Journal of Avian Biology

**JAV-02574**
Nuijten, R. J. M., Vriend, S. J. G., Wood, K. A., Haitjema, T., Rees, E. C., Jongejans, E. and Nolet, B. A. 2020. Apparent breeding success drives long-term population dynamics of a migratory swan. – J. Avian Biol. 2020: e02574

## Supplementary material

# Appendix A: Detailed description of the integrated population model

*I. Population model*

We developed a female-based, age-structured integrated population model (IPM) of three age classes (i.e., juvenile, yearling, and adult) and a pre-breeding census (Figure A.1).

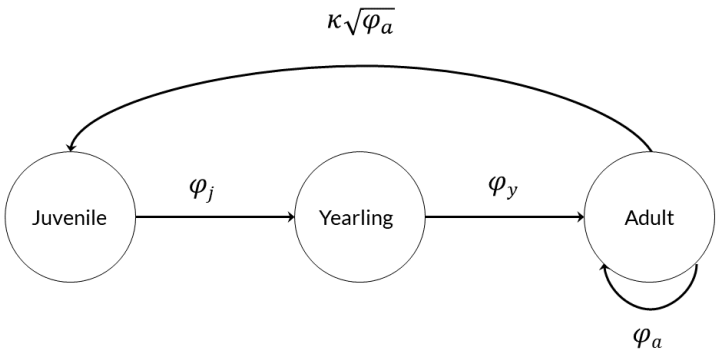


**Figure A.1.** *Age-structured life cycle of the Bewick's swan with juvenile, yearling and adult age classes.* $\varphi_x$ *is the annual survival rate between year* t *and* t+*1 for individuals in age class* x*, and* $\kappa$ is the apparent breeding success: the average number of female fledglings, per successful breeding female, that survived until first winter.

In the IPM, apparent survival was modelled for juveniles ($\varphi_j$), yearlings ($\varphi_y$) and adults ($\varphi_a$). Resighting probabilities were modelled for leg rings ($p_l$) and neck bands ($p_n$) separately, as they are known to have different resighting probabilities (Wood et al., 2018). Because reproduction data from the breeding grounds were lacking, breeding success was modelled through a latent parameter $\kappa$. Modelling the age-specific abundances in the IPM with bi-annual time step allowed us to explicitly estimate the actual number of breeding females, and their apparent breeding success, in addition to the number of females in winter. The resulting population transition matrices are as follows:

$$\mathbf{W_{t+1}} = \begin{bmatrix} W_j \\ W_y \\ W_a \end{bmatrix}_{t+1} = \begin{bmatrix} 0 & 0 & \kappa\sqrt{\varphi_a} \\ \varphi_j & 0 & 0 \\ 0 & \varphi_y & \varphi_a \end{bmatrix} \begin{bmatrix} W_j \\ W_y \\ W_a \end{bmatrix}_t \quad \text{(S1.1)}$$

which can be separated in the transition from the start of the breeding season to winter,

$$\mathbf{W_t} = \begin{bmatrix} W_j \\ W_y \\ W_a \end{bmatrix}_t = \begin{bmatrix} 0 & 0 & \kappa \\ \sqrt{\varphi_j} & 0 & 0 \\ 0 & \sqrt{\varphi_y} & \sqrt{\varphi_a} \end{bmatrix} \begin{bmatrix} B_j \\ B_y \\ B_a \end{bmatrix}_t \quad \text{(S1.2)}$$

and from winter to the start of the breeding season,

$$\mathbf{B_{t+1}} = \begin{bmatrix} B_j \\ B_y \\ B_a \end{bmatrix}_{t+1} = \begin{bmatrix} \sqrt{\varphi_j} & 0 & 0 \\ 0 & \sqrt{\varphi_y} & 0 \\ 0 & 0 & \sqrt{\varphi_a} \end{bmatrix} \begin{bmatrix} W_j \\ W_y \\ W_a \end{bmatrix}_t \quad \text{(S1.3)}$$

where $B_{j,t}$, $B_{y,t}$ and $B_{a,t}$ are the number of juveniles, yearlings and adults at the start of the breeding season in year *t*, respectively, $W_{j,t}$, $W_{y,t}$ and $W_{a,t}$ are the number of juveniles, yearlings and adults in winter in year *t*, respectively, $\varphi_{x,t}$ is the annual survival probability between *t* and *t*+1 for individuals in age class *x*, and $\kappa_t$ is apparent breeding success, i.e., the average number of female fledglings produced per successful breeding female that survived until first winter in year *t*.

This model was extended to account for demographic stochasticity, by using binomial and Poisson distributions to link between age-specific numbers in year *t* and *t*+1, and environmental

stochasticity, by allowing annual variation in all demographic rates. The projection matrix translates to the following relationships:

$$
\begin{aligned}
W_{j,t} \quad & Poisson\left(B_{a,t}\kappa_t\right) \\
W_{y,t} \quad & Binomial\left(\sqrt{\varphi_{j,t}}, B_{j,t}\right) \\
W_{a,t} \quad & Binomial\left(\sqrt{\varphi_{y,t}}, B_{y,t}\right) + Binomial\left(\sqrt{\varphi_{a,t}}, B_{a,t}\right) \\
B_{j,t+1} \quad & Binomial\left(\sqrt{\varphi_{j,t}}, W_{j,t}\right) \\
B_{y,t+1} \quad & Binomial\left(\sqrt{\varphi_{y,t}}, W_{y,t}\right) \\
B_{a,t+1} \quad & Binomial\left(\sqrt{\varphi_{a,t}}, W_{a,t}\right)
\end{aligned}
\tag{S1.4}
$$

*II. Likelihoods of the single datasets*

Combining the data on the proportion of juveniles ($j$) and the census data ($C$), we separated the counts for juveniles ($C_j = j \cdot C$) and older individuals ($C_{ya} = [1 - j]C$). These two counts were modelled using state-space models (Brooks et al. 2004). The state-space model consists of a state process and an observation process. The state process describes the true but unknown population trajectory under the population model. The observation process describes the link between the true and the observed population size (De Valpine and Hastings 2002). The state process models were described in the previous section. For the observation process models we assumed that the observation error was different between juveniles and older individuals, to account for the incorporation of the data on the proportion of juveniles, normally distributed on the log scale and constant over time.

$$\begin{aligned} \log\left(C_{j,t}\right) &\quad Normal\left(W_{j,t}, \sigma^2_{j,obs}\right) \\ \log\left(C_{ya,t}\right) &\quad Normal\left(W_{y,t} + W_{a,t}, \sigma^2_{ya,obs}\right) \end{aligned} \tag{S1.5}$$

The likelihood of the state-space model was composed of the likelihood of the observation processes and the state processes (Kéry and Schaub 2011).

Capture-mark-resighting data were modelled using a Cormack-Jolly-Seber model (Lebreton et al. 1992). We defined the latent variable $z_{i,t}$ as the true state of individual *i* at time *t*, which takes value 1 if individual *i* is alive at time *t*, and value 0 if individual *i* is dead at time *t*. Because only events after first capture are modelled in the CJS model, we also defined vector $f_i$, which denotes the occasion at which individual *i* was first captured and marked. The state of individual *i* at first capture ($z_{i,f_i}$) is 1 with probability 1. The subsequent occasions are modelled as Bernoulli trials. Conditional on being alive at time *t*, individual *i* may survive to time *t*+1 with probability $\varphi_{i,t}$, resulting in the following state process model:

$$z_{i,t+1} \mid z_{i,t} \sim Bernoulli\left(z_{i,t}\varphi_{i,t}\right) \tag{S1.6}$$

If individual *i* is alive at time *t*, it may be recaptured/resighted with a probability $p_{i,t}$. With Bernoulli trials, the true state $z_{i,t}$ can be linked to the observation $y_{i,t}$, resulting in the following observation process model:

$$y_{i,t} \mid z_{i,t} \sim Bernoulli\left(z_{i,t}p_{i,t}\right) \tag{S1.7}$$

The probabilities of apparent survival and resighting were modelled with random year effects:

$$\text{logit}(\theta_t) = \bar{\theta} + \varepsilon_{\theta,t} \tag{S1.8}$$

where $\bar{\theta}$ was the mean demographic rate over time on the logit scale and $\varepsilon_{\theta,t}$ the temporal component of the demographic rate with mean 0 and variance $\sigma_\theta^2$:

$$\varepsilon_{\theta,t} \sim Normal\left(0, \sigma_\theta^2\right) \quad \text{(S1.9)}$$

*III. Joint likelihood*

The joint likelihood of the IPM is the product of the individual likelihoods of the different datasets, assuming independence between them (Kéry and Schaub 2011). Individuals can appear in multiple datasets included in this study, so the assumption is violated to some degree. However, violation of this assumption has been shown to have little effect on estimation of parameters (Abadi et al. 2010, Schaub and Fletcher 2015), in particular when the number of marked birds is a small proportion of the studied population (Weegman et al. 2016). The joint likelihood is as follows:

$$\begin{aligned} &L_{IPM}\left(\mathbf{C}, \mathbf{j}, \mathbf{y} \mid \mathbf{W_x}, \mathbf{B_x}, \boldsymbol{\varphi}_\mathbf{x}, \boldsymbol{\kappa}, \mathbf{p_m}, \sigma^2_{j,obs}, \sigma^2_{ya,obs}\right) = \\ &L_O\left(\mathbf{C}, \mathbf{j} \mid \mathbf{W_x}, \sigma^2_{j,obs}, \sigma^2_{ya,obs}\right) \\ &\times L_S\left(\mathbf{W_x}, \mathbf{B_x} \mid \boldsymbol{\varphi}_\mathbf{x}, \boldsymbol{\kappa}\right) \\ &\times L_{CJS}\left(\mathbf{y} \mid \boldsymbol{\varphi}_\mathbf{x}, \mathbf{p_m}\right) \end{aligned} \quad \text{(S1.10)}$$

where $L_O$ is the likelihood of the census observation process model, $L_S$ the likelihood of the census state process model, $L_{CJS}$ the likelihood of the CJS model, *x* age class (i.e., juvenile, yearling, adult) and *m* mark type (i.e., leg ring, neck band). A graphical representation of this model is shown in Figure A.2.

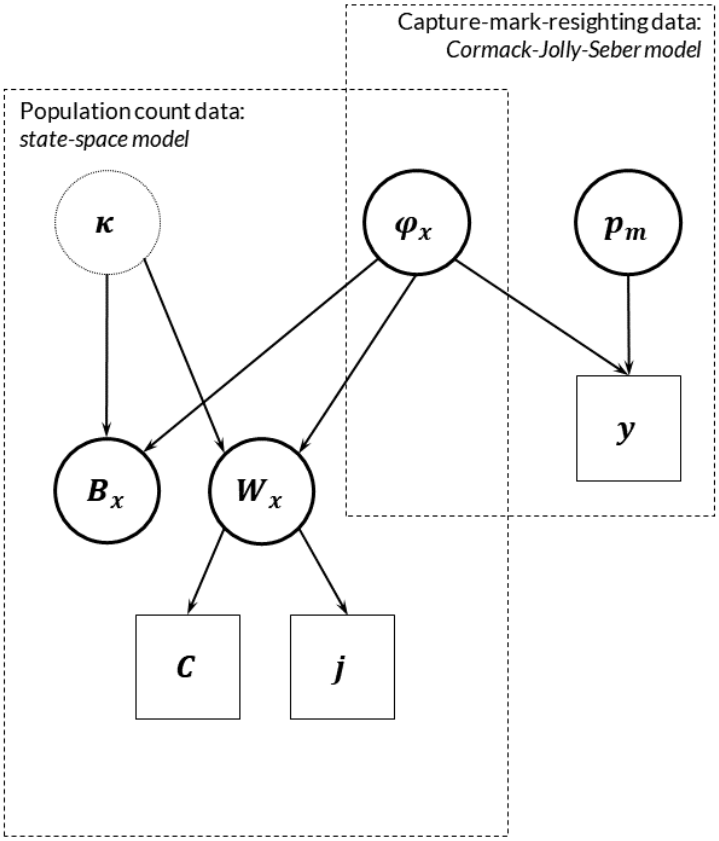


**Figure A.2.** *Directed acyclic graph of the integrated population model. Estimated parameters are represented by circles, data by rectangles. Arrows represent dependencies between nodes.* $C$ *population census data,* $j$ *proportion of juveniles,* $y$ *capture-mark-resighting data,* $W_x$ *is abundance of age class* $x$ *(i.e., juvenile, yearling, adult) in winter,* $B_x$ *is abundance of age class x in the breeding season,* $\varphi_x$ *is the survival probability of age class* $x$*,* $p_m$ *is the resighting probability of mark type* $m$ *(i.e., leg ring, neck band), and* $\kappa$ *is the latent parameter apparent breeding success.*

*IV. Computation*

To estimate the parameters, we analysed the joint likelihood combined with prior distributions to obtain posterior distributions. For all but apparent breeding success, which prior was informed by the winter brood size, we specified non-informative priors (Table S1). Markov chain Monte Carlo (MCMC) methods were used to simulate observations from the posterior distributions with JAGS version 4.3.0 (Plummer 2003) run from R with *jagsUI* version 1.5.1 (Kellner 2019). We ran 3 chains of 200,000 iterations with a burn-in of 100,000, thinning every 50th iteration, resulting in a

105 total of 6,000 posterior samples. Convergence of the MCMC chains was evaluated by ensuring
106 that the Brooks-Rubin-Gelman diagnostic $\hat{R}$ (Brooks and Gelman 1998) for each parameter was
107 below 1.1. R and JAGS code of the IPM can be found in Appendix B.

108

109 **Table A.1.** Prior distributions for the parameters in the integrated population model.

| Parameter | Prior distribution |
|---|---|
| Mean survival | $\bar{\varphi}_{j,t} \sim Normal(0,100)\mathrm{T}(-5,5)$<br>$\bar{\varphi}_{y,t} \sim Normal(0,100)\mathrm{T}(-5,5)$<br>$\bar{\varphi}_{a,t} \sim Normal(0,100)\mathrm{T}(-5,5)$ |
| Temporal variability of survival | $\varepsilon_{\varphi_j} \sim Normal\left(0,\sigma^2_{\varphi_j}\right)$<br>$\varepsilon_{\varphi_y} \sim Normal\left(0,\sigma^2_{\varphi_y}\right)$<br>$\varepsilon_{\varphi_a} \sim Normal\left(0,\sigma^2_{\varphi_a}\right)$<br>$\sigma_{\varphi_j} \sim Uniform(0,10)$<br>$\sigma_{\varphi_y} \sim Uniform(0,10)$<br>$\sigma_{\varphi_a} \sim Uniform(0,10)$ |
| Mean resighting probabilities | $\bar{p}_{l,t} \sim Normal(0,100)\mathrm{T}(-5,5)$<br>$\bar{p}_{n,t} \sim Normal(0,100)\mathrm{T}(-5,5)$ |
| Temporal variability of resighting probabilities | $\varepsilon_{p_l} \sim Normal\left(0,\sigma^2_{p_l}\right)$<br>$\varepsilon_{p_n} \sim Normal\left(0,\sigma^2_{p_n}\right)$<br>$\sigma_{p_l} \sim Uniform(0,10)$<br>$\sigma_{p_n} \sim Uniform(0,10)$ |
| Apparent breeding success (upper limit informed by average winter brood size (Wood et al. 2016)) | $\kappa_t \sim Uniform(0,2)$ |
| Observation errors census data | $\sigma_{j,obs} \sim Uniform(0,100)$<br>$\sigma_{ya,obs} \sim Uniform(0,100)$ |

| | |
|---|---|
| Abundances in the breeding season in the first year. | $B_{j,1} \sim Normal\left(300, 10^4\right)\mathrm{T}(0,)$<br>$B_{y,1} \sim Normal\left(1000, 10^4\right)\mathrm{T}(0,)$<br>$B_{a,1} \sim Normal\left(4000, 10^4\right)\mathrm{T}(0,)$ |

## References Appendix A


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## Appendix B: R and JAGS code for the integrated population model

```
# Data objects

# eh: encounter history matrix
# f: vector of first observations
# x: age matrix
# juvper: proportion of juveniles in winter
# counts: population winter counts
# gr: leg ring vs neck band

sink("ipm-season-s3.jags")
cat("
    model {

    #************************************
    # 1. Define priors and constraints
    #************************************

    #************************************
    # 1.1 Initial population sizes
    #************************************
    b1 ~ dnorm(300, 0.001)T(0,) # Number of 1-year olds in breeding
    season
    b2 ~ dnorm(1000, 0.001)T(0,) # Number of 2-year olds in breeding
    season
    b3 ~ dnorm(4000, 0.001)T(0,) # Number of 3-year olds and older in
    breeding season

    B1[1] <- round(b1)
    B2[1] <- round(b2)
    B3[1] <- round(b3)

    #************************************
    # 1.2 Observation errors
    #************************************
    sigma.y ~ dunif(0, 100)
    sigma2.y <- pow(sigma.y, 2)
    tauy <- pow(sigma.y, -2) # Precision counts 1.5-year olds and
    older

    sigma.z ~ dunif(0, 100)
    sigma2.z <- pow(sigma.z, 2)
    tauz <- pow(sigma.z, -2) # Precision counts 0.5-year olds

    #************************************************
    # 1.3 Survival probabilities (3 age classes)
    #************************************************
    for(a in 1:3){
     for(t in 1:(nyears-1)){
```

```
    eta.phi[a,t] <- mu.phi[a] + epsilon.phi[a,t]
    epsilon.phi[a,t] ~ dnorm(0, tau.phi[a])T(-15,15)
   } #t
   mu.phi[a] ~ dnorm(0, 0.01)T(-5,5)
   sigma.phi[a] ~ dunif(0, 10)
   tau.phi[a] <- pow(sigma.phi[a], -2)
   sigma2.phi[a] <- pow(sigma.phi[a], 2)
  } #a

  # Constrain parameters
  for(i in 1:nind){
   for(t in f[i]:(nyears-1)){
    logit(phi[i,t]) <- eta.phi[x[i,t],t]
   } #t
  } #i

  #************************************************
  # 1.3 Resighting probabilities (2 classes)
  #************************************************
  for(g in 1:2){ # leg rings and neck bands
   for(t in 1:(nyears-1)){
    eta.p[g,t] <- mu.p[g] + epsilon.p[g,t]
    epsilon.p[g,t] ~ dnorm(0, tau.p[g])T(-15,15)
   } #t
   mu.p[g] ~ dnorm(0, 0.01)T(-5,5)
   sigma.p[g] ~ dunif(0, 10)
   tau.p[g] <- pow(sigma.p[g], -2)
   sigma2.p[g] <- pow(sigma.p[g], 2)
  } #g

  # Constrain parameters
  for(i in 1:nind){
   for(t in f[i]:(nyears-1)){
    logit(p[i,t]) <- eta.p[group[i],t]
   } #t
  } #i

  #************************************
  # 1.4 Apparent breeding success
  #************************************
  for(t in 1:nyears){
   kappa[t] ~ dunif(0, 2) # Informed by winter brood size
  } #t

  #************************************
  # 1.5 Derived parameters
  #************************************

  # Survival
  for(t in 1:(nyears-1)){
   logit(phi.j[t]) <- eta.phi[1,t]
   logit(phi.y[t]) <- eta.phi[2,t]
```

```
246         logit(phi.a[t]) <- eta.phi[3,t]
247       } #t
248
249       # Resighting
250       for(t in 1:(nyears-1)){
251         logit(p.l[t]) <- eta.p[1,t]
252         logit(p.n[t]) <- eta.p[2,t]
253       } #t
254
255       #************************************
256       # 2 Likelihoods of single datasets
257       #************************************
258
259       #*******************************************************
260       # 2.1 Population count data (state-space model)
261       #*******************************************************
262
263       # 2.1.1 System process
264       for (t in 1:(nyears-1)){
265         B1[t+1] ~ dbin(phi.j[t]^(1/2), W1[t])
266         B2[t+1] ~ dbin(phi.y[t]^(1/2), W2[t])
267         B3[t+1] ~ dbin(phi.a[t]^(1/2), W3[t])
268       } #t
269
270       for (t in 1:(nyears-1)){
271         mean.w[t] <- B3[t] * kappa[t]
272         W1[t] ~ dpois(mean.w[t])
273         W2[t] ~ dbin(phi.j[t]^(1/2), B1[t])
274         W3a[t] ~ dbin(phi.y[t]^(1/2), B2[t])
275         W3b[t] ~ dbin(phi.a[t]^(1/2), B3[t])
276         W23[t] <- W2[t] + W3a[t] + W3b[t]
277         W3[t] <- W3a[t] + W3b[t]
278       } #t
279
280       # 2.1.2 Observation process
281       for (t in 1:(nyears-1)){
282         cen[t] ~ dnorm(W23[t], tauy)
283         cenjuv[t] ~ dnorm(W1[t], tauz)
284       } #t
285
286       #*****************************************************
287       # 2.2 Capture-mark-resighting data (CJS model)
288       #*****************************************************
289
290       for(i in 1:nind){
291         # Define latent state at first capture
292         z[i,f[i]] <- 1
293         for (t in (f[i]+1):nyears){
294           # State process
295           z[i,t] ~ dbern(mu1[i,t])
296           mu1[i,t] <- phi[i,t-1] * z[i,t-1]
297           # Observation process
```

```
        y[i,t] ~ dbern(mu2[i,t])
        mu2[i,t] <- p[i,t-1] * z[i,t]
      } #t
    } #i

    }
    ",fill = TRUE)
sink()


# Bundle data
jags.data.season.s3 <-
    list(
        y = eh,
        f = f,
        x = x,
        z = known.state.cjs(eh),
        nind = dim(eh)[1],
        nyears = dim(eh)[2],
        cen = round((1 - juvper/100) * counts/2),
        cenjuv = round(juvper/100 * counts/2),
        group = gr
    )

# Initial values
inits.season.s3 <-
    function() {
        list(
            z = cjs.init.z(eh, f),
            epsilon.phi = array((0), dim = c(3, dim(eh)[2] - 1)),
            epsilon.p = array((0), dim = c(2, dim(eh)[2] - 1)),
            mu.phi = runif(3, 0.01, 1),
            mu.p = runif(2, 0.01, 1),
            kappa = runif(dim(eh)[2] - 1, 0.01, 2),
            sigma.phi = runif(3, 0.1, 10),
            sigma.p = runif(2, 0.1, 10),
            sigma.y = runif(1, 0.1, 10),
            sigma.z = runif(1, 0.1, 10),
            b1 = rpois(1, 300),
            b2 = rpois(1, 2000),
            b3 = rpois(1, 3000)
        )
    }

# Parameters to be monitored
parameters.season.s3 <- c("phi.j", "phi.y", "phi.a", "p.l", "p.n",
"kappa", "B1", "B2", "B3", "W1", "W2", "W3", "W23", "sigma2.phi",
"sigma2.p", "sigma2.y", "sigma2.z")
```

```
# MCMC settings
ni <- 200000
nt <- 50
nb <- 100000
nc <- 3

# Run model with jagsUI
ipm.season.s3 <-
    jags(
        jags.data.season.s3,
        inits.season.s3,
        parameters.season.s3,
        "ipm-season-s3.jags",
        n.chains = nc,
        n.thin = nt,
        n.iter = ni,
        n.burnin = nb
    )
```

## Appendix C: Transient life table response experiment

To calculate the contributions of demographic parameters and components of the population structure to the population dynamics, we performed a transient life table response experiment (transient LTRE) based on developments by Caswell (2007) and Koons et al. (2016, 2017).

For a time-varying population matrix model $\mathbf{A}_t$, the realized population growth rate at any time step can be expressed as:

$$\lambda_t = \hat{\mathbf{n}}_{t+1} / \hat{\mathbf{n}}_t = \mathbf{A}_t \hat{\mathbf{n}}_t / \hat{\mathbf{n}}_t \quad \text{(S1.11)}$$

where $\hat{\mathbf{n}}_{t+1}$ and $\hat{\mathbf{n}}_t$ are vectors of structured population abundances at time $t$+1 and $t$, respectively. To decompose the variance in $\lambda_t$ into contributions from the variance in underlying demographic parameters and components of the population structure, we first expanded eq. S3.1 for our age-structured population model:

$$\lambda_t = \frac{\sqrt{\varphi_{a,t}} \cdot \kappa_t \cdot \hat{w}_{a,t} + \varphi_{j,t} \cdot \hat{w}_{j,t} + \varphi_{y,t} \cdot \hat{w}_{y,t} + \varphi_{a,t} \cdot \hat{w}_{a,t}}{\hat{w}_{j,t} + \hat{w}_{y,t} + \hat{w}_{a,t}} \quad \text{(S1.12)}$$

where $\hat{w}_{j,t}$, $\hat{w}_{y,t}$ and $\hat{w}_{a,t}$ are the number of juveniles, yearlings and adults in winter in year $t$, respectively, $\varphi_{x,t}$ is the annual apparent survival rate between $t$ and $t$+1 for individuals in age class $x$, and $\kappa_t$ is the annual apparent breeding success. Each demographic parameter (i.e., each element of $\mathbf{A}_t$) and each component of the population structure (i.e., each element of $\mathbf{w}_t$) is combined in a vector $\mathbf{\Theta}_t$. Contrary to Koons et al. (2016), but in line with Layton-Matthews et al. (2019), we used non-normalized values for the components of the population structure because actual rather than relative abundances more appropriately represent possible density dependent consequences for the population dynamics. Next, we calculated the sensitivity of $\lambda_t$ to change in

each element of $\boldsymbol{\Theta}_t$, which are the first derivatives of $\lambda_t$ with respect to changes in each element of $\boldsymbol{\Theta}_t$

$$\frac{\partial \lambda_t}{\partial \kappa_t} = \frac{\sqrt{\varphi_{a,t}} \cdot \hat{w}_{a,t}}{\mathbf{w}_t}$$

$$\frac{\partial \lambda_t}{\partial \varphi_{j,t}} = \frac{\hat{w}_{j,t}}{\mathbf{w}_t}$$

$$\frac{\partial \lambda_t}{\partial \varphi_{y,t}} = \frac{\hat{w}_{y,t}}{\mathbf{w}_t}$$

$$\frac{\partial \lambda_t}{\partial \varphi_{a,t}} = \frac{\hat{w}_{a,t}}{\mathbf{w}_t} \cdot \left( 1 + \frac{\kappa_t}{2\sqrt{\varphi_{a,t}}} \right)$$

$$\frac{\partial \lambda_t}{\partial \hat{w}_{j,t}} = \frac{\varphi_{j,t} \cdot \mathbf{w}_t - \mathbf{w}_{t+1}}{\mathbf{w}_t^{\,2}}$$

$$\frac{\partial \lambda_t}{\partial \hat{w}_{y,t}} = \frac{\varphi_{y,t} \cdot \mathbf{w}_t - \mathbf{w}_{t+1}}{\mathbf{w}_t^{\,2}}$$

$$\frac{\partial \lambda_t}{\partial \hat{w}_{a,t}} = \frac{\left( \kappa_t \sqrt{\varphi_{a,t}} + \varphi_{a,t} \right) \cdot \mathbf{w}_t - \mathbf{w}_{t+1}}{\mathbf{w}_t^{\,2}} \qquad \text{(S1.13)}$$

where $\mathbf{w}_t$ is the denominator of eq. S3.2, i.e., $\mathbf{w}_t = \hat{w}_{j,t} + \hat{w}_{y,t} + \hat{w}_{a,t}$, and $\mathbf{w}_{t+1}$ the numerator of eq. S1.2, i.e., $\mathbf{w}_{t+1} = \sqrt{\varphi_{a,t}} \cdot \kappa_t \cdot \hat{w}_{a,t} + \varphi_{j,t} \cdot \hat{w}_{j,t} + \varphi_{y,t} \cdot \hat{w}_{y,t} + \varphi_{a,t} \cdot \hat{w}_{a,t}$. Sensitivites were evaluated at the mean values of each element in $\boldsymbol{\Theta}_t$ across the time series. These sensitivities were then combined with the covariances among all elements of $\boldsymbol{\Theta}$ to achieve the first-order approximation of the variance in $\lambda_t$. The contribution of variation in each element of $\boldsymbol{\Theta}$ to var($\lambda_t$) was obtained by summing over the covariances (Horvitz et al. 1997):

398 $$\text{contribution}_{\theta_i}^{\text{var}(\lambda_t)} \approx \sum_j \text{cov}\left(\theta_{i,t}, \theta_{j,t}\right) \frac{\partial \lambda_t}{\partial \theta_{i,t}} \frac{\partial \lambda_t}{\partial \theta_{j,t}}\bigg|_{\bar{\theta}} \quad \text{(S1.14)}$$

399 Results of the LTRE are visualized in Figure 2 in the main text and Table C.1. Relative
400 contribution and relative absolute contribution of vital rates to variation in population growth rate
401 was 106% and 94%, respectively, whilst the population structure contributed -6% and 6%,
402 respectively.

403

404 **Table C.1.** Estimated variance, sensitivities of realized population growth rate to changes in
405 underlying vital rates and population structure components, transient life table response
406 experiment (LTRE) contributions (eq. S3.4), relative contributions (
407 $\text{contribution}_{\theta_i}^{\text{var}(\lambda_t)} \Big/ \sum_i \text{contribution}_{\theta_i}^{\text{var}(\lambda_t)}$) and relative absolute contributions (
408 $\text{abs}\left(\text{contribution}_{\theta_i}^{\text{var}(\lambda_t)}\right) \Big/ \sum_i \text{abs}\left(\text{contribution}_{\theta_i}^{\text{var}(\lambda_t)}\right)$) to variation in realized population growth
409 rates. Estimates are provided as posterior means and 95% credible intervals.

| Parameter | Variance | Sensitivity | LTRE contribution | Relative contribution | Relative absolute contribution |
|---|---|---|---|---|---|
| $\kappa$ | 0.0066 | 0.7159<br>(0.7110, 0.7211) | 0.0034<br>(0.0029, 0.0038) | 0.521<br>(0.457, 0.592) | 0.461<br>(0.409, 0.516) |
| $\varphi_j$ | 0.0059 | 0.1225<br>(0.1204, 0.1246) | 0.0002<br>($1.116 \cdot 10^{-5}$, 0.0005) | 0.033<br>(0.002, 0.072) | 0.029<br>(0.003, 0.063) |
| $\varphi_y$ | 0.0004 | 0.1116<br>(0.1092, 0.1140) | 0.0001<br>($-2.667 \cdot 10^{-5}$, 0.0002) | 0.010<br>(-0.004, 0.033) | 0.009<br>(0.000, 0.029) |
| $\varphi_a$ | 0.0034 | 0.8417<br>(0.8388, 0.8445) | 0.0032<br>(0.0025, 0.0041) | 0.501<br>(0.437, 0.560) | 0.444<br>(0.381, 0.501) |
| $w_j$ | $1.987 \cdot 10^5$ | $-1.102 \cdot 10^{-5}$<br>($-1.281 \cdot 10^{-5}$, $-9.321 \cdot 10^{-6}$) | -0.0002<br>(-0.0003, -0.0002) | -0.032<br>(-0.040, -0.026) | 0.029<br>(0.023, 0.035) |
| $w_y$ | $2.085 \cdot 10^5$ | $-8.287 \cdot 10^{-6}$<br>($-1.026 \cdot 10^{-6}$, $-6.502 \cdot 10^{-6}$) | -0.0001<br>(-0.0001, -0.0001) | -0.012<br>(-0.017, -0.008) | 0.011<br>(0.007, 0.015) |
| $w_a$ | $5.135 \cdot 10^6$ | $2.972 \cdot 10^{-6}$<br>($2.649 \cdot 10^{-6}$, $-3.316 \cdot 10^{-6}$) | -0.0001<br>(-0.0002, -0.0001) | -0.020<br>(-0.025, -0.016) | 0.018<br>(0.015, 0.022) |

410

411

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## References Appendix C


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# Appendix D

**Table D.1.** Pearson correlations between original explanatory variables Year, Whooper swan estimate, Tailwind, Lake Peipsi water level, negative degree days (ndd) Naryan-Mar, cumulative degree days (cdd) Naryan-Mar and Bewick's swan estimate.

| | Year | Whooper est. | Tail-wind | Lake Peipsi | ndd | cdd | Bewick's est. |
|---|---|---|---|---|---|---|---|
| Year | 1 | 0.959 | -0.047 | -0.132 | 0.134 | 0.281 | 0.575 |
| Whooper est. | 0.959 | 1 | 0.005 | -0.165 | 0.211 | 0.231 | 0.591 |
| Tailwind | -0.047 | 0.005 | 1 | 0.080 | -0.054 | -0.121 | 0.002 |
| Lake Peipsi | -0.132 | -0.165 | 0.008 | 1 | -0.244 | -0.065 | 0.042 |
| ndd Narjan | 0.134 | 0.211 | -0.054 | -0.244 | 1 | 0.274 | 0.045 |
| cdd Narjan | 0.281 | 0.231 | -0.121 | -0.065 | 0.274 | 1 | 0.016 |
| Bewick's est. | 0.575 | 0.591 | 0.002 | 0.042 | 0.045 | 0.016 | 1 |

**Table D.2.** AIC values of the different GLM models with demographic parameters as response variables (columns) and environmental variables as predictors. The three different models are indicated by their unique predictors (year, whooper swan estimate and Bewick's swan estimate) as these only occur in one of the models. The other predictor variables (see Table D.1) are present in all three models. Where the differences in AIC values are >2, models are not considered different.

| | Adult survival | Yearling survival | Juvenile survival | Kappa |
|---|---|---|---|---|
| Year | 116.19 | 108.73 | 100.11 | 108.18 |
| Whooper swan estimate | 116.18 | 108.74 | 103.70 | 108.11 |
| Bewick's swan estimate | 115.38 | 104.27 | 104.18 | 110.26 |

**Table D.3.** Model output of GLM with demographic parameters estimated by the IPM as response variables (adult, yearling and juvenile survival, and apparent breeding success) and the explanatory variables as predictors (Year, Whooper swan estimate, Bewick's swan estimate, Tailwind in the Baltic sea in autumn, water level in Lake Peipsi in autumn, negative degree days in Naryan-Mar in spring, cumulative degree days in Naryan-Mar in summer and autumn combined). Because Year, Whooper swan estimate and Bewick's swan estimate correlate strongly, we only included one of them in a separate model. Table A shows the results of the GLM with year, B shows the results of the GLM with Whooper swan estimates, C shows the results of the GLM with Bewick's swan estimates. For adult survival and yearling survival, the model with Bewick's swan estimates was the most parsimonious (see Table D.1.), for juvenile survival and kappa the model with year was the most parsimonious (see Table D.1). These results are therefore presented in the main text.

A

~ year + Tailwind + Lake Peipsi water level + ndd Narjan Mar + cdd Narjan Mar

| | Adult survival | | | | Yearling survival | | | | Juv. survival | | | | Apparent breeding success | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Est | SE | t | P | Est | SE | t | P | Est | SE | t | P | Est | SE | t | P |
| (Intercept) | -.146 | 0.175 | -.837 | 0.409 | 0.015 | 0.158 | 0.099 | 0.922 | -.070 | 0.141 | -.498 | 0.622 | 0.057 | 0.157 | 0.363 | 0.719 |
| Year | 0.090 | 0.198 | 0.453 | 0.654 | 0.013 | 0.179 | 0.075 | 0.940 | **0.584** | **0.160** | **3.660** | **0.001** | **-.560** | **0.178** | **-3.149** | **0.004** |
| Tailwind | 0.148 | 0.167 | 0.875 | 0.388 | 0.006 | 0.153 | 0.037 | 0.971 | 0.208 | 0.137 | 1.529 | 0.136 | 0.027 | 0.152 | 0.179 | 0.859 |
| Lake Peipsi | 0.259 | 0.173 | 1.490 | 0.146 | 0.205 | 0.157 | 1.309 | 0.200 | **0.426** | **0.140** | **3.049** | **0.005** | -.092 | 0.156 | -.591 | 0.559 |
| ndd Narjan | 0.165 | 0.208 | 0.793 | 0.434 | 0.063 | 0.188 | 0.336 | 0.739 | **0.344** | **0.168** | **2.051** | **0.049** | 0.030 | 0.187 | 0.161 | 0.873 |
| cdd Narjan | -.164 | 0.183 | -.895 | 0.378 | -.210 | 0.166 | -1.267 | 0.215 | -.167 | 0.148 | -1.130 | 0.267 | 0.046 | 0.164 | 0.282 | 0.780 |

B

~ Whooper swan estimate + Tailwind + Lake Peipsi water level + ndd Narjan Mar + cdd Narjan Mar

| | Adult survival | | | | Yearling survival | | | | Juv. survival | | | | Apparent breeding success | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Est | SE | t | P | Est | SE | t | P | Est | SE | t | P | Est | SE | t | P |
| (Intercept) | -.144 | 0.175 | -.827 | 0.415 | 0.016 | 0.158 | 0.104 | 0.917 | -.054 | 0.147 | -.364 | 0.718 | 0.044 | 0.156 | 0.282 | 0.780 |
| Whooper est. | 0.087 | 0.187 | 0.463 | 0.647 | 0.000 | 0.170 | 0.003 | 0.998 | **0.484** | **0.159** | **3.049** | **0.005** | **-.533** | **0.168** | **-3.161** | **0.004** |
| Tailwind | 0.144 | 0.170 | 0.850 | 0.402 | 0.006 | 0.154 | 0.036 | 0.971 | 0.186 | 0.143 | 1.298 | 0.204 | 0.052 | 0.152 | 0.342 | 0.734 |
| Lake Peipsi | 0.259 | 0.174 | 1.490 | 0.145 | 0.203 | 0.157 | 1.297 | 0.204 | **0.420** | **0.147** | **2.864** | **0.007** | -.096 | 0.156 | -.619 | 0.540 |
| ndd Narjan | 0.156 | 0.210 | 0.745 | 0.462 | 0.063 | 0.190 | 0.335 | 0.740 | 0.295 | 0.177 | 1.664 | 0.106 | 0.086 | 0.188 | 0.457 | 0.651 |
| cdd Narjan | -.159 | 0.180 | -.881 | 0.385 | -.207 | 0.163 | -1.267 | 0.215 | -.116 | 0.152 | -.762 | 0.452 | 0.012 | 0.162 | 0.071 | 0.944 |

C

~ Bewick's swan estimate + Tailwind + Lake Peipsi water level + ndd Narjan Mar + cdd Narjan Mar

| | Adult survival | | | | Yearling survival | | | | Juv. survival | | | | Apparent breeding success | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Est | SE | t | P | Est | SE | t | P | Est | SE | t | P | Est | SE | t | P |
| (Intercept) | -.150 | 0.173 | -.867 | 0.393 | -.000 | 0.149 | -.001 | 1.0 | -.058 | 0.149 | -.390 | 0.699 | 0.047 | 0.161 | 0.290 | 0.774 |
| Tailwind | 0.148 | 0.168 | 0.885 | 0.383 | 0.005 | 0.144 | 0.038 | 0.970 | 0.208 | 0.144 | 1.447 | 0.158 | 0.027 | 0.157 | 0.174 | 0.862 |
| Lake Peipsi | 0.238 | 0.170 | 1.402 | 0.171 | 0.188 | 0.146 | 1.282 | 0.209 | **0.328** | **0.146** | **2.242** | **0.032** | 0.003 | 0.159 | 0.022 | 0.983 |
| ndd Narjan | 0.156 | 0.206 | 0.756 | 0.455 | 0.043 | 0.178 | 0.245 | 0.808 | **0.326** | **0.177** | **1.839** | **0.075** | 0.049 | 0.193 | 0.253 | 0.802 |
| cdd Narjan | -.141 | 0.175 | -.807 | 0.426 | -.206 | 0.150 | -1.368 | 0.181 | -.017 | 0.150 | -.115 | 0.909 | -.097 | 0.163 | -.597 | 0.555 |
| Bewick's est. | 0.174 | 0.183 | 0.949 | 0.350 | 0.315 | 0.158 | 1.995 | 0.055 | **0.466** | **0.157** | **2.962** | **0.006** | **-.474** | **0.171** | **-2.772** | **0.009** |