

Size- and stage-dependence in cause-specific mortality of migratory brown trout

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1 Abstract

- 2 1. Evidence-based management of natural populations under strong human in-
3 fluence frequently requires not only estimates of survival but also knowledge
4 about how much mortality is due to anthropogenic versus natural causes.
5 This is the case particularly when individuals vary in their vulnerability to
6 different causes of mortality due to traits, life-history stages, or locations.
- 7 2. Here, we estimated harvest and background (other cause) mortality of a
8 landlocked migratory salmonid over half a century. In doing so, we quanti-
9 fied among-individual variation in vulnerability to cause-specific mortality
10 resulting from differences in body size and spawning location relative to a
11 hydropower dam.
- 12 3. We constructed a multistate mark-recapture model to estimate harvest and
13 background mortality hazard rates as functions of a discrete state (spawning
14 location) and an individual time-varying covariate (body size). We further
15 accounted for among-year variation in mortality and migratory behavior and
16 fit the model to a unique 50-year time-series of mark-recapture-recovery data
17 on brown trout (*Salmo trutta*) in Norway.
- 18 4. Harvest mortality was highest for intermediate-sized trout, and outweighed
19 background mortality for most of the observed size range. Background mor-
20 tality decreased with body size for trout spawning below the dam and in-
21 creased for those spawning above. All vital rates varied substantially over
22 time, but a trend was evident only in estimates of fishers' reporting rate,
23 which decreased from over 50% to less than 10% throughout the study pe-

24 rioid.

25 5. We highlight the importance of body size for cause-specific mortality and
26 demonstrate how this can be estimated using a novel hazard rate parameter-
27 isation for mark-recapture models. Our approach allows estimating effects of
28 individual traits and environment on cause-specific mortality without con-
29 founding, and provides an intuitive way to estimate temporal patterns within
30 and correlation among different mortality sources.

31 **Keywords**

32 Bayesian statistics, dam, harvesting, hazard rate, mark-recapture, mortality, NIM-
33 BLE, trout.

34 **Introduction**

35 Population dynamics – particularly of long-lived species – are often highly sensi-
36 tive to changes in mortality (Sæther and Bakke 2000). Mortality can have a wide
37 variety of causes (e.g. starvation, predation, disease, harvest), and vulnerability to
38 cause-specific mortality may depend on individual factors such as age or life stage
39 (Ronget et al. 2017). As a consequence, population-level responses to changes in
40 mortality may vary greatly depending on the underlying cause, and disentangling
41 different causes of mortality may provide insights crucial for population manage-
42 ment and conservation (Williams et al. 2002). This is particularly important in
43 populations where a significant portion of mortality is linked to human activity;
44 in such cases, knowledge about the relative impact of human-induced mortality

45 and its effects on other mortality sources is crucial for developing sustainable and
46 successful management strategies (Hilborn and Walters 2013, Koons et al. 2014).

47 Studies of marked individuals constitute a highly valuable source of demo-
48 graphic data for wild animal populations and are essential for estimating survival,
49 as well as cause-specific mortality. The recovery of a dead marked animal often pro-
50 vides information on the cause of death. However, unless animals are marked with
51 radio- or satellite transmitters, most dead individuals will not be found, and this
52 imperfect detection needs to be accounted for when estimating mortality parame-
53 ters. Moreover, when considering multiple mortality causes, detection probability
54 frequently depends on the cause of mortality, and some causes of mortality may
55 not be observable at all. This is usually the case for natural mortality when dead
56 recoveries are exclusively based on the reports of hunters or fishers (e.g. Servanty
57 et al. 2010, Koons et al. 2014).

58 Schaub and Pradel (2004) developed a multistate mark-recapture-recovery frame-
59 work that allows separately estimating mortality from different causes while ac-
60 counting for cause-dependent detection probabilities. Specifically, cause-specific
61 mortalities are estimated as transitions from an “alive” state to several “dead from
62 cause of interest” states. When this framework is extended to also include mul-
63 tiple “alive” states, it becomes possible to estimate differences in vulnerability to
64 cause-specific mortality depending on, for example, an individual’s life-stage (e.g.
65 juveniles vs. adults, Schaub and Pradel 2004) or location (Fernández-Chacón et al.
66 2015). Such group-level differences in mortality can be tremendous and accounting
67 for them is crucial for modelling population dynamics (Ronget et al. 2017). How-
68 ever, in addition to that, vital rates and population dynamics are often strongly
69 affected by individual differences in continuous, dynamic traits such as body size

70 (De Roos et al. 2003, Vindenes and Langangen 2015). Particularly in species that
71 are harvested and/or have indeterminate growth (e.g. fish species), cause-specific
72 mortality is expected to depend strongly on body size. Fernández-Chacón et al.
73 (2017) demonstrated this by estimating cause-specific mortalities for different sizes
74 of Atlantic cod (*Gadus morhua*). However, they did so by lumping individuals
75 into either of two size classes (“small” or “large”), thus foregoing the possibility of
76 investigating the continuous relationship between body size and mortality from
77 different causes. Knowledge about the relationships between continuous traits and
78 vital rates is, however, invaluable for studying population-level trait dynamics (e.g.
79 using integral projection models Ellner and Rees 2006).

80 Migratory salmonid fishes are extensively studied due to their ecological, cul-
81 tural and economical value (Drenner et al. 2012). Nonetheless, studies at the pop-
82 ulation level are frequently hindered by a lack of knowledge about the mortality
83 of adults residing in the sea or large lakes (Piccolo et al. 2012). Many salmonid
84 populations are heavily impacted by human activity, not only in the form of har-
85 vesting, but also through pollution, fish farming, habitat fragmentation, and hydro-
86 electrical power production (dams) in rivers (Aas et al. 2010), making the study
87 of population-level consequences of such impacts a priority.

88 Here we study a population of migratory brown trout (*Salmo trutta*, hereafter
89 “trout”) which inhabits a river-lake system in Eastern Norway and has been a pop-
90 ular target for fishing for decades due to its large body size. The spawning river is
91 dammed, and trout migrating to spawning grounds above the dam face additional
92 risks linked to dam passage on their up- and downriver migrations. Trout spawning
93 below the dam, on the other hand, completely avoid these risks but may, in turn,
94 incur costs related to poor river condition and crowding on the spawning grounds

95 below the dam. Mortality risks are thus likely associated with spawning location
96 in addition to individual body size and environmental conditions. To account for
97 this heterogeneity, we re-parameterized mark-recapture models for cause-specific
98 mortality in terms of mortality hazard rates (Cox 1972, Quinn 2003, Ergon et al.
99 2018) and extended the framework to include a continuous individual- and time-
100 varying trait (body size) as a predictor of vulnerability within groups of individuals
101 with different migration patterns. Fitting the resulting model to a unique 50-year
102 time-series of recaptures and recoveries of marked trout enabled us to investigate
103 the effects of individual (size, spawning location, origin) and environmental (river
104 discharge) factors on, and temporal variation in, several key vital rates: the vul-
105 nerability of adult trout to mortality due to harvest, dam passage, and natural
106 causes, and the probability of using a fish ladder within the dam to access upriver
107 spawning areas.

108 **Materials and methods**

109 **STUDY SYSTEM AND DATA**

110 The studied population of landlocked migratory (potamodromous) brown trout
111 inhabits the lake Mjøsa and its main inlet river, Gudbrandsdalslågen, in Eastern
112 Norway. Eggs are deposited in the river in fall and develop over winter. After
113 hatching in spring, juvenile trout remain in the river for an average of 4 years
114 before smolting and migrating to the lake. They typically mature after 2 - 3 years
115 of piscivorous diet and fast growth in the lake, and from that point on migrate up
116 the river to spawn every other year (usually in August/September, Figure 1). See
117 Aass et al. (1989) for a more detailed description of the life history. The population

118 consists of wild-hatched trout and stocked (first-generation hatchery-reared) trout,
119 which are recognizable by their clipped adipose fin. Stocked trout are released into
120 the river and lake as smolts but then follow the same general life history as wild-
121 hatched individuals (Aass 1993).

122 Shortly after the river was dammed in the 1960's, a fish ladder was installed to
123 restore connectivity to the spawning grounds above the dam. Depending on body
124 size and hydrological conditions, trout may either pass the dam by using the fish
125 ladder on their upriver spawning migration, or reproduce below the dam (Aass
126 et al. 1989, Haugen et al. 2008). Trout spawning above the dam have to pass the
127 dam again on their return migration to the lake (in October/November or in the
128 following spring). Since the fish ladder cannot be used for moving downriver, these
129 trout must pass either through the floodgates or the turbine shaft. Whether or not
130 an individual uses the fish ladder thus determines not only its spawning location,
131 but also the potential risks it encounters during the return to the lake.

132 From 1966 to 2016 a trap was operated within the fish ladder, allowing for
133 all trout passing the ladder to be captured, measured, and individually marked.
134 Thus, all adult trout were marked with Carlin tags (Carlin 1955) when they used
135 the fish ladder on an upriver spawning migration for the first time, and could be
136 recaptured on subsequent spawning migrations given that they passed the ladder
137 again. Subsequent spawning runs occur two years later for the majority of fish
138 (98.5%), which adhered to a strictly biennial spawning cycle (Figure 1). Over
139 the 50-year time period, 13,975 adult trout were marked and 2,106 of these were
140 recaptured in the ladder later. Since the population has been exposed to fishing
141 over the entire time period, an additional 2,322 marked trout were reported dead by
142 fishers. For more details on the marking scheme, sampling protocol, and resulting

143 data from the mark-recapture-recovery study, see Moe et al. (2019).

144 In the present study we performed mark-recapture analyses over intervals of
145 two years, as estimating parameters for spawning and non-spawning years sepa-
146 rately was not possible (due to trout being unobservable in non-spawning years,
147 Figure 1). We thus summarised the data into individual capture histories $y_{i,t}$, in
148 which each time index t corresponds to a two-year time step (interval from current
149 spawning year to next spawning year). For each time step, we coded three types
150 of observations: 1 = alive and captured in the ladder, 2 = dead from harvest and
151 reported, and 3 = not observed. We set $y_{i,t} = 1$ when an individual was captured in
152 the fish ladder in any month during time interval t . Harvest of trout happens year-
153 round (Figure S1.1) and if an individual was harvested and reported at any point
154 during interval t we set $y_{i,t} = 2$, unless (a) the individual had also been caught
155 in the fish ladder during interval t or (b) the harvest happened after August of
156 the second year within the interval t . If either (a) or (b) was the case, we moved
157 the harvest observation to the next interval such that $y_{i,t+1} = 2$. Furthermore, we
158 excluded all individuals that did not follow a strictly biennial spawning cycle (1.5%
159 of all individuals), did not have a single size measurement taken (<1%), or were of
160 unknown origin (wild vs. stocked, <1%). The analyses presented here are based on
161 the remaining 13,003 capture histories containing 1,498 trap recaptures and 2,252
162 harvest recoveries from both wild-hatched and stocked (hatchery-reared) trout.

163 MODEL FORMULATION

164 General model structure

165 We analysed the trout mark-recapture-recovery data in a multistate mark-recapture
166 framework (Lebreton et al. 1999) with both “alive” and cause-specific “newly dead”
167 states (Figure 2). Since trout are marked in the fish ladder while passing the dam
168 on an upriver spawning migration, all individuals are in state 1, “spawning upriver”,
169 at the start of their first 2-year time interval. State 1 individuals i may survive
170 from the current (t) to the next ($t + 1$) spawning migration with probability $S_{1,i,t}$
171 and will then either use the fish ladder (probability $p_{i,t+1}$) to spawn above the dam
172 again, or remain below the dam for spawning (probability $1 - p_{i,t+1}$). Individuals
173 using the ladder and thus remaining in state 1 are guaranteed to be observed,
174 while individuals not using the ladder transition to state 2, “spawning downriver”,
175 and are unobservable. Since spawning location may have a considerable effect on
176 mortality, state 2 individuals have their own survival probability $S_{2,i,t}$, but we as-
177 sume that their probability of using the fish ladder during the next spawning run
178 ($p_{i,t+1}$) does not differ from that of state 1 individuals.

179 When deaths of marked individuals can be observed and attributed to a cause,
180 multistate mark-recapture models can be used to estimate the probability of dying
181 from cause X as the transition from an “alive” state to “newly dead from cause
182 X” state (Schaub and Pradel 2004, Servanty et al. 2010). For the studied trout
183 population, deaths due to harvest are clearly distinguishable from deaths due to
184 other causes since fishers may report catching marked trout. Extending the model
185 with the state “newly dead from harvest” (state 3) thus allows us to include the
186 probability of an individual i in state n ($n = 1$ for above-dam spawners, $n = 2$ for

187 below-dam spawners) dying due to harvest, $\Psi_{n,i,t}^H$, and dying due to other causes
 188 $\Psi_{n,i,t}^O$ over the time interval t to $t + 1$. Individuals that have recently died due to
 189 harvest (state 3) may be reported by fishers with reporting rate r_t . Individuals
 190 that die due to other causes are not observable and therefore transition directly to
 191 the “dead” state (state 4; see Figure 2).

192 The resulting multistate model for the trout mark-recapture-recovery data can
 193 be expressed with the following state transition matrix and associated observation
 194 probabilities:

		<i>state</i> ($t + 1$)				<i>obs.</i> (t)
		1	2	3	4	
<i>state</i> (t)	1	$S_{1,i,t}p_{i,t+1}$	$S_{1,i,t}(1 - p_{i,t+1})$	$\Psi_{1,i,t}^H$	$\Psi_{1,i,t}^O$	1
	2	$S_{2,i,t}p_{i,t+1}$	$S_{2,i,t}(1 - p_{i,t+1})$	$\Psi_{2,i,t}^H$	$\Psi_{2,i,t}^O$	0
	3	0	0	0	1	r_t
	4	0	0	0	1	0

195 Parameterisation by mortality hazard rates

196 Different cause-specific mortality probabilities (Ψ) are not independent of one an-
 197 other; if a certain cause of mortality becomes more prevalent (e.g. due to some
 198 event or change in the environment), not only will the probability of dying from
 199 that cause increase, but the probability of dying from any other cause will decrease
 200 at the same time. This confounding complicates inference (e.g. Cooch et al. 2014),
 201 but Ergon et al. (2018) have recently re-emphasized that this can be avoided – also
 202 in the context of discrete-time mark-recapture analyses – by parameterising with

203 mortality hazard rates instead of probabilities (Cox 1972, Quinn 2003). Assuming
204 that the intensities of mortality from different causes remain proportional within
205 time intervals, we can define the survival- and mortality probabilities in the trout
206 model using harvest (m^H) and other-cause (hereafter “background”) mortality haz-
207 ard rates (m^O):

$$S_{n,i,t} = \exp(-(m_{n,i,t}^H + m_{n,i,t}^O))$$
$$\Psi_{n,i,t}^H = (1 - S_{n,i,t}) \frac{m_{n,i,t}^H}{m_{n,i,t}^H + m_{n,i,t}^O}$$
$$\Psi_{n,i,t}^O = (1 - S_{n,i,t}) \frac{m_{n,i,t}^O}{m_{n,i,t}^H + m_{n,i,t}^O}$$

208 (see derivation in Ergon et al. (2018))

209 In the present implementation, we further constrained harvest mortality to be
210 the same for trout spawning above and below the dam: $m_{1,i,t}^H = m_{2,i,t}^H = m_{i,t}^H$.
211 This constraint was necessary to obtain an identifiable model, but also biologically
212 reasonable because most harvest happens in the lake and fishing in the river is
213 restricted during the spawning season (which is also short relative to the two-year
214 interval of analysis).

215 MODEL IMPLEMENTATION

216 Individual and temporal variation in vital rate parameters

217 Body size and hydrological conditions are often key determinants of vital rate
218 variation in freshwater fish, including our study population (e.g. Carlson et al. 2008,
219 Letcher et al. 2015, Haugen et al. 2008). We thus used individual body size (length;
220 mm) at the beginning of the time-interval and average river discharge during the

221 relevant season as covariates for mortality and ladder usage in our model. We
222 further accounted for potential effects of hatchery origin and additional among-year
223 variation in all parameters x using intercept offsets for stocked individuals (β_{stock}^x)
224 and temporal random effects (ϵ_t^x), respectively. Random effects on all parameters
225 were assumed to be independently normally distributed on the link scale (but
226 see Supporting Information (SI) S6 for a model extension with correlated random
227 effects).

228 Harvest in our study system has been done mostly using fishing rods or gillnets;
229 the selectivity of the former is often positively correlated with body size (Lewin
230 et al. 2006) while the latter typically have bell-shaped selectivity curves (Hamley
231 1975). Since we here pooled harvest by all gear types, we modelled linear and
232 quadratic effects of size on harvest hazard rate on the log-scale:

$$\log(m_{i,t}^H) = \log(\mu^H) + \beta_{stock}^H * origin_i + \beta_S^H * size_{i,t} + \beta_{SS}^H * size_{i,t}^2 + \epsilon_t^H$$

233 where μ^H is the median harvest hazard rate, β_S^H and β_{SS}^H are slope parameters
234 for linear and quadratic size effects respectively. $size_{i,t}$ is the individual length at
235 spawning and $origin_i$ is a binary variable taking values of 1 for stocked fish and 0
236 for wild-hatched fish.

237 Background mortality, is expected to depend not just on body size but also
238 on spawning location and river discharge, as above- and below-dam spawners en-
239 counter different hydrological conditions during/after spawning and only the for-
240 mer need to pass the dam on their downriver migration. Mortality associated with
241 the spawning migration in general, and passing of the dam in particular, may also

242 depend on body size. We thus modelled background mortality hazard rate as:

$$\log(m_{n,i,t}^O) = \log(\mu_n^O) + \beta_{stock}^O * origin_i + \beta_{D,n}^O * discF_t + \beta_{S,n}^O * size_{i,t} + \epsilon_t^O$$

243 Here μ_n^O is the median background mortality hazard rate of state n , $discF_t$ is the
244 average discharge during the fall when many post-spawned trout are expected to
245 migrate downriver (Oct - Nov), and $\beta_{D,n}^O$ and $\beta_{S,n}^O$ are slope parameters for dis-
246 charge and size effects respectively. Stocking effects (β_{stock}^O) and temporal random
247 effects (ϵ_t^O) for background mortality are assumed to be shared across states n .

248 The probability of using the fish ladder and thus spawning above the dam was
249 previously found to depend on a complex interplay of individual body size and
250 river discharge (Haugen et al. 2008). We adopted the basic model structure from
251 this earlier analysis and extended it by allowing for stocking effects and random
252 among-year variation such that

$$\begin{aligned} \text{logit}(p_{i,t}) = \text{logit}(\mu^p) + \beta_{stock}^p * origin_i + \beta_D^p * discS_t + \beta_S^p * size_{i,t} + \\ \beta_{DS}^p * discS_t * size_{i,t} + \beta_{SS}^p * size_{i,t}^2 + \epsilon_t^p \end{aligned}$$

253 The discharge covariate used here, $discS_t$, differs from the one used above and
254 represents the average discharge over the summer season when trout undertake
255 their upriver spawning migration (Jul-Oct).

256 **Size imputation under imperfect detection**

257 Using continuous, time-varying individual traits such as body size as covariates in
258 mark-recapture models is problematic due to imperfect detection: information on
259 body size will be missing for sampling occasions when an individual is not cap-
260 tured (Pollock 2002). There are several ways to approach this problem, including
261 integrated growth models (e.g. Bonner et al. 2010) and inter-/extrapolation using
262 other available data and/or separate models. Due to the prohibitively large com-
263 putational demands of an integrated analysis, we here adopted the latter approach
264 and used a detailed growth model previously developed for the study population
265 of brown trout (Nater et al. 2018) to impute missing values in the individual size
266 covariate. Specifically, we re-fitted the growth model of Nater et al. (2018) to an
267 extended set of growth data from 6,843 individuals spanning the years 1952 to 2003
268 and used the resulting parameter estimates, plus a correction factor, to calculate
269 all missing entries in the body size covariate. The imputation procedure, as well
270 as implementation and results of the growth analysis, are described in detail in SI
271 S5.

272 **Autoregressive reporting rate model**

273 Time-dependent reporting rate r_t can be expected to vary considerably over a
274 period of 50 years. To accommodate this, we followed the example of Zhao et al.
275 (2018) and used a flexible, autoregressive model for time-dependent reporting rates:

$$\text{logit}(r_t) = \text{logit}(r_{t-1}) + \epsilon_t^r$$

276 where ϵ_t^r are independently normally distributed random effects. For details on the

277 implementation of the autoregressive model in the context of the overlapping 2-year
278 time-intervals in our model, we refer readers to the model code (supplementary
279 file `nimbleDHMM.R`).

280 **Implementation with NIMBLE**

281 We implemented the model in a Bayesian framework in NIMBLE (de Valpine
282 et al. 2017). Building on the work of Turek et al. (2016), we developed a highly ef-
283 ficient custom likelihood function to greatly reduce MCMC runtimes and memory
284 load of our analysis (detailed description/evaluation of the custom implementation
285 and code are provided in SI S2 and `nimbleDHMM.R`). To accommodate the 2-year
286 interval of our analysis, we split the data into two sets containing only individ-
287 uals spawning in even years and in odd years respectively. We then formulated
288 the likelihood for both datasets separately, but analysed them jointly under the
289 assumption of shared intercept-, slope-, and variance parameters. We used non-
290 informative priors for all parameters, and made use of NIMBLE’s default set of
291 samplers. The MCMC algorithm was run for 4 chains of 35,000 iterations, dis-
292 carding the first 5,000 samples as burn-in. Analyses were run in R 3.5.0 (R Core
293 Team 2018) using version 0.6-13 of the `nimble` package (NIMBLE Development
294 Team 2018).

295 **MODEL IDENTIFIABILITY AND FIT**

296 With increasing model complexity, and particularly when unobserved states are
297 included, it is not obvious whether all parameters within a multi-state mark-
298 recapture model can be estimated (Lebreton and Pradel 2002, Gimenez et al.
299 2003). Using an extended (hybrid) symbolic method (Cole et al. 2010, Cole 2012,

300 Choquet and Cole 2012) implemented in the computer algebra package Maple, we
301 looked at intrinsic parameter redundancy in the above described model including
302 different covariate- and random effect structures. Analyses of intrinsic parame-
303 ter redundancy, as well as investigation of potential near-redundancy using prior-
304 posterior overlap (Garrett and Zeger 2000, Gimenez et al. 2009), are described in
305 detail in SI S3. Maple code is provided as supplementary material.

306 Subsequently, we tested the fit of our model to the data using posterior predic-
307 tive checks (PPCs, Conn et al. 2018). Specifically, we selected 500 evenly spaced
308 samples from our posterior distributions and used them to simulate 10 replicate
309 mark-recapture-recovery datasets per sample. From each simulated dataset, we
310 then extracted several test statistics representing numbers and size distributions
311 of recaptured/harvested trout and compared them to the same quantities obtained
312 from the real data using visual tools and Bayesian p-values. Methodology and re-
313 sults of the PPCs are described in detail in SI S4.

314 Results

315 MODEL IDENTIFIABILITY AND FIT

316 We found that in the absence of random effects, the only model structures that
317 were intrinsically identifiable were those where harvest mortality depended on an
318 individual time-varying covariate (e.g. body size) and background mortality was
319 either constant or dependent on an environmental covariate (Table S3.1). However,
320 all models (irrespective of covariate structure) became identifiable when random
321 year effects were included on at least harvest hazard or reporting rates (Table S3.1).
322 Prior-posterior overlaps were below 35% for all parameters except r_1 , indicating

323 no major problems with near-identifiability (SI S3.3).

324 PPCs indicated that overall, the model produced a decent fit to the data, with
325 Bayesian p-values for the majority of considered data properties falling into an
326 acceptable range (0.10 - 0.90 for the whole dataset, 0.37 - 0.59 for averages across
327 marking cohorts, SI S4.3). We found some evidence for lack of fit for a subset
328 of data properties: mean/median size of individuals recaptured two years after
329 marking and the number of individuals harvested two to four years after marking.
330 In both cases, lack of fit was most pronounced in the beginning the time series
331 (Figures S4.3 & S4.7). Graphical tools illustrated that the model's predictions of
332 whole size distributions were generally realistic despite Bayesian p-values for size
333 mean, median, and standard deviation sometimes indicating some degree of lack
334 of fit (Figure S4.4). For detailed PPC results, refer to SI S4.4.

335 **SIZE-DEPENDENT FISH LADDER USAGE**

336 Posterior distributions for all estimated parameters are plotted in Figures S1.2
337 to S1.10. Numerical results in the following text are displayed as median [95%
338 credibility interval].

339 The probability of using the fish ladder – and thus spawning above the dam –
340 depended strongly on individual size and, to a lesser degree, on river discharge (Fig-
341 ure 3). Intermediate-sized trout (600-700 mm) were most likely to pass the dam
342 under any discharge conditions. Small to intermediate-sized trout had a higher
343 probability of using the ladder when river discharge was high, whereas the prob-
344 ability decreased markedly with size for larger trout irrespective of hydrological
345 conditions. Ladder usage probability fluctuated considerably over time (Figure 4c)
346 and was predicted to be lower for stocked (0.476 [0.414, 0.546]) than wild-hatched

347 (0.533 [0.477, 0.592]) trout (Figure S1.11).

348 CAUSE- AND SIZE-DEPENDENT MORTALITY

349 Median mortality hazard rates were estimated at 1.285 [1.090, 1.437] (harvest),
350 0.084 [0.021, 0.320] (background above-dam), and 0.115 [0.024, 0.540] (background
351 below-dam) per two years for average-sized trout (670 mm). The resulting probabil-
352 ities of dying during a 2-year interval due to harvest (Ψ_n^H) and due to other causes
353 (Ψ_n^O) were 0.700 [0.600, 0.752] and 0.045 [0.011, 0.173] for above-dam spawners
354 and 0.692 [0.561, 0.751] and 0.063 [0.013, 0.324] for below-dam spawners. Harvest
355 hazard rate was predicted to be highest for individuals with a size around 550
356 mm (Figure 5a). Background mortality hazard rate, while mostly lower than har-
357 vest hazard rate, decreased with size for above-dam spawners and increased with
358 size for below-dam spawners (Figure 5a). Consequently, total survival probabil-
359 ity increased with size for all trout up to 870 mm, but flattened out for larger
360 below-dam spawners (Figure 5b). River discharge was predicted to increase back-
361 ground mortality of above-dam spawners only (Figure S1.2). Residual among-year
362 random variation was substantial in harvest and especially background mortality,
363 with hazard rates at the 97.5 percentile being 1.28- and 69.67-fold higher than
364 at the 2.5 percentile respectively, but no temporal trends were evident in either
365 mortality cause (Figures 4a & 4b).

366 Model results did not support differences in harvest- or background mortality
367 due to trout origin: hazard ratios of stocked and wild trout were 0.988 [0.886,
368 1.081] and 0.991 [0.617, 1.601] for harvest and background mortality respectively
369 (Figure S1.11).

370 **TEMPORAL PATTERNS IN REPORTING RATE**

371 A clear decrease in estimates of reporting rate over the 50-year time-period was
372 evident (Figure 4d), with values exceeding 50% in early years but dropping below
373 10% towards the end of the time series.

374 **Discussion**

375 Individuals can differ greatly in their vulnerability to mortality from different
376 causes depending on traits like body size and variation in exposure to mortality
377 risk (e.g. as a consequence of reproductive state or location). Particularly when
378 some mortality causes are directly linked to human activity, understanding and
379 accounting for such individual differences in vulnerability can be crucial for man-
380 agement and conservation. In this study, we combined recent advances in mark-
381 recapture methodology and Bayesian modelling to investigate factors determining
382 vulnerability of large migratory brown trout to harvest- and background mortality
383 in a system heavily impacted by fishing and hydropower production.

384 **SIZE-DEPENDENCE OF CAUSE-SPECIFIC MORTALITY**

385 Size-dependent survival is well documented for salmonid fishes like brown trout,
386 but direction and strength of size effects vary widely across habitats, populations,
387 years, and life history stages (Carlson et al. 2008, Drenner et al. 2012). Here,
388 we were able to not only reproduce previous findings of positively size-dependent
389 survival for the studied trout population (Figure 5b, Haugen et al. 2008), but to
390 disentangle the underlying contributions from mortality due to harvest and other
391 causes.

392 Model results supported our initial expectation of non-linear dependence of
393 vulnerability to harvest and body size : harvest mortality was highest for trout
394 with sizes of around 550 mm and decreased for both smaller and larger individu-
395 als (Figure 5a). Bell-shaped selectivity curves such as this are typical for gillnets
396 (Hamley 1975), which have been commonly used in our study area. The low har-
397 vest mortality of large trout, however, may seem surprising given that 44% of the
398 reported harvests were due to angling, which often targets larger fish (Lennox et al.
399 2017). This may indicate that large trout escape harvest either through their in-
400 dividual behavior (e.g. different foraging habitats and prey preferences, learning,
401 Lewin et al. 2006, Arlinghaus et al. 2008) or because cohort selection favours more
402 cautious fish, allowing them to survive and grow to large sizes (Lennox et al. 2017).

403 Effects of body size on background mortality were predicted to be markedly
404 different for trout spawning above and below the dam, in particular for larger trout
405 (Figure 5a). Trout spawning above the dam generally had low background mortal-
406 ity, possibly indicating limited mortality risk associated with dam passage for adult
407 fish. Nonetheless, smaller individuals were slightly more vulnerable to dying from
408 non-harvest causes than larger ones (92% of posterior samples indicated a negative
409 effect of size on background mortality, Figure S1.2). Two mechanisms that may
410 be (partially) responsible for this are turbine mortality and energetic costs of dam
411 passage. During downriver migration after spawning above the dam, trout have to
412 pass through the floodgates or the turbine shaft to return to the lake. As on many
413 hydroelectric dams, racks are installed in front of the Hunderfossen power plant's
414 turbine intake to prevent fish from entering, but small fish may slip through the
415 grid and subsequently suffer severe injury and die passing the turbine (e.g. Fjeld-
416 stad et al. 2018). Alternatively, smaller fish may have reduced survival following

417 dam passage due to large energy expenditures resulting from dam passage (on up-
418 and/or downriver migration) itself (e.g. Roscoe et al. 2011) or as a consequence of
419 migration delays, particularly if these force individuals to overwinter in the river
420 (Fjeldstad et al. 2018). Both of these mechanisms are plausible here when also
421 considering that background mortality of above-dam spawners was predicted to
422 increase at higher levels of river discharge (Figure S1.2): stronger water flow could
423 increase both the risk of being swept into the turbine shaft and the energetic costs
424 of passage.

425 Unlike trout spawning above the dam, trout spawning below the dam were
426 predicted more vulnerable to background mortality at larger sizes (Figure 5a).
427 Many mechanisms may be responsible for this; one possibility is related to trout
428 density downriver of the dam, which can be very high during the spawning season
429 (Kraabøl 2006) and likely results in elevated levels of stress, aggressive interaction,
430 and disease transmission. Mortality below the dam could increase with body size
431 if larger individuals (due to their size, age, or other traits correlated with large
432 body size) were less able to cope with these challenges and/or increased their
433 investment into reproduction at the cost of survival under adverse conditions. At
434 the same time as having higher background mortality below the dam, large trout
435 were also much more likely to spawn below the dam in the first place (Figure
436 3), and thus incur the resulting higher mortality. The hydropower dam therefore
437 has the potential to function as an ecological trap (Schlaepfer et al. 2002) via its
438 size-selective fish ladder and adverse conditions on downriver spawning grounds,
439 particularly when considering that the reproductive output of large fish is often
440 central to the viability of salmonid populations (Jonsson and Jonsson 2011).

441 A second, more practical consequence of the selectivity of the fish ladder is

442 that it substantially limited comparisons of background mortality of above- and
443 below-dam spawning trout of the same size in the present study. With small and
444 large trout predominantly spawning above and below the dam respectively, direct
445 comparisons are only informative for a relatively narrow size range ($\sim 700 - 850$
446 mm). Within this range, predictions for above- and below-dam spawners mostly
447 overlap, with the exception of the largest sizes (Figure 5). Additional data – par-
448 ticularly on the fates of individuals spawning below the dam – would be necessary
449 for a more detailed assessment of the interactive effects of hydropower production
450 and spawning location on mortality and for investigating potential mechanisms
451 explaining higher mortality large fish below relative to above the dam. What our
452 approach did allow, however, was an unbiased quantitative comparison of size-
453 dependent harvest and background mortality: the risk of dying due to fishing was
454 higher than the risk of dying due to any other cause for almost the entire size
455 range, suggesting fishing as the main source of adult mortality in this population
456 (see Kleiven et al. 2016, for a similar result on Atlantic cod).

457 **TEMPORAL VARIATION OVER 50 YEARS**

458 The present analysis extended over half a century, in which the river-lake system
459 experienced variation in abiotic and biotic factors due to river regulation, lake
460 restoration, and changes in climate and human activities (Hobæk et al. 2012). It is
461 therefore unsurprising that we found high among-year variation in cause-specific
462 mortality and fish ladder usage over the course of the 50-year study period (Figure
463 4a-c). Background mortality in particular was subject to large fluctuations and
464 displayed a marked increase during the period 1997-2001 (also visible in overall
465 mortality and survival, Figure S1.12). This coincides with a documented outbreak

466 of a fungal disease in the study population (*Saprolegnia* spp. infections, possibly
467 in combination with ulcerative dermal necrosis, Johnsen and Ugedal 2001). This
468 suggests that disease may be a key driver of changes in adult trout mortality
469 and has the potential to substantially affect population viability (Hudson et al.
470 2002). Since freshwater ecosystems are particularly vulnerable to infectious diseases
471 (Okamura and Feist 2011), studying fungal disease dynamics and how are affected
472 by harvest, river regulation, and other environmental factors (e.g. temperature,
473 Letcher et al. 2015) represents an important venue for future research.

474 Unlike cause-specific mortality and ladder usage, which displayed strong fluctu-
475 ations but no obvious trends, fisher's reporting rate decreased clearly and rapidly
476 over time: from over 50% of catches being reported in the beginning of the study
477 period to less than 10% in the last two decades (Figure 4d). Declining fisher en-
478 gagement over time is a known problem in tagging studies without reward tags
479 (Piccolo et al. 2012), and highlights the importance of maintaining volunteer par-
480 ticipation in long-term studies by providing appropriate feedback and keeping up
481 with technological development of tools and platforms for reporting (Dickinson
482 et al. 2012).

483 **MODEL LIMITATIONS**

484 When analysing long-term ecological data even complex hierarchical models, like
485 the ones used here, can fail to sufficiently capture heterogeneity (overdispersion)
486 in the data, resulting in lack of model fit (Richards 2008). PPCs (Conn et al. 2018)
487 showed that overall our final model fit the data reasonably well, but also revealed
488 that goodness-of-fit varied substantially across the study period. Particularly the
489 early years in the data, which correspond to the first two decades following dam

490 construction, were characterized by relatively poorer model fit (Figures S4.3 &
491 S4.7) Many individuals present during this period were hatched while the river was
492 still free flowing and prior to implementation of the stocking programme. They may
493 have experienced environmental conditions vastly different from individuals later
494 in the time series, possibly resulting in long-lasting cohort effects not uncommon
495 for salmonid fishes (e.g. Vincenzi et al. 2016). Furthermore, given the profound
496 changes in harvest practices (gradual shift from gillnet to rod fishing, Aass and
497 Kraabøl 1999), river regulation (flow regimes, turbine intake grid sizes, etc.), and
498 disease prevalence during the 50-year study period, it is also not unlikely that
499 size-dependence of mortality and migratory behavior itself has changed over time.
500 Overdispersion in our data could thus be related to changes in selection pressures,
501 something that may warrant attention in future studies.

502 Both parameter estimates and resulting model fit were sensitive to the way we
503 imputed body size, illustrating that covariate imputation remains the main chal-
504 lenge of mark-recapture models with continuous individual time-varying covariates
505 like body size (Pollock 2002, Bonner et al. 2010). Imputing body size using mean
506 estimates from an externally run growth model, as we have done here, comes with
507 several limitations. First, data used to estimate growth may not be representative
508 of the individuals contained in the mark-recapture data. In our case, most data
509 on growth in the lake pertains to the subadult life stage (prior to maturation) and
510 resulting growth estimates may thus be less well suited for the mature, spawning
511 trout that make up the mark-recapture data. Second, growth data is only avail-
512 able for 53% of individuals and 74% of years (only up to 2003) contained in the
513 mark-recapture data. Size imputation for a non-random sample of individuals was
514 thus lacking estimates of year and individual random effects. Finally, and per-

515 haps most importantly, by directly imputing size using mean estimates of growth
516 model parameters, we omitted all uncertainty in size estimates arising from residual
517 variation in growth (stochasticity) and parameter uncertainty. Since the reduced
518 growth model we used matched well with observations (Figure S5.1) and fit of the
519 mark-recapture-recovery model was overall decent, it is unlikely that the results
520 we present here are biased to a degree as to invalidate any of the main conclusions.
521 However, as a result of direct size imputation and likely related lack of model fit,
522 some of the patterns and effects may be estimated with inflated precision and this
523 has to be considered when interpreting the presented relationships.

524 **OUTLOOK: DATA INTEGRATION AND POPULATION PERSPECTIVE**

525 The fundamental issues arising from imputing missing individual covariate values
526 can be addressed through integrated analysis of growth and survival/state transi-
527 tion processes (Bonner et al. 2010, Letcher et al. 2015), which allows imputation
528 of the “true” latent body size and estimation of its effects on vital rates without
529 bias and under full consideration of uncertainty. In our case, not just one but
530 two distinct data sources provide information on growth: length measurements
531 from trout captured in the fish ladder (mark-recapture data) and lengths back-
532 calculated from scale year rings of a subset of marked individuals. This provides a
533 unique opportunity for integrated analysis of multiple data sets which is likely to
534 result in more precise estimates of vital rates, more comprehensive understanding
535 of variation therein, and insights into potential discrepancies among different types
536 of data (Plard et al. 2019b, Saunders et al. 2019).

537 The large drawback of Bayesian integrated analysis is its high computational
538 costs, and in the case of the present data and model, computational demands

539 precluded a fully integrated analysis. However, in SI S2 we have shown how imple-
540 menting the mark-recapture-recovery model with a custom distribution in NIM-
541 BLE can lead to dramatic increases in computational efficiency (32-times faster
542 MCMC than with standard JAGS). With the continuing development of both
543 computational power and flexible, user-friendly MCMC software, large integrated
544 analyses will likely become more feasible in the future.

545 More efficient computational solutions are also becoming invaluable when look-
546 ing beyond single vital rates (growth, survival) and towards more holistic models
547 of population dynamics. Several of the results presented here may have impor-
548 tant implications for brown trout management but questions such as whether
549 the high harvest mortality of adult trout has consequences for population via-
550 bility or whether the dam does indeed function as an ecological trap, can only
551 be addressed by adopting a population perspective. The framework of integrated
552 population models (Plard et al. 2019b) in general, and recent extensions for pop-
553 ulations structured by continuous traits in particular (Plard et al. 2019a), lend
554 themselves well to the study of these questions for our system and will follow nat-
555 urally from the integration of growth and survival estimation. Fully integrated,
556 size-structured population models will further provide new opportunities to study
557 the joint impacts of harvesting, stocking, habitat alteration, climate change, and
558 disease dynamics (Plard et al. 2019b) and are thus highly relevant for future stud-
559 ies aiming to improve understanding and inform management of the trout in lake
560 Mjøsa and of animal population inhabiting ecosystems heavily impacted by human
561 activity in general.

562 CONCLUSION

563 Multi-state mark-recapture models are powerful tools for estimating and under-
564 standing survival in animal populations that experience mortality from both natu-
565 ral and anthropogenic causes (Schaub and Pradel 2004). We used such a model to
566 disentangle harvest- and background mortality of adult brown trout and showed
567 that (1) harvest generally outweighed all other sources of mortality and (2) that
568 vulnerability to both mortality causes was determined by individual differences in
569 body size and migration pattern (dam passage). The use of a novel hazard rate
570 parameterization (Ergon et al. 2018) and data from both recaptures and harvest
571 recoveries allowed to estimate size-dependence and among-year variation in cause-
572 specific mortality, state transition probabilities, and reporting rate without con-
573 founding. This framework, including the computationally efficient implementation
574 of it, is highly applicable to other studies of cause-specific mortality in populations
575 whose vital rates are strongly affected by continuous traits, and may prove particu-
576 larly valuable also in the context of estimating correlation among different sources
577 of mortality. Finally, we illustrated that the use of an appropriate year random
578 effects structure can be a prerequisite to establishing identifiability of complex
579 mark-recapture models and is therefore crucial to obtain reliable estimates of vi-
580 tal rate parameters. In practice, such random effects can only be estimated when
581 data are collected over a sufficient number of years, emphasizing the importance
582 of investing in the (continued) collection of individual-based data over long time
583 periods (Clutton-Brock and Sheldon 2010).

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593 **Authors' contributions**

594 CRN, TE, ØL, YV, and LAV conceived the ideas; CRN and TE designed method-
595 ology; CRN, PA, SJM, and AR prepared the data for analysis; CRN analysed the
596 data and led the writing of the manuscript; DT developed and tested the cus-
597 tom likelihood and drafted SI S2. DC designed identifiability analyses and drafted
598 SI S3. All authors contributed critically to the drafts and gave final approval for
599 publication.

600 **Data accessibility**

601 The complete mark-recapture-recovery and growth data sets will be made available
602 on the Dryad Digital Repository (DOI to be added) and are documented in Moe
603 et al. (2019).

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783 Supporting information

784 The following supporting information is available for this publication: Appendices
785 S1 - S6.

786 **Figures**

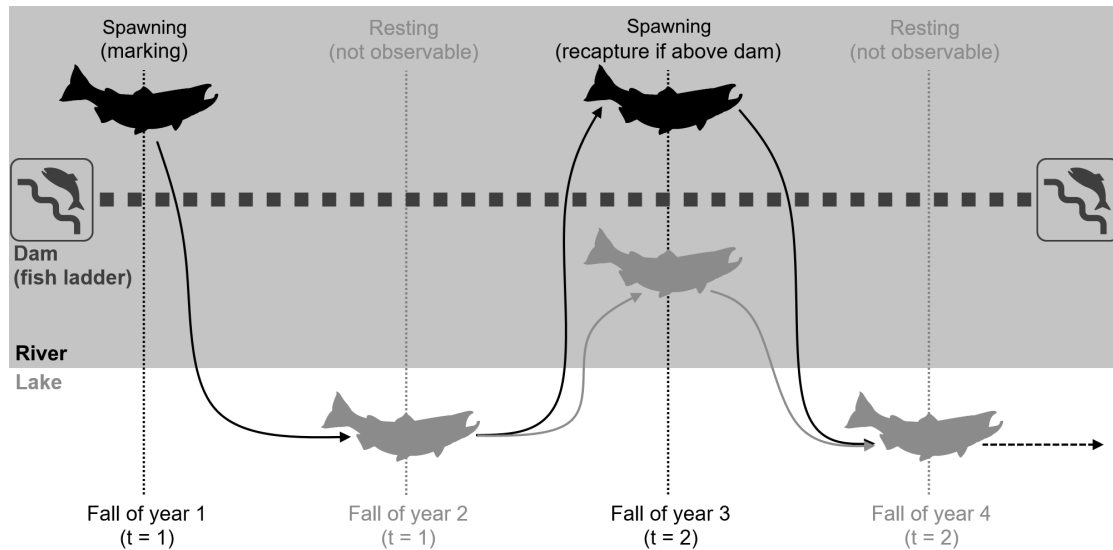


Figure 1: Illustration of the biennial spawning cycle and mark-recapture scheme of the studied trout population. All individuals are marked in the fish ladder while passing the dam on an upriver spawning migration. Two years later they may be recaptured on the next spawning migration, but only if they pass the fish ladder to spawn above the dam (if they spawn below the dam, they are unobservable). Trout remain in the lake and are unobservable during non-spawning years.

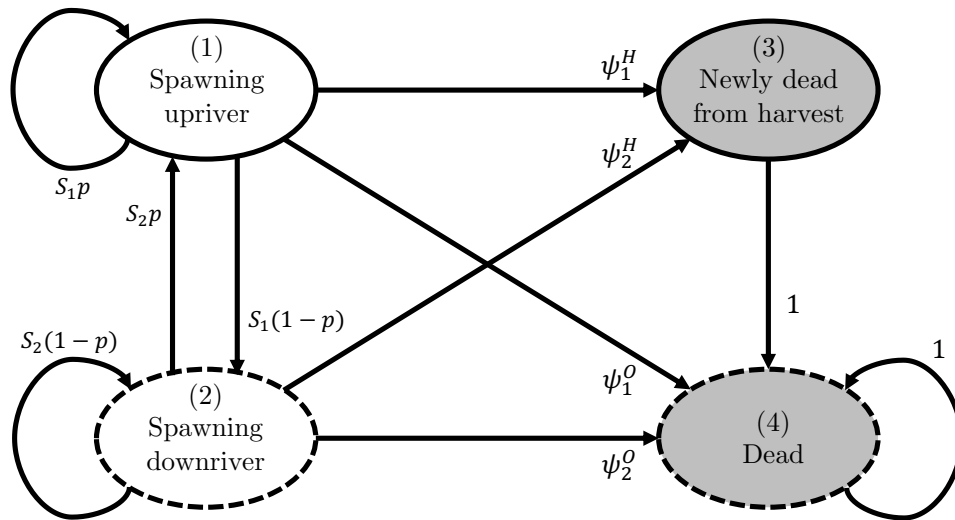


Figure 2: Design of the trout mark-recapture-recovery model (transitions on two-year intervals). White states are alive, grey states are dead. Solid borders indicate states that are at least partially observable, whereas dashed borders indicate unobservable states. S_n = survival probabilities. ψ_n^H / ψ_n^O = harvest / background mortality probabilities (where n indicates the state). p = ladder usage probability. Indices for individual i and time t are omitted here for simplicity.

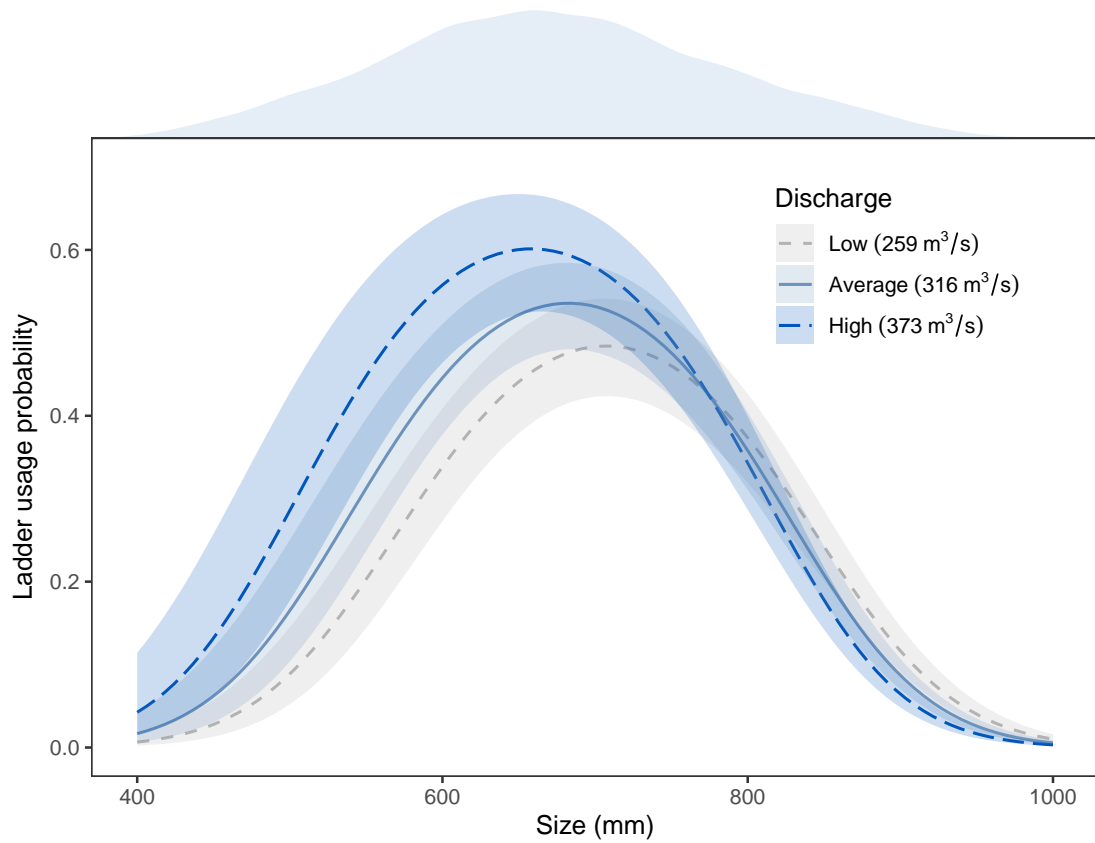


Figure 3: Predictions of the effects of body size on ladder usage probability at different levels of river discharge. Grey, dashed = low discharge (mean – SD). Grey-blue, solid = average discharge (mean). Blue, longdashed = high discharge (mean + SD). Lines represent median prediction, ribbons indicate 95% credibility intervals. The blue density kernel above the plot visualizes the size distribution of trout caught in the ladder (data).

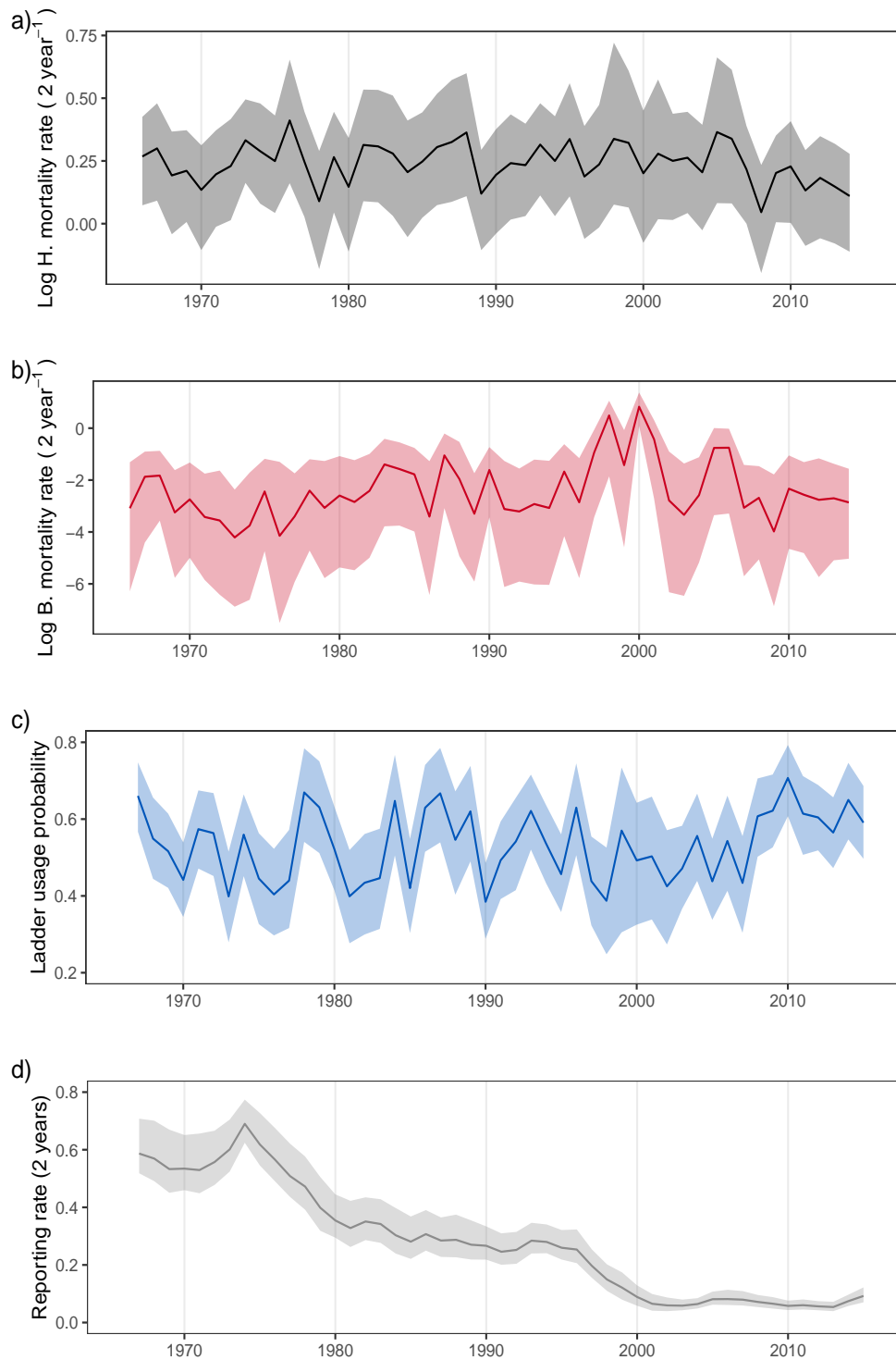


Figure 4: Estimates for time-dependent a) log harvest hazard rate, b) log background mortality hazard rate (above-dam spawners), c) ladder usage probability, and d) reporting rate (calculated using random variation and discharge effects). Lines represent median predictions, ribbons indicate 95% credibility intervals.

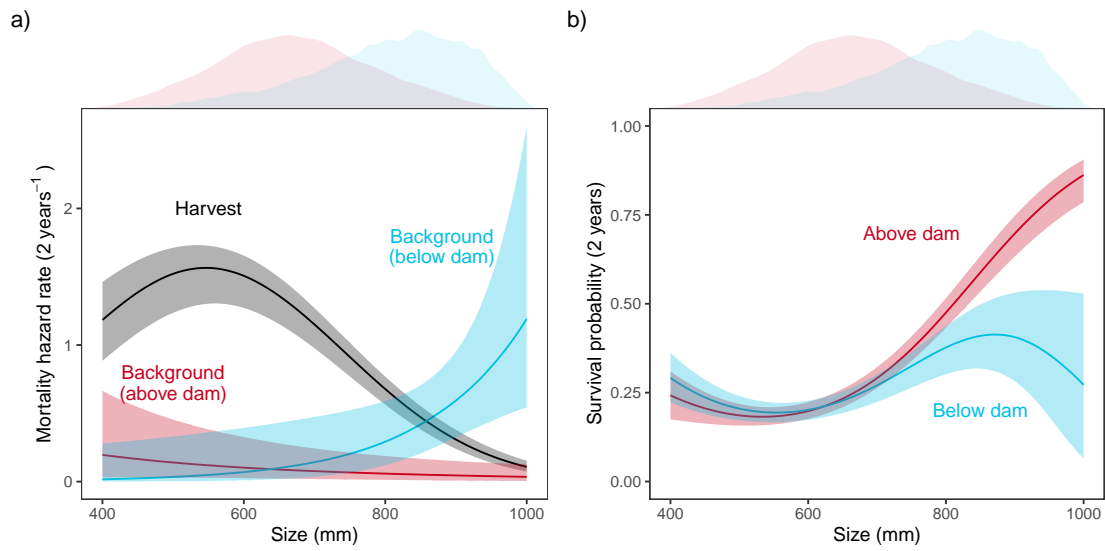


Figure 5: Predictions of the effects of body size on a) harvest and background mortality hazard rates and b) survival probabilities (under consideration of both mortality sources). Red and blue curves apply to individuals that have last spawned above and below the dam respectively. The black curve (harvest) applies to all individuals irrespective of their last spawning location. Lines represent median predictions, ribbons indicate 95% credibility intervals. Density kernels above the panels illustrate the informative data range: red = size distribution of individuals captured in the fish ladder (above-dam spawners, raw data), blue = simulated size distribution of unobservable below-dam spawners.