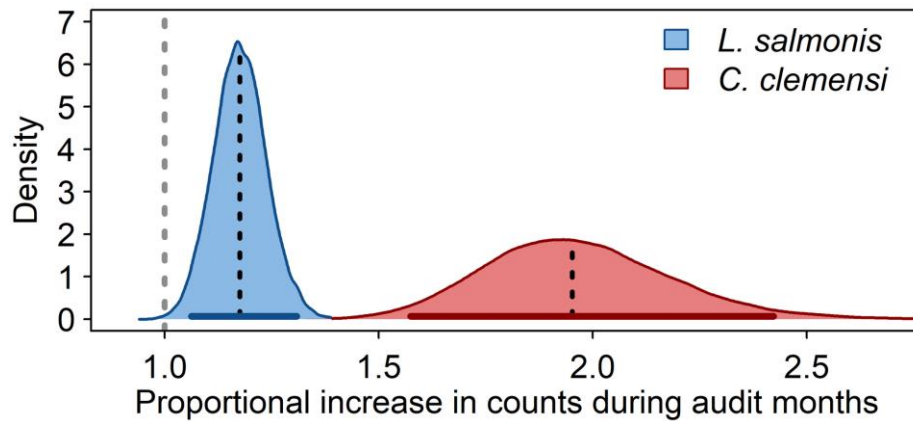
308 We found that industry sea-louse counts are biased downwards. In months when DFO
309 performed its pre-arranged audits, the industry's mean monthly *C. clemensi* counts were 1.95
310 (95% credible interval: 1.57, 2.42) times counts in months when DFO did not audit (Fig. 2), after
311 accounting for all the other variables in our model. Given this *C. clemensi* audit effect and the
312 30% background underestimation of *C. clemensi* due to dislodgement during counting (Saksida
313 et al. 2007), we expect that the true *C. clemensi* abundances on farms is approximately 2.55
314 times reported counts (Fig. 3).

315 For *L. salmonis*, counts in audit months were 1.18 (1.06, 1.31) times counts in non-audit
316 months (Fig. 2). When this correction factor was applied to the reported counts in months that
317 DFO did not audit, the number of mean monthly counts that exceeded the three-louse threshold
318 rose from 376 to 437 – an increase of 16%. On average, farms waited 1.2 ± 0.1 months (mean \pm
319 SE) before treating or harvesting following a month when the mean *L. salmonis* count exceeded
320 the treatment threshold. When using counts corrected for the audit effect, this delay lengthened
321 to 1.6 ± 0.2 months – a 30% increase. During the wild juvenile salmon migration (March to
322 June), the mean delay before action was 0.7 ± 0.2 months, according to the reported counts, but
323 the corrected counts reveal a 22% increase in delay time, to 0.9 ± 0.2 months.

324 Our model predicted that unaudited counts were reduced by a factor of 0.51 (0.41, 0.63)
325 and 0.85 (0.76, 0.94) relative to the audited *C. clemensi* and *L. salmonis* counts, respectively
326 (Fig. 4). In comparison, treatments in the previous month reduced counts by a factor of 0.31
327 (0.23, 0.1) for *C. clemensi* and by 0.38 (0.28, 0.50) for *L. salmonis*. In the absence of audits and

328 treatments, the predicted contributions of population growth rate and colonization rate to louse
329 counts were drastically different between the two species. For *C. clemensi*, estimated on-farm
330 population growth contributed 25% (20%, 29%) to counts, on average, and estimated
331 colonization contributed 65% (61%, 68%). For *L. salmonis*, these contributions were almost
332 perfectly reversed, with population growth contributing 65% (61%, 68%) to counts and
333 colonization contributing 28% (25%, 32%).

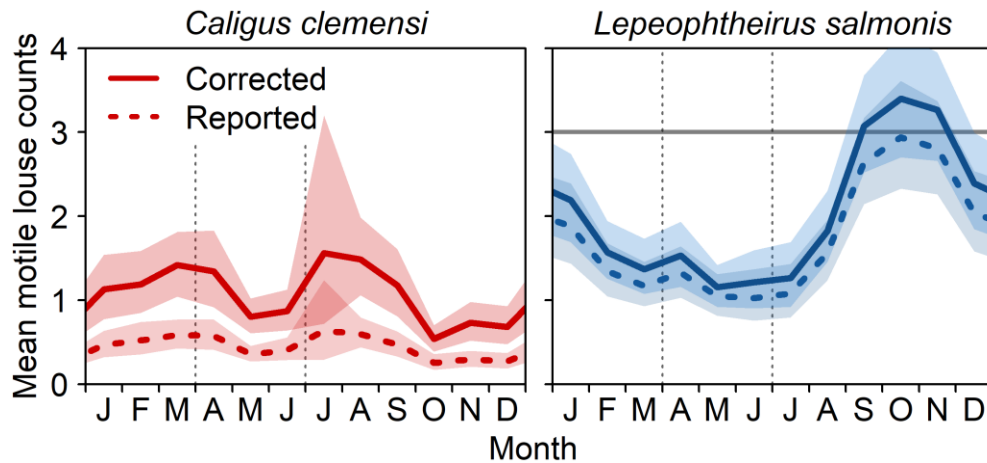
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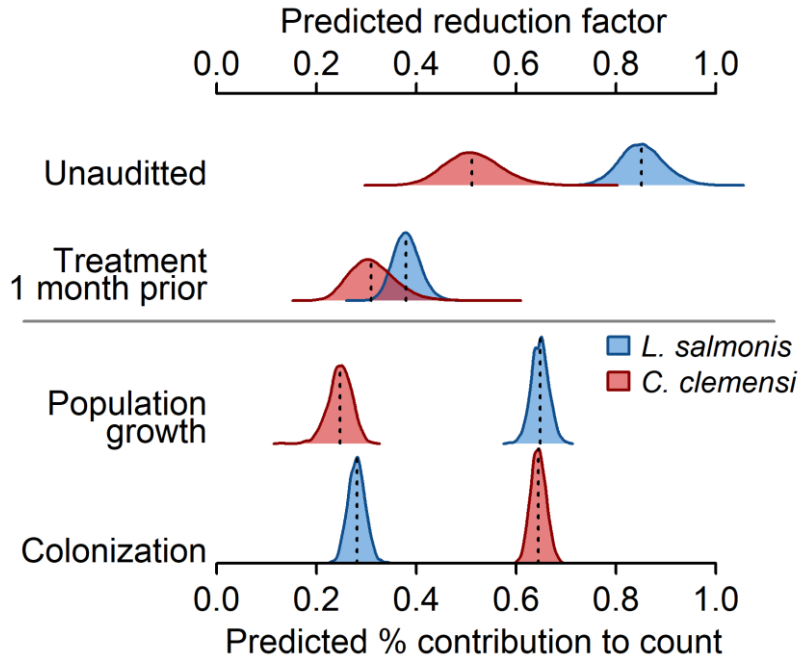
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336 Fig. 2. Proportional increase in farm louse counts in months when DFO audited farms, as shown
337 by the exponentiated posterior distributions for the audit parameters in our model. The coloured
338 horizontal lines give the 95% credible intervals and the dotted black vertical lines describe the
339 exponentiated median parameter estimates. The dashed grey vertical line at 1.0 indicates no
340 difference in counts between months with and without a DFO audit.

341



342
 343 Fig. 3. Monthly variation in reported and corrected mean motile *Caligus clemensi* (left panel)
 344 and *Lepeophtheirus salmonis*) counts on BC salmon farms between 2011 and 2016. Shaded
 345 regions depict 95% confidence intervals for the monthly means and do not reflect uncertainty in
 346 the audit effect (Fig. 2); these confidence intervals were calculated by bootstrapping the counts
 347 10,000 times while maintaining the hierarchical structure with respect to year (see methods).
 348 Reported counts were corrected by the median estimate of the audit effect (Fig. 2) for both
 349 species; reported *C. clemensi* counts were also corrected by 30% to account for background
 350 underestimation due to dislodgement during counting (Saksida et al. 2007). Dashed vertical lines
 351 delineate the wild juvenile salmon migration period (April to June) and the horizontal line in the
 352 right panel represents the current threshold for delousing treatment. We show the monthly means
 353 connected by lines for visual effectiveness, but we note that these are discrete monthly data.
 354



355
 356 Fig. 4. Relative effects of the four main components of the model (audit, treatment, population
 357 growth, and colonization from equation (7)) for both *L. salmonis* (blue) and *C. clemensi* (red).
 358 The audit and treatment terms are represented as reduction factors that proportionally change
 359 louse counts. The reduction factor for the treatment term is its exponentiated posterior and the
 360 reduction factor for the audit term is the reciprocal of its exponentiated posterior. The population
 361 growth and colonization components are presented as their predicted percent contributions to
 362 unaudited and untreated counts. The dashed vertical lines denote the median values.

363
 364 **Discussion**

365 Our results suggest that sea-louse counts reported by the salmon farming industry are
 366 lower than the true abundance of parasites on their fish. When the federal government audited a
 367 sea-louse count, the industry’s mean counts for that month increased by a factor of 1.18 for *L.*
 368 *salmonis* and by 1.95 for *C. clemensi*. This underestimation bias has likely led to fewer
 369 treatments and longer delays before management action is taken during sea-louse outbreaks, thus

370 reducing the effectiveness of environmental policy designed to safeguard wild salmon
371 populations.

372 When we corrected the reported sea-louse counts for the audit effect and for *C. clemensi*
373 dislodgement prior to counting ((30% Saksida et al. 2007)), we found considerable differences
374 between reported and corrected counts. For *C. clemensi*, corrected counts were 2.55 times
375 reported counts and nearly reached the same levels as *L. salmonis* during migration months for
376 wild juvenile salmon (Fig. 3). These high *C. clemensi* levels on farms have the potential to affect
377 wild populations given recent correlative work linking *C. clemensi* abundance with decreased
378 foraging success, competitive ability, and growth in wild juvenile salmon (Godwin et al. 2015,
379 Godwin et al. 2017, Godwin et al. 2018). Despite the growing evidence for effects of *C. clemensi*
380 on wild salmon and the unexpectedly high abundances of this species on farms during the wild
381 juvenile migration, *C. clemensi* are not currently targeted by management on salmon farms. For
382 *L. salmonis* – the louse species targeted by management – corrected average counts were higher
383 than the three-louse treatment threshold for one-quarter of the year (September, October, and
384 November; Fig. 3). By contrast, there were no months in which the average reported counts
385 exceeded the treatment threshold.

386 The management implication of biased sea-louse counts is that delousing treatments to
387 control outbreaks may be delayed or not occur at all. After correcting the reported *L. salmonis*
388 counts for the audit effect, we found a 16% increase in the number of mean monthly counts that
389 broke this three-louse threshold. This increase does not imply that there should have been 16%
390 more treatments – to make this calculation we would need to know how many *individual* counts
391 broke the threshold, and industry counts are only reported as monthly means – but it does
392 suggest that underestimated counts may well influence treatment decisions. Indeed, we found the

393 average delay between a month with a threshold-breaking count and the subsequent management
394 action increased by 30% when using corrected counts instead of reported counts, and by 22%
395 during months in which wild juvenile salmon migrate. The corrected delay during the migration
396 window, while shorter than the corrected average year-round delay (0.9 ± 0.2 months during
397 migration and 1.6 ± 0.2 months year-round), is still longer than the 15 calendar days license
398 conditions allow farms before they must “implement a plan which will reduce absolute sea lice
399 inventory” during migration months (Fisheries and Oceans Canada 2016).

400 One solution to remove bias from self-reported data would be for monitoring to be
401 conducted by an independent third party. However, regulatory transitions from self-monitoring
402 to third-party monitoring are rare and, to our knowledge, their effect on data accuracy remains
403 unassessed. Other options for increasing data accuracy include improving data collection training
404 for industry staff (Dasgupta et al. 2000) and performing audits or inspections without advance
405 notice *after* data collection takes place, so that data are always collected with the risk of
406 subsequent review (Laplante and Rilstone 1996). The latter solution eliminates the potential for
407 finding statistical agreement between industry and auditor counts during the audits themselves
408 (as is the case for sea-louse monitoring (Elmoslemany et al. 2013, Fisheries and Oceans Canada
409 2018)), only to observe a drop in accuracy when auditors are absent (as our results show). In the
410 case of sea lice, the counting protocol itself could be improved, for example by discontinuing the
411 use of dip nets to avoid dislodging lice (Godwin et al. 2015). The current protocol requires high
412 diligence to minimize or retrieve dislodged sea lice; this is especially true for the highly mobile
413 *C. clemensi* (Saksida et al. 2015, Atkinson et al. 2018), which could explain why our results
414 indicated that *C. clemensi* are more underestimated than *L. salmonis*.

415 A final option to improve the accuracy of sea-louse counts would be to systematically

416 apply correction factors (here estimated to be 1.18 for *L. salmonis* and 2.55 for *C. clemensi*) to
417 the reported monthly means. These correction factors could be dynamic over time and informed
418 by empirical quantitative analyses like the one we present here; the prospect of reduced
419 correction factors could provide incentive for industry to improve data accuracy. It should be
420 noted that the actual bias in *individual* counts (i.e., audited vs. non-audited counts) is probably
421 greater still than the bias reported here, because the count data in the public dataset are given as
422 monthly means. Bias in audited counts was thus diluted in the pool of each month's counts
423 (mean = 1.64 counts month⁻¹).

424

425 **Conclusions**

426 Industry self-reported data are often thought to be unbiased because incentives exist for
427 accurate self-reporting. For example: a) self-reporting is done under surveillance (Short and
428 Toffel 2010), b) audits or inspections are performed without advance notice (Russell 1992,
429 Makofske 2019), c) misreporting is met with administrative, legal, or financial penalties
430 (Shimshack and Ward 2005, Gray and Shimshack 2011), d) accurate data are easy to obtain
431 (Gunningham and Rees 1997, Gray and Shimshack 2011), or e) industry is not penalized when
432 self-reporting demonstrates violations to regulations (Livernois and McKenna 1999). None of
433 these conditions exist for sea-louse counts on salmon farms; in particular, self-reported violations
434 (i.e., *L. salmonis* counts above three motile lice per fish) result in the farm having to perform a
435 costly delousing treatment or harvest its fish earlier than it would otherwise. Our results suggest
436 that when incentives for accurate self-reporting are not strong, bias can occur in industry self-
437 reported data. By providing explicit and strong incentives for accurate self-reporting,
438 environmental policies can reap the benefits of industry data while also increasing compliance

439 and effectiveness.

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630
631

632 Table 1. Overview of model notation.

Symbol	Description	Data or prior details
<i>Response variable</i>		
N	motile louse count per ten fish	integer
<i>Indices for predictor variables</i>		
t	index for timestep (month)	72 months (January 2011 - December 2016)
f	index for farm	91 farms (all active BC farms in 2011 - 2016)
$treat$	index for treatment status	3 treatment statuses (treated in t , in $t-1$, or not)
$zone$	index for fish health surveillance zone	7 health zones (all health zones for the 91 farms)
$year$	index for year	6 years (2011 - 2016)
$month$	index for month-of-year	12 months-of-year (January - December)
$class$	index for age class of farmed fish	2 age classes (< 1 year in sea, > 1 year in sea)
<i>Model predictions and parameters</i>		
μ	predicted motile louse count per ten fish	
λ	per-capita louse population growth rate	
γ	louse colonization rate	
τ	effect of delousing treatment	fixed, $U(-100,100)$
α	effect of DFO audit	fixed, $U(-100,100)$
ρ	negative binomial shape parameter	$U(-100,100)$
<i>Sub-model predictions and parameters</i>		
η	linear function for λ ($\lambda = e^\eta$)	
η_i	coefficient in η , associated with predictor i	fixed, all $U(-100,100)$ *
φ	varying-coefficients term for farms in η	random, $U(-100,100)$
β	linear function for γ ($\gamma = e^\beta$)	
β_i	coefficient in β , associated with predictor i	fixed, all $U(-100,100)$
ψ	varying-coefficients term for farms in β	random, $U(-100,100)$
<i>Subscripts</i>		
L	subscript for <i>L. salmonis</i>	
C	subscript for <i>C. clemensi</i>	
o	subscript for reported louse count	

633 * with the exception of $\eta_{C,zone3-1}$, which was constrained to be $U(-10,10)$ due to low sample
634 size, as discussed in the methods.

635