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ADAPTIVE HARVEST MANAGEMENT FOR THE SVALBARD POPULATION OF PINK-FOOTED GEESE

2018 Progress Summary[1]

Report prepared by the AEWA European Goose Management Platform Data Centre

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Summary

This report describes progress on development and implementation of an adaptive harvest management program for maintaining the Svalbard population of Pink-footed Geese (*Anser brachyrhynchus*) near their target level (60,000) by providing sustainable harvests in Norway and Denmark. Specifically, this report provides an assessment of recent monitoring information and its implications for hunting seasons in 2018.

An Adaptive Harvest Management (AHM) program requires specification of four elements: (a) A set of alternative population models, which bound the uncertainty about population dynamics; (b) A set of weights describing the relative credibility of the alternative models, which are updated each year based on a comparison of model predictions and monitoring information; (c) A set of alternative harvest quotas from which to choose; and (d) An objective function, by which alternative harvest strategies are evaluated and an optimal strategy chosen.

The most current set of monitoring information was used to update model weights for the 1991-2017 period. Current model weights suggest little evidence for density-dependent survival and reproduction. These results suggest that the Pink-footed Goose population may have experienced a release from density-dependent mechanisms, corresponding to the period of rapid growth in population size. There is equivocal evidence for the effect of the number of days above freezing in May in Svalbard on survival, but the evidence for an effect on reproduction has been increasing in recent years.

Since the 2016 hunting season, harvest quotas are prescribed on an annual basis rather than every three years because of the potential to better meet management objectives. Based on updated model probabilities, the

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November 2017 population size (72,000), the proportion of the population comprised of one-year-old birds (0.076), and days above freezing in Svalbard in May 2018 (27), the optimal harvest quota for the 2018 hunting season is approximately 27,000. With the agreed upon harvest allocation of 30% Norway and 70% Denmark, the national quotas are 8,100 and 18,900, respectively, which are higher than the harvests realized in previous years. In 2017 the quota for the two countries combined was 36,000, but only a harvest of about 11,400 was realized. The decrease in harvest quota for 2018 is largely attributable to the apparent decline in population size.

We also describe the ongoing development of an Integrated Population Model (IPM), which uses all available demographic data for Pink-footed Geese in a single, unified analysis. IPM estimates of harvest rates of adult geese were variable and relatively low prior to the implementation of AHM (2013), and have been relatively high since. The increase in harvest rates has been accompanied by a decline in annual survival. The ratio of young-of-the-year to older birds just prior to the hunting season has been variable over time, and since about 2005 has been highly correlated with the number of days above freezing in May in Svalbard. IPM estimates of population size suggest that abundance of Pink-footed Geese has been relatively stable, or declining slightly, in recent years. Based on the IPM estimate of population size in November 2017 of 68,800 (95% credible interval: 58,200 – 79,400), the optimal harvest quota for the 2018 hunting season is 15,000. This is lower than that derived from the set of nine discrete models because the IPM estimate of November population size is lower than the November count, and because the IPM model does not consider May temperatures in Svalbard, but rather assumes reproductive success varies randomly about the mean.

Introduction

The Svalbard population of Pink-footed Geese has increased from about 10,000 individuals in the early 1960's to around 80,000 today. Although these geese are a highly valued resource, the growing numbers of geese are causing agricultural conflicts in wintering and staging areas, as well as tundra degradation in Svalbard. The African-Eurasian Waterbird Agreement (AEWA; http://www.unep-aewa.org/) calls for means to manage populations which cause conflicts with certain human economic activities. This document describes progress on the implementation of an AHM program for maintaining Pink-footed Goose abundance near their target level (60,000) by providing sustainable harvests in Norway and Denmark (Madsen and Williams 2012). Specifically, this report provides relevant information for establishing the 2018 hunting seasons.

Johnson et al. (2014) described the compilation of relevant demographic and weather data, and specified an annual-cycle model for Pink-footed Geese. By combining varying hypotheses about survival and reproduction, a suite of nine models was developed representing a range of possibilities concerning the extent to which demographic rates are density dependent, and the extent to which spring temperatures influence survival and reproduction. These nine models vary significantly in their predictions of the harvests required to maintain the population near the goal of 60,000.

The passive form of adaptive management (Johnson and Williams 2015) is used to formulate an optimal harvest strategy for Pink-footed Geese. In passive adaptive management, alternative population models (or model parameterizations) and their associated weights are explicitly considered in the development of an optimal harvest strategy. Model-specific weights represent the relative credibility of the alternative models, and are based on a comparison of predicted and observed population sizes. Models that are better predictors of observed population size gain probability mass (weight) according to Bayes' theorem. Models with higher weights have more influence on the optimal harvest strategy. Model weights are updated each year based on information from the monitoring program; thus, the harvest strategy evolves over time as uncertainty about population dynamics is reduced.

This report focuses on updates of population status and alternative model weights, given the prescription for an annual harvest quota of 36,000 for the 2017 hunting season. It also provides an optimal harvest strategy and associated harvest-quota for the 2018 hunting season. It uses the most recent data on harvest (autumn 2017), population size (autumn 2017), and weather conditions on the breeding grounds (May 2018). This report also describes the ongoing development of an IPM, which uses all the available demographic data for Pink-footed Geese in a single, unified analysis.

Methods

The development of a passively adaptive harvest management strategy requires specification of four elements: (a) A set of alternative population models, which bound the uncertainty about population dynamics; (b) A set of model weights describing the relative credibility of the alternative models; (c) A set of alternative harvest quotas from which to choose; and (d) An objective function, by which alternative harvest strategies can be evaluated and an optimal strategy identified. An optimal management strategy prescribes a harvest quota based on model weights and population abundance and environmental conditions that are observed at the time a decision is made.

Models of population dynamics

Since implementation of AHM in 2013, we have used a set of nine discrete models (Table 1), whose relative weights are evaluated each year by comparing model-specific predictions with observations of population size in November. This year we also include a preliminary integrated population model. The key difference in the two modeling approaches is that with the set of nine discrete models, parameters are fixed and it is the weight on individual models that is updated each year. With the IPM, there is a single model structure and the parameters of the model are updated each year. We provide comparisons of the optimal harvest strategies

derived from the two different modeling approaches. Detailed descriptions of population models for Pink-footed Geese are provided in Appendix A.

Alternative harvest quotas

We considered a set of possible harvest quotas of 0 to 50,000 in increments of 1,000. A quota of zero represents a closure of hunting seasons in Norway and Denmark.

Table 1. Nine alternative models of Pink-footed Goose population dynamics and their associated carrying capacities (K, in thousands). Model covariates include N and A, which are total population size and the number of sub-adults plus adults, respectively. TempDays is the number of days above freezing in May in Svalbard. The sub-models represented by (.) denote randomly varying demographic rates (i.e., no covariates). Models M3, M4, M6, and M7 are density-independent growth models and thus have no definitive carrying capacity.

Model	Survival sub-model	Reproduction sub-model	*K* (sd)
M0	(.)	(TempDays, A)	120 (8)
M1	(TempDays)	(TempDays, A)	129 (8)
M2	(TempDays, N)	(TempDays, A)	59 (4)
M3	(.)	(TempDays)	
M4	(TempDays)	(TempDays)	
M5	(TempDays, N)	(TempDays)	66 (3)
M6	(.)	(.)	
M7	(TempDays)	(.)	
M8	(TempDays, N)	(.)	65 (5)

Objective function

The International Working Group established a management objective to maintain the population size within acceptable limits by regulating harvest in Norway and Denmark. For computational purposes, the optimal value (V^*) of a harvest-management strategy (A) at time t is the maximum (max) of the expectation (E) of the temporal sum of population utility:

$$V^*(A_t|x_t) = \max_{(A_t|x_t)} E\left[\sum_{\tau=t}^{\infty} u(a_\tau|x_\tau)|x_t\right],$$

where population utility $u(a_\tau|x_\tau)$ is action (a_τ) and resource-dependent (x_τ). Population utility is defined as a function of a time-dependent action conditioned on system state:

$$u(a_\tau|x_\tau) = \frac{1}{1 + exp(|N_{t+1} - 60| - 10)}.$$

where N_{t+1} is the population size (in thousands) expected due to the realized harvest quota and the population goal is 60,000 (Figure 1). The 10 (thousand) in the equation for population utility represents the difference from the population goal when utility is reduced by one half. Thus, the objective function devalues harvest-quota choices that are expected to result in a subsequent population size different than the population goal, with the degree of devaluation increasing as the difference between population size and the goal increases.

Derivation of harvest strategies

The harvest management process can be described as a Markov decision process (Marescot et al. 2013). A solution algorithm for a Markov decision process is stochastic dynamic programming, which we used to derive harvest strategies for the Svalbard population of Pink-footed Geese. We used the open-source software MDPSolve© (https://sites.google.com/site/mdpsolve/) for Matlab (https://www.mathworks.com/) to compute optimal solutions. See Appendix A for more details.
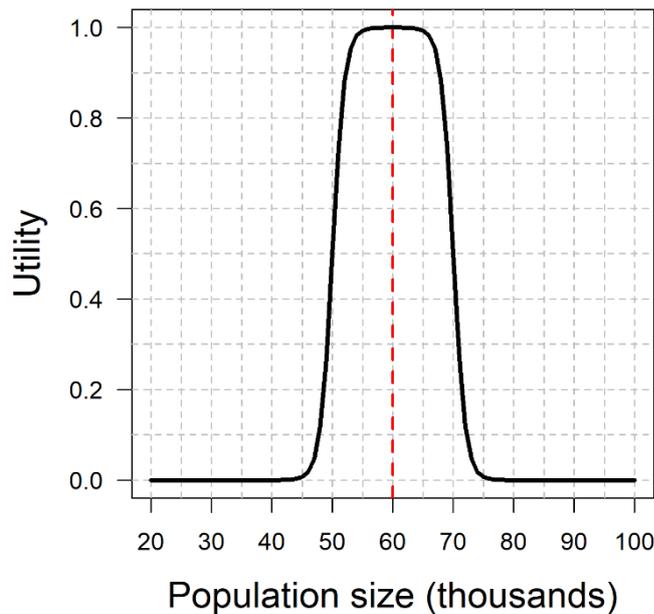

Fig 1. *Utility (i.e., stakeholder satisfaction) expressed as a function of population size of Pink-footed Geese.* Population sizes between about 50,000 and 70,000 are acceptable (and thus have high utility), while those outside that range are undesirable (and thus have low utility).

Results and Discussion

Set of nine discrete models

Population status and harvest

Pink-footed Goose abundance traditionally has been determined in November, but counts in April or May have also been conducted for the last nine years because of concerns about negative bias in the November counts. Indeed, in five of those years, May counts have exceeded those in November, suggesting the possibility that birds were missed during the November counts (because only population losses occur between November and May). For the purposes of updating weights on the set of nine discrete models, we use an admittedly *ad hoc* solution, in which the November or May count that is deemed the most reliable indicator of autumn population size is used (i.e., when under-counts or over-counts in either November or May were recognized by observers). The IPM uses both November and May counts, and provides posterior estimates of population size based on additional demographic data. Thus, the reliance on a single, possibly biased, count is greatly reduced with the IPM.

The population count in November 2017 was 72,000, and in May 2018 it was 67,000 (we used the November count for updating model weights). The proportion of young-of-the-year in November 2017 was 0.076, which is much lower than the long-term average of 0.135 (sd = 0.050). Thus, the population was comprised of about 5,500 young-of-the-year and about 66,500 adults. Harvest during the 2017 hunting season in Norway and Denmark was about 11,400. This figure does not include those shot under derogation, which only occurs in Denmark and averages <100 birds (Madsen et al. 2018). Svalbard has experienced a very warm spring this year, with 27 days above freezing in May 2018.

Updating model weights

We used the most up-to-date set of monitoring information (Appendix B; Madsen et al. 2018) to update model weights for the 1991 – 2017 period. Discrimination among the nine alternative models became most pronounced after 2006 (Figure 2). Current model weights suggest no evidence for density-dependent survival ($p_{DD-S} = 0.0000$, Figure 3) (model weight is on a scale of 0.0 – 1.0, with 0.0 indicating no evidence and 1.0 indicating conclusive evidence). Similarly, the evidence for density-dependent reproduction is very low ($p_{DD-R} = 0.1127$, Figure 3). Model weights thus suggest that the Pink-footed Goose population may have experienced a release from density-dependent mechanisms, corresponding to the period of rapid growth in population size. There is equivocal evidence for the effect of May temperatures on survival ($p_{DAYS-S} = 0.6179$, 2 of 3 survival models), but increasing evidence for its effect on reproduction ($p_{DAYS-R} = 0.8017$, 2 of 3 reproductive models) (Figure 3). We also calculated predictions of population size for each year based on each model, and then compared them with observed population sizes (Figure 4). The predictive ability of most models has been relatively poor for population sizes exceeding 60,000, with a tendency towards predictions of population size that are less than those observed. Nonetheless, the model set has produced a distribution of predictions that do not differ significantly from the distribution of observed population sizes (two-tailed Kolmogorov-Smirnov test: $D = 0.18, P = 0.47$).

Harvest strategy for the 2018 season

Beginning with the 2016 hunting season, harvest quotas are prescribed on an annual basis rather than every three years because of the potential to better meet population management objectives. The optimal harvest strategy is computed based on current model weights and prescribes a harvest quota for each possible combination of adult and young abundance and TempDays that might be observed in the monitoring program.

The harvest strategy reflects the effect of TempDays, with harvest quotas quickly increasing as the number of adults exceed 60,000 (Figure 5). The optimal harvest strategy, however, is "knife-edged," meaning that only small changes in population size (particularly around the goal of 60,000) are required to produce large changes in the harvest quota. This result can be primarily attributed to the lack of evidence for density dependence, such that the weighted or "average" model is essentially an exponential growth model. Exponential growth models can produce wide swings in population size with only small changes in harvest because there are no self-regulating mechanisms that would dampen changes in population size.

Based on updated model probabilities, the November count of 72,000 (66,500 adults and 5,500 young), and 27 days above freezing in May 2018 in Svalbard, the optimal harvest quota for the 2018 hunting season in Norway and Denmark combined is approximately 27,000. With the agreed upon harvest allocation of 30% Norway and 70% Denmark, the national quotas are 8,100 and 18,900, respectively, which are higher than the harvests realized in previous years. The 2018 quota represents a decrease from the 2017 harvest quota of 36,000, and this is largely attributable to the apparent decline in population size. If the number of days above freezing in May 2018 in Svalbard had been average (8 TempDays), the 2018 harvest quota would only be 17,000. The harvest quota has been ≥15,000 each year of the AHM process (2013-2017), yet realized harvest has averaged only 12,900 (sd = 2,400) and has never exceeded the annual quota. Nonetheless, current levels of harvest mortality may be sufficient to stabilize population size (Clausen et al. 2017).

Integrated population model

The IPM uses additional sources of monitoring data than those used for the set of nine discrete models. In the IPM, both May and November population counts are used, as well as annual survival rates (estimated from mark-recapture data), and the proportion of harvest occurring in Denmark prior to the November count (based on wings submitted by hunters). Using the model structure described in Appendix A, we estimated 341 observed and latent (unobserved) quantities for the 1991 - 2017 period. The large number of parameters results from the assumption that harvest mortality, the portion of harvest in Denmark prior to the November count, annual survival, and reproduction are all year-specific.

The IPM estimates of May population sizes are generally lower, and estimates of November population size are generally higher, than their respective counts (Figure 6). The estimated population sizes and actual counts are slightly different due to the use of annual survival and reproduction data to better estimate population size. The estimated population sizes also exhibit smoother changes among years than the counts, reflecting the autoregressive nature of the population model and the use of additional monitoring information. Unlike the raw population counts, IPM estimates of population size suggest abundance has been relatively stable, or declining slightly, in recent years.

With respect to rates of harvest mortality and reproduction, we must rely on the IPM to estimate these latent quantities. Harvest rates of adult Pink-footed Geese were variable and relatively low prior to the implementation of AHM (2013), and have been relatively high since. The increase in harvest rates has been accompanied by a decline in annual survival (Figure 7). The fact that the mark-recapture estimates of survival are lower than the IPM estimates was expected due to bias resulting from neck-band loss (Clausen et al. 2015). However, differences in mark-recapture and IPM estimates of survival also result from the inclusion of additional information (e.g., population counts, proportion of young in autumn) in the IPM.

Reproductive success is defined as the ratio of young-of-the-year to older birds just prior to the hunting season. The estimated ratio has been highly variable over time, and since 2005 has been highly correlated with the number of days above freezing in May in Svalbard (Figure 8).

We used IPM estimates of the mean and variance of reproductive success, survival in the absence of harvest, and model process error to derive an optimal harvesting strategy using stochastic dynamic programming (Appendix A). Based on the IPM estimate of population size in November 2017 of 68,800 (95% credible interval: 58,200 – 79,400), the optimal harvest quota for the 2018 hunting season is 15,000. This is lower than that derived from the set of nine discrete models because the IPM estimate of November population size is less than the November count, and because the IPM model does not consider May temperatures in Svalbard, but rather assumes reproductive success varies randomly about the mean. This spring in Svalbard has been unusually warm, and with little evidence of density-dependent reproduction (Figure 3B), reproductive success this summer is expected to be higher than average. The harvest strategy from a preliminary IPM including the effect of spring temperatures is relatively conservative (Figure 9), but we lack confidence in this strategy due to the preliminary nature of this model. We are continuing work on integrated population models and will report progress next year. Ultimately, we believe an IPM is a better choice to guide harvest management because it has several advantages over traditional modeling techniques, including the leveraging of data to estimate latent quantities, better precision of estimated parameters, and a full accounting of process and sampling variability. An IPM is also more likely to be responsive to possible changes in system dynamics than a set of discrete models and associated weights.

Acknowledgements

U.S. Geological Survey. Any use of trade, product, or firm names in this report is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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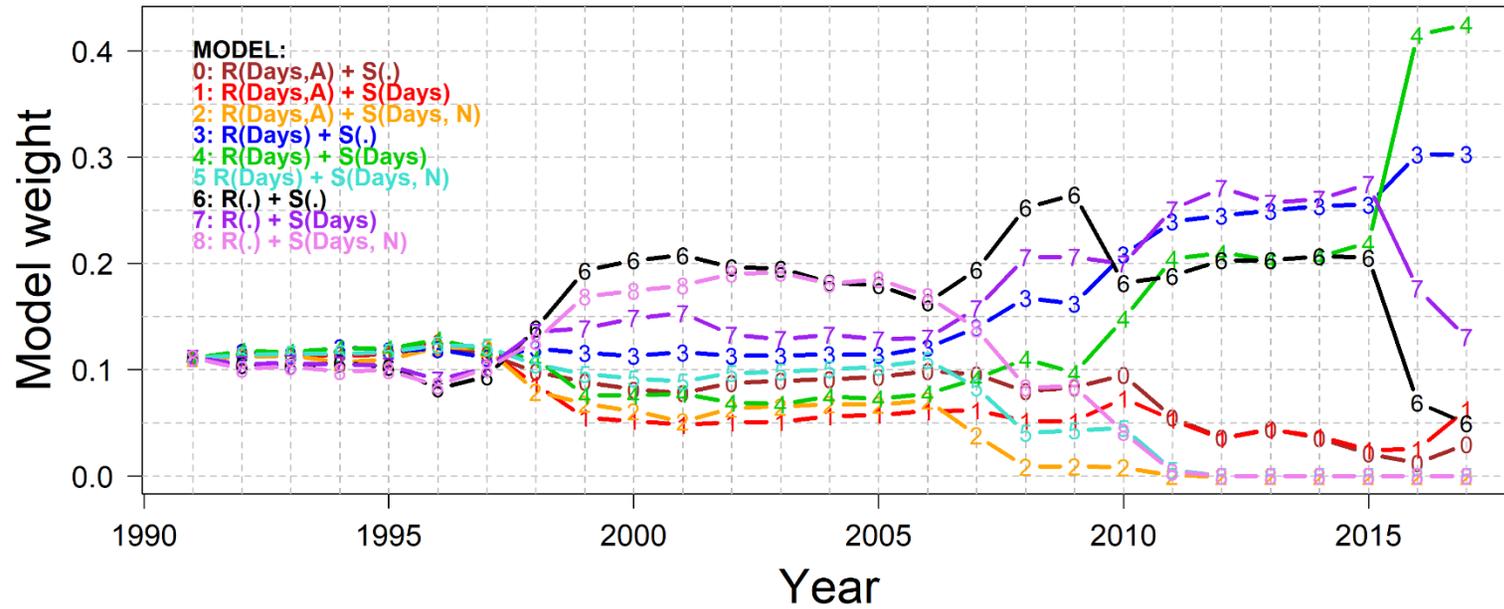
Figure 2. *Posterior model weights for nine alternative models describing the dynamics of the Svalbard Pink-footed Goose population, assuming equal prior model weights in 1991. See Table 1 and Appendix A for a description of the models.*
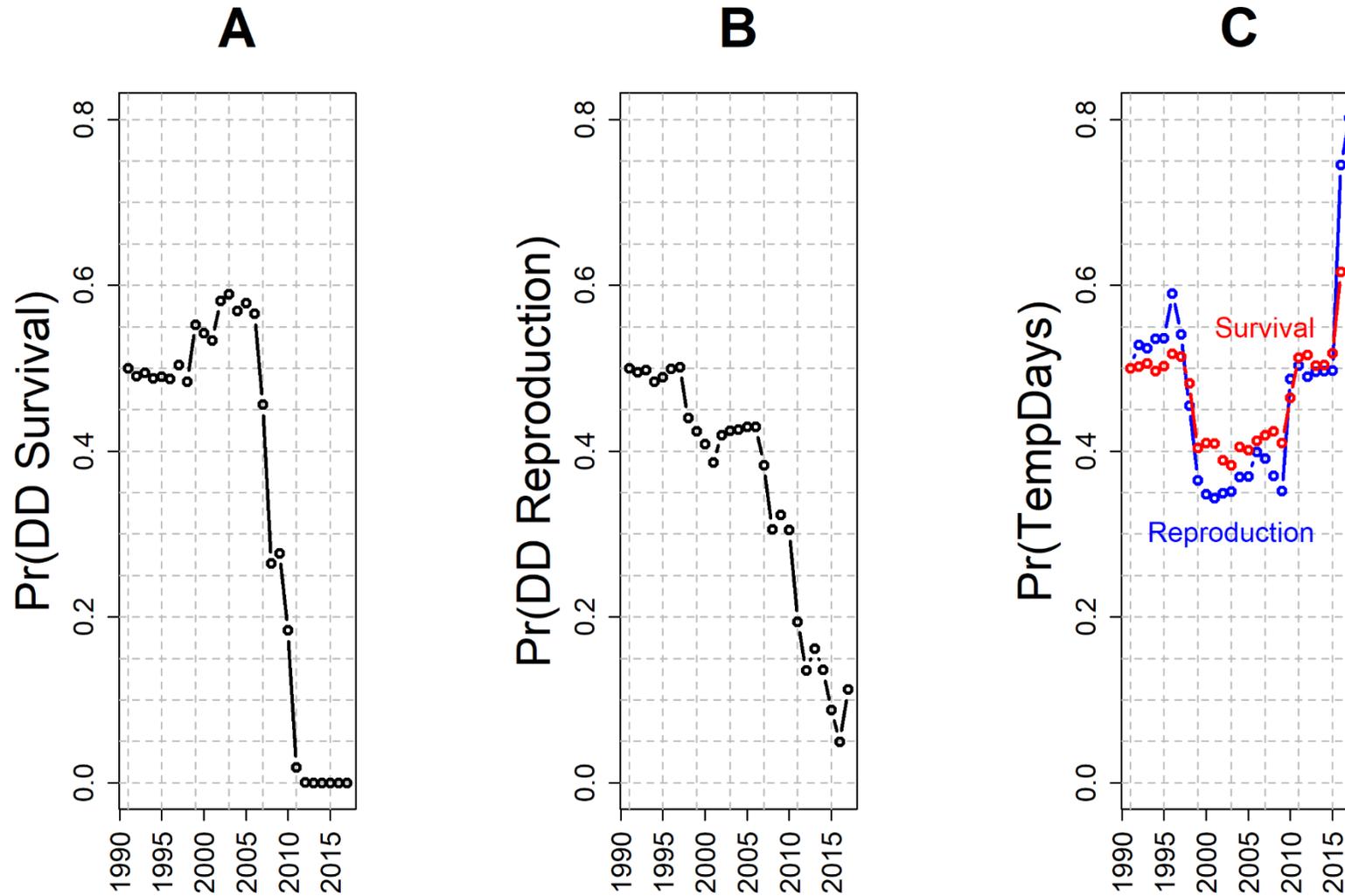
Figure 3. *Aggregate weight on Svalbard Pink-footed Goose population models that incorporate (A) density-dependent survival; (B) density-dependent reproduction; and (C) days above freezing in May in Svalbard (TempDays) in the reproductive and survival processes.*
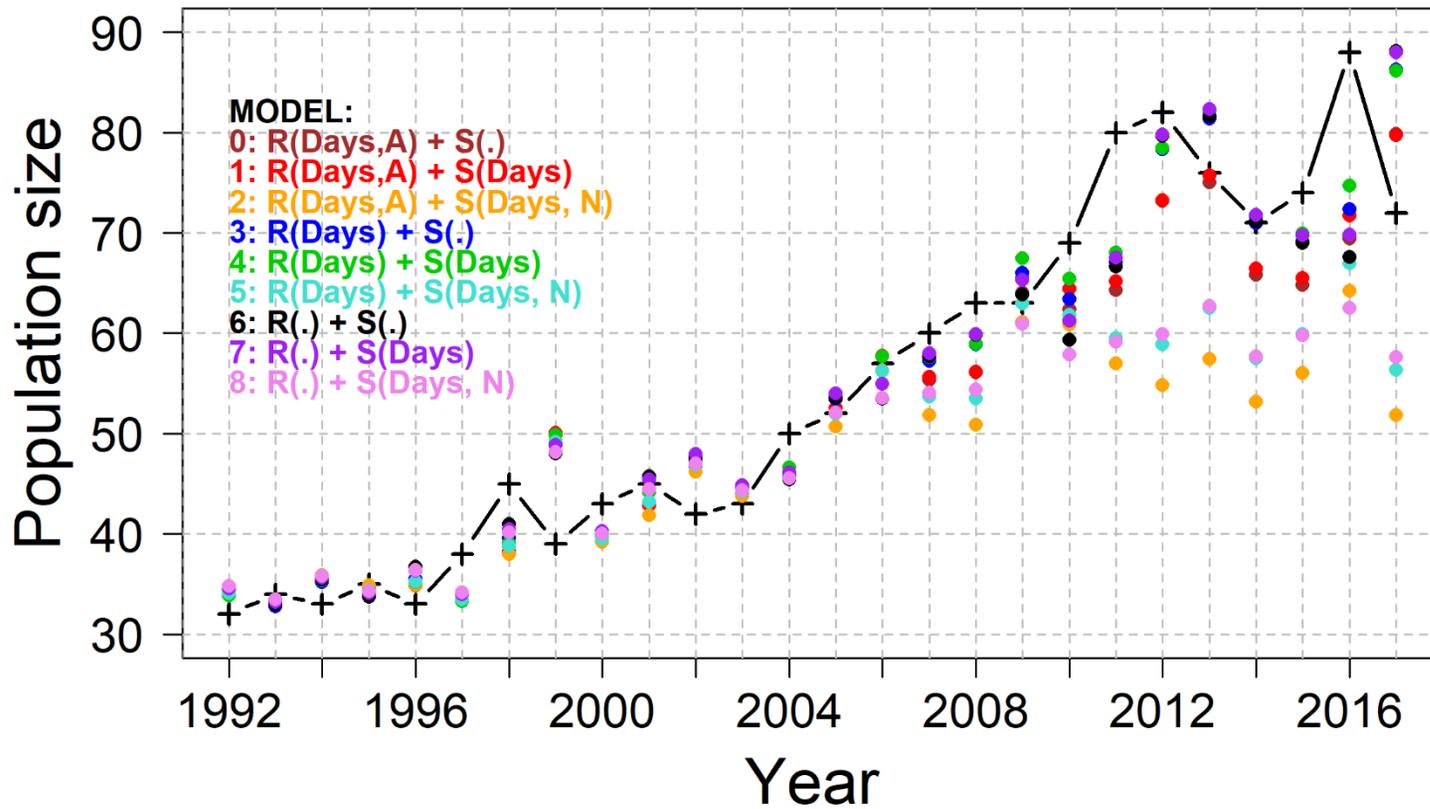
Figure 4. *Comparison of observed population sizes (line) and those predicted by nine alternative models (circles) describing the annual dynamics of the Svalbard Pink-footed Goose population. See Table 1 and Appendix A for a description of the models. Predictive ability declined as population size grew beyond about 60,000.*
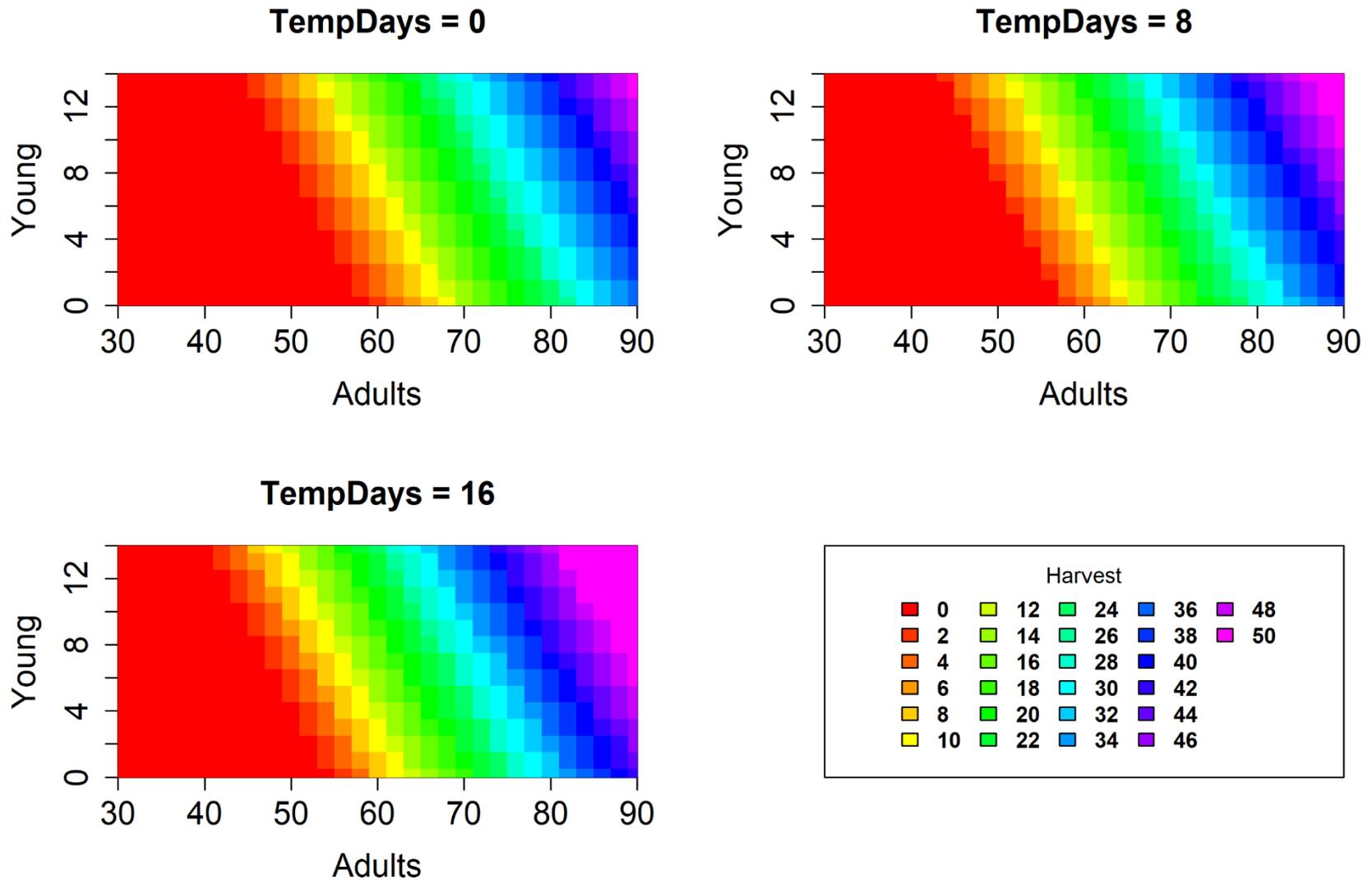
Figure 5. *Optimal harvest quotas (in thousands) for Svalbard Pink-footed Geese in 2018 based on the number of adults and young (both in thousands) and the number of days above freezing in May (TempDays), as based on the most recent weights on the alternative population models*
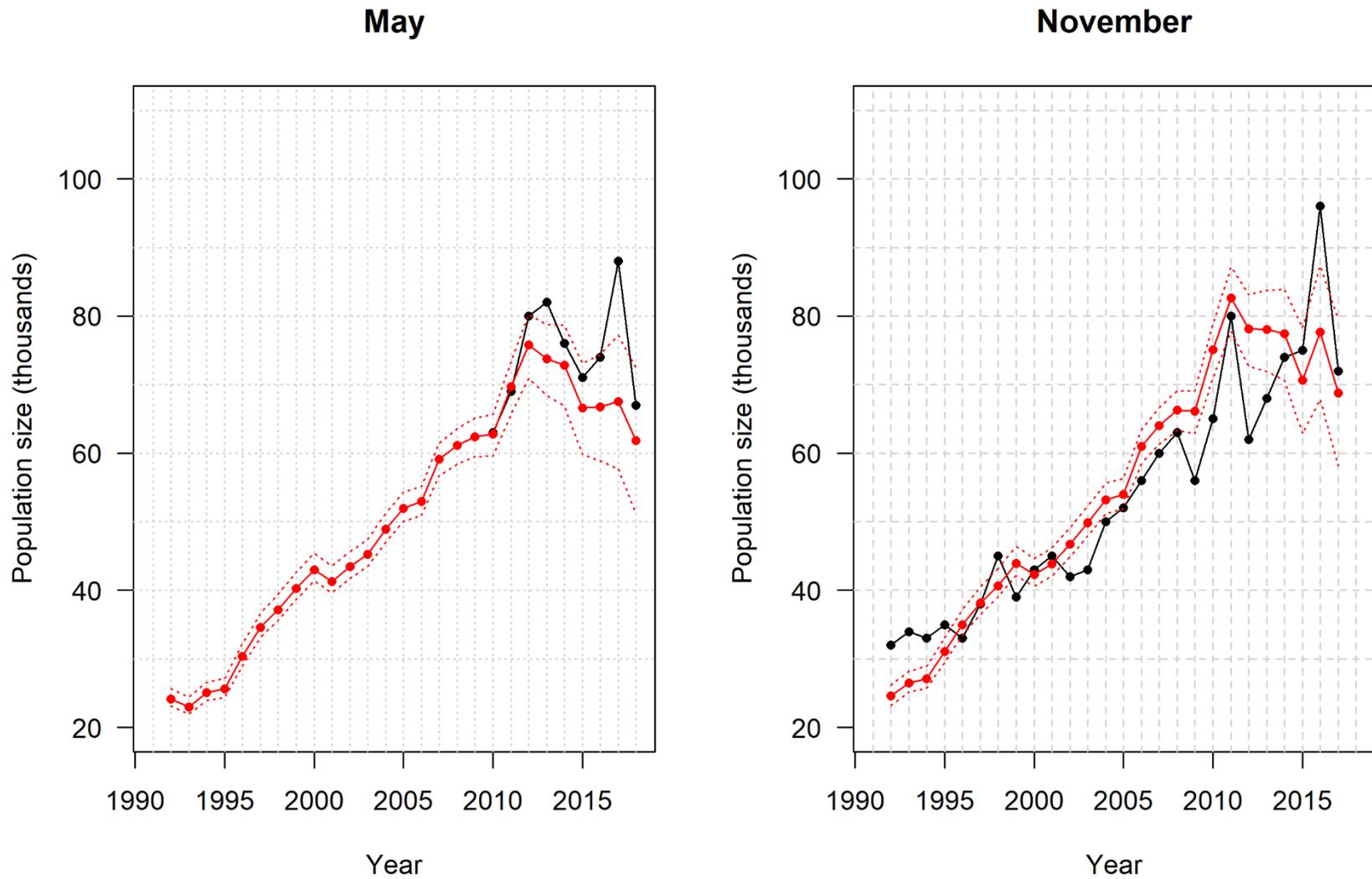
Figure 6. *IPM estimates of May and November population size of Svalbard Pink-footed Geese (red, with 95% credible intervals), compared with the observed counts (black).* May counts have only been conducted since 2010.

Figure 7. *IPM estimates of adult harvest rate and annual survival (red, with 95% credible intervals) for Svalbard Pink-footed Geese.* IPM estimates of annual survival are also compared to those from a mark-recapture analysis (black, with 95% confidence intervals).

Figure 8. *IPM estimates of reproductive success of Svalbard Pink-footed Geese, as measured by the ratio of young-of-the-year to older birds just prior to the hunting season (red, with 95% credible intervals).* These ratios are correlated with the number of days above freezing in May in Svalbard (TempDays; black), especially after 2005.

Figure 9. *Optimal harvest quotas (in thousands) for Svalbard Pink-footed Geese derived from a preliminary IPM.* The quota is based on the estimate of May population size (in thousands) and the number of days above freezing in May (TempDays).

Appendix A. Models of population dynamics for the Svalbard population of Pink-footed Geese

Set of nine discrete models

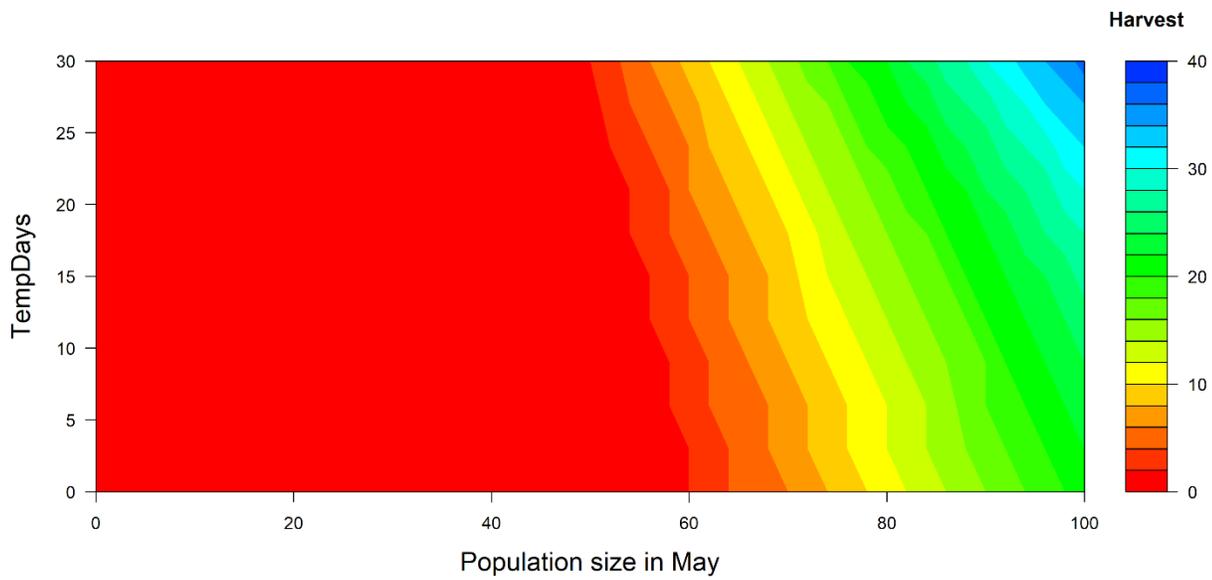Nine alternative models of population dynamics suggest how reproductive and survival rates of Pink-footed Geese vary over time (Johnson et al 2014). The nine models represent the combination of three alternative models of survival with three alternative models of reproduction.

The three alternative models describing the dynamics of survival from non-hunting sources of mortality, θ_t are: (1) Survival varies randomly from year to year; (2) Survival varies depending on weather conditions and population size at the start of the year (1 November); and (3) Survival varies depending only on weather conditions.

The first model assumes that $\hat{\theta}_t$ has a mean of 0.951 and a standard deviation of 0.019. We used the method of moments to parameterize a beta distribution as $\hat{\theta}_t \sim Beta(125.16, 6.46)$.

For the other two models of survival, we used the logit of $\hat{\theta}_t$, total population size N on 1 November, various weather variables X in the interval 1 November – 31 October, and used least-squares regression to fit the model. The model including temperature days (days above freezing in Svalbard in May; hereafter temperature days of TempDays) and population size had the lowest AIC of all models examined:

$$ln\left(\frac{\hat{\theta}_t}{\left(1 - \hat{\theta}_t\right)}\right) = 4.293 + 0.053X_t - 0.044N_t,$$

where X is the number of days above freezing in May in Svalbard and population size N is in thousands. The regression coefficients for both covariates were of the expected sign and different from zero ($P < 0.05$).

Due to uncertainty about contemporary rates of survival and the degree of density dependence (especially given the recent growth in population size), we also considered a third model that included temperature days but not population size. This density-independent model had the form:

$$ln\left(\frac{\hat{\theta}_t}{\left(1 - \hat{\theta}_t\right)}\right) = 2.738 + 0.049X_t,$$

Annual survival is then the product of survival from natural causes $\hat{\theta}$ and hunting:

$$\hat{S}_t = \hat{\theta}_t\left(1 - \hat{h}_t\right),$$

where $\hat{h}$ = estimated harvest rate (including retrieved and un-retrieved harvest) of birds that have survived at least one hunting season.

To model reproduction, we considered the counts of young during the autumn census, 1980-2011, as arising from binomial (or beta-binomial) trials of size N_t, and used a generalized linear model with a logit link to explain annual variability in the proportion of young (p_t). The best fitting models were based on a beta-binomial distribution of counts, which permits over-dispersion of the data relative to the binomial. The best model, as based on AIC, included population size and temperature days:

$$ln\left(\frac{\hat{p}_t}{\left(1 - \hat{p}_t\right)}\right) = -1.687 + 0.048X_t + 0.014A_t,$$

where X is May temperature days and A is the number of sub-adults and adults on 1 November. The regression coefficients for both covariates were of the expected sign, but only the coefficient for temperature days was highly significant ($P = 0.01$). The coefficient for adult population size was only marginally significant ($P = 0.06$), and this appears to be because of a lack of evidence for density dependence post-2000.

To allow for the possibility that reproduction is not (or no longer is) density-dependent, we considered a model with only temperature days:

$$ln\left(\frac{\hat{p}_t}{(1 - \hat{p}_t)}\right) = -1.989 + 0.027X_t.$$

Finally, we considered a second density-independent reproduction model in which the number of young in autumn was described as rising from a beta-binomial distribution with no covariates. The parameters of this distribution were estimated by fitting an intercept-only model ($\bar{p} = 0.14, \theta = a/\bar{p} = b/(1 - \bar{p}) = 43.77$).

Five of the nine life-cycle models incorporate density-dependent mechanisms that would maintain the population near a carrying capacity (i.e., in the absence of harvest) of $65,000 - 129,000$ depending on the specific model. The remaining four models are density independent and predict an exponentially growing population even with moderate levels of harvest. Consideration of these density-independent models is not intended to suggest that population size is truly unregulated, but that density dependence may only manifest itself at abundances exceeding those experienced thus far. All nine models fit the available data and at the time of their development it was not possible to say with any confidence which was more appropriate to describe the contemporary dynamics of Pink-footed Geese.

Bayesian posterior probabilities (weights) can be used to express the relative ability of each model to accurately predict the changes in population size that occurred. We calculated posterior probabilities for each of the nine models for each of the years 1992 - 2017, assuming equal prior probabilities in 1991 (i.e., $p_i = 1/9$). Posterior model probabilities were calculated as:

$$p_i(t + 1) = \frac{p_i(t)\mathcal{L}_i(t + 1)}{\sum_i p_i(t)\mathcal{L}_i(t + 1)},$$

where t denotes the year, and $\mathcal{L}_i$ denotes the likelihood of the observed population size, given model i. The likelihoods, in turn, were calculated from the normal density function:

$$\mathcal{L}_i(t + 1) = \frac{1}{\sigma\sqrt{2\pi}}e^{-\frac{1}{2}\left(\frac{log\left(N_*(t+1)\right) - log\left(N_i(t+1)\right)}{\sigma}\right)^2},$$

where N_* is the observed population size, N_i is a model-specific prediction of population size, and σ is a prediction error common to all models. This error was estimated by averaging the mean squared errors from all nine models:

$$\sigma = \sqrt{\sum_i^m \frac{\sum_t \left(log\left(N_*(t + 1)\right) - log\left(N_i(t + 1)\right)\right)^2}{mn}} = 0.11116,$$

where $m = 9$ models and sample size for yearly comparisons at the time models were formulated was $n = 12$. This error reflects so-called process error, which is the variation in population size not explained by the models.

We also assessed the ability of the model set to predict population sizes by comparing the cumulative distribution of predictions with that of observations. The two distributions were compared using a two-tailed Kolmogorov-Smirnov test (Marsaglia et al. 2013).

Integrated population model

An expanding set of monitoring data now provides the ability to develop an IPM. An IPM represents a single, unified analysis of population count data and demographic data (Schaub and Abadi 2011). Unlike the set of nine discrete models in which parameters are fixed and model weights are updated annually, all parameters of the IPM are updated annually based on available monitoring data.

We developed a preliminary IPM for the Svalbard population of Pink-footed Geese (Figure A1) by exploiting the following sources of monitoring data:

n_t^M = population count in May

s_t = May to May survival from all causes based on capture-mark-recapture data (ultimately these estimates will be generated within the IPM, but here are considered as input data)

w_t = number of wings submitted by Danish hunters prior to the November count

p_t = proportion of young in observed November population

Hn_t = total harvest September – January - Norway

Hd_t = total harvest September – January - Denmark

n_t^N = population count in November

Latent quantities that can be estimated include:

N_{t+1}^M, N_{t+1}^N = May and November population sizes, respectively

σ_M^2, σ_N^2 = process error of May and November population sizes, respectively

θ_t = spring to spring survival from natural mortality factors

hn_t = harvest rate of birds having survived at least one hunting season (i.e., all birds except young of the year) - Norway

hd_t = harvest rate of birds having survived at least one hunting season (i.e., all birds except young of the year – Denmark

$h_t = hn_t + hd_t$ = total harvest rate

α_t = portion of Denmark harvest occurring during September – October

h_t^O = harvest rate of adults during September – October in Denmark

r_t = ratio of young to adults at start of hunting season in September

We made the following assumptions concerning population dynamics of Pink-footed Geese:

- Young are twice as vulnerable to harvest as older birds;

- Annual harvest mortality is additive to natural mortality;

- All harvest in Norway occurs prior to the November count;

- Natural mortality is constant, distributed evenly throughout the year, and is not age-specific; and

- Reproductive success varies annually.

Population dynamics are then described by a series of equations:

May population size:

$$N_{t+1}^M = N_t^M \theta_t \left[(1-h_t) + r_t (1-2h_t) \right]$$
$$= N_t^M \theta_t \left[(1-(hn_t + hd_t)) + r_t (1-2(hn_t + hd_t)) \right]$$

Annual survival:

$$s_t = \theta_t (1-h_t)$$
$$= \theta_t (1-(hn_t + hd_t))$$

Proportion of young in November population:

$$p_t = \frac{N_t^M \theta_t^{6/12} r_t \left(1 - 2(hn_t + h_t^O)\right)}{N_t^M \theta_t^{6/12} \left(1 - (hn_t + h_t^O)\right) + N_t^M \theta_t^{6/12} r_t \left(1 - 2(hn_t + h_t^O)\right)}$$
$$= \frac{r_t \left(1 - 2(hn_t + h_t^O)\right)}{\left(1 - (hn_t + h_t^O)\right) + r_t \left(1 - 2(hn_t + h_t^O)\right)}$$

Total season harvest:

$$H_t = h_t N_t^M \theta_t^{4/12} + 2h_t N_t^M \theta_t^{4/12} r_t$$
$$= h_t N_t^M \theta_t^{4/12} (1 + 2r_t)$$
$$= (hn_t + hd_t) N_t^M \theta_t^{4/12} (1 + 2r_t)$$

November population size:

$$N_t^N = N_t^M \theta_t^{6/12} \left(1 - \left(hn_t + h_t^O\right)\right) + N_t^M \theta_t^{4/12} r_t \left(1 - 2\left(hn_t + h_t^O\right)\right) \theta_t^{2/12}$$

$$= N_t^M \theta_t^{6/12} \left(1 - \left(hn_t + h_t^O\right)\right) + N_t^M \theta_t^{6/12} r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)$$

$$= N_t^M \theta_t^{6/12} \left[\left(1 - \left(hn_t + h_t^O\right)\right) + r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)\right]$$

Adult harvest rate in Denmark in September-October:

$$h_t^O = \frac{hd_t N_t^M {}_t\theta_t^{4/12} \left(1 + 2r_t\right)\alpha_t}{N_t^M {}_t\theta_t^{4/12} \left(1 + 2r_t\right)}$$

$$= hd_t \alpha_t$$

Portion of Denmark harvest occurring September-October:

$$\alpha_t = \frac{h_t^0}{hd_t}$$

Ratio of young to adults at the start of hunting season:

$$p_t = \frac{r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)}{\left(1 - \left(hn_t + h_t^O\right)\right) + r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)}$$

so

$$p_t \left[\left(1 - \left(hn_t + h_t^O\right)\right) + r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)\right] = r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)$$

and

$$p_t \left(1 - \left(hn_t + h_t^O\right)\right) + p_t r_t \left(1 - 2\left(hn_t + h_t^O\right)\right) = r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)$$

and

$$p_t \left(1 - \left(hn_t + h_t^O\right)\right) = r_t \left(1 - 2\left(hn_t + h_t^O\right)\right) - p_t r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)$$

and

$$p_t \left(1 - \left(hn_t + h_t^O\right)\right) = r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)\left(1 - p_t\right)$$

and

$$\frac{p_t \left(1 - \left(hn_t + h_t^O\right)\right)}{\left(1 - p_t\right)} = r_t \left(1 - 2\left(hn_t + h_t^O\right)\right)$$

so

$$r_t = \frac{p_t \left(1 - \left(hn_t + h_t^O\right)\right)}{\left(1 - p_t\right) + \left(1 - 2\left(hn_t + h_t^O\right)\right)}$$
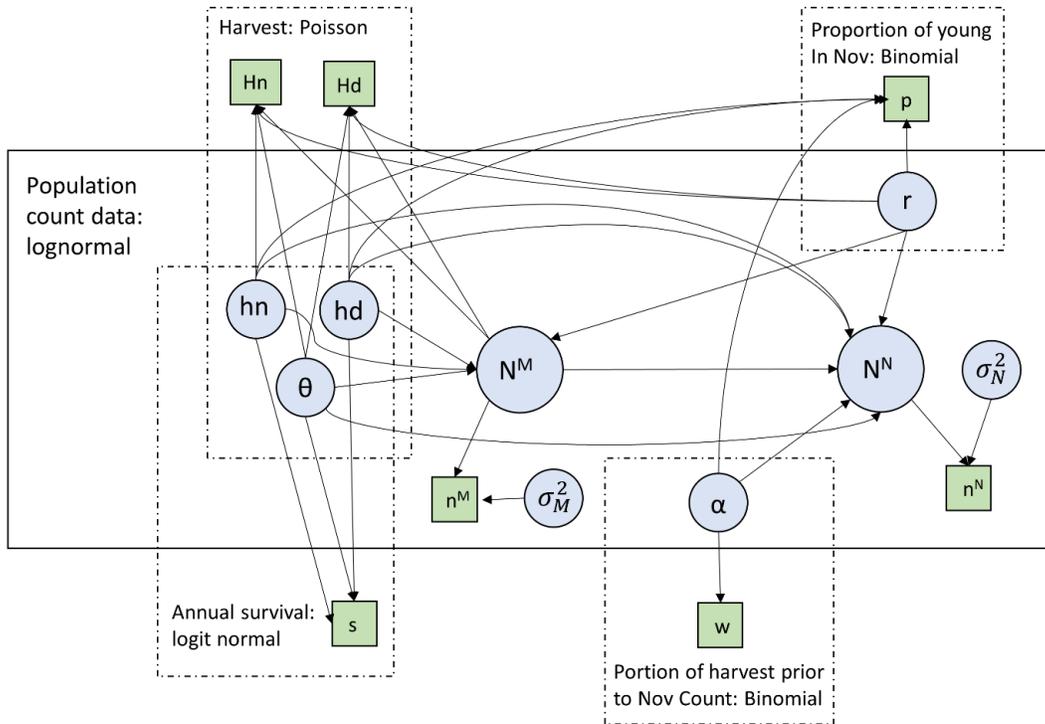
Figure A1. *Graphical representation of the IPM for Svalbard Pink-footed Geese in which blue circles are model parameters and green boxes are data*. Arrows indicate the flow of information. Model parameters are as described above.

We fit this IPM using Markov Chain Monte Carlo simulation implemented in JAGS (http://mcmc-jags.sourceforge.net/), which was accessed using library "runjags" in version 3.4.4 of the computing language R (R Core Team 2018). We used vague or uninformative priors, three chains, a burn-in of 100,000 – 200,000 samples, and 20,000 samples per chain. Convergence was checked using the psrf statistic of JAGS; values of psrf ≤ 1.2 were assumed to indicate convergence (Kéry and Schaub 2011).

We also fit an IPM in which reproductive success (defined as the ratio of young to older birds at the start of the hunting season) is a function of the number of days above freezing in May in Svalbard (TempDays). Although we achieved parameter convergence, some estimates did not appear reasonable when including monitoring data from 2017. A preliminary model for 1992 – 2016 that includes the effect of spring temperatures was used for purposes of this report.

Optimal harvest strategies for the set of nine discrete models and the IPM were calculated as passively adaptive strategies using stochastic dynamic programming. We used the open-source software MDPSolve© (https://sites.google.com/site/mdpsolve/) to compute optimal solutions. We also used MDPSolve to simulate the optimal policies to estimate their expected performance. For the purposes of optimization, we modeled the number of days above freezing in May in Svalbard as a beta-binomial distribution with probability = 0.278 and over-dispersion parameter = 6.594.

The optimal harvest strategy for the nine alternative models is a large table of four dimensions (number of young and adults, days above freezing in Svalbard, and corresponding harvest quota) and thus is difficult to display graphically and to interpret. Therefore, we depict a portion of the strategy with TempDays days fixed near their average (8), as well as at those associated with late (0 days) and early (16 days) springs. The optimal harvest strategy for the IPM is simpler, in that it only requires an estimate of May population size derived from the model, along with TempDays for the IPM including the effect of spring temperatures.

Appendix B. Monitoring information for the Svalbard population of Pink-footed Geese

N and Prop(Y) represent total population size (rounded to the nearest thousand) and the proportion of young, respectively, TempDays is the number of days above freezing in May in Svalbard, and HarvDen and HarvNor are harvests (rounded to the nearest hundred) from Denmark and Norway, respectively. All values pertain to calendar year (except those cases in recent years when the November count has been replaced by the count in the following spring; gray shading).

Year	N	PropYng	TempDays	HarvDen	HarvNor
1991	33,000	0.222	9	3,000	NA
1992	32,000	0.062	4	2,500	200
1993	34,000	0.181	7	2,300	900
1994	33,000	0.124	7	2,600	400
1995	35,000	0.236	9	2,800	800
1996	33,000	0.184	1	2,000	900
1997	38,000	0.144	4	2,500	800
1998	45,000	0.122	0	1,400	600
1999	39,000	0.123	13	2,000	900
2000	43,000	0.049	6	2,600	1,400
2001	45,000	0.109	2	2,400	500
2002	42,000	0.106	8	2,600	700
2003	43,000	0.127	8	2,300	700
2004	50,000	0.112	11	2,100	1,100
2005	52,000	0.073	8	1,700	1,300
2006	57,000	0.173	18	3,600	1,700
2007	60,000	0.127	7	4,600	2,200
2008	63,000	0.130	5	5,400	2,600
2009	63,000	0.109	15	4,800	2,600
2010	69,000	0.220	20	8,800	3,100
2011	80,000	0.195	10	8,000	3,400
2012	82,000	0.099	5	8,600	2,200
2013	76,000	0.118	8	9,300	1,800
2014	71,000	0.103	8	13,200	1,600

2015	74,000	0.138	9	8,800	2,500
2016	88,000	0.196	20	13,300	2,800
2017	72,000	0.076	4	9,700	1,700