



Adaptive Harvest Management for the Svalbard Population of Pink-Footed Geese

Cooperator Report

Progress Summary Prepared for the
AEWA Svalbard Pink-Footed Goose International Working Group



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Executive Summary

This document describes progress to date on the development of a harvest-management strategy for maintaining pink-footed goose abundance near their target level by providing for sustainable harvests in Norway and Denmark. Many goose populations in western Europe have increased dramatically in recent decades. The Svalbard population of pink-footed geese (*Anser brachyrhynchus*) is a good example, increasing from about 10 thousand individuals in the early 1960's to roughly 80 thousand today. Although these geese are a highly valued resource, the growing numbers of geese are causing agricultural conflicts in wintering and staging areas. 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.

We compiled relevant demographic and weather data and specified an annual-cycle model for pink-footed geese that reconciles the different dates of monitoring activities and the timing of harvest-management decisions. We then developed dynamic models for survival and reproductive processes and parameterized them using available data. By combining varying hypotheses about survival and reproduction, we developed a suite of nine models that represent a wide range of possibilities concerning the extent to which demographic rates are density dependent or independent, and the extent to which spring temperatures are important. These nine models varied significantly in their predictions of the harvest required to stabilize current population size, ranging from a low of about 500 to a high of about 17 thousand. For comparison, the harvest in Norway and Denmark was about 11 thousand in 2011 and the population increased from 70 to 80 thousand.

We relied on the passive form of adaptive management in formulating a harvest strategy. In passive adaptive management, alternative population models and their associated weights of evidence are explicitly considered in the development of an optimal harvest strategy. Unlike active adaptive management, however, there is no explicit consideration of how harvest management actions could reduce uncertainty as to the most appropriate model of population dynamics. In optimizing a harvest strategy, we assumed equal probabilities for all nine models and assumed relatively course control over harvest. We used a management objective that seeks to maximize sustainable harvest, but avoids harvest decisions that are expected to result in a subsequent population size different than the population goal of 60 thousand. Optimal harvest strategies were calculated using stochastic dynamic programming, and Monte Carlo simulations were used to investigate expected strategy performance.

The optimal passive adaptive-management strategy is expected to maintain mean population size near 60 thousand, regardless of the most appropriate model. However, mean harvest rates and harvests varied substantially depending on the most appropriate model of population dynamics. With an average number of days above freezing in May in Svalbard, optimal harvest rates (i.e., the proportion of the population to be harvested in autumn) increase rapidly once there are more than about 50 thousand birds in the population. Generally, optimal harvests were on the order of 10 – 20 thousand for population sizes > 60 thousand, and 0 – 5 thousand for population sizes < 60 thousand. For the observations of young of 15.4 thousand and adults of 54.6 thousand in autumn 2010, and 10 days above freezing in May 2011 (a relatively warm spring compared to the average

of about 7), the optimal harvest rate in autumn of 2011 would have been 0.16, or a harvest of about 14 thousand. Based on the optimal strategy, hunting-season closures would be required as the number of adults in the autumn population falls below about 52 thousand, regardless of the number of young in the population. As the number of adults and young decrease, the number of warm days in May required to keep the hunting season open increases. We also investigated the ability of the optimal strategy to stabilize the population at around 60 thousand birds, assuming varying values of the maximum harvest rate that could be implemented. Harvest strategies that contained a maximum harvest rate of 0.16 (equivalent to a harvest of about 17 thousand) were effective at stabilizing the population at 60 thousand within 4-5 years, regardless of climate scenario. Harvest strategies with a maximum harvest rate of 0.12 (harvest \approx 13 thousand) were also able to stabilize the population near 60 thousand, although it took more time. Harvest strategies with a maximum harvest rate of 0.08 (harvest \approx 8 thousand) were unsuccessful at stabilizing the population at 60 thousand.

Continued monitoring of the pink-footed goose population on an annual basis is critical to an informed harvest management strategy. At a minimum, the ground census in November should be continued to determine population size and proportion of young. Continued estimates of harvest from Norway and Denmark are also necessary to help judge the credibility of the alternative population models. However, an adaptive management process that relies on periodic updating of model weights will depend on acquiring either estimates of the realized harvest rate of adults or the age composition of the harvest. We also recommend that a census conducted during spring migration be operationalized, and that estimates of survival based on mark-recapture data be updated. Finally, the International Working Group has expressed a desire to adopt a three-year cycle of decision making related to the regulation of pink-footed goose harvests. The idea is that once a target harvest level is adopted, it would remain in place for three years, after which time population status would be assessed and a potentially new management action chosen. We have developed a preliminary framework to implement a three-year cycle using stochastic dynamic programming, and we hope to have it fully operational later this year. We note, however, that application of this 3-year framework will still require annual resource monitoring and assessments to facilitate learning, and to allow managers the opportunity to respond to any unforeseen change in resource conditions.

Introduction

Many goose populations in western Europe have increased dramatically in recent decades. The Svalbard population of pink-footed geese (*Anser brachyrhynchus*) is a good example, increasing from about 10 thousand individuals in the early 1960's to roughly 80 thousand today. Although these geese are a highly valued resource, the growing numbers of geese are causing agricultural conflicts in wintering and staging areas.

Conservationists are also concerned that large numbers of pink-footed geese may have deleterious effects on fragile tundra habitats used during the breeding season.



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. The Svalbard population of the pink-footed goose has been selected as the first test case for such an international species management plan to be developed. The goal of this international species management plan is to maintain the favorable conservation status of the Svalbard Pink-footed Goose population at a flyway level while taking into account economic and recreational interests. To achieve this goal the following set of objectives has been established in consultation with national authorities and key stakeholders:

- Maintain a sustainable and stable pink-footed goose population and its range.
- Keep agricultural conflicts to an acceptable level.
- Avoid increase in tundra vegetation degradation in the breeding range.
- Allow for recreational use that does not jeopardize the population.

To attain these objectives the plan calls for the implementation of an adaptive-management framework for the flyway population that in part will:

- 1) maintain a population size of around 60,000, within a range to prevent the population from either collapsing or irrupting; and
- 2) optimize hunting regulations and practices to regulate the population size if needed and in range states where hunting is permitted.

This document describes progress to date on the development of a harvest-management strategy for maintaining pink-footed goose abundance near their target level by providing for sustainable harvests in Norway and Denmark. This project has been funded for a total of four years, with the following schedule of deliverables:

- December 2012 – Progress summary based on action items identified at the August 2012 workshop in Svalbard

- April 2013 – Stakeholders workshop and at least two manuscripts describing population models and optimization approaches ready for submission to peer-reviewed journals
- August 2013 – Annual report and working group meeting
- August 2014 – Stakeholders workshop (if needed) and annual report
- August 2015 – Stakeholders workshop (if needed) and annual report
- December 2015 – Final project report; additional draft manuscripts for publication

The primary purpose of this progress summary is to facilitate review of population models and optimal harvest strategies by the AEWA Svalbard Pink-Footed Goose International Working Group. We describe the annual cycle of pink-footed goose population dynamics as it relates to the timing of harvest management decisions, available data and the process of developing predictive models of survival and reproductive rates, the combination of those models into a complete annual cycle of population dynamics, and the implications of those models for optimal harvest management. The report includes the following sections:

- I. Compilation of relevant demographic and weather data
- II. The annual cycle of pink-footed geese as it relates to harvest management
- III. Development of models to predict survival and reproductive rates
- IV. Annual-cycle models
- V. Implications for harvest management
- VI. Future needs

I. Data

Abundance. – Population estimates of pink-footed geese were available from ground censuses and from capture-recapture methods (Ganter and Madsen 2001). Ground counts have been made around November 1 each year since 1965 in Denmark, the Netherlands, and Belgium. Geese were counted simultaneously in the three countries to avoid double-counting. Capture-recapture estimates of fall population size were available from 1991-2003, based on neck-banding during spring migration and re-sighting efforts during the migration and wintering periods. Estimates from the two methods were highly correlated ($r = 0.68$), although the capture-recapture estimates were about 6% higher on the average.

Survival. – Estimates of survival based on neck-banding were available from the period 1990-2002 (Kéry et al. 2006). We used survival estimates provided by M. Kéry (Swiss Ornithological Institute, personal communication) for the first interval after marking (10 months) because of concern over potential band loss in subsequent periods. We projected annual rates by raising 10-month survival rates to a power of 12/10. Survival rate estimates have an anniversary date of approximately February 1, meaning they apply to the period February 1 in year t to January 31 in year $t+1$. Thus, it was necessary to partition survival into that during November – January and that during February – October in order to align anniversary dates with those of the population census. In doing so we assumed that natural mortality was evenly distributed throughout the year. For the

period in which survival rate estimates were available, we assumed that harvest mortality was additive to natural mortality, and that harvest mortality represented one-half of total mortality. We believed these assumptions were reasonable given studies of other Arctic geese (Francis et al. 1992, Gauthier et al. 2001, Menu et al. 2002). We note, however, that there has been a concerted effort to increase harvest pressure on pink-footed geese in Norway and Denmark in recent years, and we acknowledge the possibility that current harvest rates are substantially higher than those during 1990-2002.

Harvests. – Estimates of harvest are available from Denmark during 1990-2010, and from Norway during 2001-2010. Estimates from Denmark were derived from a combination of hunter-collected goose wings and survey questionnaires. Denmark also has recently begun to allow hunters to report their bag of pink-footed geese on line, but we did not consider those estimates here. Estimates from Norway were based on an on-line reporting system.

Reproduction. – The proportion of juveniles in the population and average brood size have been assessed since 1980 on the staging grounds in Denmark and the Netherlands during autumn when it is possible to distinguish juveniles from adults by plumage characteristics (Ganter and Madsen 2001). For the purposes of modelling population demography we used the proportion of juveniles as an indicator of reproductive success during the preceding breeding season.

Weather Covariates. – We examined the ability of weather-related variables to explain annual variation in survival and reproductive success. We believed that snow cover during late May in Svalbard would have a substantive effect because of its potential impact on breeding effort. However, the proportion of nesting areas covered by snow, as well as a covariate indicating the onset of snow melt, were available from satellite-based imagery (Madsen et al. 2007) only for the period 2000-2011. In order to use the entire record of survival and reproduction we relied on covariates that we believed to be reasonable proxies for snow conditions on the breeding grounds. These included the number of days in May in which mean temperature was $>0^{\circ}\text{C}$ (TempDays), and the cumulative sum of temperatures for days in which mean temperature $>0^{\circ}\text{C}$ (TempSum) (both of which were derived by averaging data from weather stations in Longyearbyen and Ny Ålesund). Both variables were highly correlated with snow conditions in Svalbard during 2000-2011 (TempDays: $r = -0.80$; TempSum: $r = -0.74$). We also investigated other weather covariates examined by Kéry et al. (2006), but those covariates tended to be moderately to highly correlated with TempDays and TempSum, and generally did not improve the predictive ability of the survival and reproductive models.

Demographic and weather data used in this study are presented in Appendix 1. A digital copy may be obtained from Jesper Madsen at Aarhus University (jm@dmu.dk), and it will also be made available on line at <http://kortnaeb.au.dk/>. For weather variables examined by Kéry et al. (2006) see the supplementary material provided with their article.

II. The Annual Cycle of Pink-Footed Geese

For assessment purposes, we considered November 1 as the anniversary date of the annual cycle for pink-footed geese (Fig. 1), corresponding to the annual census of population size. Using estimates of the proportion of young observed during the survey, total population size can then be decomposed into the number of young-of-the-year (aged $\frac{1}{2}$ year), and the number sub-adults (aged $1\frac{1}{2}$ years) plus adults (aged $\geq 2\frac{1}{2}$ years) (Fig. 2). Pink-footed geese may not be sexually mature until age three (Boyd 1956), but plumage characteristics in autumn do not permit us to distinguish sub-adults (i.e., those that will be age two in the coming breeding season) from adults (i.e., those that will be age three in the coming breeding season). Moreover, age-specific estimates of survival rate were not available, so the age-structure of our population models was necessarily limited. It is well known that significant age-structure in a population can have important implications for harvest management (Hauser et al. 2006), but available data were insufficient to characterize the degree of age-specificity that may be appropriate for pink-footed geese. This issue will be discussed in more detail in the section entitled Future Needs.

Before constructing models based on annual estimates of survival and reproductive rates, we were interested in whether available estimates suggested changes in population size that were comparable to those derived from the population census. Throughout this section and in the remainder of the report, we emphasize the need to ensure that the dates of various sources of monitoring information are both internally consistent, as well as consistent with the timing of management decision making (hereafter referred to as anniversary dates).

Let:

t = year

Y = number of birds aged $\frac{1}{2}$ year on November 1 (i.e., young fledged in the previous breeding season and that survived the first hunting season)

SA = number of birds aged $1\frac{1}{2}$ years on November 1

A = number of birds aged $\geq 2\frac{1}{2}$ years on November 1

$N = A + SA + Y$ = population size on November 1

$\hat{\theta}$ = estimated annual survival from natural (non-hunting) causes

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

$\hat{S} = \hat{\theta}(1 - \hat{h})$ = annual survival rate

\hat{p} = estimated proportion of young (Y) in the November 1 population

We then assumed:

- All birds that survived their first hunting season had the same annual survival rates.
- Hunting mortality was additive to natural mortality and a constant one-half of total annual mortality:

$$\hat{h}_t = (1 - \hat{S}_t)/2$$

- $\hat{\theta}_t = \hat{S}_t / (1 - (1 - \hat{S}_t) / 2)$
- Natural mortality was distributed evenly throughout the year (this was required because the anniversary date of survival estimates did not correspond with that of the population census):
 - $\hat{\theta}_t^{0.25}$ = survival from natural causes during Nov 1 – Jan 31
 - $\hat{\theta}_{t+1}^{0.75}$ = survival from natural causes during Feb 1 – Oct 31

The number of geese in each age class in year $t+1$ was then calculated from population size in year t as:

$$\begin{aligned}\hat{A}_{t+1} &= A_t \hat{\theta}_t^{0.25} \hat{\theta}_{t+1}^{0.75} (1 - \hat{h}_{t+1}) + SA_t \hat{\theta}_t^{0.25} \hat{\theta}_{t+1}^{0.75} (1 - \hat{h}_{t+1}) \\ &= (A_t + SA_t) \hat{\theta}_t^{0.25} \hat{\theta}_{t+1}^{0.75} (1 - \hat{h}_{t+1}) \\ &= N_t (1 - \hat{p}_t) \hat{\theta}_t^{0.25} \hat{\theta}_{t+1}^{0.75} (1 - \hat{h}_{t+1})\end{aligned}$$

$$\begin{aligned}\widehat{SA}_{t+1} &= Y_t \hat{\theta}_t^{0.25} \hat{\theta}_{t+1}^{0.75} (1 - \hat{h}_{t+1}) \\ &= N_t \hat{p}_t \hat{\theta}_t^{0.25} \hat{\theta}_{t+1}^{0.75} (1 - \hat{h}_{t+1})\end{aligned}$$

$$\begin{aligned}\hat{Y}_{t+1} &= (A_{t+1} + SA_{t+1}) (\hat{p}_{t+1} / (1 - \hat{p}_{t+1})) \\ &= (A_t + SA_t + Y_t) \hat{\theta}_t^{0.25} \hat{\theta}_{t+1}^{0.75} (1 - \hat{h}_{t+1}) (\hat{p}_{t+1} / (1 - \hat{p}_{t+1})) \\ &= N_t \hat{\theta}_t^{0.25} \hat{\theta}_{t+1}^{0.75} (1 - \hat{h}_{t+1}) (\hat{p}_{t+1} / (1 - \hat{p}_{t+1}))\end{aligned}$$

We then compared the observed N_{t+1} with the predicted $\widehat{N}_{t+1} = \hat{A}_{t+1} + \widehat{SA}_{t+1} + \hat{Y}_{t+1}$ to check for evidence of systematic bias in estimates of survival and reproduction (Fig. 3). We estimated the slope of the line through the points $(N_{t+1}, \widehat{N}_{t+1})$ using least-squares and assuming an intercept of zero. The slope was not significantly different from one ($\beta_1 = 1.00, P > 0.9$), suggesting that survival and reproductive estimates were unbiased, which is in contrast to the strong positive bias in estimates of demographic rates for some North American waterfowl

(<http://www.fws.gov/migratorybirds/NewReportsPublications/AHM/Year2012/AHMReport2012.pdf>).

For the purpose of calculating a state-dependent harvest strategy (i.e., one in which the optimal harvest depends on extant population size and environmental conditions), we defined two population states: (1) young (Y); and (2) sub-adults + adults (hereafter referred to as just “adults”, A). The one-year transition for the adult state is:

$$A_{t+1} = (A_t + Y_t) \theta_t (1 - h_t)$$

We remind the reader that the anniversary date for the model is November 1, after the bulk of the harvest has occurred (although this is less true in more recent years - a point which will be discussed in the section entitled Future Needs). Thus, the survival rate θ_t applies to November 1 of year t to October 31 of year $t+1$, and the harvest rate h_t applies to the harvest in the autumn of the *next* calendar year after population size is measured.

The transition equation for the young state is:

$$Y_{t+1} = (A_t + Y_t)\theta_t(1 - h_t)R_t$$

where the first three terms provide the number of geese surviving from November 1 of year t to year $t+1$, and where the production of young is determined using the ratio of young to adults on November 1: $R_t = p_{t+1}/(1 - p_{t+1})$.

Given a harvest rate h for birds having survived at least one hunting season, the harvest of adults is:

$$H_t^A = (A_t + Y_t)\theta_t h_t$$

and the harvest of young is:

$$H_t^Y = \frac{(A_t + Y_t)\theta_t(1 - h_t)R_t}{(1 - dh_t)} dh_t$$

where the d is the vulnerability of young to harvest relative to that of adults. The quotient in this formula represents the pre-harvest population of young (assuming that all mortality during the hunting season is hunting related). Total harvest is then simply:

$$H_t = H_t^A + H_t^Y$$

To determine the differential vulnerability of young, we used the relationship between the percent of young in the harvest (bag) and the percent of young in the population as reported by Madsen (2010):

$$(\%Y)_{bag} = 22.06 + 0.89(\%Y)_{pop}$$

Notice, however, that this equation does not have an intercept of zero. In reality the intercept must be zero because there can be no young in the harvest if none exists in the population. Setting the intercept to zero and recalculating the slope provides an estimate of differential vulnerability of $d = 1.99 \approx 2.0$. We recognize that the differential harvest vulnerability of young likely varies over time, space, and with population structure, but we lacked data to model that process.

III. Models of Survival and Reproduction

Here we describe the development of dynamic models for survival and reproductive processes. We emphasize that our goal was not solely to identify the models that best described extant data. Rather, it was to develop a suite of models that fit the data but that also make different predictions of demographic rates outside the realm of experience. Inference based on extant data is constrained both by the years in which estimates of survival and reproduction are available, and by

the range of covariates during those years. For the purposes of developing harvest-management strategies, the behavior of models outside the range of experience is often more important than that for which data are available (Walters 1986, Runge and Johnson 2002). Thus, our goal was to develop models that represent a wide range of possibilities concerning the extent to which demographic rates are density dependent or independent, and the extent to which weather is important in regulating population size of pink-footed geese and their response to harvest.

Survival. – We considered three alternative models to describe the dynamics of survival from non-hunting sources of mortality, θ_t : (1) survival varies randomly from year to year; (2) survival varies depending on weather conditions; and (3) survival varies depending on weather conditions and population size at the start of the year (November 1). The first two models are density-independent, while the third is density-dependent.

We calculated θ_t using the annual survival estimates \hat{S}_t provided by M. Kéry for the period 1990-2002, and assumed hunting mortality was additive to natural mortality and was a constant 50% of total annual mortality:

$$\begin{aligned}\hat{h}_t &= (1 - \hat{S}_t)/2 \\ \hat{\theta}_t &= \hat{S}_t / (1 - \hat{h}_t) \\ &= \hat{S}_t / (1 - (1 - \hat{S}_t)/2)\end{aligned}$$

The estimates of $\hat{\theta}_t$ had a mean of 0.951 and a standard deviation of 0.019.

To parameterize a model in which survival varies randomly (model (1) above), we used the method of moments and the mean and standard deviation above to parameterize a beta distribution: $\hat{\theta}_t \sim \text{Beta}(125.16, 6.46)$. Next, we discretized this distribution by first specifying a range of discrete survival rates. The probability mass associated with each discrete survival rate was calculated as the probability density function for each survival rate, divided by the sum of the densities of all discrete rates (i.e., normalizing so the total probability mass for all discrete rates was one). We used discrete values of survival of $\theta_t \in \{0.90, 0.92, 0.94, 0.96, 0.98\}$ with probabilities $P(\theta_t) \in \{0.0159, 0.0916, 0.3201, 0.4756, 0.0967\}$, respectively.

For the other two models of survival, we used the logit of $\hat{\theta}_t$, total population size N on November 1, various weather variables X in the interval November 1 – October 31, and used least-squares regression to fit the model:

$$\ln\left(\frac{\hat{\theta}_t}{(1 - \hat{\theta}_t)}\right) = \beta_0 + \beta_1 X_t + \beta_2 N_t$$

Predictions of survival from non-hunting sources of mortality thus were:

$$\hat{\theta}_t = 1 / \left(1 + e^{-(\hat{\beta}_0 + \hat{\beta}_1 X_t + \hat{\beta}_2 N_t)}\right)$$

Of those models that included population size, but varied depending on the specific weather variable included (model (3) above), only two had delta AIC values < 2.0: one with temperature days and one with temperature sum (as described in the section entitled Data). The delta AIC between these models was only 0.1, suggesting they were virtually indistinguishable based on the data. The model including temperature days and population size had the lowest AIC of all models examined:

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

where X is temperature days and population size N is in thousands. The regression coefficients for both covariates were of the expected sign and different from zero ($P < 0.05$). This model suggests rather dramatic reductions in survival when population size exceeds 60 thousand and the number of days above freezing in May is very low (Fig. 4). We emphasize, however, that this conclusion involves extrapolating beyond the limits of the data and thus lacks empirical evidence.

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 (model (2) above) that included temperature days but not population size. This density-independent model had the form:

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

Finally, we briefly considered development of a model in which reductions in natural mortality compensate for increases in harvest mortality. We believed a compensatory model might be appropriate because of initial concern that contemporary harvest estimates and population trajectory seemed inconsistent with the process of additive hunting mortality. Of course, an alternative explanation to resolve the apparent inconsistency is that harvest estimates are biased high, as is the case with waterbird harvest estimates in the U.S. (Padding and Royle 2012). We eventually concluded, however, that there was no substantive conflict between estimates of harvest and an additive mortality hypothesis. Assuming that harvest mortality represented one-half of total mortality during the period in which survival rates are available (1990-2002), the harvest should have been on the order of 2-3 thousand, which is in agreement with estimates of harvest during that period (at least in Denmark; harvest estimates are not available from Norway during most of this period, but they averaged only about 500 birds per year during 2001-2004, prior to when they began increasing substantially) (Fig. 5). Contemporary estimates of harvest are about 11k for Denmark and Norway combined, which would represent a harvest rate on adults of approximately 0.1. Even assuming additive harvest mortality, estimates of demographic rates suggest the pink-footed goose population is capable of increasing with this harvest rate as long as springs are warm in Svalbard (which they were for most of the last decade).

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:

$$\ln\left(\frac{\hat{p}_t}{(1 - \hat{p}_t)}\right) = \beta_o + \beta_1 X_t + \beta_2 A_t$$

where X is a weather variable and where A is the number of adults (i.e., sub-adults plus adults) on November 1 of the previous calendar year. Predictions of the proportion of young were thus:

$$\hat{p}_t = 1 / \left(1 + e^{-(\hat{\beta}_o + \hat{\beta}_1 X_t + \hat{\beta}_2 A_t)}\right)$$

We recognize that only birds aged three years or older in spring are potential breeders, but census data did not permit us to partition sub-adults and adults. We used the number of sub-adults plus adults rather than total population size as the measure of density because we believed it would better reflect potential competition for nesting sites in Svalbard.

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:

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

where X is May temperature days and A is the number of sub-adults and adults on November 1 (Fig. 6). 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 (Fig. 7). This also corresponds to a period of above-average temperature days in Svalbard (Fig. 8), suggesting that reproduction may be “released” from density-dependent mechanisms during exceptionally warm years on the breeding grounds. One plausible explanation is that there is a threshold in the number of temperature days, beyond which nesting sites are not limited due to snow cover. Other explanations are possible. 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 ($\bar{p} = 0.14$, $\theta = a/\bar{p} = b/(1 - \bar{p}) = 43.77$). We then discretized this distribution in the same manner as that

described for survival rates. We used discrete values of $p_t \in \{0.05, 0.10, 0.15, 0.20, 0.25\}$ with probabilities $P(p_t) \in \{0.0691, 0.3359, 0.3542, 0.1821, 0.0587\}$, respectively.

Dynamics of Temperature Days. – The number of days above freezing in May, 1969-2011, in Svalbard averaged 7.3 (sd = 4.4). There was no evidence of autocorrelation for lags up to 20 years (Fig. 9), so we predicted the number of temperature days as independent draws from a specified probability distribution. We investigated a number of candidate distributions, and chose a beta-binomial for the proportion of warm days out of a possible 31 days in May ($\bar{p} = 0.23, \theta = a/\bar{p} = b/(1 - \bar{p}) = 11.04$) (Fig. 9). Using this distribution, we calculated the probabilities of observing n days where $n \in \{0, 4, 8, 12, \dots, 28\}$. As part of our assessment we also posited a warmer environment as might be the case due to climate change. For this distribution we assumed that the mean number of days increased by one standard deviation, such that the mean was 12 days rather than 7.3. We then calculated the probabilities of observing n days above freezing from this shifted distribution. The predicted distributions of days under static and warm climates are provided in Fig. 11.

IV. Annual-Cycle Models and Their Implications for Harvest Management

We combined the three alternative survival models with the three alternative reproductive models to form a set of nine annual-cycle models. These models represent a wide range of possibilities concerning the extent to which demographic rates are density dependent or independent, and the extent to which spring temperatures are important. The nine models varied greatly in their predictions of carrying capacity – i.e., the population size expected in the absence of harvest. We estimated carrying capacity by setting the harvest rate to zero, and then simulating population size over time until the mean had stabilized. Models in which survival was density independent and reproduction was density dependent tended to have the highest carrying capacities (Table 1). Of course, models that had no source of density dependence did not have finite carrying capacities (i.e., they are exponential growth models by definition). The three models in which survival is density dependent seem to imply unrealistically low carrying capacities, given that the population is currently being harvested and consists of approximately 80 thousand birds. We note, however, that these models (as well as the other models) imply higher carrying capacities under the warmer conditions observed in May over the last decade in Svalbard.

Table 1. Nine alternative models of pink-footed goose population dynamics and their associated carrying capacities (K , in thousands) for randomly varying days above freezing in May in Svalbard (TempDays). N and SA+A are total population size and the number of sub-adults plus adults, respectively. The sub-models represented by (.) denote randomly varying demographic rates.

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

One can also query these models to determine the amount of harvest required to stabilize the population at a given level. We used population size and composition in November 2010 ($N = 70k$; $Y = 15.4k$ and $A = 54.6k$) and temperature days in May 2011 (10 days), and calculated the required (model-specific) harvest rate on birds having survived one hunting season as:

$$h_i^* = 1 - \frac{1}{\theta_i(1 + R_i)}$$

where $R_i = p_i/(1 - p_i)$ and i represents one of the nine population models. We then calculated the total harvest associated with each of these model-specific rates as described previously. The required harvest to stabilize the population at 70 thousand ranged from 0 - 500 for models M2 and M5 (recall that these models imply carrying capacities below 70k), to about 17 thousand for models M6 and M7 (density-independent models). The other models had required harvests of 5 - 11 thousand. The harvest in Norway and Denmark in 2011 was estimated at just over 11k, and the post-harvest population size increased to 80 thousand. Thus, additional harvest may be needed to stabilize the population.

Bayesian posterior probabilities (or weights) can be used to express the relative ability of each model to accurately predict the changes in population size that actually occurred. We calculated posterior probabilities for each of the nine models for each of the years 1991-2002, assuming equal prior probabilities in 1990 (i.e., $p_i = 1/9$). We restricted our attention to 1991-2002 because this was a period of relatively stable harvests, and was just prior to the time in which harvests in Norway and Denmark began to increase substantially. This was deemed necessary because we have no direct estimates of harvest rate (nor age composition of the harvest), which are required to

calculate the posterior probabilities. Thus, as before, we assumed that harvest accounted for half of the total mortality rate during this period, and calculated posterior model probabilities 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:

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

where N_* is the observed population size, N_i is a model-specific prediction of population size, and σ^2 is a prediction variance common to all models. This variance was estimated by averaging the mean squared errors (MSE) from all nine models:

$$MSE = \sum_i \frac{(\log(N_*(t+1)) - \log(N_i(t+1)))^2}{n} / 9$$

where sample size for yearly comparisons was $n = 12$. The final estimate of variance was $\sigma^2 = (0.1115)^2$.

The most distinctive pattern in the changes in model weights over the 1990-2002 period is the decline after 1997 in weights for those models with density-dependent reproduction (models M0, M1, M2), and an increase for those models with randomly varying reproduction (models M6, M7, M8) (Fig. 12). There was little discrimination among survival models over the time frame. Unfortunately, more recent model weights could not be calculated because we have no estimates of harvest rate over the last decade (nor estimates of survival from which to make inference). The question arises then as to what weights should be used to initialize an adaptive-management process. We chose to use equal prior probabilities for all models, as was done with the program for mallards in the United States (Johnson 2011). Equal weights for all models reflect complete uncertainty as to which models are currently most appropriate. Considerations for updating model weights in the future will be discussed in the section entitled Future Needs.

V. Harvest Management Implications

Here we provide a formal description of the framework for optimizing harvest strategies. To begin, let decision making occur over a discrete time frame $\{0, 1, \dots, T\}$, beginning at some initial time 0 and terminating at a terminal time T that may be infinite. To simplify notation, we can think of decisions as being made at regular intervals, for example annually or at multi-year intervals.

A resource system that is subjected to management is characterized by a system state x_t at each time t over the time frame. System state represents the resource in terms of key resource elements, features, and attributes that evolve through time. Examples include population size or density, environmental conditions, and structural habitat features. We assume that the state of the system at any given time can be observed, and structural components of the system that influence dynamics are at least stochastically known.

A harvest action a_t is assumed to be chosen at time t from a set of options that are available at that time. Policy (or strategy) A_0 describes actions to be taken at each time starting at time 0 and continuing to the terminal time T . A policy covering only part of the time frame, starting at some time t after the initial time 0 and continuing until T , is expressed as A_t .

System dynamics are assumed to be Markovian – i.e., the system state at time $t+1$ is determined stochastically by the state at time t and action taken at time t . These transitions are specified by a probability $P(x_{t+1}|x_t, a_t)$ of transition from x_t to x_{t+1} assuming action a_t is taken. If there is uncertainty about the transition structure, several candidate models can be used to describe state transitions, with $P_i(x_{t+1}|x_t, a_t)$ representing a particular model $i \in \{1, 2, \dots, K\}$. Structural (or model) uncertainty can be characterized by a distribution q_t of model probabilities or weights, with elements $q_t(i)$ that may or may not be stationary. Here we refer to the distribution of model probabilities as the *model state*.

Assuming the transition structure is known, an objective or value function $V(A_t|x_t)$ captures the value of decisions made over the time frame in terms of the transition probabilities $P(x_{t+1}|x_t, a_t)$ and accumulated utilities ($a_t|x_t$). Utility is thus influenced (at least potentially) by both the action a_t taken at time t as well as the system state x_t at that time. Dynamic decision making typically is based on an objective or value function that accumulates utilities from the current time to the terminal time T :

$$V(A_t|x_t) = E \left[\sum_{\tau=t}^T U(a_\tau|x_\tau)|x_t \right]$$

On condition that there is uncertainty about transition structure, a value function $V(A_t|x_t, q_t)$ accumulates utilities over time based on the transition probabilities $P(x_{t+1}|x_t, a_t)$. In this situation, an overall value function $V(A_t|x_t, q_t)$ for the problem can incorporate the model-specific value functions in different ways.

With this notation the generic control problem can be stated as:

$$\max_{A_0} V(A_0|x_0, q_0)$$

subject to:

$$\begin{aligned} x_{t+1} &= f_i(x_t, a_t, z_t) & t \in \{0, 1, \dots, T-1\}, & \quad i \in \{1, \dots, K\} \\ q_{t+1} &= g(q_t, x_{t+1}) & t \in \{0, 1, \dots, T-1\} \end{aligned}$$

Two points are noteworthy. First, the random variable z_t represents an uncontrolled environmental process that induces stochasticity in the transition function $x_{t+1} = f_i(x_t, a_t, z_t)$, and thus produces the Markovian probabilities $P(x_{t+1}|x_t, a_t)$. Second, the updating function $g(q_t, x_{t+1})$ for q_t is typically (but not necessarily) Bayes' theorem.

A key issue in determining the way optimal decisions are identified concerns the updating of the model state in the decision process. Decision making at each time uses the current model state q_t in the decision making algorithm, along with an update of the model state for the next time step based on q_t and the system response x_{t+1} . This is the essence of adaptive management, which can be either passive or active (Williams et al. 2002). Our focus here is on the passive form.

In passive adaptive management, decision making at a given time t utilizes the model state q_t to weight both the immediate utilities and their anticipated accumulation over the remainder of the time frame:

$$V(A_t|x_t, q_t) = U(a_t|x_t, q_t) + \sum_{x_{t+1}} P(x_{t+1}|x_t, a_t, q_t) V(A_{t+1}|x_{t+1}, q_t)$$

where the model weights $q_t(i)$ are used to compute an average utility:

$$U(a_t|x_t, q_t) = \sum_k q_t(i) U_k(a_t|x_t),$$

probability:

$$P(x_{t+1}|x_t, a_t, q_t) = \sum_k q_t(i) P_i(x_{t+1}|x_t, a_t),$$

and future value:

$$V(A_{t+1}|x_{t+1}, q_t) = \sum_k q_t(i) V_i(A_{t+1}|x_{t+1}).$$

The corresponding optimization form is:

$$V[x_t, q_t] = \max_{a_t} \left\{ U(a_t|x_t, q_t) + \sum_{x_{t+1}} P(x_{t+1}|x_t, a_t, q_t) + V[x_{t+1}, q_t] \right\}$$

with optimization proceeding by standard backward induction starting at the terminal time T . In this framework, the model state q_t is a fixed parameter over the timeframe $[t, T]$ of the

optimization. The updating of the model state occurs outside the optimization algorithm, after a decision is implemented and system response x_{t+1} is recorded. At that time a new model state q_{t+1} is derived from x_{t+1} and another optimization is conducted over the new timeframe $[t + 1, T]$ based on the updated system and model states. With this sequence it is clear that at any particular time the choice of an action is influenced by both the current system and model state. However, the choice is not influenced by the anticipated impacts of decisions on future model state (i.e., learning). In this sense, adaptive decision making is held to be “passive.”

The identification of an optimal harvest strategy for pink-footed geese involves integrating:

(a) a harvest management objective, expressed in terms of state and action dependent utilities

$$V(A_t|x_t) = E \left[\sum_{\tau=t}^T H(a_\tau|x_\tau)u(a_\tau|x_\tau)|x_t \right]$$

where $H(a_\tau|x_\tau)$ is harvest, and harvest utility is:

$$u(a_\tau|x_\tau) = e^{-\frac{1}{2}\left(\frac{N_{t+1}-60k}{10k}\right)^2} \quad \text{if } N_{t+1} > 0$$

$$= 0 \quad \text{otherwise}$$

and N_{t+1} is total population size. Harvest-utility is thus a bell-shaped curve with a maximum value of 1.0 corresponding to a goal for population size of 60 thousand (Fig. 13). The objective function therefore seeks to maximize sustainable harvest, but devalues harvest decisions 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.

(b) a set of potential harvest-management actions available at each time $A_\tau \in \{a_\tau^{(1)}, a_\tau^{(2)}, a_\tau^{(3)}, \dots\}$.

The degree to which harvest rates can be manipulated is unknown, but we assumed that managers have only coarse control. We also do not know the maximum harvest rate that is either attainable or socially acceptable. For our purposes, we used potential harvest rates of $h_\tau \in \{0.00, 0.04, 0.08, \dots, 0.16\}$ on birds having survived at least one hunting season. We then assumed harvest rate on young of the year is twice that of adults. These assumptions imply a maximum harvest of approximately 17k (about 40% higher than the observed maximum harvest) out of a population of 80 thousand birds. We also assessed the consequences of smaller maximum harvest rates.

Note that we were obliged to use harvest rates, rather than absolute harvest, as the control variable because of a computational problem arising from the post-harvest population census (Appendix 2). To derive an optimal harvest we must first specify the number of young and adults in the total harvest, but this cannot be known a priori because it depends on the age composition of the pre-harvest population. Yet, the age composition of the pre-harvest population cannot be predicted

from our models without knowing the age composition of the harvest. Therefore, we derived strategies of optimal harvest rates and then calculated the associated total harvests.

(c) one or more models that predict the consequences of those actions in terms that are relevant to the management objectives $P_i(x_{t+1}|x_t, a_t, q_t)V(A_{t+1}|x_{t+1}, q_t)$. The nine models of population dynamics have been described previously and are summarized in Table 1.

(d) a time-specific observation of system state x_t (number of young and adults in November, temperature days in May) with which to identify the optimal state-dependent harvest action and to update model weights $q_{t+1} = g(q_t, x_{t+1})$.

Given these components, optimal harvest strategies were calculated using the public-domain software SDP (Lubow 1995) that implements the backward-induction algorithm know as stochastic dynamic programming (Puterman 1994). The SDP code for optimizing and simulating optimal strategies is provided in Appendix 3.

We assumed equal weight for all models because of the uncertainty about contemporary model weights. We used Monte Carlo simulations to investigate the performance of the optimal strategy under all alternative models of system dynamics. The optimal strategy is expected to maintain mean population size near 60 thousand (range 55.7 – 61.0), regardless of the most appropriate model (Table 2). However, mean harvest rates and harvests varied substantially depending on the most appropriate model of system dynamics.

Table 2. Mean performance (sd) (in thousands, except for harvest rate) from Monte Carlo simulations of the optimal strategy that assumed equal model weights, under varying models of system dynamics. See text for a description of models and objective value.

Performance metric	System model								
	M0	M1	M2	M3	M4	M5	M6	M7	M8
Young (sd)	6.7 (1.4)	6.7 (1.5)	6.6 (1.6)	8.6 (0.9)	8.7 (1.0)	8.1 (1.0)	8.7 (3.6)	8.8 (3.6)	8.04 (3.3)
Adults (sd)	51.3 (2.2)	51.8 (1.6)	47.8 (1.1)	51.4 (2.1)	51.7 (1.6)	48.0 (1.1)	51.6 (2.5)	52.2 (2.2)	47.7 (1.3)
Harvest rate (sd)	0.07 (0.04)	0.07 (0.04)	0.03 (0.03)	0.10 (0.04)	0.10 (0.03)	0.05 (0.03)	0.10 (0.05)	0.10 (0.05)	0.05 (0.05)
Harvest (sd)	5.0 (3.0)	5.4 (3.0)	2.1 (2.3)	7.8 (3.4)	8.4 (3.2)	3.5 (2.4)	8.0 (5.0)	8.6 (4.9)	3.5 (3.6)
Objective value (sd)	4.8 (2.8)	5.3 (3.0)	1.8 (2.1)	7.7 (3.3)	8.3 (3.1)	3.3 (2.2)	7.1 (4.3)	7.7 (4.3)	3.1 (3.2)

The state-dependent strategy for managing harvest rates is difficult to depict because it has four dimensions (number of young, number of adults, number of temperature days, and optimal harvest rate) and a large number of entries. When examining adult population sizes ranging from 0 - 120 thousand (in increments of 2k), young abundance from 0 – 20 thousand (also in increments of 2k), and temperature days from 0 – 28 (in increments of 4 days), the optimal strategy consists of a look-up table of 5,368 rows. Therefore, we plotted optimal harvest rates for combinations of young and adults for temperature days $\in \{0, 8, 16\}$ for the strategy that assumes equal model weights (Fig. 14). For eight temperature days (near the average of 7.3), optimal harvest rates increase rapidly once there are more than about 50 thousand birds in the population (Fig. 15). A digital copy of the full

state-dependent harvest strategy can be obtained from Jesper Madsen at Aarhus University (jm@dmu.dk).

Using optimal harvest rates, we calculated optimal *harvests* under each of the population models. For any particular system state and optimal harvest rate, the total harvest varied depending on the most appropriate model of system dynamics. Therefore, we simply averaged harvests across models (i.e., assumed equal model weights). Generally, optimal harvests were on the order of 10 – 20 thousand for population sizes > 60 thousand, and 0 – 5 thousand for population sizes < 60 thousand (Fig. 15). For the observations of young = 15.4 thousand and adults = 54.6 thousand in autumn 2010, and temperature days = 10 in May 2011, the optimal harvest rate in autumn of 2011 would have been 0.16, or a model-averaged harvest of 14.2 thousand. This compares to the estimated harvest in Denmark and Norway in 2011 of 11.4 thousand.

Based on the optimal strategy, hunting-season closures would be required as the number of adults in the autumn population falls below about 52 thousand, regardless of the number of young in the population (Fig. 16). As the number of adults and young decrease, the number of temperature days required to keep the hunting season open increases.

Finally, we investigated the ability of the optimal strategy to stabilize the population at around 60 thousand birds, assuming varying values of the maximum harvest rate $h_{max} \in \{0.08, 0.12, 0.16\}$. As before, we assumed that harvest rates could be manipulated in increments of 0.04. After deriving the optimal strategy for each of the maximum harvest rates, we simulated its use under both normal (mean = 7 temperature days) and warm (mean = 12 temperature days) climates. We initialized the system state at the population size observed in 2011 (young = 16k, adults = 64k), and near-average temperature days = 8. We then determined average population size for each year in a 10-year period. Harvest strategies that contained a maximum harvest rate of 0.16 were effective at stabilizing the population at 60 thousand within 4-5 years, regardless of the climate scenario (Fig. 17). Harvest strategies with a maximum harvest rate of 0.12 were also able to stabilize the population near 60 thousand, although it took more time. Harvest strategies with a maximum harvest rate of 0.08 were unsuccessful at stabilizing the population at 60 thousand. Under maximum harvest rates of 0.12 or 0.16, it would be necessary to maintain harvests of 10 – 16 thousand for about four years to reduce the population to near 60 thousands. After that, harvest could be reduced to roughly 5 – 10 thousand depending on climate. We remind the reader that these conclusions are based on an assumption of equal model weights. Higher harvests and more years to stabilize the population would be necessary if the most appropriate models tend to be those in which reproduction or survival is density independent.

VI. Future Needs

Monitoring. – Continued monitoring of the pink-footed goose population on an annual basis is critical to an informed harvest management strategy. At a minimum, the ground census in November should be continued to determine population size and proportion of young. Continued

estimates of harvest from Norway and Denmark are also necessary to help judge the credibility of the alternative population models. However, an adaptive management process that relies on periodic updating of model weights will depend on acquiring either estimates of the realized harvest rate of adults or the age composition of the harvest. This will require a concerted effort in both Denmark and Norway to obtain and refine estimates of total harvest, age composition of the harvest, and the number of banded geese that are harvested.

In the long term, a ground census at the beginning of November is problematic. In the early years, this was essentially a post-harvest census, which provided the age structure of the population after young and adults had been exposed to hunting. Ideally, however, we would like to know the age structure of the population prior to harvesting. It is the post-harvest assessment of age structure that prevented us from using absolute harvest as a control variable. The availability of estimates of harvest rate or age composition of the harvest would allow us to overcome this limitation. There are other problems with a November census, however. An assessment of population status just prior to making a decision about appropriate hunting seasons is preferred. With the November census, the time between population assessment and the subsequent hunting season is long (9 – 10 months), meaning that our predictions of population status just prior to the hunting season are very uncertain. Even more problematic, however, is the fact that in recent years more of the harvest has been occurring after the November census because geese are staying in Denmark longer. The fact that the November census increasingly occurs before the effects of the current hunting season are realized is a problem that can only be addressed by making critical assumptions that cannot be verified. For all of these reasons, we believe it is prudent to consider a census conducted either on the breeding grounds or on staging areas during spring migration, recognizing that the latter option is likely to be more logistically feasible.

Finally, there is a pressing need to assess current rates of survival. A high priority should be to examine all mark-recapture data since 1990 as part of a comprehensive analysis targeted at supporting the adaptive-management framework. In particular, we would like to know whether survival rates differ among age classes. For long-lived species like geese, survival is the most critical rate determining an appropriate harvest strategy, and significant age dependency in survival has important implications for how populations respond to harvest. Specifically, we would like to understand whether the pink-footed goose population could be expected to exhibit transient dynamics in response to harvest because of the phenomenon of population momentum (Koons et al. 2006). Population momentum resulting from significant age dependency in demographic rates can induce time delays in the response to harvest (or other environmental factors). A failure to recognize important age dependencies thus raises the risk of changing a harvest-management action before the effects of the original action are fully realized (Hauser et al. 2006).

Decision-Making Cycle. – The International Working Group has expressed a desire to adopt a three-year cycle of decision making related to the regulation of pink-footed goose harvests. The idea is that once a target harvest level is adopted, it would remain in place for three years, after which time population status would be assessed and a potentially new management action chosen. There are no theoretical limitations of this approach within the analytical framework described

herein. However, a three-year cycle will introduce additional uncertainty into the projections of harvest and population size, which are required to optimize a harvest strategy. This additional uncertainty will erode expected management performance (however measured), but the degree of loss in performance is unknown at this time. We have developed a preliminary framework to implement a three-year cycle using stochastic dynamic programming, and we hope to have it fully operational later this year. We note, however, that application of this 3-year framework will still require annual resource monitoring and assessments to facilitate learning, and to allow managers the opportunity to respond to any unforeseen change in resource conditions.

Acknowledgements

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Annual cycle in monitoring, modeling and decision-making



Fig. 1. Annual cycle for managing the harvest of the Svalbard population of pink-footed geese, depicting monitoring, assessment, and decision-making processes.

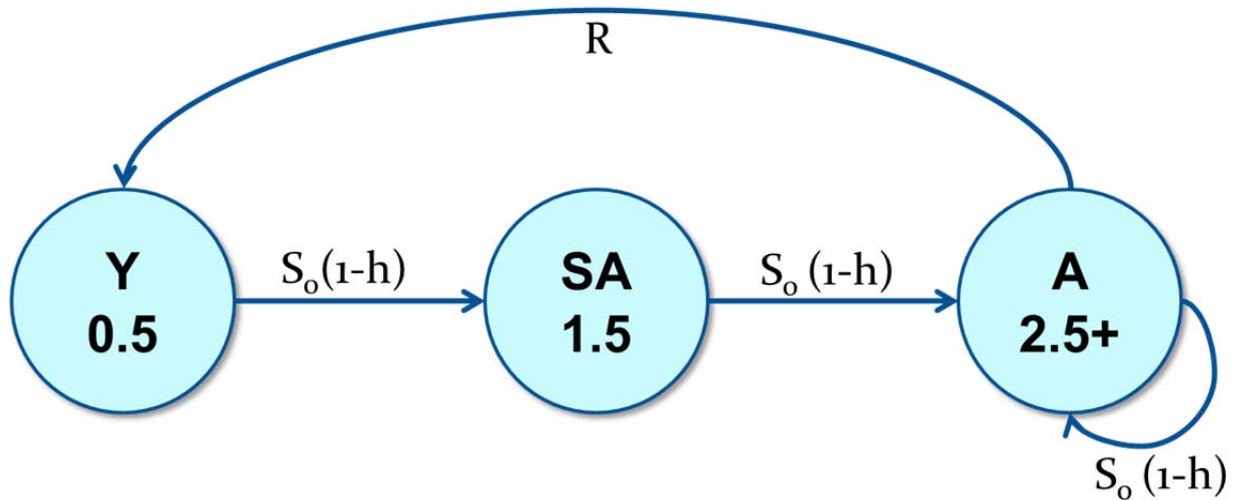


Fig. 2. Annual cycle of pink-footed goose population dynamics with an anniversary date of November 1 (when population counts are conducted), in which there are three age classes (Y = young aged 0.5 years, SA = sub-adults aged 1.5 years, and A = adults aged at least 2.5 years). Demographic rates are S_0 = survival from natural (non-hunting) causes, h = harvest rate of birds having survived at least one hunting season, and R = reproductive rate.

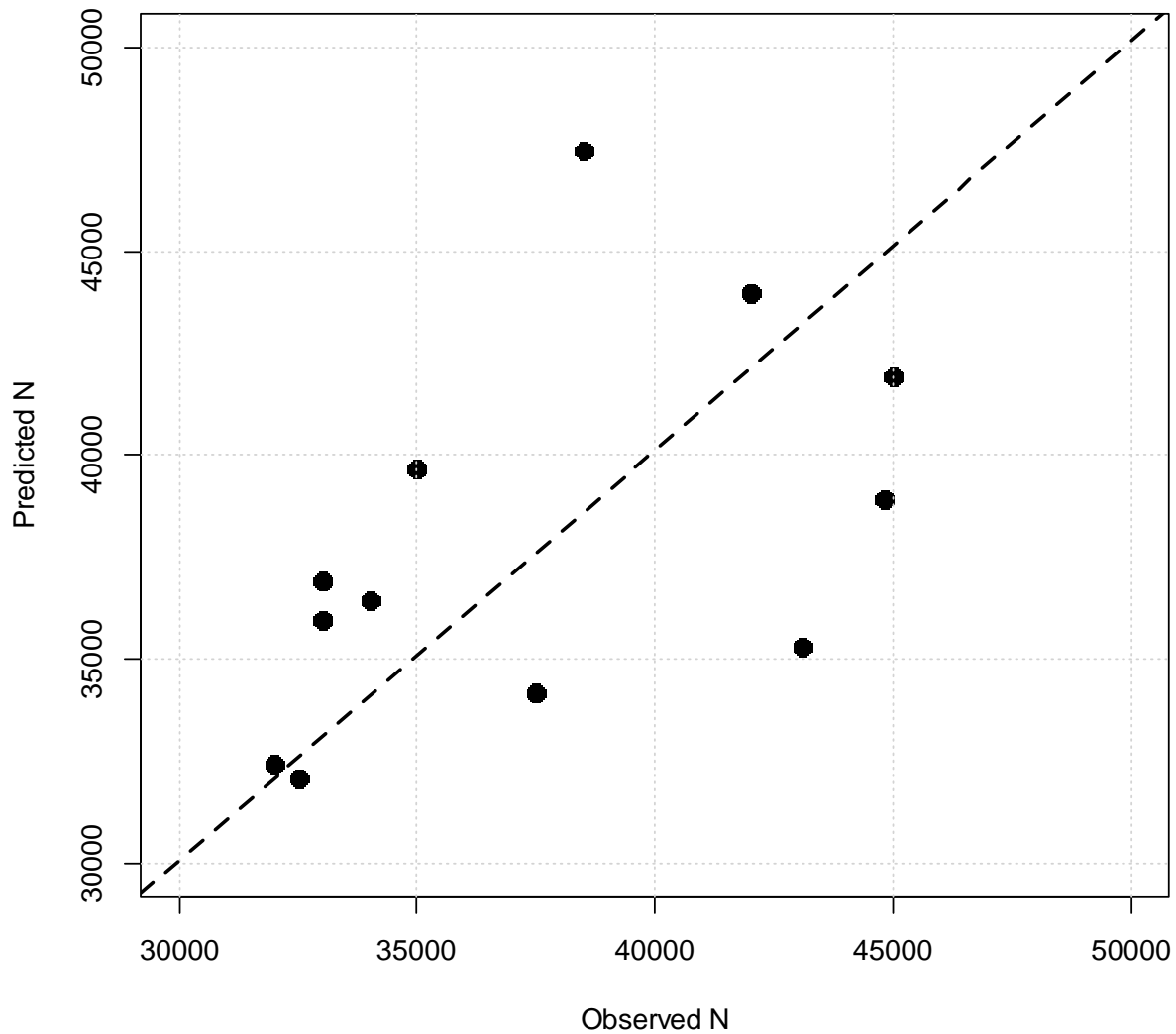


Fig. 3. A comparison of observed population sizes with those predicted using observed population size the previous year and estimates of annual survival and reproduction. The dashed line is the best fitting slope assuming an intercept of zero. The slope of the fitted line is close to 1.0, suggesting that changes in population size predicted from estimates of survival and reproductive rates closely correspond with those from ground counts.

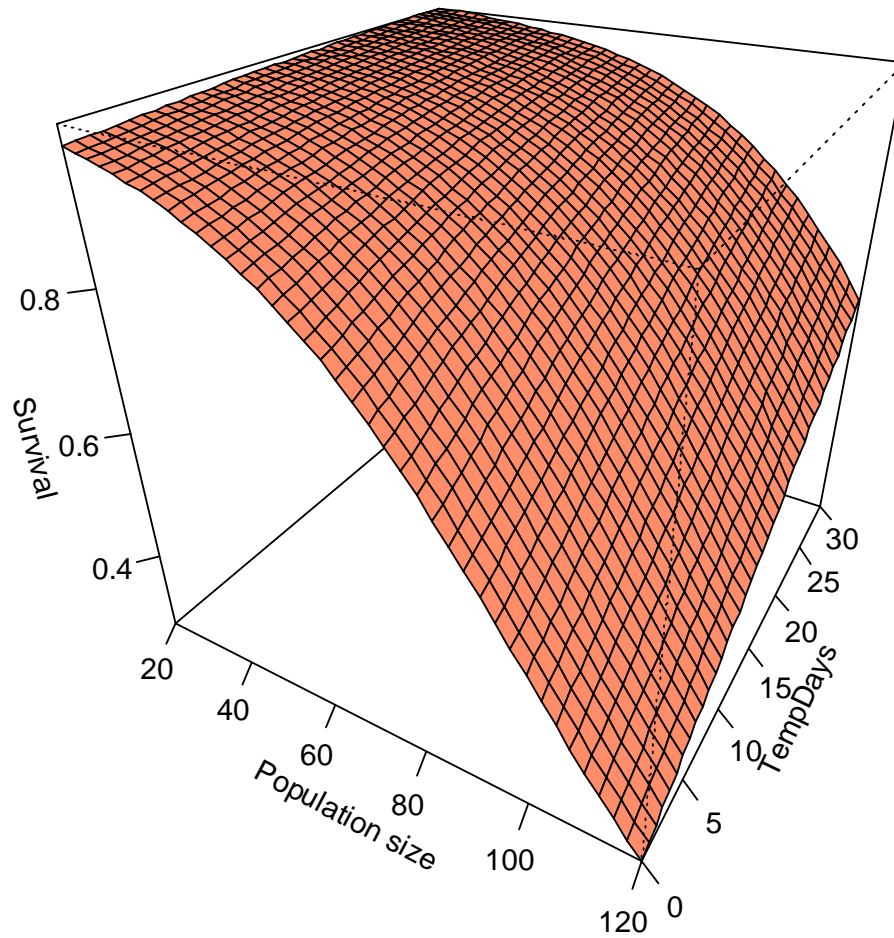


Fig. 4. Predictions of survival from non-hunting causes for varying levels of population size (in thousands) and the number of days above freezing in May in Svalbard. The model is strongly density-dependent, suggesting relatively large declines in survival accompany increasing population sizes.

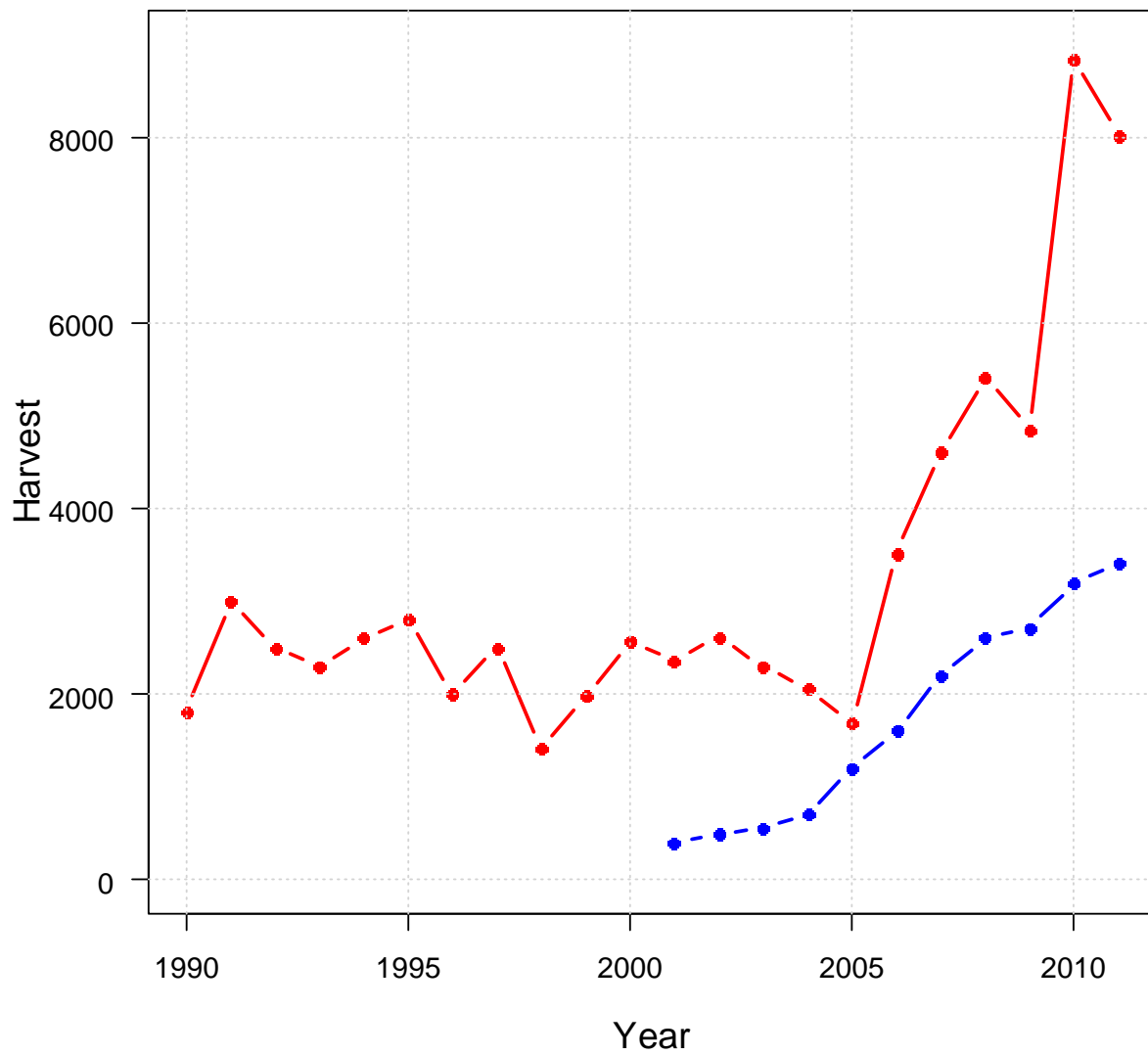


Fig. 5. Estimated harvest of pink-footed geese in Denmark (red) and Norway (blue).

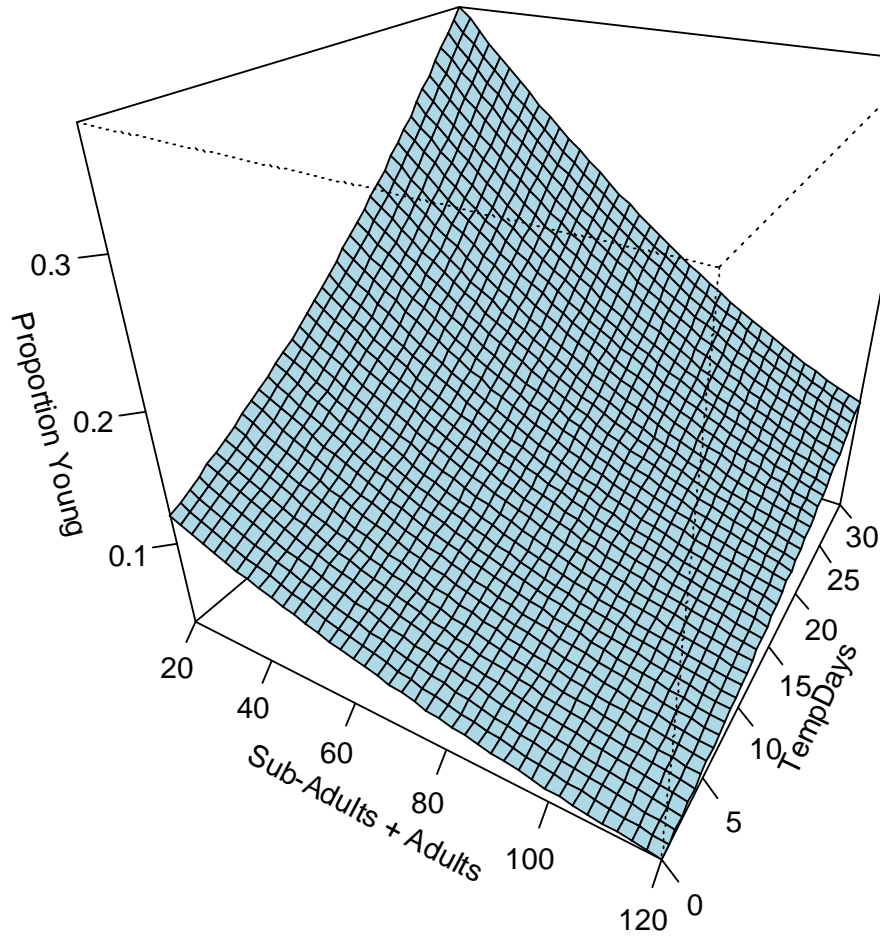


Fig. 6. The predicted proportion of young on November 1 as a function of the sub-adult and adult population the previous year and the number of days above freezing in May in Svalbard. This model suggests a density-dependent decrease in recruitment, which can be moderated by warm springs on the breeding grounds.

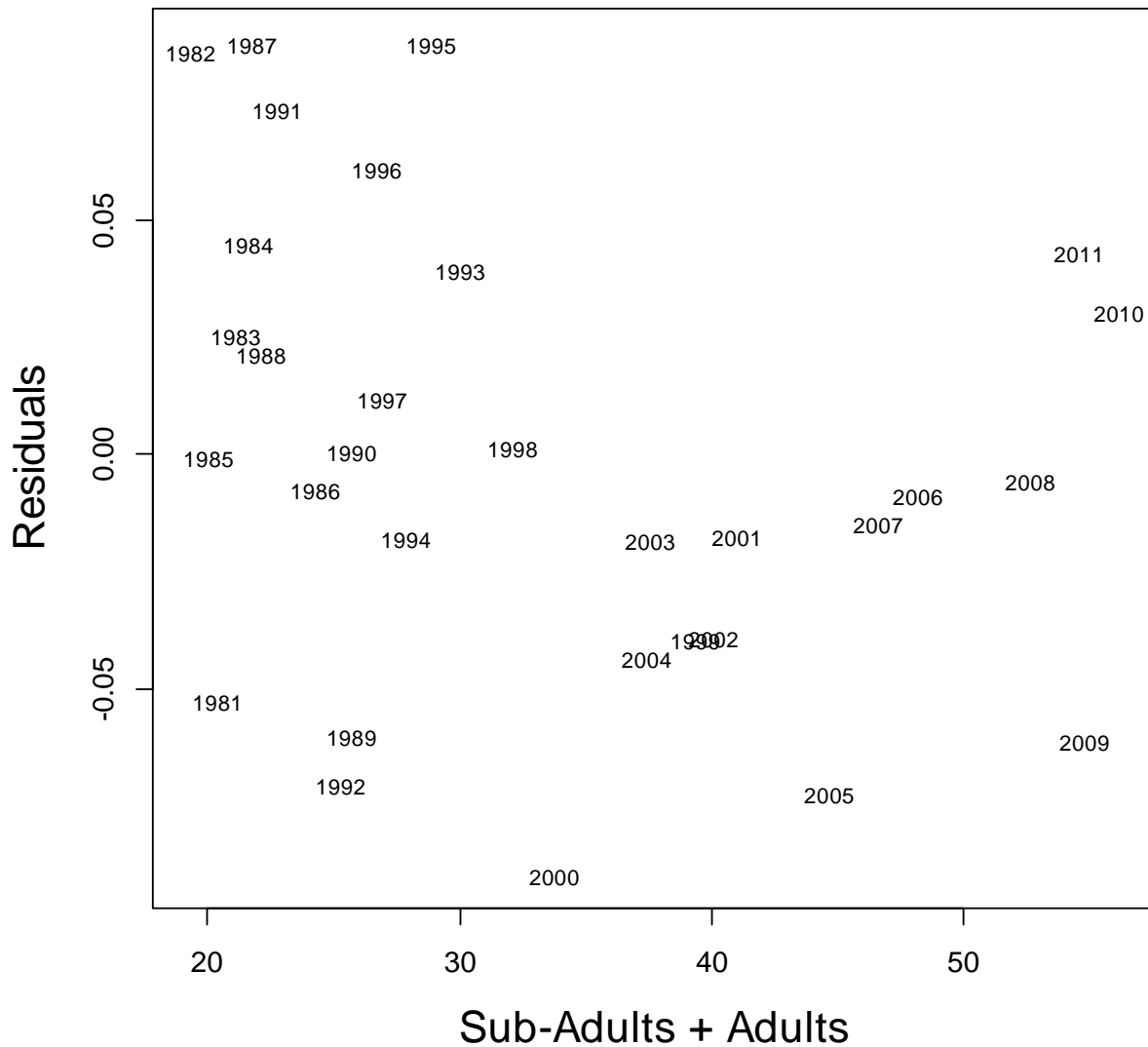


Fig. 7. Residuals from the reproductive model using only the number of days in May above freezing in Svalbard as a covariate, plotted against the number of sub-adults and adults in the population. Data points are labeled by year. Prior to 2000, there is a negative relationship between reproduction and population size, but little suggestion of density-dependent reproduction after the year 2000.

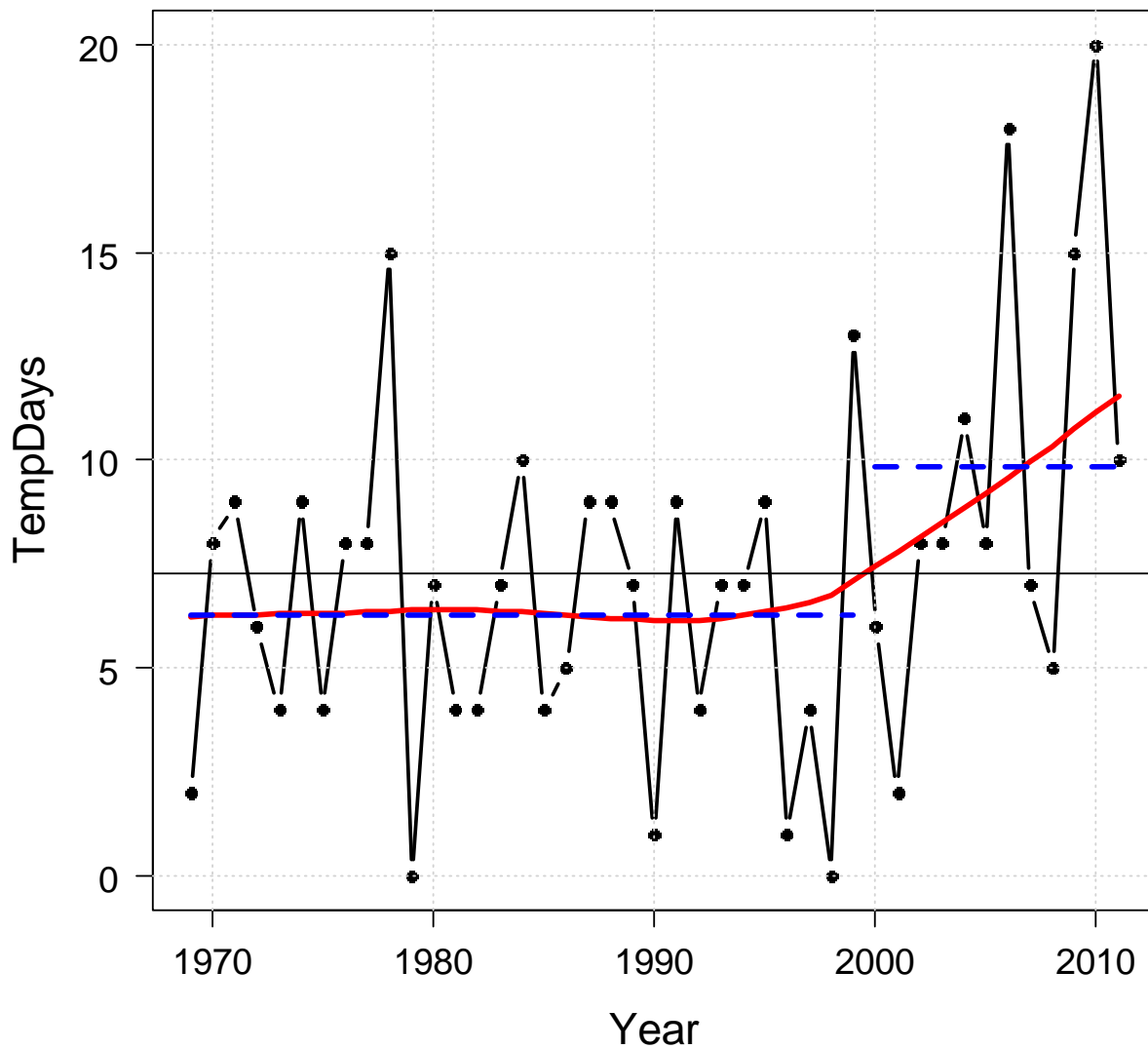


Fig. 8. The number of days in Svalbard in May with an average temperature $>0^{\circ}\text{C}$, as based on weather stations in Longyearbyen and Ny Ålesund. The solid black line represents the overall mean, the dashed blue lines represent pre-2000 and post-2000 means, and the red solid line is the locally-weighted polynomial regression (LOWESS).

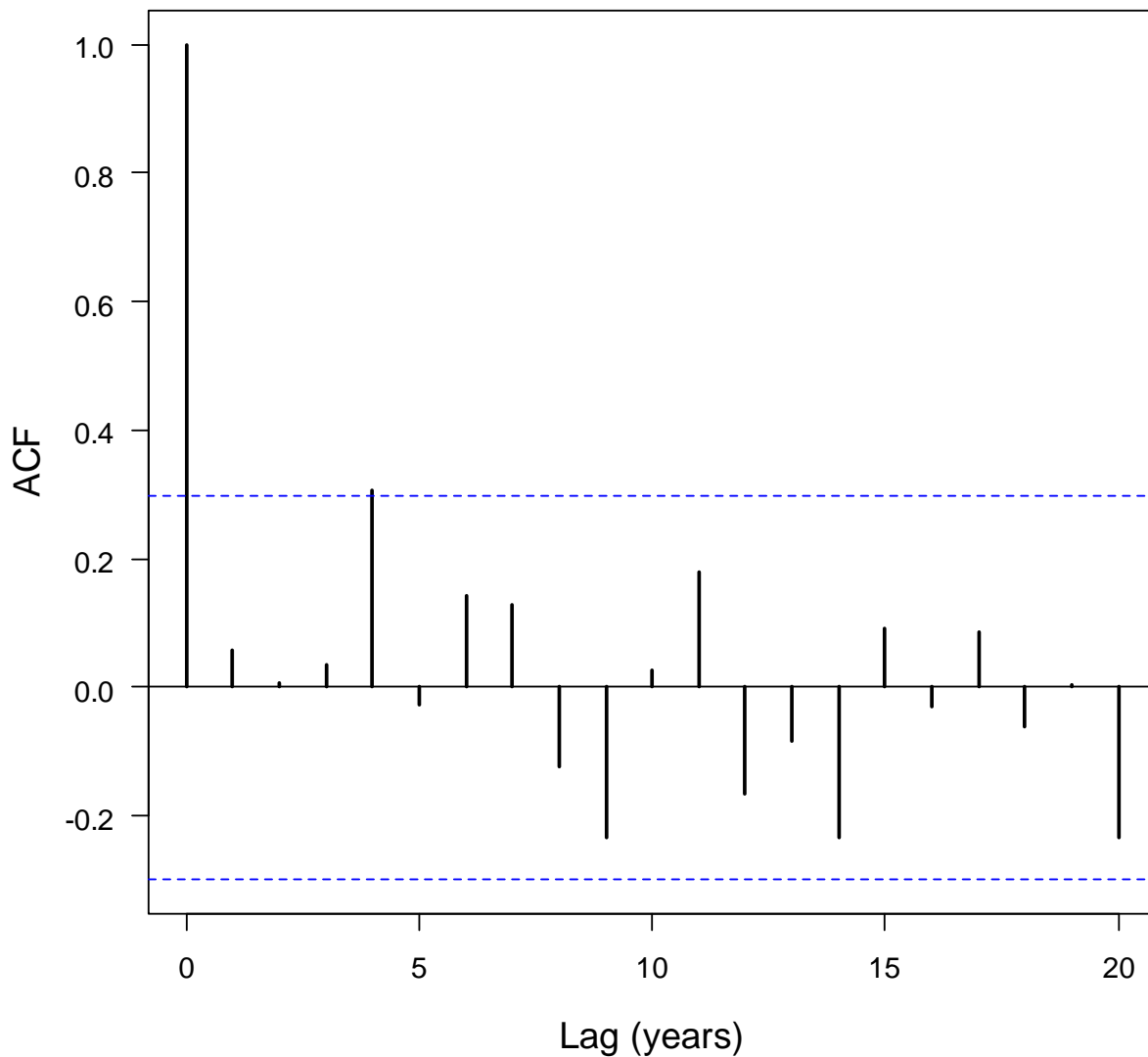


Fig. 9. Autocorrelation in the number of days above freezing in Svalbard in May, 1969-2011, for varying time lags. The autocorrelation at lag 4 is significant ($P < 0.05$); however, under the null hypothesis that all lags are equal to zero, we would expect up to 5% (i.e., in this case, one) of the autocorrelations to be significant (i.e., the experiment-wise error rate).

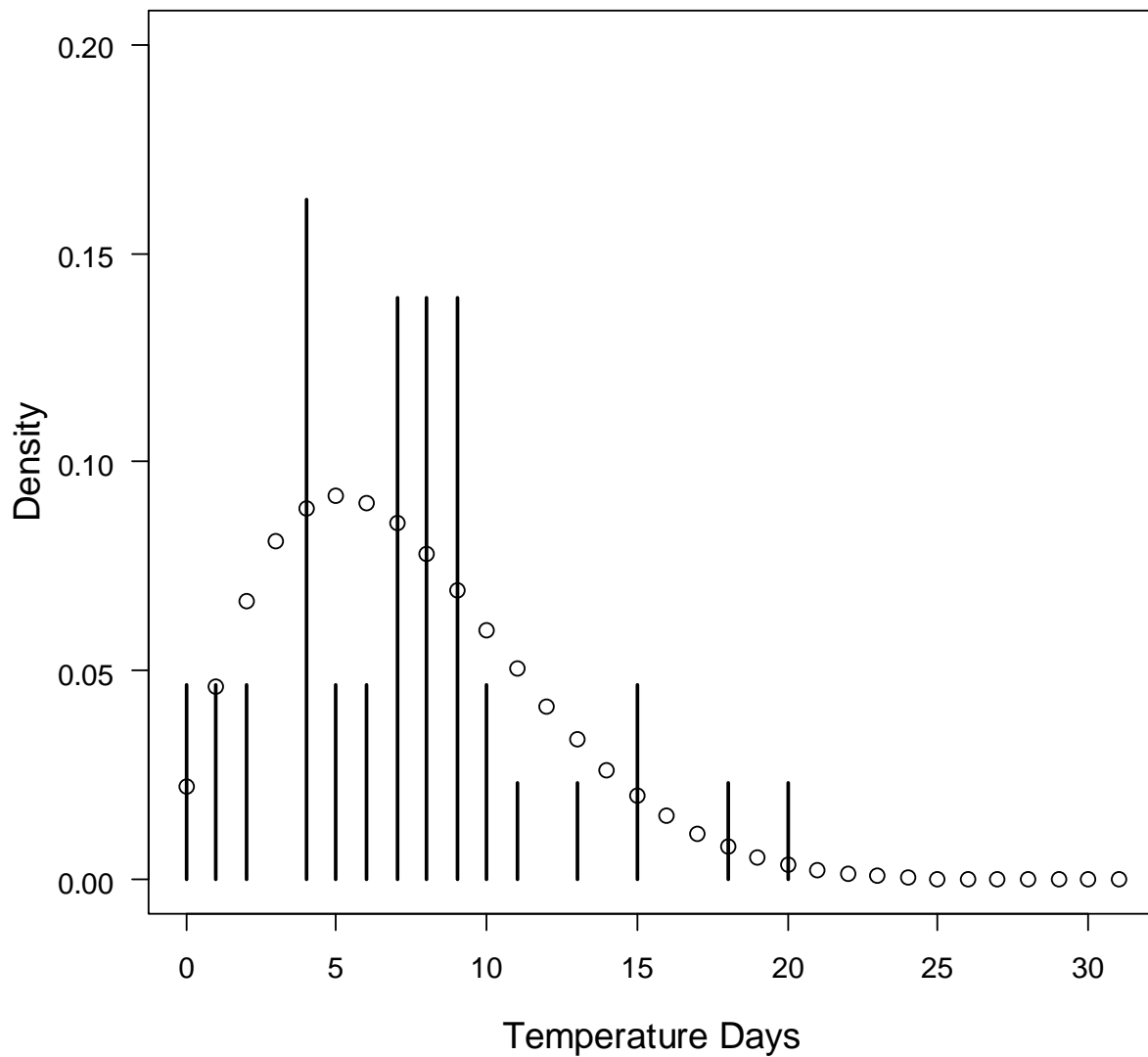


Fig. 10. Probability density of the number of days above freezing in May, 1969-2001, in Svalbard. Vertical lines are the observed data and the open circles represent the fit of a beta-binomial distribution for the proportion of days above freezing (out of 31 total days).

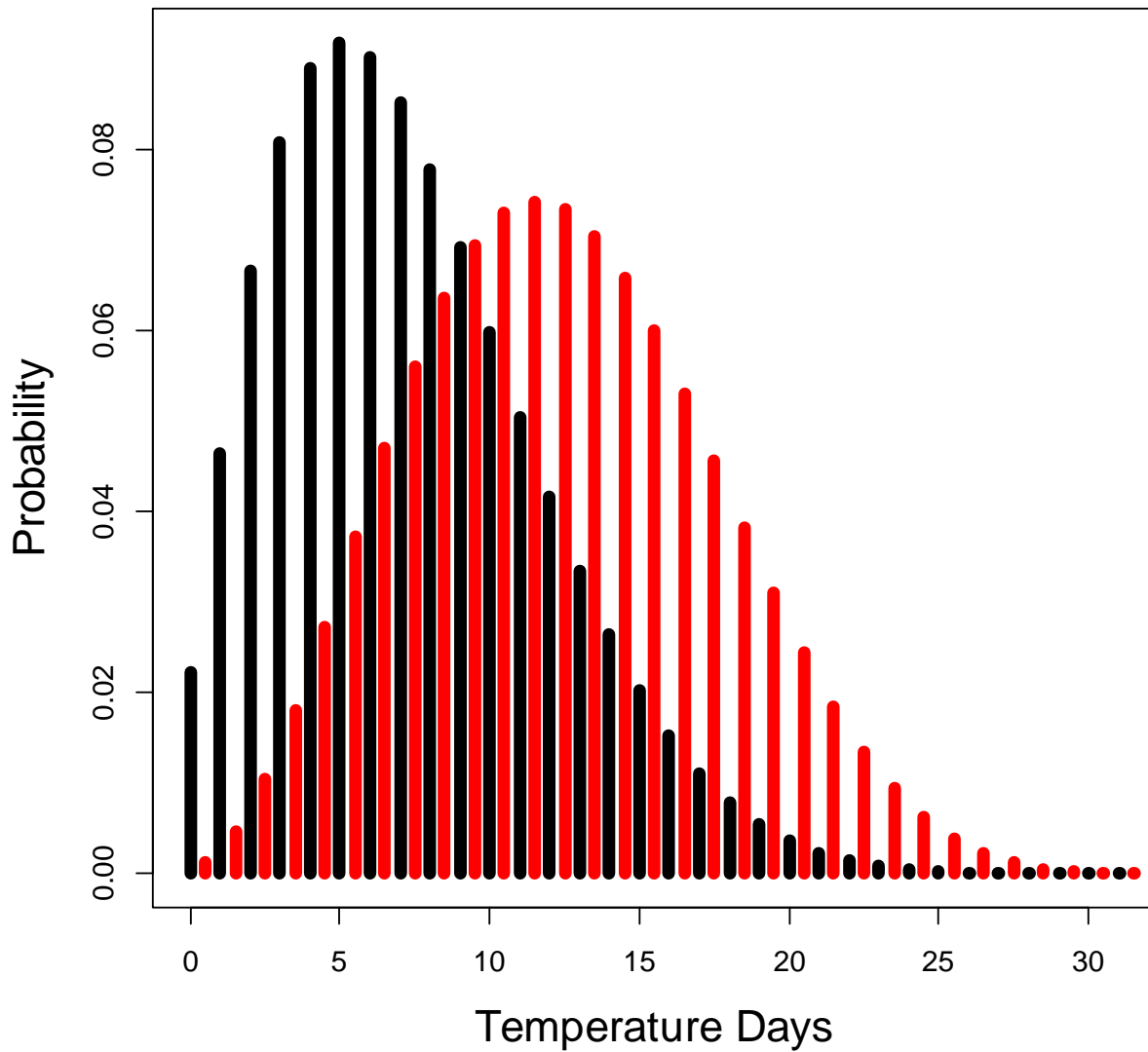


Fig. 11. Predicted distribution of days in May above freezing in Svalbard based on the observed days during 1969-2001 (in black) and that postulated under a warmer climate (i.e., a shift in the mean by one standard deviation)(in red).

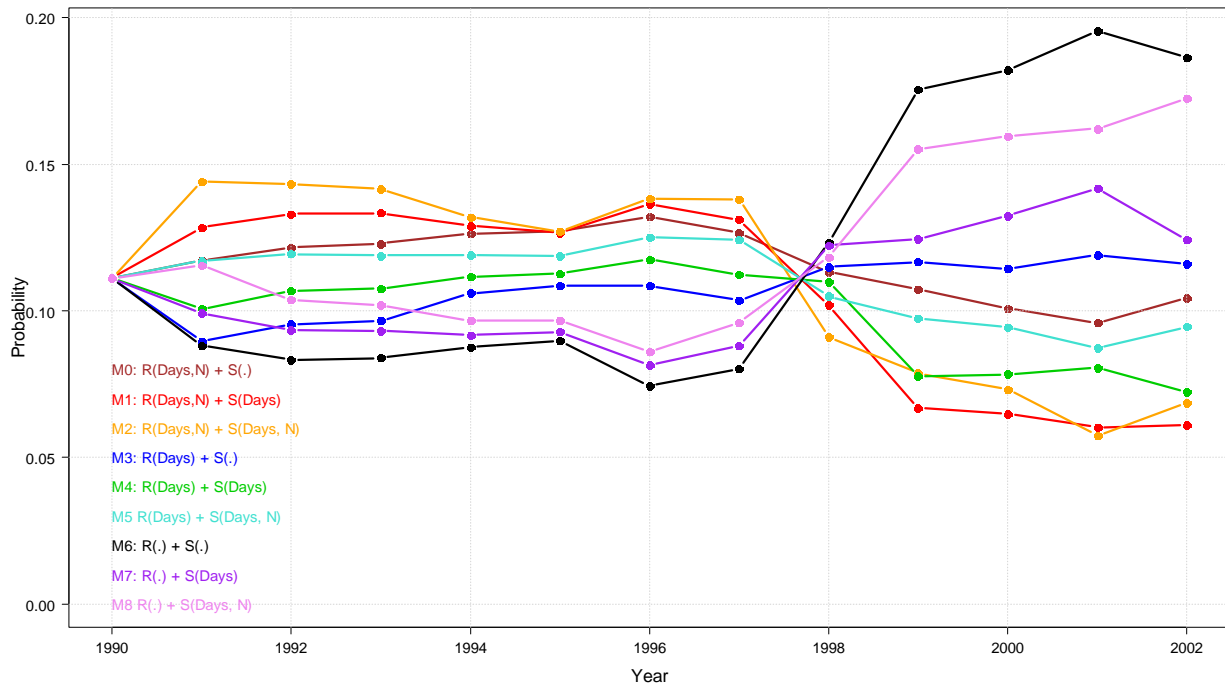


Fig. 12. Model credibility characterized as Bayesian posterior probabilities, assuming equal prior probabilities in 1990, for nine models describing the annual dynamics of the pink-footed goose population. See text for a description of the models. The cause for the apparent reversal in model credibility starting in 1998 is unknown, but may be related to some release from density-dependent regulation mechanisms.

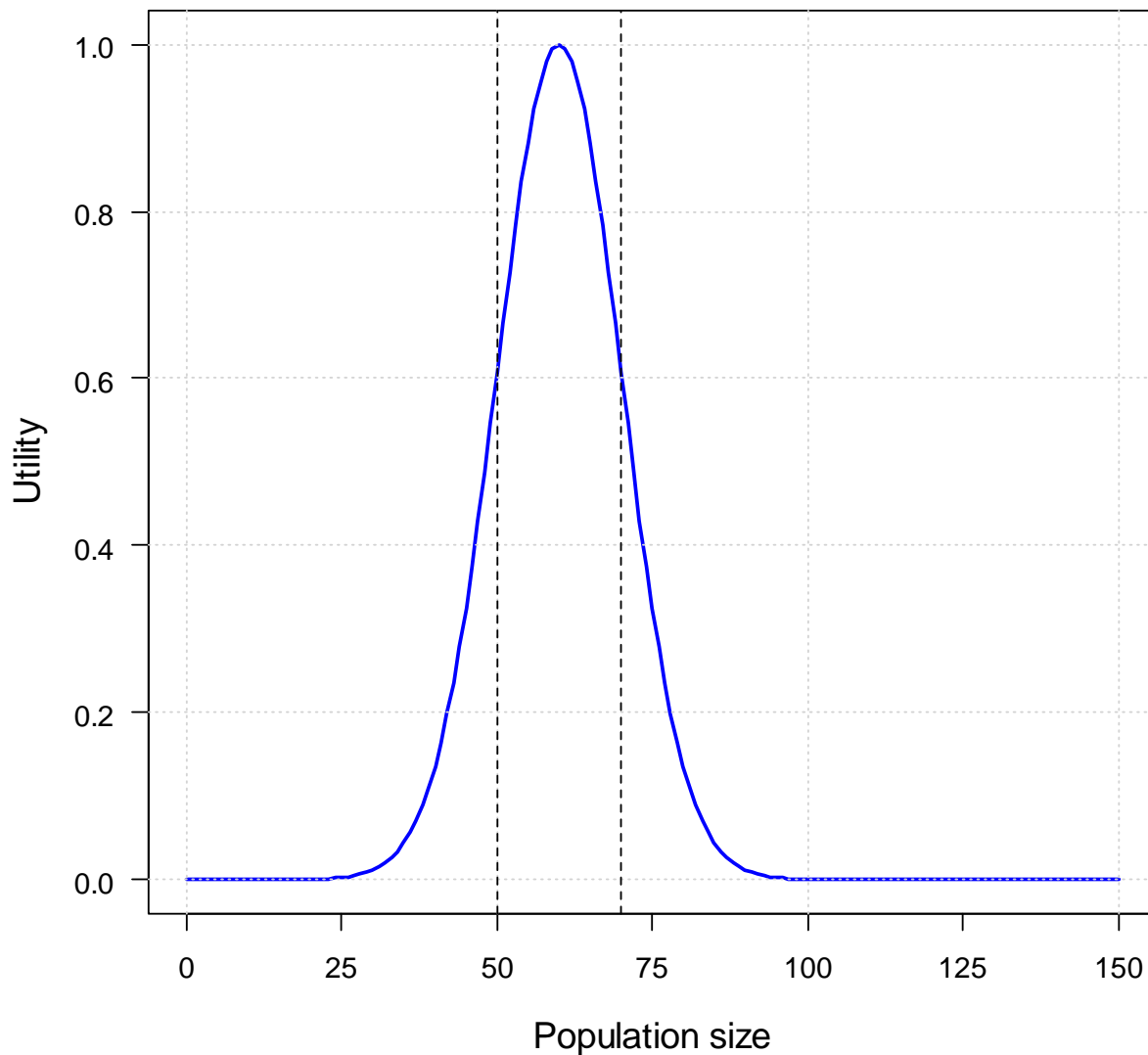


Fig. 13. The relative utility of pink-footed goose harvest as function of subsequent population size. This function gives full value (i.e., 1) to harvest when subsequent population size is expected to be the goal of 60 thousand. Harvests are devalued as subsequent population sizes are expected to diverge from the goal. Use of this utility function in deriving optimal harvest strategies has the effect of avoiding harvest decisions that result in a population size very different from the goal.

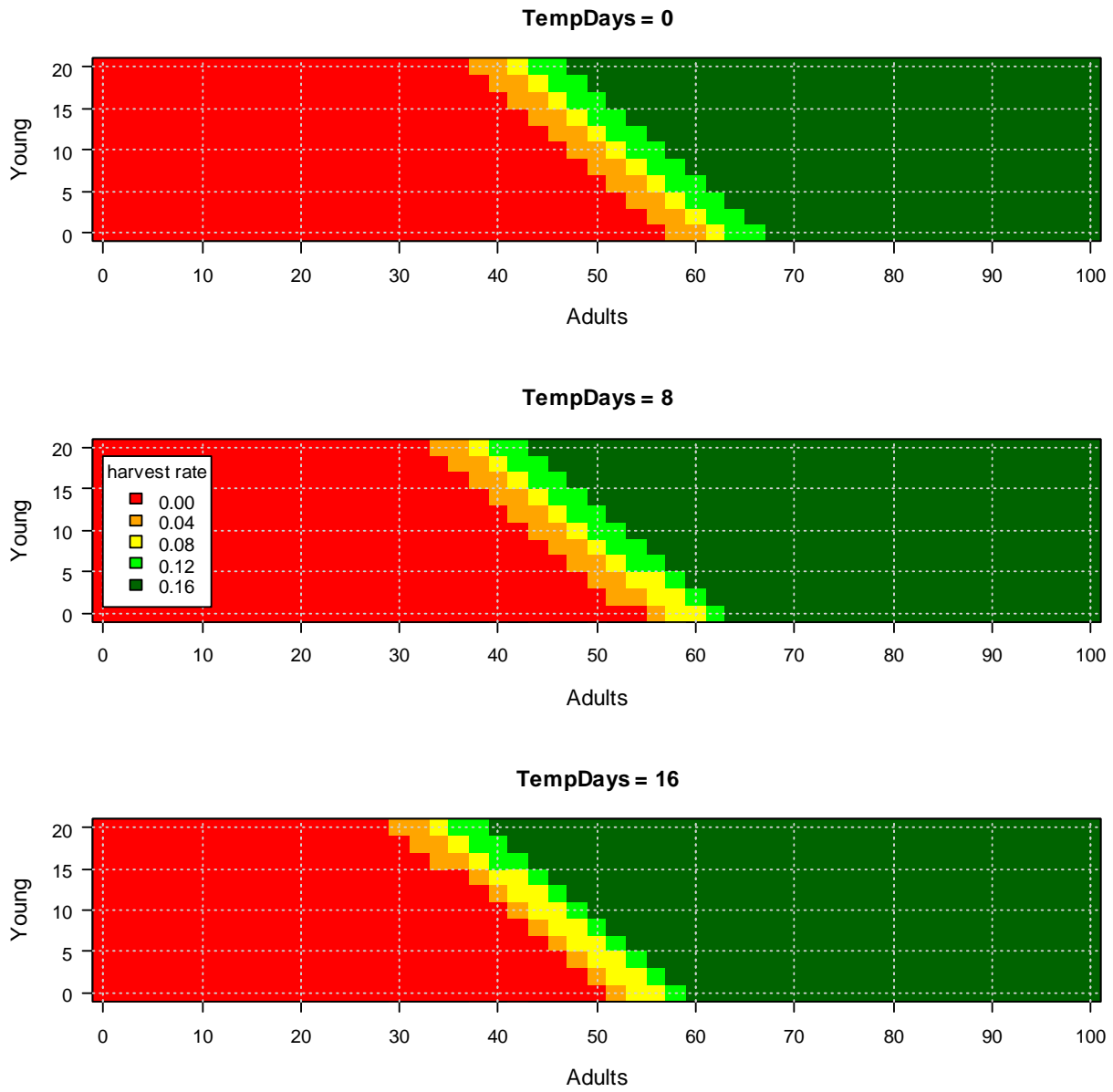


Fig. 14. Optimal harvest rates (proportion of the autumn population harvested) for adult pink-footed assuming equal model weights, where TempDays is the number of days above freezing in May in Svalbard. See text for a description of the models.

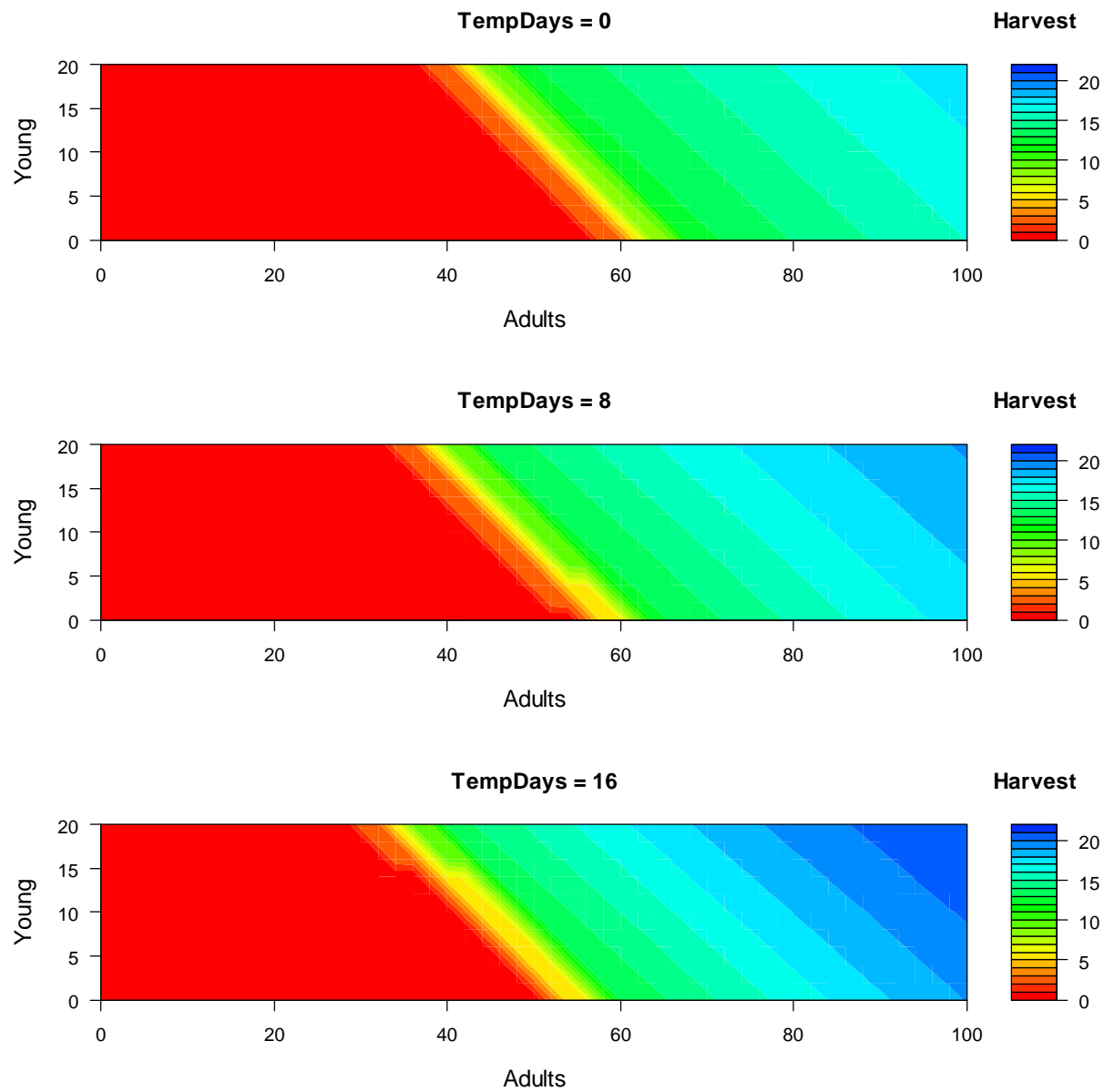


Fig. 15. Optimal *harvests* (in thousands) for pink-footed geese, based on optimal harvest rates of the strategy that assumes equal model weights. TempDays is the number of days above freezing in May in Svalbard. See text for a description of the models.

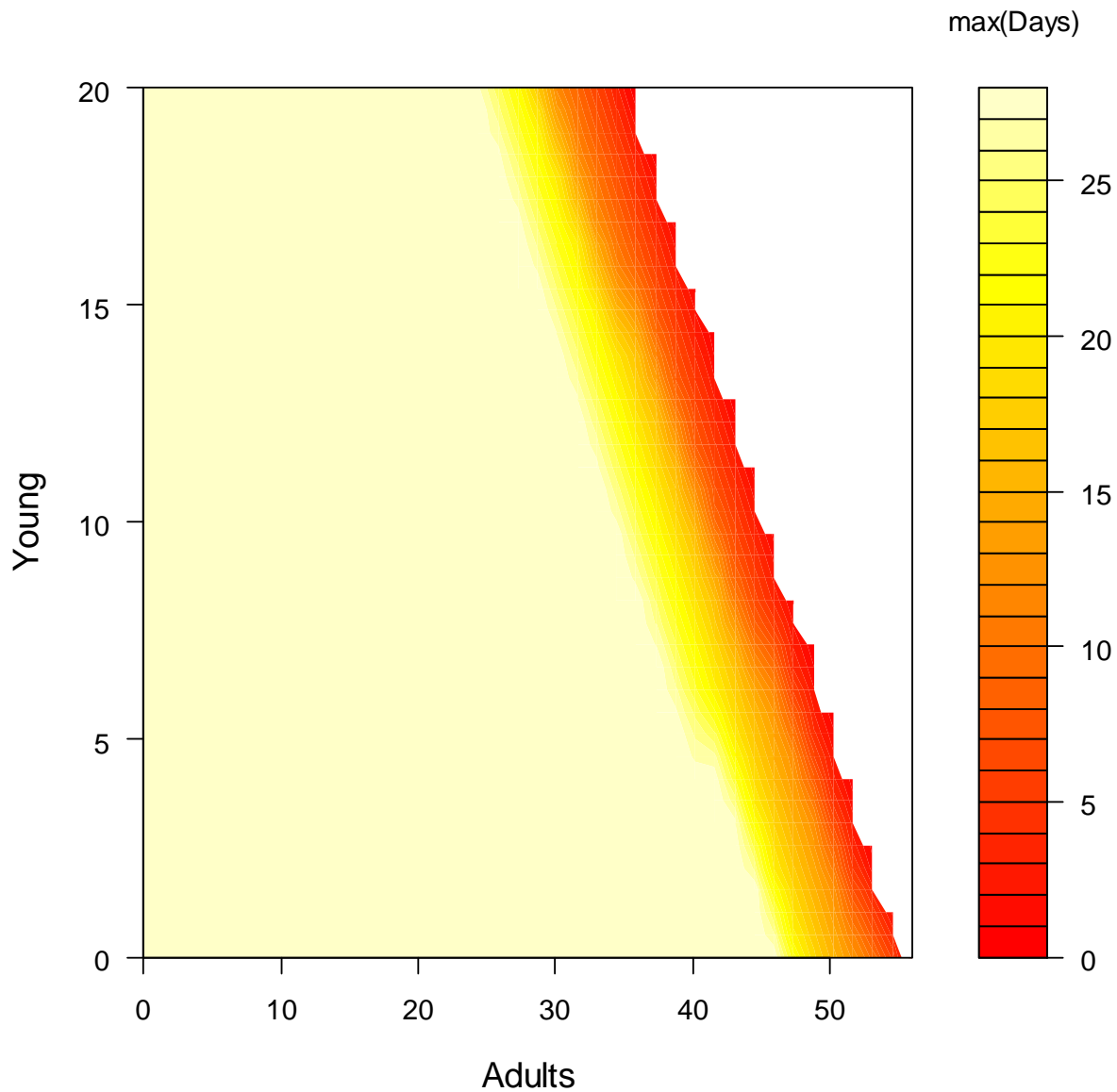


Fig. 16. Conditions under which a closed hunting season (yellow through red shaded area) for pink-footed geese is optimal, conditioned on equal weights for all nine population models. The value $\max(\text{Days})$ represents the maximum number of temperature days under which a closed season is required. The white area in the upper right of the plot represents open hunting seasons regardless of the number of temperature days. See text for a description of the models.

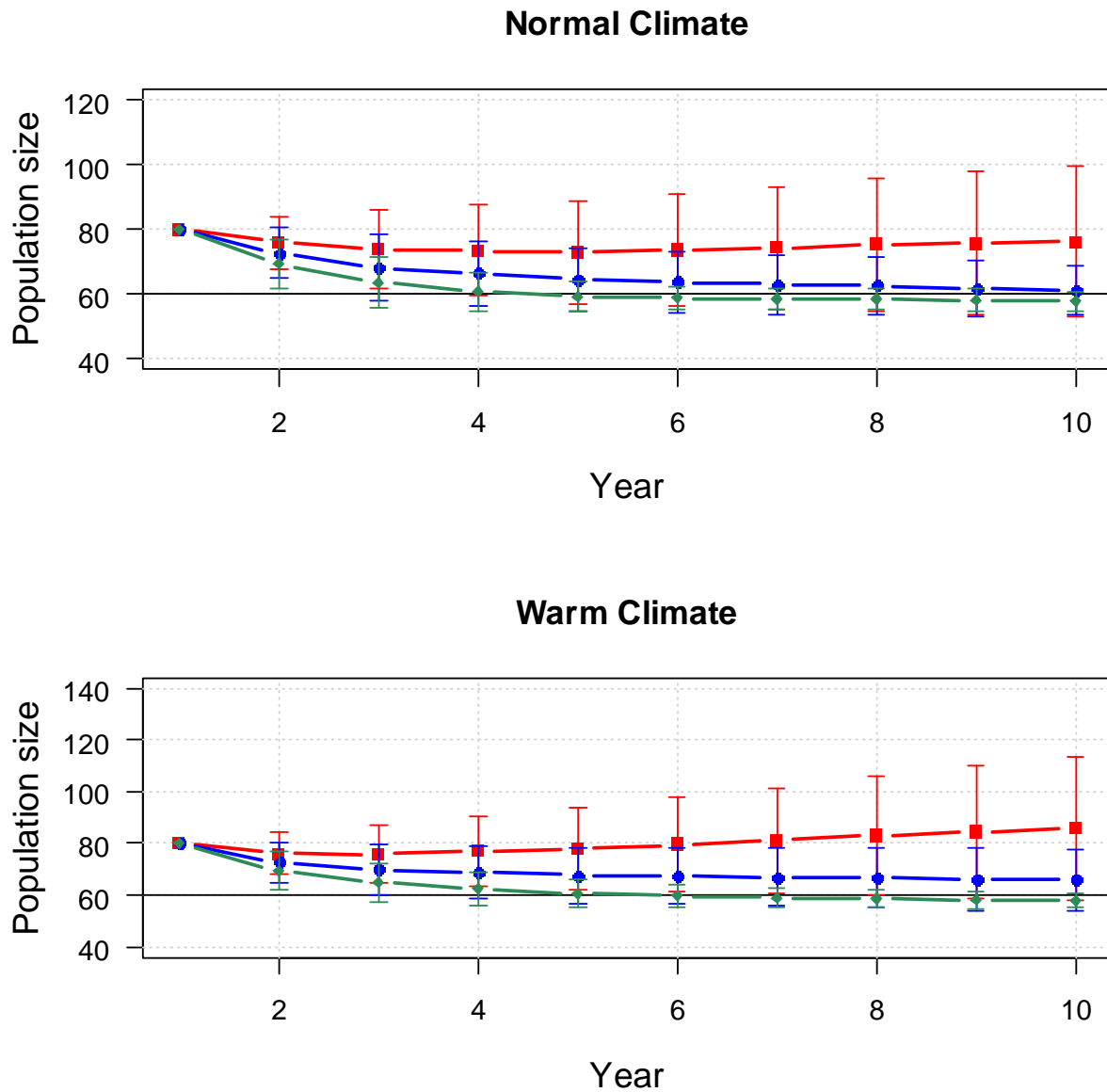


Fig. 17. Simulations of total population size of pink-footed geese using an optimal harvest strategy that assumes equal model weights. The red, blue, and green lines indicate maximum harvest rates in the optimal strategies of 0.08, 0.12, and 0.16, respectively. The graph labeled “Normal Climate” and “Warm Climate” used mean temperature days of 7 and 12, respectively. See text for a description of the models.

Appendix 1. Data used to model the dynamics of the Svalbard population of pink-footed geese for the purpose of harvest management. (markN = capture-recapture estimates of population size, census = ground census in Novemeber, censusJuv = number of juveniles in census, Survival = annual survival rate, Snow = percent cover of snow in May in Svalbard, TempDays = number of days above freezing in may in Svalbard, TempSum = sum of temperatures for days above freezing in May, and HarvDen and HarvNor = harvests in Denmark and Norway, respectively)

Year	markN	censusN	censusNjuv	Survival	Snow	TempDays	TempSum	HarvDen	HarvNor
1965	NA	15000	NA	NA	NA	NA	NA	NA	NA
1966	NA	15000	NA	NA	NA	NA	NA	NA	NA
1967	NA	15000	NA	NA	NA	NA	NA	NA	NA
1968	NA	12200	NA	NA	NA	NA	NA	NA	NA
1969	NA	13100	NA	NA	NA	2	1.25	NA	NA
1970	NA	18800	NA	NA	NA	8	21.6	NA	NA
1971	NA	12000	NA	NA	NA	9	15.8	NA	NA
1972	NA	17700	NA	NA	NA	6	6	NA	NA
1973	NA	18000	NA	NA	NA	4	5.05	NA	NA
1974	NA	12500	NA	NA	NA	9	12.85	NA	NA
1975	NA	15000	NA	NA	NA	4	3.95	NA	NA
1976	NA	20000	NA	NA	NA	8	21.2	NA	NA
1977	NA	25000	NA	NA	NA	8	6.7	NA	NA
1978	NA	20000	NA	NA	NA	15	23.35	NA	NA
1979	NA	28500	NA	NA	NA	0	0	NA	NA
1980	NA	26900	6510	NA	NA	7	8.1	NA	NA
1981	NA	21000	1680	NA	NA	4	6.15	NA	NA
1982	NA	27000	5886	NA	NA	4	4.2	NA	NA
1983	NA	26000	4342	NA	NA	7	6.1	NA	NA
1984	NA	25000	4925	NA	NA	10	18.25	NA	NA
1985	NA	28000	3696	NA	NA	4	1.9	NA	NA
1986	NA	25000	3200	NA	NA	5	4.65	NA	NA
1987	NA	29000	6844	NA	NA	9	8.15	NA	NA
1988	NA	31000	5270	NA	NA	9	13.7	NA	NA
1989	NA	28000	2296	NA	NA	7	10	NA	NA
1990	NA	26000	3224	0.9201	NA	1	0.95	1800	NA
1991	31968	32500	7215	0.9672	NA	9	15.95	3000	NA
1992	33599	32000	1984	0.9321	NA	4	3.25	2500	NA
1993	40919	34000	6154	0.9328	NA	7	8.55	2300	NA
1994	29633	33000	4092	0.9256	NA	7	8.05	2600	NA
1995	39277	35000	8260	0.9171	NA	9	12.9	2800	NA
1996	38630	33000	6072	0.8531	NA	1	0.3	2000	NA
1997	44723	37500	5400	0.8917	NA	4	5	2500	NA
1998	44124	44800	5466	0.9149	NA	0	0	1414	NA
1999	40733	38500	4736	0.9315	NA	13	19.25	1973	NA
2000	38246	43100	2112	0.8639	92.2	6	6.5	2567	NA
2001	41315	45000	4905	0.8671	79.2	2	1	2353	400
2002	51243	42000	4452	0.8743	83.7	8	18.2	2611	500
2003	47358	42900	5448	NA	75.2	8	4.8	2299	550
2004	NA	50300	5634	NA	74.8	11	11.2	2056	700
2005	NA	52000	3796	NA	83.4	8	10.55	1694	1200
2006	NA	56400	9757	NA	57.4	18	39.55	3518	1600
2007	NA	60300	7658	NA	79.5	7	11.05	4597	2200
2008	NA	63000	8190	NA	94.4	5	5.9	5416	2600
2009	NA	63000	6867	NA	79.2	15	13.35	4846	2700
2010	NA	70000	15400	NA	57.9	20	22.95	8841	3200
2011	NA	80000	15600	NA	73.9	10	15.15	8019	3410

Appendix 2. Why *harvest rate* must be used as the control variable in optimization rather than total *harvest*

1. To optimize a total harvest quota (or target), we must first be able to specify (for varying harvest quotas) the portion of the harvest that is expected to be young and the portion that is expected to be adults (actually sub-adults + adults). The expected age composition of the harvest, in turn, depends on the *pre-harvest age composition* of the population (i.e., prior to both the census and harvesting) and the *differential vulnerability of young*.

2. We can easily calculate the pre-harvest population of adults as:

$$A_t = (Y_{t-1} + A_{t-1})\theta_{t-1}$$

3. The pre-harvest population of young is:

$$Y_t = (Y_{t-1} + A_{t-1})\theta_{t-1} \left(\frac{1-h_t}{1-d \cdot h_t} \right) R_t$$

where both h and R are post-harvest and post-census. But h is not known (or specified) when total harvest is the control variable.

However, this equation could provide the pre-harvest population of young (and therefore resolve our problem), if we could assume $\left(\frac{1-h_t}{1-d \cdot h_t} \right)$ is constant. But even if d is constant

(which we do assume), $\left(\frac{1-h_t}{1-d \cdot h_t} \right)$ is not (i.e., it depends on the value of h).

4. Another possibility we explored was to assume that

$$\theta_{t-1} \left(\frac{1-h_t}{1-d \cdot h_t} \right) \approx 1.$$

This was found to be a reasonable assumption, but only based on the assumptions used to partition survival into non-hunting and hunting components for the period in which we had survival rate estimates. If harvest rate varies from the approximately 4% assumed during the period of survival estimates, then the above equation is no longer a valid assumption. Of course, we are explicitly investigating the impacts of varying harvest rates.

5. We concluded that a post-harvest assessment of population size and reproductive success imposes restrictions on the investigation of optimal harvest strategies that cannot be circumvented. This is part of the basis for recommending a pre-harvest population census and some measure of reproductive success prior to harvesting (which could be accomplished by assessing the age composition of the harvest). The problem could also be resolved if estimates of realized harvest rates of both young and adults were available.

Appendix 3. Code for optimizing and simulating harvest strategies for pink-footed geese using the public-domain software SDP (Lubow 1995).

```

!-----
!      PF25 Scenario File
!      (originally PF24 until 12/12/12 revisions)
!
!      MODELS:
!          m0 = R(days,SAA) x S
!          m1 = R(days,SAA) x S(days)
!          m2 = R(days,SAA) x S(days,N)
!          m3 = R(days) x S
!          m4 = R(days) x S(days)
!          m5 = R(days) x S(days,N)
!          m6 = R x S
!          m7 = R x S(days)
!          m8 = R x S(days,N)
!
!      CONTROL: Harvest rate (with harvest in ObjFcn)
!
!      CODED:   July 19, 2012      (PF23)
!      REVISIONS:
!          Oct 30, 2012      warm climate = 12 days
!          Dec 7, 2012      (a) added additional reproduction model (beta dist);
!                          (b) removed prediction errors for balance equation
!          Dec 12, 2012      (a) revised survival models to account
!                          for mis-alignment of anniversary dates;
!                          (b) discretized R, S, variates based on
!                          specified values (rather than probs);
!                          (c) reduced the # of deviates for days;
!                          (d) uses a Guassian obj fcn;
!                          (e) uses a RV "switch" for choosing opt. or sim. -
!                          assures that Cur_Val in sim. is actual harvest
!-----

```

!----- BASIC PARAMETERS -----

```

MAX;
ITERATIONS 20;
ITERATIONS 10|500;
NO_CHANGE 3;
NO_INTERP 2;
NO_EXTRAP;
TITLE "PF25: ";

INIT_STATE 16.0 64.0 8.0 ;
SIM_REPORT 0 1 0 0 0 0 0;
SIM_TRIALS 50;

STATE "Y";
STATE "A";
STATE "DAYS";
DECISION "h";

```

!----- MODEL WEIGHTS -----

```

DISTRIB "MODEL";
RV "m0";
RV "m1";
RV "m2";
RV "m3";
RV "m4";
RV "m5";
RV "m6";
RV "m7";
RV "m8";

```

```
!... choose a single model
!EVENT 0.0 1 0 0 0 0 0 0 0;
!EVENT 0.0 0 1 0 0 0 0 0 0;
!EVENT 0.0 0 0 1 0 0 0 0 0;
!EVENT 0.0 0 0 0 1 0 0 0 0;
!EVENT 0.0 0 0 0 0 1 0 0 0;
!EVENT 0.0 0 0 0 0 0 1 0 0;
!EVENT 0.0 0 0 0 0 0 0 1 0;
!EVENT 1.0 0 0 0 0 0 0 0 1;
```

```
!... equal model wts (no-covariate model gets margin)
```

```
EVENT 0.1111 1 0 0 0 0 0 0 0;
EVENT 0.1111 0 1 0 0 0 0 0 0;
EVENT 0.1111 0 0 1 0 0 0 0 0;
EVENT 0.1111 0 0 0 1 0 0 0 0;
EVENT 0.1111 0 0 0 0 1 0 0 0;
EVENT 0.1111 0 0 0 0 0 1 0 0;
EVENT 0.1112 0 0 0 0 0 0 1 0;
EVENT 0.1111 0 0 0 0 0 0 0 1;
EVENT 0.1111 0 0 0 0 0 0 0 1;
```

```
!----- DAYS ABOVE FREEZING IN MAY -----
```

```
DISTRIB "MAY";
RV "MAY";
!EVENT 1.0 7.2;
```

```
! based on a fitted beta-binomial with p=7.3/31
```

```
EVENT 0.0892 0;
EVENT 0.3563 4;
EVENT 0.3112 8;
EVENT 0.1663 12;
EVENT 0.0607 16;
EVENT 0.0144 20;
EVENT 0.0018 24;
EVENT 0.0001 28;
```

```
! based on a beta-binomial with p=12/31 (and fitted theta)
```

```
!EVENT 0.0052 0;
!EVENT 0.1090 4;
!EVENT 0.2548 8;
!EVENT 0.2938 12;
!EVENT 0.2124 16;
!EVENT 0.0978 20;
!EVENT 0.0249 24;
!EVENT 0.0021 28;
```

```
!----- ANNUAL SURVIVAL (NATURAL MORTALITY ONLY) -----
```

```
DISTRIB "S";
RV "S";
! Mean
!EVENT 1.0 0.9509;
```

```
EVENT 0.0159 0.90;
EVENT 0.0916 0.92;
EVENT 0.3201 0.94;
EVENT 0.4757 0.96;
EVENT 0.0967 0.98;
```

```
!----- ANNUAL REPRODUCTION -----
```

```
DISTRIB "R";
RV "R";
! Mean
!EVENT 1.0 0.147;
```

```
EVENT 0.0691 0.05;
```

```

EVENT 0.3359 0.10;
EVENT 0.3542 0.15;
EVENT 0.1821 0.20;
EVENT 0.0587 0.25;

```

```

!----- OPTIMIZATION (0) OR SIMULATION (1) -----

```

```

DISTRIB "OptSim";
RV "OptSim";
EVENT 1.0 0;

```

```

!----- STATE-SPACE, HARVEST RATES, RVs -----

```

```

! NOTE: do not permit the max harvest rate * diff. vul. of young > 1
! Diff. vul. of young specified in model by default is 2.0
! With this default, the max harvest rate here is 0.5

```

```

STAGE 2.0 2.0 4.0;

```

```

COMBINE 0.0|20.0 0.0|120.0 0.0|28.0, 0.0|0.16|0.04, "MODEL" "MAY" "S" "R" "OptSim" ;

```

```

#include "sd.h"

```

```

{
/*-----*/
INT
Y          = 0,      /* STATE index - young          */
A          = 1,      /* STATE index - adults + subadults */
DAYS       = 2,      /* STATE index - May days        */
M0         = 0,      /* RV index - model M0: R(days,SAA) x S */
M1         = 1,      /* RV index - model M1: R(days,SAA) x S(days) */
M2         = 2,      /* RV index - model M2: R(days,SAA) x S(days,N) */
M3         = 3,      /* RV index - model M3: R(days) x S */
M4         = 4,      /* RV index - model M4: R(days) x S(days) */
M5         = 5,      /* RV index - model M5: R(days) x S(days,N) */
M6         = 6,      /* RV index - model M6: R x S */
M7         = 7,      /* RV index - model M7: R x S(days) */
M8         = 8,      /* RV index - model M8: R x S(days,N) */
MAY        = 9,      /* RV index - May days          */
S          = 10,     /* RV index - natural annual survival */
R          = 11,     /* RV index - reproduction      */

h          = 0;      /* DEC index - harvest rate of adults */

DECIMAL
p1,        /* R(days,SAA) proportion young-of-year */
r1,        /* R(days,SAA) reproductive rate        */
p2,        /* R(days) proportion young-of-year     */
r2,        /* R(days) reprodctive rate             */
r3,        /* R(.) reproductive rate               */
s2,        /* S(days) survival                    */
s3,        /* S(days,N) survival                  */
d          = 2.0,   /* differential vulnerability of young  */
N,         /* total population size                */
z,         /* (1-h)/(1-dh)                        */
nxtY0,     /* model-specific predictions of next young */
nxtY1,
nxtY2,
nxtY3,
nxtY4,
nxtY5,
nxtY6,
nxtY7,
nxtY8,
nxtA1,     /* model-specific predictions of next adults */
nxtA2,
nxtA3,
Yhat,Ahat; /* model-weighted prediction - young, adults */
}

```

```

// Intermediate calculations
p1 = 1 / (1 + exp(-(-1.6874 + 0.0482*cur_state[DAYS] - 0.0142*cur_state[A]]));
r1 = p1/(1-p1);
p2 = 1 / (1 + exp(-(-1.9893 + 0.0268*cur_state[DAYS]]));
r2 = p2/(1-p2);
r3 = outcome[R] / (1-outcome[R]);
s2 = 1 / (1 + exp(-(-2.7382 + 0.0488*cur_state[DAYS]]));
s3 = 1 / (1 + exp(-(-4.2934 + 0.0531*cur_state[DAYS] - 0.0437*(cur_state[Y]+cur_state[A]))));
N = cur_state[Y] + cur_state[A];
z = (1-dec[h]) / (1-d*dec[h]);

// Calculate next states
//...young
nxtY0 = maxx(0.0, N* r1*outcome[S] *z*(1-d*dec[h]) );
nxtY1 = maxx(0.0, N* r1*s2 *z*(1-d*dec[h]) );
nxtY2 = maxx(0.0, N* r1*s3 *z*(1-d*dec[h]) );
nxtY3 = maxx(0.0, N* r2*outcome[S] *z*(1-d*dec[h]) );
nxtY4 = maxx(0.0, N* r2*s2 *z*(1-d*dec[h]) );
nxtY5 = maxx(0.0, N* r2*s3 *z*(1-d*dec[h]) );
nxtY6 = maxx(0.0, N* r3*outcome[S] *z*(1-d*dec[h]) );
nxtY7 = maxx(0.0, N* r3*s2 *z*(1-d*dec[h]) );
nxtY8 = maxx(0.0, N* r3*s3 *z*(1-d*dec[h]) );
Yhat = nxtY0*outcome[M0] + nxtY1*outcome[M1] + nxtY2*outcome[M2] +
nxtY3*outcome[M3] + nxtY4*outcome[M4] + nxtY5*outcome[M5] +
nxtY6*outcome[M6] + nxtY7*outcome[M7] + nxtY8*outcome[M8];
if (Yhat<=0.0) nxt_state[Y] = 0.0;
else nxt_state[Y] = Yhat;

//...adults+subadults
nxtA1 = maxx(0.0, N* outcome[S] *(1-dec[h]) );
nxtA2 = maxx(0.0, N* s2 *(1-dec[h]) );
nxtA3 = maxx(0.0, N* s3 *(1-dec[h]) );
Ahat = nxtA1*(outcome[M0] + outcome[M3] + outcome[M6]) +
nxtA2*(outcome[M1] + outcome[M4] + outcome[M7]) +
nxtA3*(outcome[M2] + outcome[M5] + outcome[M8]);

if (Ahat<=0.0) nxt_state[A] = 0.0;
else nxt_state[A] = Ahat;

//...days above freezing
nxt_state[DAYS] = outcome[MAY];

/*-----*/
return;
}

#include "obj.h"
{
/*-----*/
INT
Y = 0, /* STATE index - young */
A = 1, /* STATE index - adults + subadults */
DAYS = 2, /* STATE index - May days */

M0 = 0, /* RV index - model M0: R(days,SA A) x S */
M1 = 1, /* RV index - model M1: R(days,SA A) x S(days) */
M2 = 2, /* RV index - model M2: R(days,SA A) x S(days,N) */
M3 = 3, /* RV index - model M3: R(days) x S */
M4 = 4, /* RV index - model M4: R(days) x S(days) */
M5 = 5, /* RV index - model M5: R(days) x S(days,N) */
M6 = 6, /* RV index - model M6: R x S */
M7 = 7, /* RV index - model M7: R x S(days) */
M8 = 8, /* RV index - model M8: R x S(days,N) */
MAY = 9, /* RV index - May days */

```

```

S          = 10,      /* RV index - natural annual survival */
R          = 11,      /* RV index - reproduction */
OptSim     = 12,      /* RV index - optimization or simulation */

h          = 0;       /* DEC index - harvest rate */

DECIMAL
p1,        /* R(days,SAA) proportion young-of-year */
r1,        /* R(days,SAA) reproductive rate */
p2,        /* R(days) proportion young-of-year */
r2,        /* R(days) reprodutive rate */
r3,        /* R(.) reproductive rate */
s2,        /* S(days) survival */
s3,        /* S(days,N) survival */
N,         /* total population size */
d          = 2.0,     /* differential vulnerability of young */
z,         /* (1-h)/(1-dh) */
H0,H1,H2,H3,H4,H5, /* model-specific harvests */
H6,H7,H8,
H,         /* model-weighted harvest */
nxtN,     /* next pop size */
pi =      3.14159265, /* pi */
u;        /* utility of population size */

/*-----*/
// Intermediate calculations
p1      = 1 / (1 + exp(-(-1.6874 + 0.0482*cur_state[DAY] - 0.0142*cur_state[A])));
r1      = p1/(1-p1);
p2      = 1 / (1 + exp(-(-1.9893 + 0.0268*cur_state[DAY])));
r2      = p2/(1-p2);
r3      = outcome[R] / (1-outcome[R]);
s2      = 1 / (1 + exp(-(-2.7382 + 0.0488*cur_state[DAY])));
s3      = 1 / (1 + exp(-(-4.2934 + 0.0531*cur_state[DAY] - 0.0437*(cur_state[Y]+cur_state[A]))));
N       = cur_state[Y] + cur_state[A];
z       = (1-dec[h]) / (1-d*dec[h]);

// Calculate harvests
H0      = dec[h] * (d*N* r1*outcome[S] *z + N* outcome[S]);
H1      = dec[h] * (d*N* r1*s2 *z + N* s2);
H2      = dec[h] * (d*N* r1*s3 *z + N* s3);
H3      = dec[h] * (d*N* r2*outcome[S] *z + N* outcome[S]);
H4      = dec[h] * (d*N* r2*s2 *z + N* s2);
H5      = dec[h] * (d*N* r2*s3 *z + N* s3);
H6      = dec[h] * (d*N* r3*outcome[S] *z + N* outcome[S]);
H7      = dec[h] * (d*N* r3*s2 *z + N* s2);
H8      = dec[h] * (d*N* r3*s3 *z + N* s3);
H       = H0*outcome[M0] + H1*outcome[M1] + H2*outcome[M2] +
H3*outcome[M3] + H4*outcome[M4] + H5*outcome[M5] +
H6*outcome[M6] + H7*outcome[M7] + H8*outcome[M8];

/*-----*/
// Alternative utility functions for population size (choose only one)

//...get pop size resulting from harvest rate and last pop size from sd module
nxtN     = nxt_state[Y] + nxt_state[A];

//... PIECEWISE LINEAR
//      if (nxtN>=55 && nxtN<=65) u=1.0;
//      else u=0.0;

//... PARABOLA (peaks at 60, zero at 0 & 120)
//      if (nxtN>120) u = 0.0;
//      else u = -0.000277778 * pow((nxtN-60.0),2) + 1;

//... RICKER function (peaks at 60)

```

```

//      u      =      0.0453047*nxtN*exp(-0.0166667*nxtN);

if (outcome[OptSim] == 0)
{
//... GUASSIAN (with normalizing constant so u=1 when N=60)
//..... norm. constant = pdf(60,mu=60,s=10)
      if (nxtN<=0.0)      u=0.0; /* truncate normal */
      else      u = (exp(-0.5 * pow( ((nxtN-60.)/10.), 2.0) ) / (10.*sqrt(2.*pi))) / 0.03989423;
}
else
//... for maximizing harvest or simulating performance
      u = 1;

/*-----*/
result= u * H;
/*-----*/
return(result);
}

#include "tv.h"
{
/*-----*/
/* No terminal values.      */
/*-----*/
return(result);
}

```

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