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

***Briefing Summary***

*Prepared for:*
AEWA Svalbard Pink-Footed Goose
International Working Group
Copenhagen, Denmark
April 23, 2013

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## Introduction

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. This document describes progress to date on the development of an adaptive harvest management (AHM) strategy for maintaining pink-footed goose abundance near their target level by providing for sustainable harvests in Norway and Denmark. This briefing supplements material provided in the *Progress Summary* distributed to the International Working Group on February 1, 2013.

We emphasize that peer review is an essential aspect of the process of developing and implementing an AHM program for pink-footed geese, and we will continue to solicit reviews by the International Working Group and their staff, as well as scientists not engaged in this effort. We wish to make the Working Group aware that the following two manuscripts have been submitted recently to refereed journals and are available upon request from the senior authors:

Jensen, G. H., J. Madsen, F. A. Johnson, and M. Tamstorf. Snow conditions as an estimator of the breeding output in high-Arctic pink-footed geese *Anser brachyrhynchus.* Polar Biology: *In review.*

Johnson, F. A., G. H. Jensen, J. Madsen, and B. K. Williams. Uncertainty, robustness, and the value of information in managing an expanding Arctic goose population. Ecological Modelling: *In review.*

In addition to these manuscripts, the *Progress Summary* (February 1, 2013), and this *Briefing Summary* (April 23, 2013), an annual report will be produced in August 2013 and every summer thereafter. Additional manuscripts for journal publication are also anticipated.

## AHM Development

The *Progress Summary* described the development of nine alternative models of population dynamics that suggest how reproductive and survival rates of pink-footed geese vary over time (Table 1). Five of the models incorporate density-dependent mechanisms that would maintain the population near a carrying capacity (i.e., in the absence of harvest) of 65k – 129k depending on the specific model. The remaining four models are density independent and predict an exponentially growing population even with moderate levels of harvest. Consideration of these density-independent models is not intended to suggest that population size is truly unregulated, but that density dependence may only manifest itself at abundances far exceeding those experienced thus far. All nine models fit the available data and it is not possible to say with any confidence which is more appropriate to describe the contemporary dynamics of pink-footed geese. Therefore, we assigned equal probability to all nine models and calculated an optimal strategy for the use of harvest *rates*. The strategy was based on an objective to maintain population size in November around 60k using sustainable harvests in Norway and Denmark. With maximum harvest *rates* of at least 12%, we predicted the population could be stabilized around 60k even if the face of continued warm springs 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 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 | (.) | (TempDays, A) | 120 (8) |
| M1 | (TempDays) | (TempDays, A) | 129 (8) |
| M2 | (TempDays, N) | (TempDays, A) | 59 (4) |
| M3 | (.) | (TempDays) | |
| M4 | (TempDays) | (TempDays) | |
| M5 | (TempDays, N) | (TempDays) | 66 (3) |
| M6 | (.) | (.) | |
| M7 | (TempDays) | (.) | |
| M8 | (TempDays, N) | (.) | 65 (5) |

Efforts since distribution of the *Progress Summary* have focused on better understanding the implications of model uncertainty and on developing an optimal strategy for setting harvest *quotas* that would remain in effect for three years. 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. 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 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 uncertainty were resolved and the best performance that could be expected in the face of continuing model uncertainty. 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 processes 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 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. In our case, we have three alternative survival models and three reproductive models.

We determined that the EVPI represents an increase of only 3% in objective value. The increase in objective value is calculated using a Markov Decision Process and an objective function, which expresses the decision makers degree of satisfaction in terms of system state ($x_t$) (e.g., population size and breeding-ground conditions) and action ($a_t$) (i.e., varying harvest levels) (see details in the *Progress Summary*):

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

where $H(a_\tau|x_\tau)$ is harvest, and where the relative desirability of a harvest amount (i.e., utility) is a function of resulting population size:

$$\begin{array}{ll} u(a_\tau|x_\tau) = e^{-\frac{1}{2}\left(\frac{N_{t+1}-60k}{10k}\right)^2} & \text{if } N_{t+1} > 0 \\ = 0 & \text{otherwise,} \end{array}$$

and $N_{t+1}$ is total population size. The population-related utility is thus a bell-shaped curve with a peak at 1.0, corresponding to a goal for population size of 60 thousand. The full 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.

The increase in management performance expected from eliminating uncertainty about the survival process was substantially higher (EVPXI = +2.1%) than that for the reproductive process (EVPXI = +0.1%), consistent with evidence that variation in survival is more important than variation in reproduction in relatively long-lived avian species. Overall, the low value of information calculated for pink-footed geese suggests that a *robust* harvest strategy could be nearly as effective as an *adaptive* one. Robust harvest strategies are those that are expected to perform reasonably well regardless of which population model is most appropriate.

We used two approaches to determine a robust harvest strategy. In the first, we identified the model-specific 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 conservative because it emphasizes the worst possible outcome. In the second approach, we identified the model-specific harvest strategy that is expected to minimize the maximum loss. 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 population models were equally plausible. The use of informative prior weights on the models could lead to different robust strategies.

In the face of complete uncertainty as to the most appropriate model of population dynamics, the optimal strategy assuming that both survival and reproduction were a function of goose abundance and temperature days (i.e., days above freezing in May in Svalbard) (model M2) maximized the expected minimum objective value. In contrast, the optimal strategy based on model averaging (using equal model weights) minimized the expected maximum loss in objective value. This is also the strategy that maximized expected value across all nine models. 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. We have made the tentative decision to use a model-averaged harvest strategy (i.e., the one that both minimizes maximum loss and that also maximizes expected value) as a basis for an initial harvest strategy. However, we intend to update the model weights associated with this strategy as soon as experience permits, so that the strategy will evolve over time based on what is learned in an adaptive process.

We next focused on the development of a strategy for prescribing harvest *quotas* in a 3-year decision-making cycle (i.e., once chosen, a quota would remain in effect for three hunting seasons). The following specifics are noteworthy:

1. Based on input from the International Working Group, the utility curve related to population size was modified to express more satisfaction with a range of population sizes in the vicinity of 60k and less satisfaction of population sizes outside that range (Fig. 1). The revised utility curve is:

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

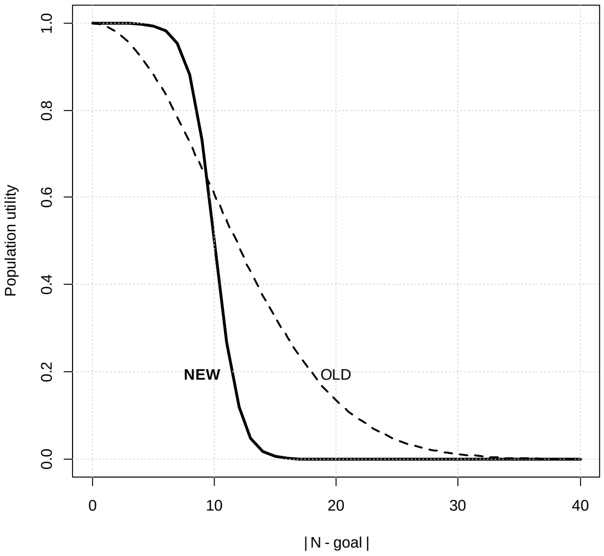

Fig. 1. Old (from the *Progress Summary*) and new utility curves expressing utility (or satisfaction) as a function of the difference between pink-footed goose population size and the population goal (in thousands).

2. We assumed a set of available harvest quotas of H = {0, 5k, 10k, 15k, and 20k) for use in both 1-year and 3-year cycles of decision making. This set seemed reasonable given the current harvest in Norway and Denmark of approximately 12k and only coarse control over harvests. As explained in the *Progress Summary*, calculation of an optimal strategy of absolute harvest (rather than harvest *rates*) requires that we 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. To resolve this dilemma requires the ability to specify $z = \frac{1-h_t}{1-d \cdot h_t}$, where $h$ is the harvest rate of adults and d ≈ 2 is the differential vulnerability of young to adults. The problem is that $z$ is not constant, but depends on the value of $h$ (which is not known a priori). Therefore, we examined values of $z$ for a range of realistic harvest rates (0.00 – 0.15) and calculated a "typical" $z \approx 1.1$. We assumed this constant value for the purpose of optimization. This approach is considered preliminary and we intend to evaluate the sensitivity of the optimal strategy to variation in $z$.

3. We calculated a "quasi-optimal" harvest strategy based on an assumption of equal model weights and a completely deterministic system using dynamic programming. With a 1-year decision-making cycle (as described in the *Progress Summary*), a bona fide optimal strategy could be calculated by explicitly accounting for all sources of variability (stochasticity) in survival and reproductive rates (i.e., 200 possible outcomes each year for each system state and each harvest action). With a 3-year decision-making cycle, variation is compounded annually between quota decisions and a truly optimal solution was computationally

intractable with available software. Therefore , we calculated a deterministic strategy based on equal model weights and simulated its application in a fully stochastic environment to assess its expected performance.

Fig. 2 depicts simulated population sizes under the deterministic, quasi-optimal strategy. Each graph depicts total population size for 100 simulations of a 15-year period for the model listed in the graph title. The open red circles represent application of an optimal harvest strategy based on a 3-year cycle of decision making. The solid black dots represent application of an optimal strategy based on annual decision making. All simulations begin with a population comprised of 16k young and 64k adults (i.e., the Nov 2011 population). Both the 1-year and 3-year harvest policies were based on equal model weights (determined previously to be a relatively robust strategy) and each strategy was limited to a maximum harvest quota of 20k geese. A number of interesting patterns are apparent:

- As expected, there is generally more variability in population size under the 3-year cycle of decision making than under annual decisions. Also, there is more uncertainty about population size in the latter part of the period than in the beginning (because environmental variation is compounded over time). These patterns are less true of models with density dependence than without (because populations with density dependence are more self-regulating).

- Generally, there is greater risk of low populations (i.e., N << 60k) with the 3-year cycle than the 1-year cycle. This is particularly true in early years for models with density dependence. Over the longer term, however, density-dependence in these models tends to help keep the population closer to 60k.

- There is considerable risk of the population escaping our ability to control it (with a maximum harvest quota = 20k) if the most appropriate model lacks density dependence. This risk is higher under the 3-year cycle than in the 1-year cycle (because you can act more quickly in the latter to bring the population under control after a series of years with good environmental conditions).

We also examined expected changes in harvest quotas. Table 2 depicts the expected frequency of 3-year runs of the same harvest quota under both the 3-year and 1-year decision-making cycles. With the 3-year cycle, harvest quotas remain unchanged for 3-year periods, but managers could also expect occasional runs of the same harvest quota for multiple 3-year cycles (i.e., 6, 9, 12 years, etc.). Harvest quotas hardly ever remain the same for three years in a row under a 1-year cycle of decision making. However, the magnitude of change in harvest quota was substantially lower than in a 3-year cycle (i.e., relatively infrequent changes in harvest quota are accompanied by relatively large changes in the quota when a change is necessary). Fig. 2 and Table 2 help demonstrate the tradeoffs associated with using a 3-year cycle of decision making rather than allowing for the establishment of a harvest quota every year.

Finally, we simulated population size assuming that the current level of harvest (12k) could not be modified. In other words, we wanted to understand the worst-case scenario if harvest could not be reduced when necessary. Fig. 3 depicts a relatively high probability of a population crash under all nine models. Under some density-independent models there is also a relatively high probability of populations increasing beyond our ability to control them.

The quasi-optimal strategy based on equal model weights and a deterministic system is a look-up table consisting of 4 columns and 6,248 rows for combinations of the number of young from 0 to 20k in increments of 2k, number of adults from 0 to 140k in increments of 2k, and temperature days from 0 to 28 in increments of 4 (although other discretizations are possible). This table provides the 3-year harvest quota for each potential combination of young and adults in November and temperature days the following May in Svalbard. Because it is not practical to depict the strategy here, we used a linear model and least-squares regression to calculate an *approximate* decision rule for population sizes <100k`:

$$Q = -13.942 + 0.304Y + 0.352A + 0.102D,$$

where $Q$ is harvest quota in thousands, $Y$ and $A$ are the number of young and adults in thousands in November, respectively, and $D$ = temperature days in May. Thus, the decision rule implies adding 304 to the harvest quota for every thousand young, adding 352 to the quota for every thousand adults, and adding 102 to the quota for every temperature day.

The full harvest strategy suggests that the appropriate harvest quota for 2012-2014 would be 15k (based on Y = 16k, A = 64k, and D = 5). Based on *very* preliminary data, assume that Y = 6k and A = 64k in November 2012 and that D = 8 (i.e., near average) in May 2013. The harvest strategy prescribes a harvest quota for 2013-2015 of 10k. These examples are for illustrative purposes only; we don't anticipate a strategy being implemented before the summer of 2014 (i.e., for 2014-1016).

Finally, we calculated the conditions under which an emergency hunting-season closure might be needed within the three years in which the harvest quota is constant. Fig. 4 depicts when closures would be optimal for varying numbers of young and adults (colored area). The colors indicate the minimum number of temperature days required to prevent season closure. As the number of young and adults decrease, the number of temperature days required to keep the season open increases.

Table 2. The frequency of 3-year runs of the same harvest quota based on 100 trials of a 15-year time frame, under both the 3-year and 1-year decision-making cycles. For the 3-year cycle most, but not all, runs of the same harvest quota were three years; the remainder were runs of the same quota for multiples of three years. IQ range is the inter-quartile range in harvest quotas when changes in quota are required. A relatively wide range suggests that the change in harvest quota will be relatively large when a change in quota is necessary.

| | 3-year cycle | | 1-year cycle | |
|---|---|---|---|---|
| Model | Frequency (%) (3-yr runs) | Quota (k) (IQ range) | Frequency (%) (3-yr runs) | Quota (k) (IQ range) |
| M0 | 83.2 | -10, 5 | 8.7 | -5, 5 |
| M1 | 78.0 | -10, 5 | 9.5 | -5, 5 |
| M2 | 54.2 | -15, 5 | 13.5 | -5, 5 |
| M3 | 86.2 | -5, 5 | 11.7 | -5, 5 |
| M4 | 84.4 | -5, 5 | 12.9 | -5, 5 |
| M5 | 75.1 | -15, 5 | 9.7 | -5, 5 |
| M6 | 76.9 | -10, 5 | 8.8 | -5, 5 |
| M7 | 77.7 | -10, 5 | 7.7 | -5, 5 |
| M6 | 76.4 | 15, 5 | 9.5 | -5, 5 |

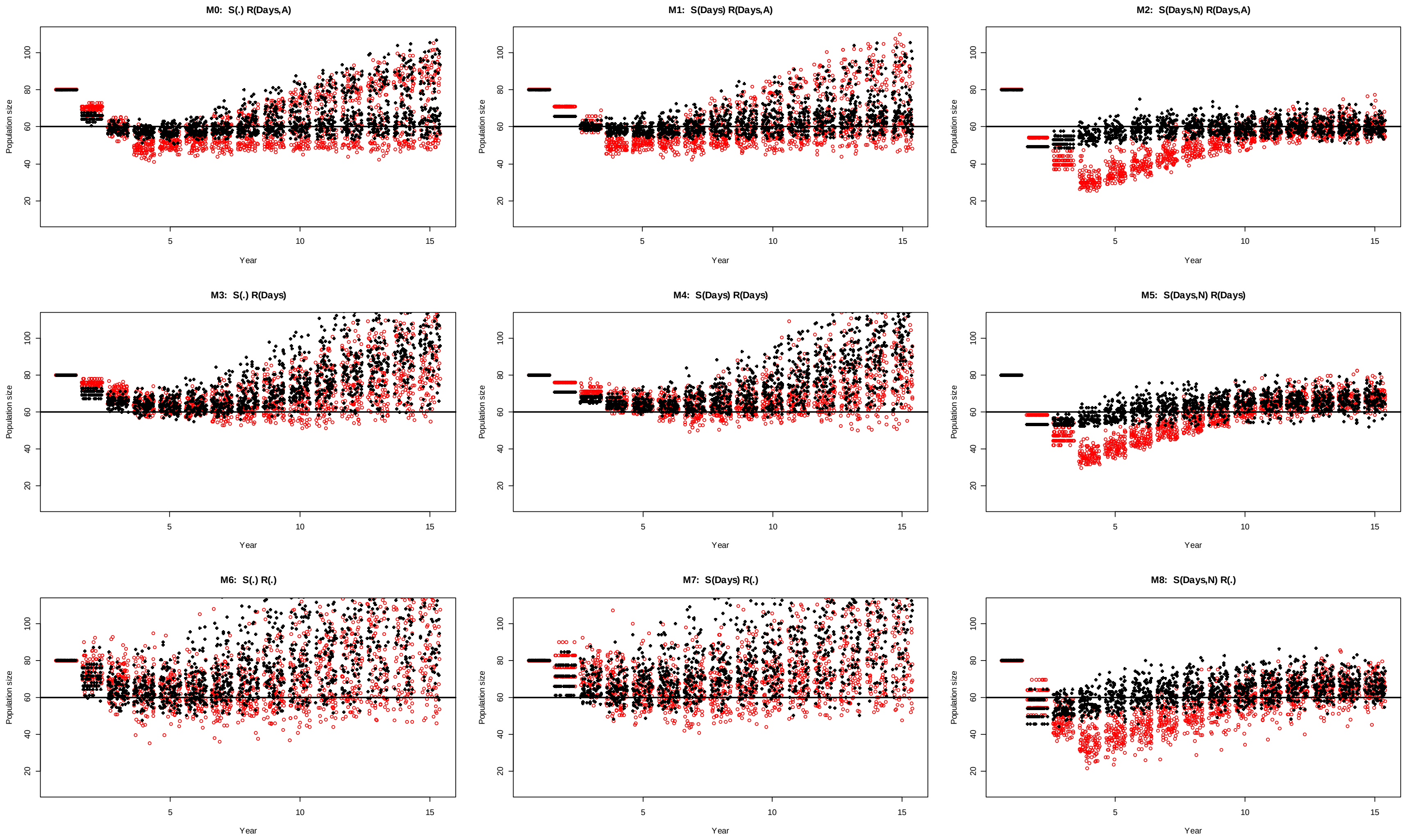

Fig. 2. Simulated population sizes of pink-footed geese (in thousands) under an optimal harvest strategy (based on equal mode weights). The open red circles represent application of an optimal harvest strategy based on a 3-year cycle of decision making. The solid black dots represent application of an optimal strategy based on annual decision making. Each graph depicts total population size for 100 simulations of a 15-year period for the model listed in the graph title.

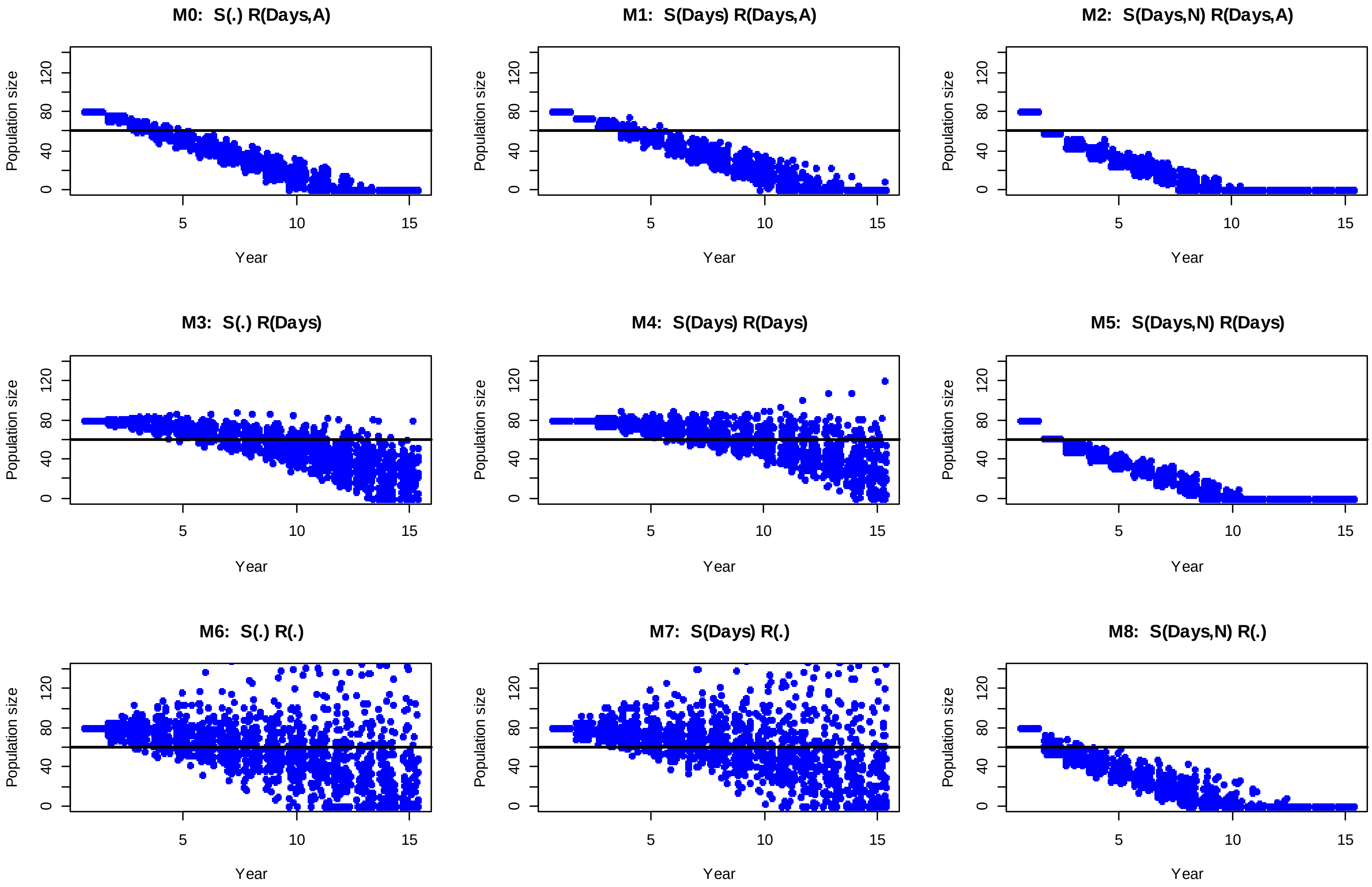

Fig. 3. Simulated population sizes of pink-footed geese (in thousands) under a constant harvest of 12k. Each graph depicts total population size for 100 simulations of a 15-year period for the model listed in the graph title.

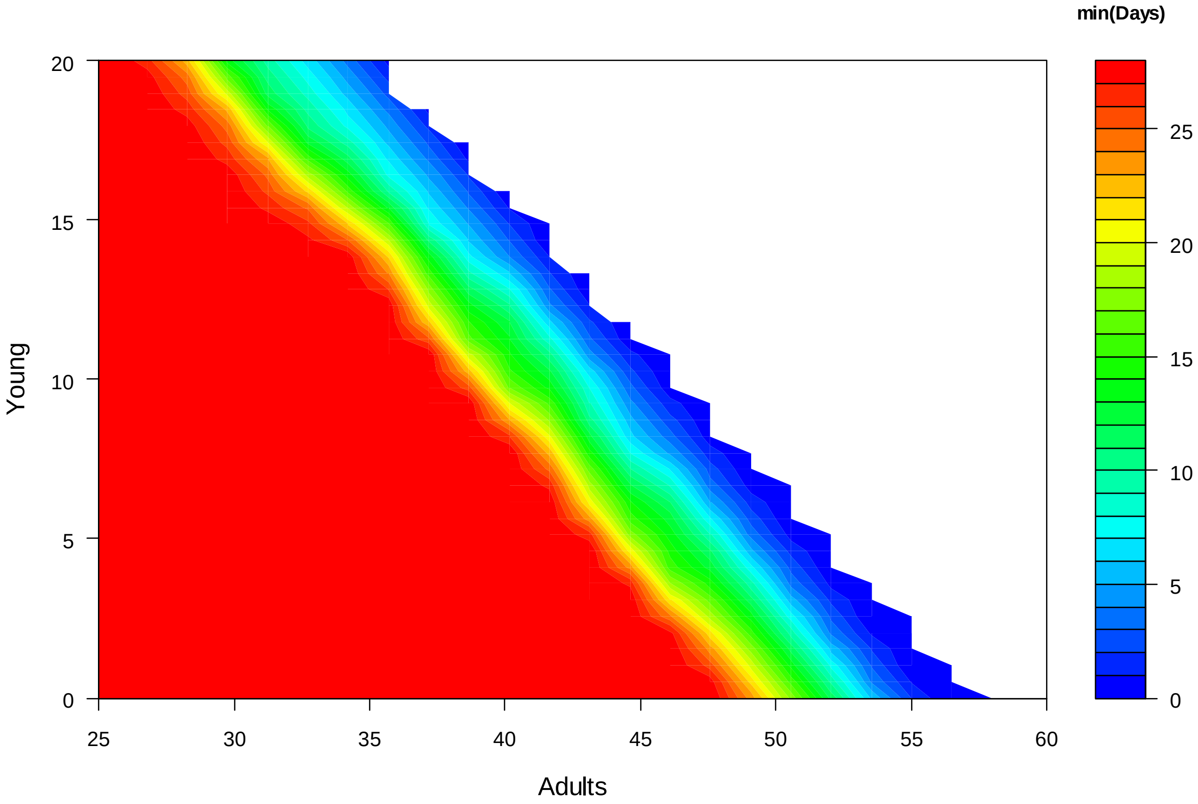

Fig. 4. Conditions under which a closed hunting season for pink-footed geese should be considered (colored area) within 3-year decision making periods. The different colors represent the minimum number of temperature days (i.e., days above freezing in May in Svalbard) required to prevent a season closure. As the number of young and adults decrease, the number of temperature days required to keep the season open increases. Numbers of adults and young are in thousands.

## AHM Process and Implementation Needs

An adaptive, 3-year cycle of decision making for pink-footed geese would follow these steps:

1. Summer of year 1 (year *t*), choose a harvest quota based on:
    - A strategy assuming equal model weights
    - Counts of young and adults from the previous November
    - Number of temperature days in May of the current year

2. Summer of years 2-3 (*t*+1, *t*+2)
    - Examine actual harvest and population response
    - Update model weights by comparing observed and predicted population response
    - Recalculate model-weighted strategy

    - Determine if an emergency closure required; otherwise take no action

3. Summer of year 4 ($t$+3)
    - Examine actual harvest and population response
    - Update model weights by comparing observed and predicted population response
    - Recalculate model-weighted strategy
    - Choose next 3-year quota
    - Reset ($t$)

4. Return to step 2

To implement this process, continued monitoring of the population size and its age structure in November is required. Moreover, we will require annual estimates of the harvest in Norway and Denmark, as well as the age composition of the harvest if practical. This information must be available by early summer of each year in order to update model weights, determine if an emergency closure should be considered, and to establish new harvest quotas after every three years.

Over the longer term, there are two key needs. The first is to transition to the use of a spring count of population size. The November count is essentially a post-harvest census, which provides the age structure of the population after young and adults have 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 causes difficulty in 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 problem. 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 the count conducted on staging areas during spring migration. To use the spring count, however, we will need to recalibrate all the models of population dynamics.

There is also 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. 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.

## Acknowledgements

Funding for this research was provided by Aarhus University and the U.S. Geological Survey. Jesper Madsen, James Williams, Ingunn Tombre, and Gitte Jensen provided helpful suggestions for the nature of the analyses described in this summary.