

## Supporting Text

**The Bayesian Approach.** A graphical representation of the quantities in the annual and seasonal model, the corresponding observation models, and their relationships are given in Fig. 6. A complete Bayesian model consists of the joint prior distribution for all unobservables, here (for the annual model)  $\alpha_1$ ,  $\alpha_2$ ,  $\sigma$ ,  $\lambda_f$ , and  $\gamma_f$  and the unknown states  $y_1, y_2, \dots, y_N$ , and the joint distribution of the observables, here the abundance data ( $z_{f,1}, z_{f,2}, \dots, z_{f,N}$ ) and the trapping effort ( $T_{f,1}, T_{f,2}, \dots, T_{f,N}$ ). Bayesian inference is then based on the posterior distribution of the unobservables given the data. By conditioning on the data, the posterior distribution (i.e., the conditional probability of the unobservable quantities of interest, given the observed data) is calculated [by successive application of Bayes theorem (1)]. The posterior distribution can usually not be obtained analytically but can be computed by using Markov Chain Monte Carlo methods, for instance, Gibbs sampling (2). Bayesian inference is readily applicable through BUGS (Bayesian inference using Gibbs sampling; [www.mrc-bsu.cam.ac.uk/bugs](http://www.mrc-bsu.cam.ac.uk/bugs)).

To fully specify our model, a prior distribution has to be defined for all unobservable parameters that are not directly conditioned on other parameters or observed data (for the annual model these are:  $\alpha_1$ ,  $\alpha_2$ ,  $\sigma$ , and  $\gamma_f$ ). Vague (i.e., essentially flat) prior distributions were used [ $\alpha_1 \sim N(0,100)$ ,  $\alpha_2 \sim N(0,100)$ ,  $\gamma_f \sim N(0,100)$ , and  $1/\sigma^2 \sim \text{Gamma}(0.001, 0.001)$ ], meaning that the prior tells us little about the parameters relative to what is learned from the sample. For both the annual and the bivariate seasonal model we performed 90 000 iterations of the Gibbs sampler, using WINBUGS 0.6, after a “burn-in” of 10,000 iterations. This was done for each of the 84 locations for which both spring and fall data were available.

**Convergence.** Autocorrelations within the Markov chains seemed to be reasonably low [indicating that the mixing of the Gibbs sampler is not too slow (3)]. Convergence was also assessed through the runs of multiple chains and Gelman–Rubin convergence statistics (4).

The annual model converged for all 84 sites. For the seasonal model, data from 74 of the total of 84 sites were judged to converge appropriately. The seasonal model failed

to converge for 10 sites (assf6, assf7, assf9, assf10, aassf28, assf37, assf59, assf68, assf74, and assf78) because of excessive auto- and cross-correlations for some of the Markov chains. Only the remaining 74 of 84 sites were used in analyses of the seasonal parameters. Including all seasonal estimates in the analyses will, we are convinced, not change the conclusions of the paper; indeed, including only 74 of the 84 is a conservative restriction of our total data set. Notice, furthermore, that data from all 84 sites are used in our main results summarized in Table 1 and depicted in Fig. 1 *B* and *C*.

**The Parameter Estimates (BUGS estimates).** Parameter estimates together with credible intervals (the Bayesian equivalent to confidence intervals) are given in Tables 3 and 4 for the annual and seasonal models, respectively (parameters of the corresponding observation model are not shown).

**The Parameter Estimates (Standard Autoregressive Modeling Ignoring Sample Variance).** Parameter estimates for an order-two annual model are given in Table 5.

**Deducing the Annual Variance from the Seasonal Variances.** We have the following model:

$$R_{wt} = x_t - y_{t-1} = a_{w1}y_{t-1} + a_{w2}x_{t-1} + a_{w3}y_{t-2} + a_{w4}x_{t-2} + \varepsilon_{wt} \quad [\mathbf{S1}]$$

$$R_{st} = y_t - x_t = a_{s1}x_t + a_{s2}y_{t-1} + a_{s3}x_{t-1} + a_{s4}y_{t-2} + \varepsilon_{st}, \quad [\mathbf{S2}]$$

where  $\varepsilon_{wt}$  is a process noise during the winter (being normally distributed with mean 0 and variance  $\sigma_w^2$ ) and  $\varepsilon_{st}$  is a process noise during the summer (being normally distributed with mean 0 and variance  $\sigma_s^2$ ). The parameters  $a_w$  and  $a_s$  define the seasonal density-dependent structure.

Together Eqs. **S1** and **S2** define the annual net growth rate, defined for instance as the fall-to-fall-growth net rate,  $R_t = y_t - y_{t-1}$ . We can now rewrite Eqs. **S1** and **S2** as a model in  $y$  only:

$$R_t = y_t - y_{t-1}$$

$$\begin{aligned}
&= (a_{w1} + a_{s1} + a_{w2} + a_{s2} + a_{w1}a_{s1})y_{t-1} \\
&+ (a_{w3} + a_{s3} + a_{w4} + a_{s4} + a_{w1}a_{s3} + a_{s1}a_{w3} - a_{w2}a_{s2})y_{t-2} + (a_{w3}a_{s3} - a_{w2}a_{s4} - a_{s2}a_{w4})y_{t-3} \\
&- a_{w4}a_{s4}y_{t-4} + \eta'_t, \tag{S3}
\end{aligned}$$

where  $\eta'_t = \varepsilon_{st} + (1 + a_{s1})\varepsilon_{wt} - a_{w2}\varepsilon_{st-1} + a_{s3}\varepsilon_{wt-1} - a_{w4}\varepsilon_{st-2}$  is no longer a white noise process (even though its components are). The covariance structure of  $\eta'_t$ , assuming no covariation between summer and winter noise, is defined by (5)

$$c_0 = \sigma_s^2(1 + a_{w2}^2 + a_{w4}^2) + \sigma_w^2[(1 + a_{s1})^2 + a_{s3}^2] \tag{S4}$$

$$c_1 = -a_{w2}\sigma_s^2 + (1 + a_{s1})a_{s3}\sigma_w^2 + a_{w2}a_{w4}\sigma_s^2 \tag{S5}$$

$$c_2 = -a_{w4}\sigma_s^2, \tag{S6}$$

where,  $c_i$  denotes the covariance of  $\eta'_t$  components having a time-lag difference of  $i$ . More appropriately, the expression for  $\eta'_t$  may be written as  $\eta'_t = \eta_t + \beta_1\eta_{t-1} + \beta_2\eta_{t-2}$  where  $\eta_t$  is normally distributed with  $N(0, \sigma_\eta^2)$ . The two expressions for  $\eta'_t$  should have an equal covariance structure, and as a result,  $\sigma_\eta^2$  may be expressed, implicitly and assuming no covariation between the variance during the winter and summer, as a function  $f(\sigma_s^2, \sigma_w^2)$  given as follows:

$$\sigma_\eta^2 + \sigma_\eta^2 c_1^2 / (\sigma_\eta^2 + c_2)^2 + c_2^2 / \sigma_\eta^2 - c_0 = 0 \tag{S7}$$

The solutions for each of the time series are given in Table 6. This has several solutions; whenever there is ambiguity with respect to solutions, we give all solutions in Table 6.

**Additional Methodological Aspects.** Simulated data were used to investigate the bias observed in the one-to-one line of Fig. 3B. Data were simulated from the seasonal bivariate model (Eqs. S1 and S2) by using the parameter estimates obtained from previous fitting of this model to data from site assf12 or assf36 (two typical populations of group 2). The simulated data represent true abundance values and therefore the sampling process was ignored. Each of 30 data sets (15 data sets were simulated for each

of the two sets with estimates) was then fitted to the seasonal bivariate model (Eqs. **S1** and **S2**) and the annual second-order model (Eq. **3**) by using BUGS. The annual density-dependent coefficients predicted from the seasonal model were compared with the corresponding coefficients directly estimated from the annual model (Fig. 7). As can be seen, there are deviations from the one-to-one expectations. A similar pattern was found when using an annual model of order four instead of order two when estimating the first and second coefficients (although the bias for the first coefficient no longer became significant; results not shown). Our results suggest that the similar bias observed when using real data (Fig. 3B) was not due to methodological aspects, such as state-space modeling (the incorporation of a sampling process), ignoring the predicted order four in the annual model or the noise term in the bivariate seasonal model not being white.

**Estimating the Relative Length of Winter.** Earlier, Stenseth *et al.* (6) used a proxy for the length of the breeding season,  $\tau$ , assumed to be directly related to the warmth index, WI, given as  $\Sigma(T - 5)$ , where the sum is taken over months for which the average monthly temperature,  $T$ , is equal to or above  $5^{\circ}\text{C}$  (7, 8). By so doing, Stenseth *et al.* demonstrated that  $\tau$  is closely related to the geographic scores. This relation is further improved when we assume that the winter length ( $\tau_w$ ;  $\tau_w = 1 - \tau$ ) is related to the WI through a logit function:  $\tau_w = \text{blogit}(c\text{WI})$ . WI may furthermore be approximated (and estimated) by using geographic coordinates [i.e., position in the south–north and west–east direction (denoted  $g_{\text{sn}}$  and  $g_{\text{we}}$ , respectively), and altitude above sea level (denoted  $H$ )]. (The latter approximation is necessary, because the meteorological stations where the WI is measured do not correspond to the sampling stations for the voles. However, all sampling stations have geographical coordinates and altitude.) The geographic coordinates  $g_{\text{we}}$  and  $g_{\text{sn}}$  are ordinary longitude and latitude, respectively, given in minutes [defining  $139^{\circ}00'$  E and  $41^{\circ}00'$  N as the origin (0,0)]. However, because 1 min of latitude does not correspond to the same geographic distance as 1 min of longitude, the values of  $g_{\text{we}}$  have to be standardized. In Hokkaido, 60 min of longitude corresponds to 80.75 km, whereas 60 min of latitude is 112.2 km. Thus, the original values of  $g_{\text{we}}$  are multiplied by 1.389. When regressing WI on geographic coordinates and altitude ( $h = \log_e(H + 1)$ ), using Akaike’s Information Criterion (AIC) as a selection criterion, we

obtain the following model:  $\hat{WI} = 80.0479 - 0.0887g_{we} - 0.0914g_{sn} - 3.0481h + 0.0003g_{we}g_{sn} + 0.0183g_{sn}h$ .

We assume that the winter length ( $\tau_w$ ) is related to the warmth index through the relation  $\tau_w = b \logit(cWI)$ , where the parameters  $b$  and  $c$  are determined by assuming the relative length of the winter to be 7/12 where the WI is the lowest and 4/12 where the WI is the highest. Furthermore, we assume that WI is appropriately modeled by using geographic coordinates [i.e., position in the south–north and west–east direction (denoted  $g_{sn}$  and  $g_{we}$  respectively), and altitude above sea level (denoted  $H$ )]. The relationship between WI and  $g_{sn}$ ,  $g_{we}$ , and  $h$  [where  $h = \log_e(H)$ ] is determined by linear regression; the best model obtained, using AIC (9), starting with the most general model  $WI = d_0 + d_1g_{we} + d_2g_{sn} + d_3h + d_4g_{we}g_{sn} + d_5g_{sn}h + d_6g_{we}h$ . On this basis, we arrive at the following expression for the relative length of winter:  $\tau_w = b \logit(p_0 + p_1g_{we} + p_2g_{sn} + p_3h + p_4g_{we}g_{sn} + p_5g_{sn}h) + \text{error}$ , where  $p_i = cd_i$ . We obtained the following model  $\tau_w = 3.63 \logit(-3.201916 + 0.003548g_{we} + 0.003656g_{sn} + 0.121924h - 0.000012g_{we}g_{sn} - 0.000732g_{sn}h)$  (see ref. 10 for further information). We have performed robustness testing by varying the assumed length of the winters (7/12 and 4/12, respectively); as can be seen, our results are robust against this variation.

To estimate the values of  $b$  and  $c$  in  $\tau_w = b \logit(c\hat{WI})$ , we assume that the longest summer is 8 months and is found at sea level in the southwestern part of Hokkaido, and that the shortest one is 5 months and found in the northeastern part of Hokkaido (10-12). Two meteorological stations are selected in each part of the island (Fig. 8), all having WI values relatively well predicted by the model described above [for selected stations:  $(\text{residual})^2 < 12$ ; overall mean  $(\text{residual})^2 = 24$ ]. Combining both selected stations in the southwest with both stations in the northeast produces four sets of equations:  $\tau_{wSWi} = b \logit(cWI_{SWi})$  and  $\tau_{wNEi} = b \logit(cWI_{NEi})$ , where  $i = 1, 2$ . The values of  $b$  and  $c$  are then determined by using the function *uniroot* in S-PLUS 2000 (13) (we obtain the estimates  $b = 3.63$  and  $c = -0.04$ ). The model for  $\hat{WI}$  is subsequently entered into the resulting expression, producing the following model of the relative length of winter  $\tau_w$ :

$$\tau_w = 3.63\text{logit}(-3.201916 + 0.003548g_{we} + 0.003656g_{sn} + 0.121924h - 0.000012g_{we}g_{sn} - 0.000732g_{sn}h) + \text{error}$$

Fig. 9A shows the curvilinear relation between the predicted  $\tau_w$  and the predicted  $\hat{WI}$ . Fig. 9B shows the relation between the predicted  $\tau_w$  and the predicted  $\hat{WI}$ , using observed WI values to calculate  $\tau_w$ .

Fig. 10 summarizes sensitivity analyses varying the maximum and minimum winter lengths. The panel shown in the main paper is highlighted in the frame. As can be seen, the overall pattern is rather robust to deviations from our assumed maximum and minimum length of the winter.

**Estimating the Annual Model on the Basis of the Spring-to-Spring Dynamics.** Fig. 11 show the pattern depicted in Fig. 1C (also see Table 1). As can be seen, the overall same pattern emerges suggesting that our results in that respect are robust.

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