

Uncertainty, robustness, and the value of information in managing an expanding Arctic goose population[☆]



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ABSTRACT

We explored the application of dynamic-optimization methods to the problem of pink-footed goose (*Anser brachyrhynchus*) management in western Europe. We were especially concerned with the extent to which uncertainty in population dynamics influenced an optimal management strategy, the gain in management performance that could be expected if uncertainty could be eliminated or reduced, and whether an adaptive or robust management strategy might be most appropriate in the face of uncertainty. We combined three alternative survival models with three alternative reproductive models to form a set of nine annual-cycle models for pink-footed geese. 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 they are influenced by spring temperatures. We calculated state-dependent harvest strategies for these models using stochastic dynamic programming and an objective function that maximized sustainable harvest, subject to a constraint on desired population size. As expected, attaining the largest mean objective value (i.e., the relative measure of management performance) depended on the ability to match a model-dependent optimal strategy with its generating model of population dynamics. The nine models suggested widely varying objective values regardless of the harvest strategy, with the density-independent models generally producing higher objective values than models with density-dependent survival. In the face of uncertainty as to which of the nine models is most appropriate, the optimal strategy assuming that both survival and reproduction were a function of goose abundance and spring temperatures maximized the expected minimum objective value (i.e., maxi-min). In contrast, the optimal strategy assuming equal model weights minimized the expected maximum loss in objective value. The expected value of eliminating model uncertainty was an increase in objective value of only 3.0%. This value represents the difference between the best that could be expected if the most appropriate model were known and the best that could be expected in the face of model uncertainty. The value of eliminating uncertainty about the survival process was substantially higher than that associated with the reproductive process, which is consistent with evidence that variation in survival is more important than variation in reproduction in relatively long-lived avian species. Comparing the expected objective value if the most appropriate model were known with that of the maxi-min robust strategy, we found the value of eliminating uncertainty to be an expected increase of 6.2% in objective value. This result underscores the conservatism of the maxi-min rule and suggests that risk-neutral managers would prefer the optimal strategy that maximizes expected value, which is also the strategy that is expected to minimize the maximum loss (i.e., a strategy based on equal model weights). The low value of information calculated for pink-footed geese suggests that a robust strategy (i.e., one in which no learning is anticipated) could be as nearly effective as an adaptive one (i.e., a strategy in which the relative credibility of models is assessed through time). Of course, an alternative explanation for the low value of information is that the set of population models we considered was too narrow to represent key uncertainties in population dynamics. Yet we know that questions about the presence of density dependence must be central to the development of a sustainable harvest strategy. And while there are potentially many environmental covariates

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that could help explain variation in survival or reproduction, our admission of models in which vital rates are drawn randomly from reasonable distributions represents a worst-case scenario for management. We suspect that much of the value of the various harvest strategies we calculated is derived from the fact that they are state dependent, such that appropriate harvest rates depend on population abundance and weather conditions, as well as our focus on an infinite time horizon for sustainability.

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1. Introduction

Decision analysis has been widely used in business and government decision making (Keefer et al., 2004), but its application to problems in natural resource management has mostly been a phenomenon of the last two decades (Huang et al., 2011). Though decision-analytic approaches vary considerably, environmental decision making typically involves (1) properly formulating the decision problem; (2) specifying feasible alternative actions; and (3) selecting criteria for evaluating potential outcomes (Tonn et al., 2000). A noteworthy aspect of the trend toward formal decision analysis in natural resource management has been the increasing application of dynamic optimization methods to analyze recurrent decisions (Possingham, 1997; Walters and Hilborn, 1978; Williams, 1989). Recurrent decision problems are ubiquitous in conservation, ranging from obvious examples like harvesting or prescribed burning, to less obvious ones like development of a biological reserve system or the control of invasive plants and animals. The growing number of resource-management examples that rely on dynamic optimization methods is testament to the general applicability of these methods, and the rapid increase in computing power has made it feasible to analyze problems of at least moderate complexity.

Dynamic optimization methods combine models of ecological system change with objective functions that value present and future consequences of alternative management actions. The general resource management problem involves a temporal sequence of decisions, where the optimal action at each decision point depends on time and/or system state (Possingham, 1997). The goal of the manager is to develop a decision rule (or management policy or strategy) that prescribes management actions for each time and system state that are optimal with respect to the objective function. Under the assumption of Markovian system transitions, the optimal management policy satisfies the Principle of Optimality (Bellman, 1957), which states that:

An optimal policy has the property that, whatever the initial state and decision are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision.

Thus, a key advantage of dynamic optimization is its ability to produce a feedback policy specifying optimal decisions for *possible* future system states rather than *expected* future states (Walters and Hilborn, 1978). In practice this makes optimization appropriate for systems that behave stochastically, absent any assumptions about the system remaining in a desired equilibrium or about the production of a constant stream of resource returns. The analysis of recurrent decision problems with dynamic optimization methods also allows for the specification of the relative value of current and future management returns through discount rates. By properly framing problems, dynamic optimization methods have been used successfully to address a broad array of important conservation issues (Bogich and Shea, 2008; Johnson et al., 2011; Martin et al., 2011; Milner-Gulland, 1997; Richards et al., 1999; Tenhumberg et al., 2004).

A key consideration in dynamic optimization of natural resource problems is the uncertainty attendant to management outcomes, which adds to the demographic and environmental variation of

stochastic resource changes. This uncertainty may stem from errors in measurement and sampling of ecological systems (partial system observability), incomplete control of management actions (partial controllability), and incomplete knowledge of system behavior (structural or model uncertainty) (Williams et al., 1996). A failure to recognize and account for these uncertainties can significantly depress management performance and in some cases can lead to severe environmental and economic losses (Ludwig et al., 1993). In recent years there has been an increasing emphasis on methods that can account for uncertainty about the dynamics of ecological systems and their responses to both controlled and uncontrolled factors (Walters, 1986; Williams, 2001).

Model uncertainty, an issue of special importance in adaptive management, can be characterized by continuous or discrete probability distributions of model parameters, or by discrete distributions of alternative model forms that are hypothesized or estimated from historic data (Johnson et al., 1997; Walters and Hilborn, 1978). Important advances have followed from the recognition that these probability distributions are not static, but evolve over time as new observations of system behaviors are accumulated from the management process. Indeed, the defining characteristic of adaptive management is the attempt to account for the temporal dynamics of this uncertainty in making management decisions (Allen et al., 2011; Walters, 1986; Walters and Holling, 1990; Williams, 2001; Williams et al., 1996).

There has been a great deal written about why adaptive management programs are not commonplace, but perhaps too little attention has been paid to whether adaptive management is the appropriate tool for a specific resource issue (Gregory et al., 2006). Doremus (2011) made an effective case that adaptive management is an information problem, in that the key question to be addressed is whether the lack of information about ecological processes and system responses to human intervention is the principal impediment to decision making and effective management. Adaptive management can be expensive, and decision makers need some assurance that those costs can be offset by improvements in management performance resulting from a reduction in uncertainty. Uncertainty in resource conservation is ubiquitous, but not all uncertainties matter when choosing the best management actions, and not all uncertainties that matter can be reduced through the application of those actions. Decision makers require some way to identify pertinent and reducible uncertainties so as to determine whether a particular resource conservation issue is a good candidate for adaptive management, whether learning through management is possible, and whether an effective adaptive management program can be designed.

We explored the application of dynamic-optimization methods to the problem of goose management in western Europe. We were especially concerned with the extent to which uncertainty in population dynamics influenced an optimal management strategy, the gain in management performance that could be expected if uncertainty could be eliminated or reduced, and whether an adaptive or robust management strategy might be most appropriate. We use robust to mean a strategy that could be expected to perform relatively well in the face of persistent uncertainty about population dynamics (i.e., regardless of which alternative model is most appropriate to describe system dynamics). Learning is neither needed nor anticipated in development of a robust strategy.

The need for more informed management of European goose populations has taken on a sense of urgency. The majority of goose populations breeding or wintering in western Europe have increased considerably in abundance during recent decades (Fox et al., 2010; Madsen et al., 1999). This constitutes one of the major successes in European wildlife conservation history, ascribed to a combination of factors such as a decrease in exploitation, more refuge areas, improved winter feeding conditions, and climate change (Bauer et al., 2008; Kéry et al., 2006). Geese are regarded as a highly valued recreational resource, beloved by birdwatchers and the general public, and harvested by hunters in some countries. However, due to their tendency to concentrate on farmlands, the continued increase in numbers has escalated agricultural conflicts during spring migration. Also, in some Arctic regions, increasing goose abundance has resulted in overexploitation of vegetation, causing long-term degradation of tundra habitats. It is now understood that successful management of these migratory populations will require international cooperation in order to achieve and maintain viable populations, while taking into account other socio-economic interests. Yet internationally coordinated management instruments or plans have little precedent in Europe. In contrast, a technically complex and well-coordinated system of waterfowl management has been in place for decades in North America (Johnson and Williams, 1999).

The African-Eurasian Waterbird Agreement (AEWA; <http://www.unep-aewa.org/>) recently called for improved management of goose populations that cause conflicts with human economic activities. The Svalbard population of the pink-footed goose was selected as the first test case for development of an international species-management plan (Madsen and Williams, 2012). The Svalbard population breeds primarily in Spitsbergen, migrates through Norway, and winters primarily in Denmark, the Netherlands, and Belgium. The goal of the 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 were 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 degradation in the breeding range.
- Allow for recreational use that does not jeopardize the population.

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

- maintain a population size of around 60,000, within a range to prevent the population from either collapsing or erupting; and
- optimize hunting regulations and practices to regulate the population size if needed and in range states where hunting is permitted (Madsen and Williams, 2012).

Our focus here is on improving the harvest management of pink-footed geese in Norway and Denmark where these geese are currently hunted. We aimed to develop an optimal, state-dependent harvest strategy, which could account for stochastic changes in population size and environmental conditions over time. Moreover, we were interested in developing a strategy that was likely to be robust to several key sources of uncertainty in population dynamics. Our ultimate goal is to develop processes for

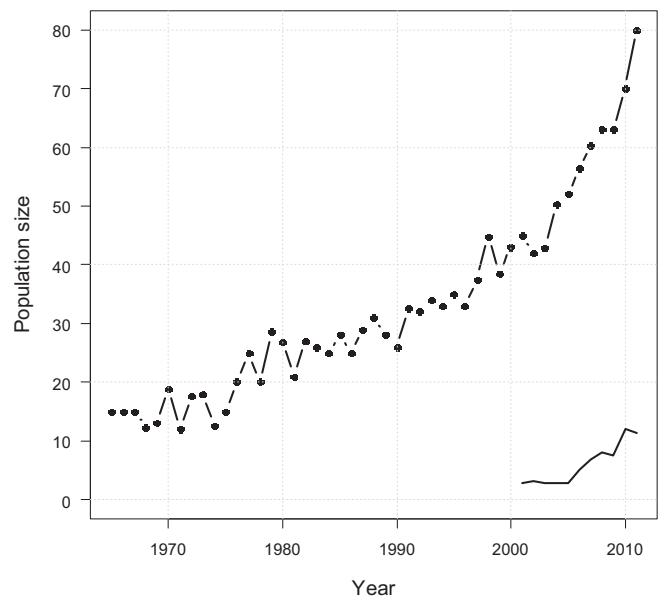


Fig. 1. Ground census of pink-footed geese (in thousands) in autumn in Denmark, the Netherlands, and Belgium. The solid line at the bottom of the graph is the estimated harvest in Norway and Denmark.

managing population size that are applicable to several species of over-abundant geese in Europe.

2. Model and methods

2.1. Data

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 in Norway, Denmark, the Netherlands, and Belgium since 1965 (Fig. 1). Geese were counted simultaneously in the three countries to avoid double-counting. The count is assumed to be a census and, thus, no measure of sampling variability is available. Capture–recapture estimates of fall population size were available from 1991 to 2003, based on neck-banding during spring migration and re-sighting efforts during the migration and wintering periods (Kéry et al., 2006). Estimates from the two survey methods were highly correlated ($r=0.68$), although the capture–recapture estimates were about 6% higher on the average.

Estimates of survival based on neck-banding were available from the period 1990–2002 (Kéry et al., 2006). We used estimates of survival provided to us 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. Because survival rate estimates have an anniversary date of approximately February 1, 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 (Calvert and Gauthier, 2005; Francis et al., 1992; Gauthier et al., 2001; Menu et al., 2002; Rexstad, 1992). 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.

Estimates of harvest were available from Denmark during 1990–2010, and from Norway during 2001–2010 (Fig. 1). Danish estimates were based on a combination of hunter-collected goose wings and reports of total goose bags. Norwegian estimates of pink-footed goose harvest were derived from on-line reports by hunters.

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 modeling population demography we used the proportion of juveniles as an indicator of reproductive success during the preceding breeding season.

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 substantial effect because of its potential impact on breeding effort (Madsen et al., 2007). 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 only for the period 2000–2011 (Jensen et al., 2013). 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, Svalbard). 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.

2.2. Annual cycle model

For assessment purposes, we considered November 1 as the anniversary date of the annual cycle for pink-footed geese, 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). 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 or more 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., 2006a), but available data were insufficient to characterize the degree of age-specificity that might be appropriate for pink-footed geese.

Before constructing models based on annual estimates of survival and reproductive rates, we were interested in whether available estimates of those rates suggested changes in population size that were comparable to those derived from the population census. Let:

t = year,

N^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),

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

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

$N = N^Y + N^{SA} + N^A$ = 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 survived at least one hunting season,

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

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

We then assumed that all birds surviving their first hunting season had the same annual survival rates and that hunting mortality was additive to natural mortality and a constant one-half of total annual mortality:

$$\hat{h}_t = \frac{1 - \hat{S}_t}{2}, \quad (1)$$

$$\hat{\theta}_t = \frac{\hat{S}_t}{1 - (1 - \hat{S}_t)/2}. \quad (2)$$

We also assumed that 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 November 1–January 31 and $\hat{\theta}_{t+1}^{0.75}$ = survival from natural causes during February 1–October 31.

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

$$\hat{N}_{t+1}^A = N_t(1 - \hat{p}_t)\hat{\theta}_t^{0.25}\hat{\theta}_{t+1}^{0.75}(1 - \hat{h}_{t+1}) \quad (3)$$

$$\hat{N}_{t+1}^{SA} = N_t\hat{p}_t\hat{\theta}_t^{0.25}\hat{\theta}_{t+1}^{0.75}(1 - \hat{h}_{t+1}) \quad (4)$$

$$\hat{N}_{t+1}^Y = N_t\hat{\theta}_t^{0.25}\hat{\theta}_{t+1}^{0.75}(1 - \hat{h}_{t+1}) \left(\frac{\hat{p}_{t+1}}{1 - \hat{p}_{t+1}} \right). \quad (5)$$

We then compared the observed N_{t+1} with the predicted \hat{N}_{t+1} to check for evidence of bias in estimates of survival and reproduction. We estimated the slope of the line through the points (N_{t+1}, \hat{N}_{t+1}) using least-squares and assuming an intercept of zero. The slope was not significantly different from one ($\beta_1 = 1.00$, $\widehat{se}(\beta_1) = 0.036$, $P > 0.9$), suggesting that survival and reproductive estimates were unbiased, which is in contrast to the positive bias in estimates of demographic rates for some North American waterfowl (Martin et al., 1979).

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

$$N_{t+1}^A = (N_t^A + N_t^Y)\theta_t(1 - h_t). \quad (6)$$

We remind the reader that the anniversary date for the model is November 1, after the bulk of the harvest has occurred. 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:

$$N_{t+1}^Y = (N_t^A + N_t^Y)\theta_t(1 - h_t)R_t, \quad (7)$$

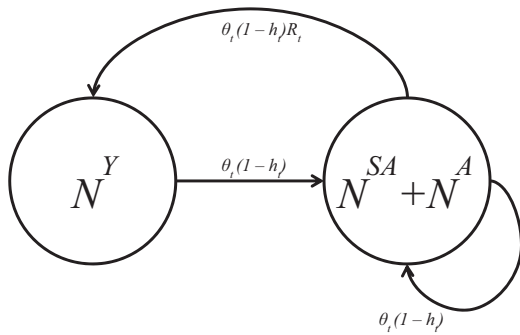


Fig. 2. Life cycle of pink-footed geese, where N^Y , N^{SA} , and N^A are the number of birds aged 0.5, 1.5, and ≥ 2.5 years on November 1, respectively. Annual survival from sources of natural mortality is θ , harvest rate is h , and reproductive rate is R .

where the first three terms provide the number of geese surviving from November 1 of year t to October 31 of 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:

$$H_t^A = (N_t^A + N_t^Y)\theta_t h_t, \quad (8)$$

and the harvest of young is:

$$H_t^Y = \frac{(N_t^A + N_t^Y)\theta_t(1-h_t)R_t}{(1-dh_t)} dh_t, \quad (9)$$

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): $(\%N_t^Y)_{bag} = 22.06 + 0.89(\%N_t^Y)_{pop}$. 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 $d = 1.99 \approx 2.0$. 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.

2.3. Model parameterization

Here we describe the development of dynamic models for survival and reproductive processes. We emphasize that our goal was not necessarily to identify the model(s) 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 covariate values 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 (Runge and Johnson, 2002; Walters, 1986).

2.3.1. 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 estimated θ_t using the annual survival estimates \hat{S}_t for the period 1990–2002 and, as before, assuming hunting mortality was additive to natural mortality and a constant 50% of total annual mortality. The estimates $\hat{\theta}_t$ had a mean of 0.951 and a standard deviation of 0.019, which incorporates both sampling error and true annual variation. We then used the method of moments to parameterize a beta distribution: $\hat{\theta}_t \sim \text{Beta}(125.16, 6.46)$. For the purpose of optimizing a harvest strategy, 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 (in thousands) on November 1, various weather variables X in the interval November 1–October 31, and used least-squares regression to fit the model:

$$\ln\left(\frac{\hat{\theta}_t}{1-\hat{\theta}_t}\right) = \beta_0 + \beta_1 X_t + \beta_2 N_t. \quad (10)$$

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

$$\hat{\theta}_t = \frac{1}{1 + e^{-(\hat{\beta}_0 + \hat{\beta}_1 X_t + \hat{\beta}_2 N_t)}}. \quad (11)$$

Of those models that included population size, but varied depending on the specific weather variable included, only two had delta AIC values < 2.0 . Delta AIC is the difference in AIC values between a fully saturated model and a reduced model, with values < 2.0 indicative of models worthy of consideration (Burnham and Anderson, 1998). The two candidate models were one with temperature days (*TempDays*) and one with temperature sum (*TempSum*) (as described in the section entitled Data). The difference in AIC values between these models was only 0.1, suggesting they were virtually indistinguishable based on the data. The model including temperature days (*TempDays*) and population size (N , in thousands) had the lowest AIC of all models examined:

$$\ln\left(\frac{\hat{\theta}_t}{1-\hat{\theta}_t}\right) = 4.293 + 0.053 \text{TempDays}_t - 0.044 N_t. \quad (12)$$

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

$$\ln\left(\frac{\hat{\theta}_t}{1-\hat{\theta}_t}\right) = 2.738 + 0.049 \text{TempDays}_t. \quad (13)$$

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. An alternative explanation 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 during 2001–2004, prior to when they began increasing substantially). 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).

2.3.2. 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:

$$\ln \left(\frac{\hat{p}_t}{1 - \hat{p}_t} \right) = \beta_0 + \beta_1 X_t + \beta_2 N_t^A, \quad (14)$$

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

$$\hat{p}_t = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_t + \beta_2 N_t^A)}}. \quad (15)$$

We recognize that only birds aged three years or older in spring are consistent 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 based on AIC included population size and temperature days:

$$\ln \left(\frac{\hat{p}_t}{1 - \hat{p}_t} \right) = -1.687 + 0.048 \text{TempDays}_t - 0.014 A_t, \quad (16)$$

where N_t^A is the number of sub-adults and adults (in thousands) on November 1. 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. This also corresponds to a period of above-average temperature days in Svalbard, 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 by 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:

$$\ln \left(\frac{\hat{p}_t}{1 - \hat{p}_t} \right) = -1.989 + 0.027 \text{TempDays}_t. \quad (17)$$

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.

2.3.3. Dynamics of temperature days

The number of days above freezing in May (TempDays_t), 1969–2011, in Svalbard averaged 7.3 (sd = 4.4). There was no evidence of autocorrelation for lags up to 20 years, 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 ($\bar{p} = 0.23$, $\theta = a/\bar{p} = b/(1 - \bar{p}) = 11.04$). Using this distribution, we calculated the probabilities of observing n days where $n \in \{0, 4, 8, 12, \dots, 28\}$ and $P(n_t) \in \{0.0892, 0.3562, 0.3112, 0.1663, 0.0607, 0.0144, 0.0018, 0.0001\}$, respectively.

2.4. Optimal harvest strategies

2.4.1. Markov decision process

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. 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 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 $i \in \{1, 2, \dots, I\}$. 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 $U(a_t | x_t)$. Utility is thus influenced 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 :

$$V(A_t | x_t) = E \left[\sum_{\tau=t}^T U(a_\tau | x_\tau) | x_t \right], \quad (18)$$

where $V(A_t | x_t)$ is the value of a state and time dependent strategy prescribing optimal actions.

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

$$\max_{A_0} V(A_0 | x_0, q_0) \quad (19)$$

subject to:

$$x_{t+1} = f_i(x_t, a_t, z_t) \quad t \in \{0, 1, \dots, T-1\}, \quad i \in \{1, \dots, I\}$$

$$q_{t+1} = g(q_t, x_{t+1}) \quad t \in \{0, 1, \dots, T-1\}.$$

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:

$$V(A_t | x_t, q_t) = U(a_t | x_t, q_t) + \sum_{x_{t+1}} P(x_{t+1} | x_t, a_t, q_t) V(A_{t+1} | x_{t+1}, q_t), \quad (20)$$

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

$$U(a_t | x_t, q_t) = \sum_i q_t(i) U_i(a_t | x_t), \quad (21)$$

as well as probabilities

$$P(x_{t+1} | x_t, a_t, q_t) = \sum_i q_t(i) P_i(x_{t+1} | x_t, x_t, a_t), \quad (22)$$

and future values

$$V(A_{t+1} | x_{t+1}, q_t) = \sum_i q_t(i) V_i(A_{t+1} | x_{t+1}). \quad (23)$$

The corresponding optimization form is:

$$V[x_t, q_t] = \max_{a_t} \left\{ U(a_t | x_t, q_t) + \sum_{x_{t+1}} P(x_{t+1} | x_t, a_t, q_t) V[x_{t+1}, q_t] \right\}, \quad (24)$$

with optimization proceeding by standard backward induction starting at the terminal time T . In this framework, the model state q_t is a fixed (i.e., constant) parameter over the timeframe $[t, T]$ of the optimization. The updating of the model state occurs “off-line” of the optimization algorithm, after a decision is implemented and

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 A are total population size and the number of sub-adults plus adults (in thousands), respectively, on November 1. 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 defined carrying capacity.

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

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 using the new model state over the new timeframe $[t+1, T]$. With this operational sequence of optimization, implementation, monitoring, and model updating, 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.”

2.4.2. Harvest management for pink-footed geese

We combined the three alternative survival models with the three alternative reproductive models to form a set of nine annual-cycle models for pink-footed geese. These models represent a wide range of possibilities concerning the extent to which demographic rates are density dependent or independent, and to the extent that 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 was 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.

The identification of an optimal harvest strategy for pink-footed geese then involved integrating: (a) a management objective; (b) a set of potential harvest actions; (c) models of population dynamics; and (d) a monitoring program to identify system state.

The harvest management objective, expressed in terms of state and action dependent utilities, was:

$$V[x_t] = \max_{(a_t)} E \left[\sum_{\tau=t}^T H(a_\tau | x_\tau) u(a_\tau | x_\tau) | x_t \right], \quad (25)$$

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

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

$$= 0 \quad \text{otherwise} \quad (26)$$

and N_{t+1} is total population size (in thousands). Harvest-utility is thus a bell-shaped curve with its peak corresponding to a goal for population size of 60 thousand. The objective function (Eq. (25)) 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. The harvest-utility curve is symmetric, but an asymmetric curve in which utility drops faster for small populations than large populations might be more appropriate in those cases where population viability is more of a concern than problems associated with high abundance. We emphasize that the population target is not a fundamental objective, but rather a means objective (Keeney, 1992) that is intended to indirectly satisfy the concerns of diverse stakeholders, including conservationists and farmers that incur crop damage.

We required a set of potential harvest-management actions available at each time $A_t \in \{a_t^1, a_t^2, a_t^3, \dots\}$, but the degree to which harvest rates can be manipulated on geese in Europe is largely unknown. We also do not know the maximum harvest rate that is either attainable or socially acceptable. For investigative purposes, we used potential harvest rates of $h_t \in \{0.00, 0.04, 0.08, \dots, 0.16\}$ 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 17 thousand (about 40% higher than the observed maximum harvest) out of a population of 80 thousand birds. 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. 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 absolute harvests.

Finally we required one or more models that predict the consequences of those actions in terms that are relevant to the management objectives. The nine models of population dynamics have been described previously and are summarized in Table 1. For the time-specific observation of system state x_t , managers would rely on the number of young and number of adults in November and temperature days in May to identify the optimal state-dependent harvest action, and ultimately to update model weights $q_{t+1} = g(q_t, x_t, a_t)$.

Given these components (Table 2), optimal harvest strategies were calculated using the public-domain software SDP (Lubow, 1995), which implements the backward-induction algorithm known as discrete stochastic dynamic programming (Puterman, 1994). We calculated the optimal harvest strategy for each of the nine models (i.e., using a model state with probability 1.0 for one model and 0.0 for the remaining eight models) and for a model state that considered all models equally plausible (i.e., each model with a weight of 1/9). We calculated harvest strategies for an infinite time horizon by continuing the backward induction until the strategy stabilized (i.e., was no longer time dependent). We then simulated each of the 10 harvest strategies for one thousand iterations under each model of population dynamics.

We used two approaches to determine a robust harvest strategy; i.e., one that would perform “well” regardless of uncertainty about the most appropriate model. In the first approach, we identified the harvest strategy that maximized the minimum level of expected performance (in terms of the average objective value) regardless of the most appropriate model. This so-called maxi–min approach has sometimes been criticized, however, as being too

Table 2

Values taken by state, decision, and random variables for optimization of pink-footed geese harvest rates.

Variable	Values
N^Y = number of young (in thousands) in November	0: 2: 20 ^a
N^V = number of sub-adults and adults (in thousands) in November	0: 2: 120 ^a
$TempDays$ = number of days above freezing in May	Pr(0) = 0.0892 Pr(4) = 0.3562 Pr(8) = 0.3112 Pr(12) = 0.1663 Pr(16) = 0.0607 Pr(20) = 0.0144 Pr(24) = 0.0018 Pr(28) = 0.0001
h = harvest rate	0.00: 0.04: 0.16 ^a
θ = annual survival from natural sources of mortality (models M0, M3, M7)	Pr(0.90) = 0.0159 Pr(0.92) = 0.0916 Pr(0.94) = 0.3201 Pr(0.96) = 0.4756 Pr(0.98) = 0.0967
p = proportion of young in November (models M6, M7, M8)	Pr(0.05) = 0.0159 Pr(0.10) = 0.0916 Pr(0.15) = 0.3201 Pr(0.20) = 0.4756 Pr(0.25) = 0.0967

^a Notation $x: y: z$ indicates minimum value, increment, and maximum value, respectively.

conservative because it emphasizes the worst possible outcome (Berger, 1985). In the second approach, we identified the harvest strategy that is expected to minimize the maximum loss (Polasky et al., 2011). In this case, the loss in performance for each model-strategy combination is calculated as the difference between the expected performance for each model-strategy combination and the best performance expected under each model. Then the robust strategy is the one that minimizes the maximum loss across all models. In both approaches to robustness, we assumed all nine population models were equally plausible. The use of informative prior weights on the models could lead to different robust strategies.

Finally, we investigated the expected value of information, which characterizes the increase in management performance that could be expected if model uncertainty were reduced or eliminated (Runge et al., 2011; Williams et al., 2011). We first calculated the expected value of perfect information (EVPI), which is the expected increase in objective value assuming that the most appropriate of the nine population models could be identified:

$$EVPI_t(x, q) = \sum_i q_t(i) \max_{A_t} V^i(A_t | x_t) - \max_{A_t} \sum_i q_t(i) V^i(A_t | x_t), \quad (27)$$

where i denotes a population model, $q(i)$ is the probability associated with model i , and $V^i(A_t | x_t)$ is the model-specific value of an optimal, state-dependent strategy. EVPI thus is the model-averaged maximum objective value across models, less the maximum of the model-averaged objective values. In other words, EVPI is the difference between the expected value if model uncertainty were resolved (the first term) and the best performance that could be expected in the face of continuing uncertainty (the second term). Note from Eq. (27) that EVPI depends on time t , system state x and model state q . For our purposes, we used the simulations described previously to determine a time- and state-averaged EVPI under the assumption of equal and constant model weights.

We also calculated the expected value of partial information (EVPXI), focusing on the expected gain in management performance if either uncertainty about the survival or reproductive models could be resolved. EVPXI can be useful for determining which source of uncertainty most limits management performance, and therefore which uncertainty may be the most important target

Table 3
Mean objective values (in thousands of geese) based on simulations of model-specific, optimal strategies for nine models of pink-footed goose population dynamics. Refer to Table 1 for a description of the models. M= represents the optimal strategy when all nine models are weighted equally. In the face of uncertainty as to the most appropriate model, the model-specific optimal strategy for model M2 is expected to maximize the minimum objective value.

Survival Reproduction Strategy	Model									min
	(.) (days, A) M0	(days) (days, A) M1	(days, N) (days, A) M2	(.) (days) M3	(days) (days) M4	(days, N) (days) M5	(.) (.) M6	(days) (.) M7	(days, N) (.) M8	
M0	4.78	5.31	1.39	7.90	8.47	2.90	7.30	7.83	2.85	1.39
M1	4.77	5.31	1.42	7.85	8.47	2.93	7.30	7.86	2.83	1.42
M2	4.31	4.87	2.12	7.45	8.30	3.26	6.79	7.40	3.23	2.12
M3	4.75	5.22	0.85	8.06	8.58	2.42	7.28	7.79	2.53	0.85
M4	4.72	5.28	0.99	8.05	8.63	2.53	7.23	7.74	2.59	0.99
M5	4.58	5.14	2.02	7.55	8.34	3.31	7.02	7.63	3.25	2.02
M6	4.68	5.12	1.04	7.81	8.31	2.58	7.42	7.75	2.68	1.04
M7	4.65	5.12	1.15	7.82	8.39	2.70	7.41	7.86	2.70	1.15
M8	4.43	4.97	2.06	7.47	8.22	3.28	7.02	7.64	3.28	2.06
M=	4.72	5.26	1.80	7.67	8.32	3.23	7.28	7.86	3.15 max	1.80 2.12

for active adaptive management or a traditional research program. EVPXI measures the loss of value corresponding to uncertainty across the models in one subset, while accounting for the residual uncertainty in the complimentary subset (Williams et al., 2011). In our case, we have three alternative survival models and three reproductive models. We calculated the value of EVPXI as:

$$\text{EVPXI}_t^l(x, q) = \sum_i q_t(i) \max_{A_t} \sum_{\hat{i}} q(\hat{i} | i) V^{ii}(A_t | x_t) - \max_{A_t} \sum_{i, \hat{i}} q_t(i, \hat{i}) V^{ii}(A_t | x_t), \quad (28)$$

where i and \hat{i} are indices corresponding to the survival and reproductive models respectively, such that model (i, \hat{i}) denotes a specific combination of one survival model and one reproductive model. Note that the second term in EVPXI is equivalent to the second term in calculating EVPI in Eq. (27) (i.e., the best that can be done in the face of continued uncertainty about which of the nine models is most appropriate). Eq. (28) denotes the value of eliminating uncertainty about the three alternative survival models. An analogous expression for the three reproductive models is obtained by switching i and \hat{i} in Eq. (28). As before, we used simulation results to obtain time- and state-averaged values of EVPXI, by considering equal and constant model weights.

3. Results

As expected, attaining the largest mean objective value depended on the ability to match a model-dependent optimal strategy with its generating model of population dynamics (Table 3). The nine models suggested widely varying objective values regardless of the harvest strategy, with the density-independent models generally producing higher objective values than models with density-dependent survival. Recall that the models with density-dependent survival suggest relatively low carrying capacities (Table 1), so that only very low rates of harvest permitted the pink-footed goose population to remain near the goal of 60 thousand. Density-independent models, on the other hand, allowed for relatively high rates of harvest that were also capable of keeping the population near its goal.

In the face of uncertainty as to the most appropriate model of population dynamics, the optimal strategy that assumed both survival and reproduction were a function of goose abundance and temperature days (i.e., the optimal strategy for model M2) maximized the expected minimum objective value across all models (Table 4). In contrast, the optimal strategy assuming equal model weights minimized the expected maximum loss in objective value.

Optimal strategies for models M5 (density-dependent survival, and both survival and reproduction a function of temperature days) and M8 (density and temperature dependent survival; random reproduction) are also expected to be relatively robust based on our criteria.

The two most robust harvest strategies exhibit both similarities and differences. The optimal strategy for model M2 suggests relatively sharp increases in harvest rate as the population increases above about 45 thousand birds, regardless of the number of days above freezing in May (Fig. 3). Note, however, that the increase in optimal harvest rate is more rapid with higher numbers of warm days in May. Regardless of the number of temperature days, the optimal strategy is rather “knife-edged,” meaning that relatively large changes in optimal harvest rate can accompany relatively small changes in goose abundance. Knife-edged strategies are typically frowned upon in practice because stakeholders often fail to understand the need for large changes in hunting regulations with small changes in goose abundance, or because relatively small changes in goose abundance are not detectable within the precision of extant monitoring programs. Interestingly, the optimal strategy for model M2 suggests that harvest rates should be decreased at very high levels of goose abundance. This counter-intuitive result follows from the fact that this model posits rather dramatic reductions in survival and reproduction at high population sizes, such that relatively low harvest rates are sufficient to reduce the population size toward the goal of 60 thousand.

The optimal strategy assuming equal model weights is similar to that for model M2, except that there is less of an effect of temperature days and the strategy is even more knife-edged (Fig. 4). For example, for eight temperature days the optimal harvest rate for 50 thousand adults changes from 0.00 when there are no young in the fall population to 0.16 when there are 14 thousand young. The optimal strategy for equal model weights, unlike that for model M2, is monotonic in that optimal harvest rates do not decrease at high levels of goose abundance. The optimal strategy based on equal model weights also had the highest expected objective value averaged over all nine models, which is a criterion sometimes used to select a strategy in the face of model uncertainty. For a given optimal strategy, the absolute harvest associated with any particular harvest rate is model-specific. Averaging absolute harvests (rather than harvest rates) over all nine models, optimal harvests for the strategy assuming equal model weights are near zero when population size <50 thousand, around 10 thousand when the population is near the goal of 60 thousand, and 15–20 thousand when population size is >70 thousand (Fig. 5).

The expected value of eliminating uncertainty over the nine models was only EVPI=0.164 thousand per year, or an increase

Table 4

The expected loss in objective value (in thousands of geese) based on simulations of model-specific optimal strategies under nine models of pink-footed goose population dynamics. Refer to Table 1 for a description of the models. M= represents the optimal strategy when all nine models are weighted equally. In the face of uncertainty as to the most appropriate model, the optimal strategy assuming equal model weights is expected to minimize the maximum loss.

Survival Reproduction Strategy	Model									
	(.) (days, N) M0	(days) (days, N) M1	(days, N) (days, N) M2	(.) (days) M3	(days) (days) M4	(days, N) (days) M5	(.) (.) M6	(days) (.) M7	(days, N) (.) M8	
M0	0.00	0.00	−0.73	−0.16	−0.16	−0.41	−0.12	−0.03	−0.43	−0.73
M1	−0.01	0.00	−0.70	−0.21	−0.16	−0.38	−0.12	0.00	−0.45	−0.70
M2	−0.47	−0.44	0.00	−0.61	−0.33	−0.05	−0.63	−0.46	−0.05	−0.63
M3	−0.03	−0.09	−1.27	0.00	−0.05	−0.89	−0.14	−0.07	−0.75	−1.27
M4	−0.06	−0.03	−1.13	−0.01	0.00	−0.78	−0.19	−0.12	−0.69	−1.13
M5	−0.20	−0.17	−0.10	−0.51	−0.29	0.00	−0.40	−0.23	−0.03	−0.51
M6	−0.10	−0.19	−1.08	−0.25	−0.32	−0.73	0.00	−0.11	−0.60	−1.08
M7	−0.13	−0.19	−0.97	−0.24	−0.24	−0.61	−0.01	0.00	−0.58	−0.97
M8	−0.35	−0.34	−0.06	−0.59	−0.41	−0.03	−0.40	−0.22	0.00	−0.59
M=	−0.06	−0.05	−0.32	−0.39	−0.31	−0.08	−0.14	0.00	−0.13	−0.39
									min	−0.39

in objective value of only 3.0%. The EVPI represents the difference between the best that could be expected if the most appropriate model were known (5.64 thousand per year) and the best that could be expected in the face of model uncertainty (i.e., that using the strategy for equal model weights; 5.48 thousand per year). The value of eliminating uncertainty about the survival process was substantially higher (0.119 thousand per year) than that associated with the reproductive process (0.006 thousand per year), which is consistent with evidence that variation in survival is

more important than variation in reproduction in relatively long-lived avian species (Stahl and Oli, 2006). Comparing the expected objective value if the most appropriate model were known with that of the robust strategy for model M2, we found EVPI=0.338 or an expected increase of 6.2%. This result underscores the conservatism of the maxi-min rule and suggests that risk-neutral managers would prefer the optimal strategy that maximizes expected value, which is also the strategy that is expected to minimize the maximum loss (i.e., the strategy based on equal model

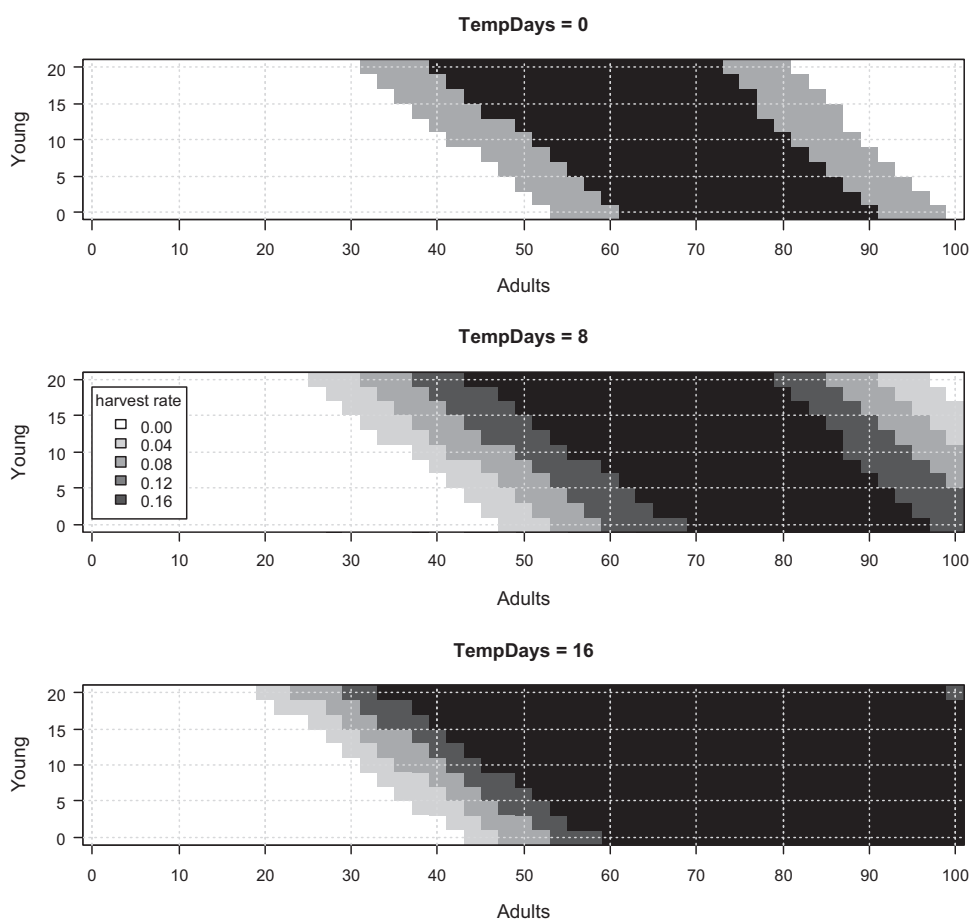


Fig. 3. Optimal harvest rates for pink-footed geese assuming model M2, which posits that both survival and reproduction are a positive function of the number of days above freezing in May in Svalbard (*TempDays*) and a negative function of goose abundance (young and adults in thousands). Optimal harvest rates decline with high numbers of adults and young because the density-dependent model posits sharp declines in survival and reproduction at these levels.

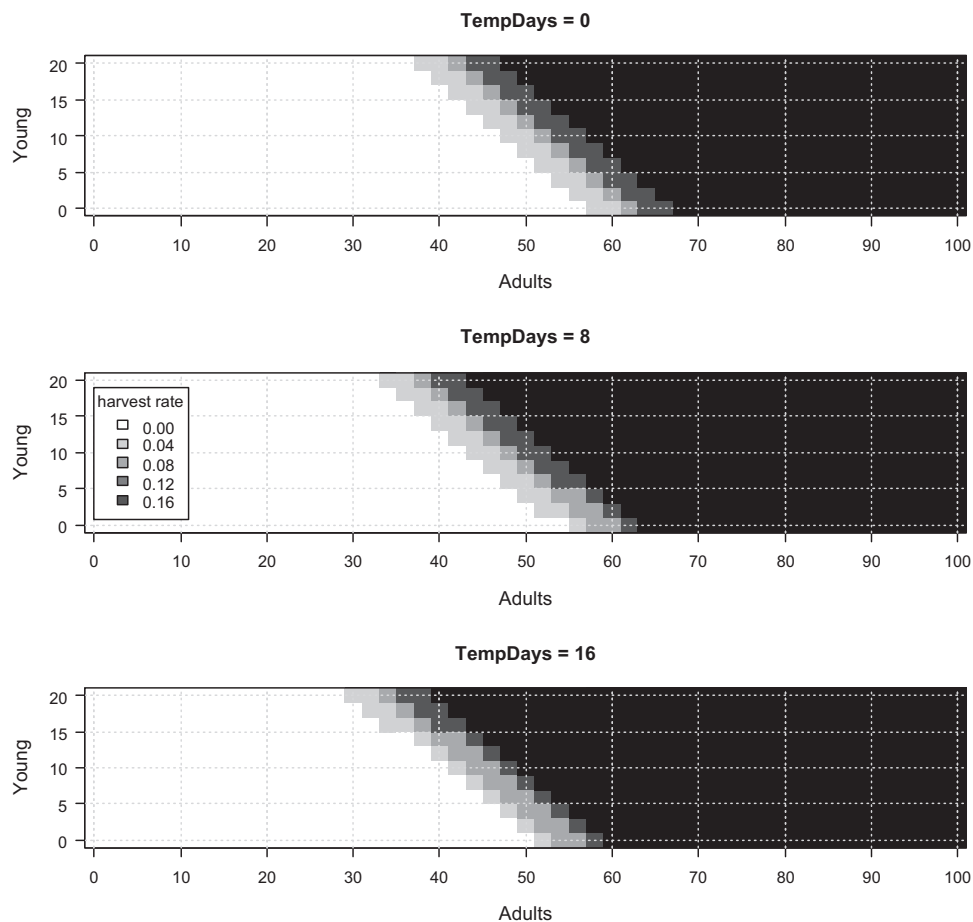


Fig. 4. Optimal harvest rates for pink-footed geese (young and adults in thousands) assuming equal weights for nine population models (see text or Table 1 for a description of the models). TempDays is the number of days above freezing in May in Svalbard.

weights). Risk-averse managers, on the other hand, would prefer the strategy for model M2 because it maximizes the minimum objective value across all models.

4. Discussion

A useful tool for addressing questions about the nature and implications of model uncertainty is the expected value of information (Clemen, 1996). The expected value of perfect information (EVPI) expresses the gain in management performance if uncertainty about a set of alternative models were eliminated. Although model uncertainty can never be eliminated in resource management problems, EVPI provides a useful heuristic for determining the extent to which a specified source of uncertainty is relevant to management decisions. EVPI is simply the difference between the objective return expected if there were no model uncertainty and the best that could be expected with values that are averaged over uncertain outcomes. EVPI is often expressed in dollars, but any relevant performance metric will suffice. Expressing EVPI in dollars is useful, however, for determining what managers should be willing to spend on monitoring and other data-collection programs designed to reduce model uncertainty.

Also of potential use in the design of adaptive management programs is the notion of the expected value of partial information, in which the value of eliminating one of multiple sources of model uncertainty is assessed. This form recognizes multiple sources of model uncertainty, but focuses on the value of reducing only one of the sources while accounting for the other. Runge et al. (2011) used the expected value of partial information to help

focus an adaptive management program by prioritizing eight competing hypotheses concerning reproductive failure in a population of endangered whooping cranes (*Grus americana*). With a relatively long-lived species like the pink-footed goose, it was not surprising that eliminating uncertainty about the alternative survival models would provide most of the gain in management performance that could be attained by eliminating all model uncertainty.

Some authors (Moore and McCarthy, 2010; Walters, 1986) have observed that EVPI is often low in practice, and we found this to be the case for the range of models considered for the pink-footed goose. EVPI will be low if uncertainty is low or if optimal management actions are insensitive to model choice. In some cases, management may be constrained (e.g., by laws or cultural norms) in such a way that it is not possible to capitalize on what is learned. Clearly, EVPI will be low where time horizons are short (Hauser and Possingham, 2008), or where the future is heavily discounted (Moore et al., 2008). Interestingly, the work of Moore and McCarthy (2010) suggests that EVPI may be higher in those cases where variability in objective returns are considered (e.g., some minimal performance is desired), because learning may have more influence on the variance of a parameter estimate than on its expected value.

EVPI can be particularly useful for the design and implementation of effective monitoring programs to support adaptive management (Moir and Block, 2001). Even if a rigorous assessment of information value is not possible, the expected-value heuristic can be helpful for bringing clarity of thought and purpose to questions concerning monitoring design (Wintle et al., 2010). For example, because of the direct and opportunity costs of monitoring, some authors have begun to explore the optimal frequency of

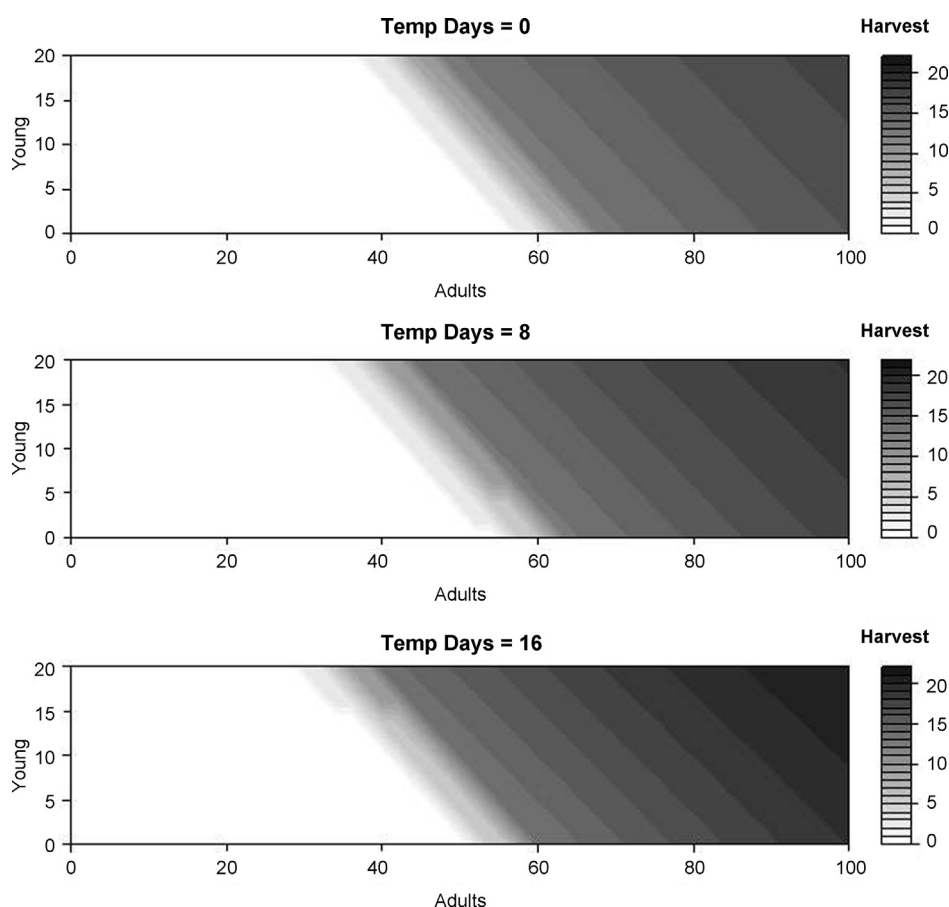


Fig. 5. Optimal harvests (rather than harvest rates) for pink-footed geese (all in thousands) assuming equal weights for nine population models (see text or Table 1 for a description of the models). *TempDays* is the number of days above freezing in May in Svalbard.

resource monitoring. Here the notion of optimality concerns the ability of a monitoring program to provide information that will improve management performance in a demonstrable and cost-effective way (Hauser et al., 2006b; McDonald-Madden et al., 2010).

The low value of information calculated for pink-footed geese suggests that a robust strategy could be as nearly effective as an adaptive one (i.e., one that will eventually identify the most appropriate model). Of course, an alternative explanation for the low value of information is that the set of population models we considered was too narrow to represent key uncertainties. Yet we know that questions about the presence of density dependence must be central to the development of a sustainable harvest strategy (Hilborn et al., 1995). And while there are potentially many environmental covariates that could help explain variation in survival or reproduction, the admission of models in which vital rates are drawn randomly from reasonable distributions represents a worst-case scenario for management. We suspect that much of the value of the various harvest strategies we calculated is derived from the fact that they are state dependent, such that appropriate harvest rates depend on population abundance and weather conditions, as well as our focus on an infinite time horizon for sustainability.

It is important to emphasize that there are other sources of uncertainty beyond model structure that might limit management performance. For example, given a specific model structure, there will be uncertainty concerning the parameters of that model. Where the most appropriate structure is relatively certain, an appropriate focus might be on parametric uncertainty, in which the sampling errors of parameter estimates can be used to posit alternative models. Another source of uncertainty is partial system observability, in which the state of the resource system can only be

known within the accuracy and precision of extant monitoring programs. Poor quality monitoring programs can lead to inappropriate management actions and slow or spurious model discrimination, yet optimal management strategies for partially observed Markov processes are notoriously hard to calculate (Williams, 2009). Another source of uncertainty we did not consider was partial controllability, in which the correspondence between intended and realized management actions is not perfect. For example, Johnson et al. (1997) used empirical data to specify distributions of harvest rates arising from different regulatory actions, and then explicitly considered these in the calculation of optimal harvest strategies. Partial controllability can erode short-term management performance, as well as slow the learning necessary to improve future management. Ultimately, partial controllability will be of concern to managers of pink-footed goose harvest, but our concern here was with the range of harvest rates that might be appropriate given various assumptions about population dynamics.

We believe the research presented here is an important first step in a more informed management strategy for the Svalbard population of pink-footed geese. We emphasize, however, that implementation of *any* informed strategy, either adaptive or robust, will require a sufficient monitoring program. At a minimum, a continued ground census in November would provide estimates of 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. Importantly, 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, the age structure of the population prior to harvesting would be available. 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 fully 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. Of great use would be an examination all mark-recapture data since 1990 as part of a comprehensive analysis targeted at supporting an adaptive-management framework. In particular, it would be useful 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, it would be helpful 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., 2006a).

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