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HARVEST ASSESSMENT FOR TAIGA BEAN GEESE IN THE CENTRAL MANAGEMENT UNIT: 2019[1]

Report prepared by the AEWA European Goose Management Platform Data Centre

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Summary

In 2016 the European Goose Management International Working Group (EGM IWG) began development of an Adaptive Harvest Management (AHM) program for Taiga Bean Geese. In 2017, the IWG adopted an Interim Harvest Strategy consisting of a constant harvest rate (on adults) of 3% for the Central Management Unit (MU) of Taiga Bean Geese. The interim strategy is intended to provide limited hunting opportunity while rebuilding the population. Based on a January count of 41,927, the harvest quota for the 2019 hunting season is 1,740 Taiga Bean Geese (compared to 2,335 and 1,610 for the 2017 and 2018 seasons, respectively). We emphasize that these quotas include both, harvest during the regular season and derogation shooting. Going forward, we describe how an Integrated Population Model (IPM) will use counts at multiple times during the year, along with other demographic information, to estimate population size (and its precision). The IPM can be used to develop an adaptive harvest strategy if unambiguous management objectives can be agreed upon. We provide some initial guidance for formulating those objectives.

Introduction

Harvest levels appropriate for rebuilding the population of Taiga Bean Geese in the Central MU and then maintaining it near the goal of 60,000 – 80,000 individuals in winter were assessed by Johnson et al. (2018). Based on that assessment, the EGM IWG adopted a constant harvest rate (on adults) of 3% as an interim strategy, intended to provide limited hunting opportunity while rebuilding the population toward the goal. This assessment report provides harvest quotas for the 2019 hunting season based on this interim harvest strategy, as well as describing ongoing development of an adaptive harvest strategy. An adaptive harvest strategy is one

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in which the harvest rate can vary each year with changes in population size. Moreover, an adaptive harvest strategy evolves over time as learning accrues from population monitoring programs.

Methods

The age-structured model for Taiga Bean Geese developed by Johnson et al. (2018) provides the foundation for prescribing harvest quotas (Fig. 1). In addition to accounting for age at first breeding, this model allows for age-specific survival rates and for young-of-the-year that may be more vulnerable to harvest than older birds (Baldassarre 2014).
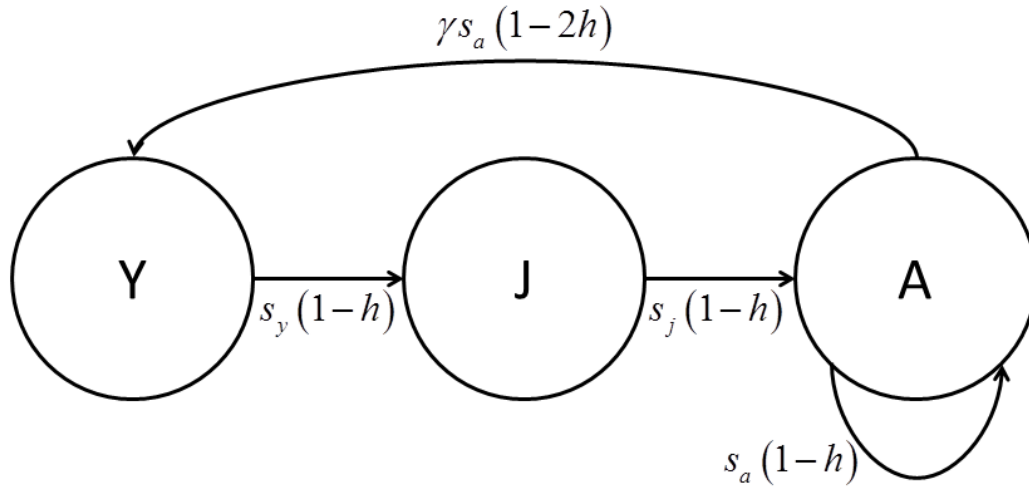

Figure 1. *Life cycle of Taiga Bean Geese based on a January anniversary date.* The three age classes represented are young (Y, birds aged 0.5 years), juvenile (J, birds aged 1.5 years) and adults (A, birds aged ≥2.5 years). Vital rates are survival in the absence of harvest, s, the harvest rate of birds that have survived at least one hunting season, h, and the reproductive rate, γ.

The matrix model representation of the life cycle is:

$$\begin{bmatrix} Y_{t+1} \\ J_{t+1} \\ A_{t+1} \end{bmatrix} = \begin{bmatrix} 0 & 0 & \gamma s_a (1-2h) \\ s_y (1-h) & 0 & 0 \\ 0 & s_j (1-h) & s_a (1-h) \end{bmatrix} \cdot \begin{bmatrix} Y_t \\ J_t \\ A_t \end{bmatrix},$$

where t represents year. After revising the model of Jensen (1995) to account for the lack of a terminal age class, the density-dependent matrix model with harvest is:

$$\vec{N}_{t+1} = \underline{h}_t \left(\vec{N}_t + \underline{D}_t \left(\underline{M} \vec{N}_t - \vec{N}_t \right) \right),$$

where $\vec{N}$ is the vector of age-specific population sizes. In this model, the transition matrix *without* harvest or density dependence is:

$$\underline{M} = \begin{bmatrix} 0 & 0 & \gamma s_a \\ s_y & 0 & 0 \\ 0 & s_j & s_a \end{bmatrix}.$$

Non-linear, age-specific density-dependence is:

$$\underline{D}_t = \begin{bmatrix} 1 - \left(\dfrac{Y_t}{K_y}\right)^\theta & 0 & 0 \\ 0 & 1 - \left(\dfrac{J_t}{K_j}\right)^\theta & 0 \\ 0 & 0 & 1 - \left(\dfrac{A_t}{K_a}\right)^\theta \end{bmatrix},$$

where $K_i = p_i K$, with p_i specified by the stable age distribution of $\underline{M}$, for $i \in \{Y, J, A\}$. The assumption of age-specific carrying capacities helps keeps the relative sizes of the age classes within biologically realistic bounds.

Following net growth in the population, we assume that young-of-the-year are twice as vulnerable to harvest as older birds; thus, the matrix of survival from harvest is:

$$\underline{h}_t = \begin{bmatrix} 1 - 2h_t & 0 & 0 \\ 0 & 1 - h_t & 0 \\ 0 & 0 & 1 - h_t \end{bmatrix}.$$

Absolute harvest is then a function of the harvest rate of adults and subadults, h_t, and the fall flight of each age class:

$$H_t = h_t \left(2Y_t^F + J_t^F + A_t^F \right).$$

The fall flight in turn is calculated by assuming that net population growth precedes harvest:

$$\vec{N}_t^F = \vec{N}_t + \underline{D}_t \left(\underline{M}\vec{N}_t - \vec{N}_t \right).$$

We parameterized the population model using the methods described by Johnson et al. (2018). Only a distribution of predicted survival rates for adults was available, but we assume that average survival from natural causes is the same among all age classes after birds survive their first winter. Estimates of demographic parameters are provided in Table 1. Harvest quotas were calculated for 100,000 random samples of model parameters from their associated probability distributions. The median harvest quota and 95% credible interval were calculated from these 100,000 samples. We assumed that the age structure associated with a specified population size was drawn from a Dirichlet distribution with parameters equivalent to the proportional stable age distributions associated with the sampled transition matrices; therefore, harvest quotas represent approximations because the true age structure of the population is unknown.

Table 1. Model-based demographic parameters of Taiga Bean Geese in the Central MU (medians and 95% credible interval) as estimated by the methods of Johnson et al. (2018). See model descriptions in text for an explanation of the parameters.

Parameter	2.5%	50%	97.5%
$s_{\{y,j,a\}}$	0.775	0.885	0.941
γ	0.285	0.511	1.040
θ	0.613	2.354	9.028
K_y (in thousands)	15.0	21.7	31.6
K_j (in thousands)	12.1	16.6	22.7
K_a (in thousands)	45.1	55.0	64.7

Harvest Quota for the 2019 Hunting Season

The interim harvest strategy agreed to by the EGM IWG relies on the matrix model described above, the January count, and a constant harvest rate on adults of 3%. Using this strategy, harvest quotas increase non-linearly with population size (Figure 2). We note that this strategy was *not* derived based on an explicit formulation of management objectives, and thus is not designed to maintain the population near the goal of 70,000. Rather, it is viewed as an interim harvest strategy, intended to allow some limited hunting opportunities while the population recovers.

According to the constant harvest-rate strategy, the harvest quota for the 2019 season is 1,740 (95% CI: 1,591 – 1,972), based on the January 2019 count of 41,927 Taiga Bean Geese (Heldbjerg et al. 2019) (Table 2). For comparison, the 2017 quota was 2,335 (95% CI: 2,123 – 2,645) and the 2018 quota was 1,610 (95% CI: 1,472 – 1,825). Table 2 provides the allocation of the 2019 harvest quota among range states based on the agreed upon proportions of 15% for Russia, 49% for Finland, 26% for Sweden, and 10% for Denmark. We emphasize that these quotas include both harvest during the regular season and derogation shooting.

Table 2. State-specific harvest quotas (median and 95% credible interval) of Taiga Bean Geese in the Central MU for the 2017, 2018, and 2019 hunting seasons, given a target adult harvest rate $h = 0.03$ and agreed-upon harvest allocation.

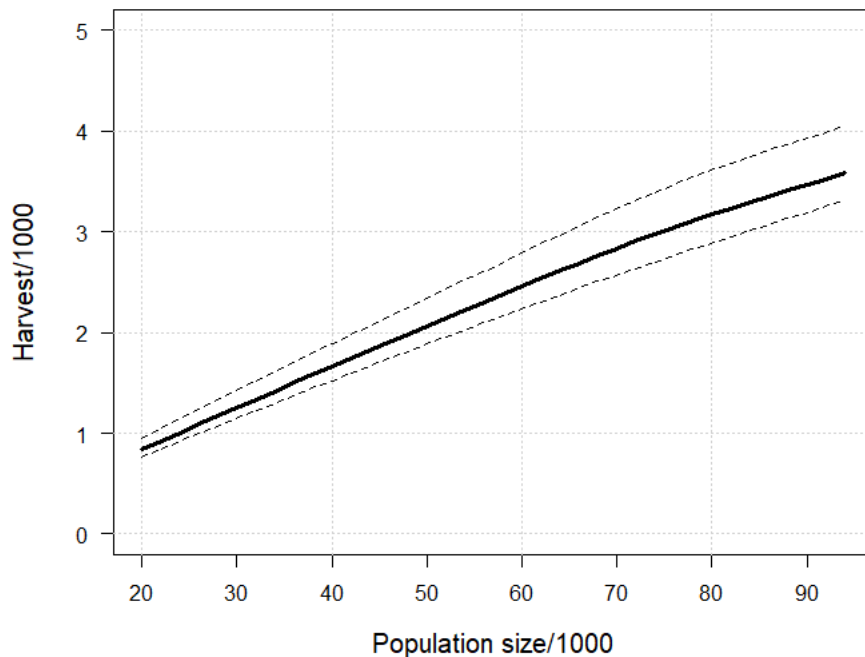| State	2017		2018		2019	
	Quota	(95% CI)	Quota	(95% CI)	Quota	(95% CI)
Russia	350	(319 – 397)	241	(221 – 274)	261	(239 – 296)
Finland	1144	(1040 – 1296)	789	(721 – 894)	852	(779 – 966)
Sweden	607	(552 – 688)	419	(383 – 475)	452	(414 – 513)
Denmark	233	(212 – 264)	161	(147 – 183)	174	(159 – 197)
Total	**2335**	(2123 – 2645)	**1610**	(1472 – 1825)	**1740**	(1591 – 1972)

Figure 2. Median harvest quotas and 95% credible interval for a range of Taiga Bean Goose population sizes in the Central MU in January based on a target adult harvest rate $h = 0.03$.

Development of an Adaptive Harvest Strategy

The interim, constant harvest-rate strategy is prescribed, rather than derived based on agreed-upon management objectives. It also does not incorporate a formal mechanism for learning. Development of an adaptive harvest strategy thus requires a dynamic model that can be updated based on monitoring data, as well as explicit and quantifiable management objectives. The next two sections address those needs.

Integrated population model – IPMs have many advantages over traditional approaches to modeling, including the proper propagation of demographic uncertainty, better precision of demographic rates and population size, the ability to handle missing data and estimate latent (i.e. unobserved) variables, and the capacity to guide development of monitoring programs. Moreover, use of a Bayesian estimation framework for IPMs provides a natural framework for adaptation, in which model parameters can be updated over time based on observations from operational monitoring programs. We plan to rely on the discrete theta-logistic model described by Johnson et al. (2018) rather than on the age-specific matrix model described above. Application of the matrix model for adaptive harvest management would require more monitoring information than is currently available (i.e. age structure of the population). Fortunately, the theta-logistic model appears to provide reasonable management performance even if the population is age structured (Johnson et al. 2018).

A key consideration in constructing the IPM is how to account for abundance that is observed at multiple times during the annual cycle, especially because seasonal demographic data are unavailable. Estimates of abundance of Taiga Bean Geese are currently available in January, March, and October (albeit with a level of corruption due to inclusion of some tundra bean geese). From a biological perspective, we would expect October abundance to be the highest, followed by January and then by March (i.e. reproduction and a limited harvest occurs between March and October; only mortality occurs between October and March). Generally, October counts are highest, but January counts in Sweden (which has the most complete data and harbors most of the geese in January) are lower than the counts in Sweden in March, which is not biologically plausible (i.e. the January counts may be biased low) (Figure 3). It is well known that Taiga Bean Geese winter in Germany and Poland, where they aren't counted. It is suggested that harsh winters drive more birds into Germany and

Poland, a conclusion supported by the positive relationship between the January count and January temperature in Sweden (Figure 4). An additional concern with the January count is the unknown portion of the harvest occurring between October and January. In 2018, 44% of the harvest in Sweden occurred in this period, but data are only available for a single year and there was reason to suspect that this proportion could be much higher in other years. Therefore, for a prototype IPM we will restrict our attention to the March and October counts; January counts may be considered in future iterations of the IPM if ways can be found to deal with the two issues identified.
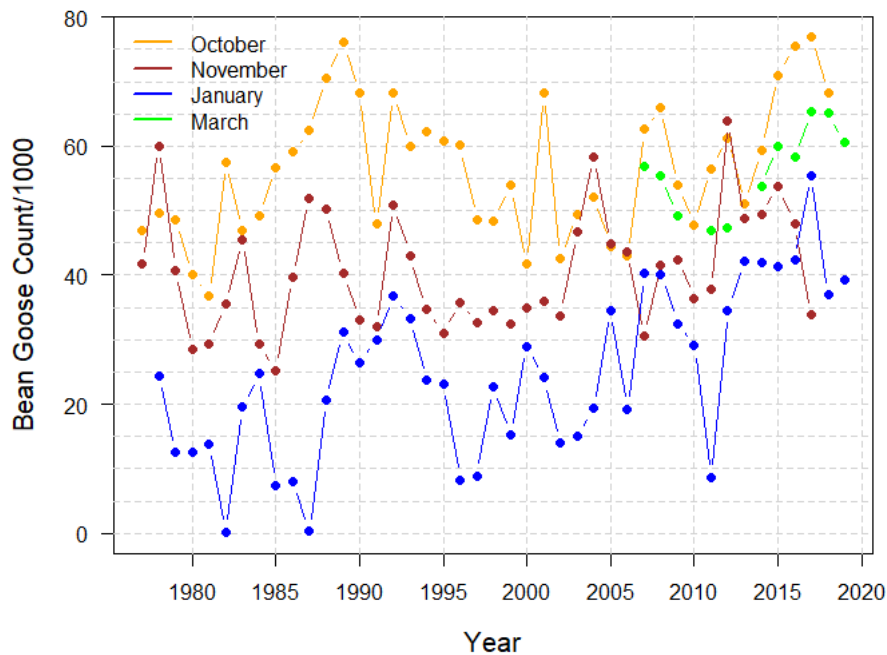

Figure 3. Counts of Bean Geese in Sweden, 1977-2019 (Sources: http://www.zoo.ekol.lu.se/waterfowl/GooseInv /gcount2.htm, https://www.fageltaxering.lu.se/sites/default/files/files/Rapporter/inventeringsjofaglargass2017_18.pdf, Ulf Skylberg and Leif Nillson, personal communication).

We will consider March abundance as the start of the breeding season and the annual cycle. The challenge is to reframe the theta-logistic model, which only predicts *annual* change in abundance, to one that will predict population size at other times during the year; October in this case. We show how this can be done, initially assuming no density dependence in survival or production, and then accounting for density dependence. In this approach we make a limited number of tentative assumptions:

(1) All production occurs between March and October;

(2) Natural mortality is evenly distributed throughout the year;

(3) Density-dependence acts on both production and annual survival and is based on abundance in March; and

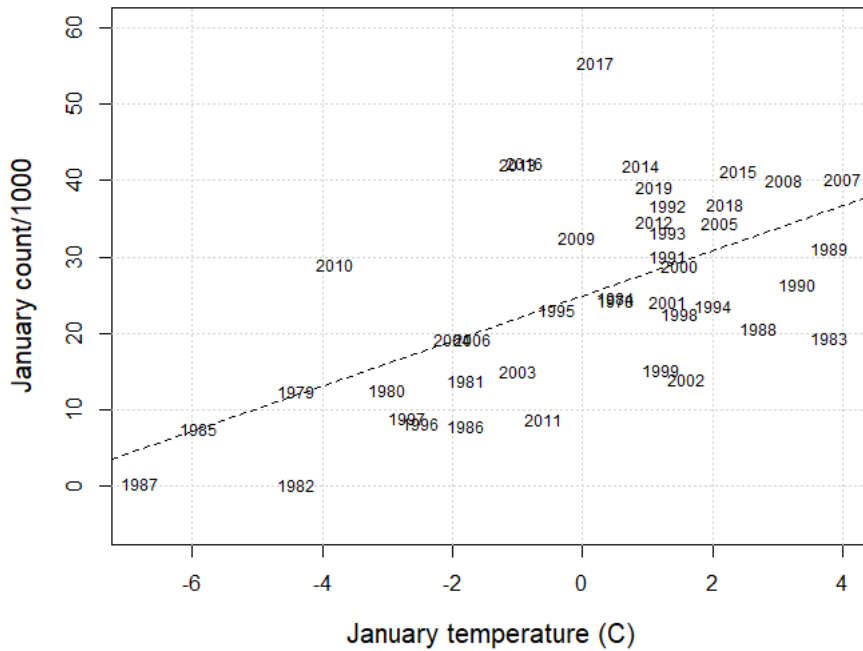(4) The Finnish harvest represents the number of birds taken prior to the October count.

Figure 4. January counts of Bean Geese by year in Sweden as a function of average January temperature at the Malmo Airport in southern Sweden (Source: https://www.tutiempo.net/clima/ws-26360.html). The dashed line is the best fitting linear model.

To accommodate counts at two times during the year, we begin with the theta-logistic model with density dependence:

$$N_{t+1} = N_t + N_t r\left(1 - \left(\frac{N_t}{K}\right)^{\theta}\right) - H_t$$

(1)

$$= N_t\left(1 + r\left(1 - \left(\frac{N_t}{K}\right)^{\theta}\right)\right) - H_t$$

where N is population size, r is the intrinsic (or maximum) rate of growth, K is carrying capacity, θ is a parameter describing the type of density dependence (i.e. concave, linear, or convex), H is total harvest, and t is year. Now we omit harvest and density dependence:

(2)
$$N_{t+1} = N_t + N_t r$$
$$= N_t(1+r)$$

The expression $(1+r)$ is the finite rate of population growth, which can also be expressed in terms of survival from natural causes, ψ, and production, δ:

(3)
$$N_{t+1} = N_t\psi + N_t\psi\delta$$
$$= N_t(\psi + \psi\delta)$$

Therefore:

(4)
$$1+r = \psi + \psi\delta$$
$$r = \psi + \psi\delta - 1$$

In the theta-logistic model, the *realized* rate of growth, r', is based on the size of the population relative to carrying capacity:

(5) $\quad r' = r\left(1 - \left(\dfrac{N_t}{K}\right)^{\theta}\right)$

Thus, to incorporate density dependence into a model with explicit survival and production rates, we simply multiply both sides of Equation 4 by $\left(1 - \left(\dfrac{N_t}{K}\right)^{\theta}\right)$

(6) $\quad r\left(1 - \left(\dfrac{N_t}{K}\right)^{\theta}\right) = (\psi + \psi\delta - 1)\left(1 - \left(\dfrac{N_t}{K}\right)^{\theta}\right)$

And now by substitution in our original theta-logistic model:

(7) $\quad N_{t+1} = N_t\left\{1 + \left[(\psi(1+\delta) - 1)\left(1 - \left(\dfrac{N_t}{K}\right)^{\theta}\right)\right]\right\} - H_t$

Having survival and production as explicit parameters allows us to implement our assumptions concerning timing of annual events. Thus, we predict abundance in October as:

(8) $\quad N_t^O = N_t + N_t\left[\left(\psi^{7/12}(1+\delta^1) - 1\right)\left(1 - \left(\dfrac{N_t}{K}\right)^{\theta}\right)\right] - H_t^F$

in which we assume seven months of natural mortality, all the reproduction, and a portion of the harvest occur prior to the October count, where H_t^F represents the harvest in Finland.

We can estimate the joint posterior distribution of model parameters using prior distributions supplied by Johnson et al. (2018) and available monitoring data. To fit the IPMs we plan to use JAGS 4.3.0 (Plummer 2003), run in the R computing environment (R Core Team 2018) using runjags (Denwood 2016). Our intent is to complete model development in early 2020.

Management objectives – The International Single Species Action Plan (ISSAP) calls for restoring and then maintaining the population of Taiga Bean Geese in the Central MU at a level of 60,000 – 80,000 individuals in winter. Based on this goal, a possible objective function for calculating dynamic harvest strategies as a solution to a Markov decision process (MDP) (Marescot et al. 2013) is:

$$V^*\left(H_t \mid N_t\right) = \underset{(H_t \mid N_t)}{\arg\max}\left\{\sum_{t=1}^{\infty}\left(1 + e^{\left(\left|\left(N_{t+1} \mid N_t, H_t\right) - \alpha\right| - \beta\right)}\right)^{-1}\right\},$$

where the optimum value V^* of a harvest strategy maximizes cumulative, expected population utility over an infinite time horizon. For example, consider a population goal of $\alpha = 70,000$ Taiga Bean Geese, and

inflection points of $[\alpha - \beta, \alpha + \beta]$, where $\beta = 15,000$. This utility function expresses near-complete satisfaction with population sizes in the range 60,000-80,000, with satisfaction declining for population sizes outside this range (Fig. 5). The form of this utility function is similar to that used for AHM of Pink-footed Geese (Johnson and Madsen 2016). However, we recognize that utility for population sizes above 80,000 may not decline (or not decline rapidly) because Taiga Bean Geese do not cause as much conflict with agriculture as do Pink-footed Geese. Thus, we emphasize that this figure is for illustrative purposes only.
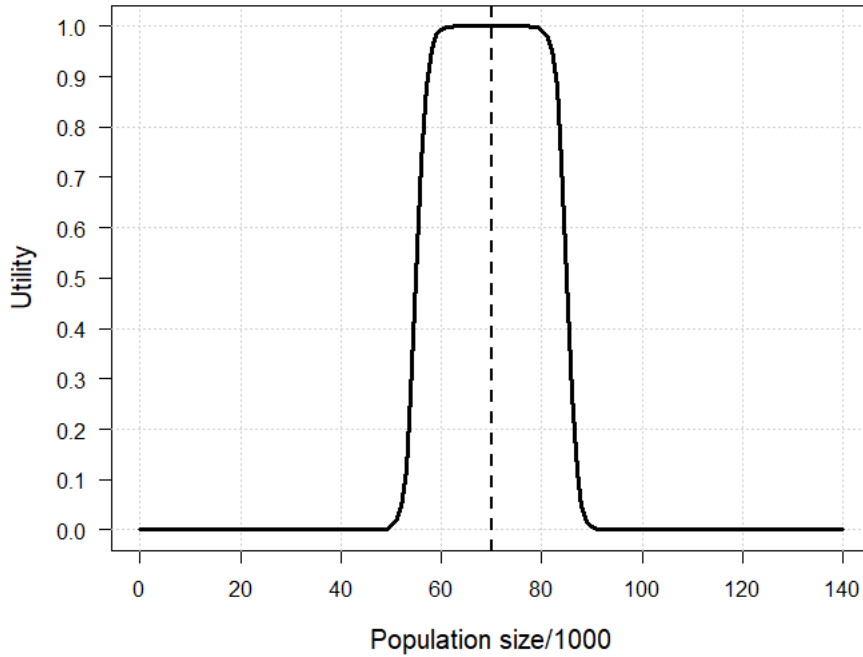

Figure 5. *Possible utility of population sizes of Taiga Bean Geese in the Central MU, relative to the population goal of 70,000.*

Note that this approach does *not* explicitly account for the value of harvest, but rather assumes harvest is merely a tool to maintain population abundance within acceptable limits. Yet we know that hunters value the hunting opportunity afforded by sustainable populations of waterbirds (Buij et al. 2017). Thus, we can specify (at least) two, potentially competing objectives. One is to maintain population size within a range that satisfies conservation, agricultural, and public health and safety concerns. Another is to maximize sustainable hunting opportunity. Therefore, we can consider a utility function that accounts for both the desire to maintain a population near its goal and the desire to provide sustainable hunting opportunities:

$$V^{*}\left(H_{t} \mid N_{t}\right) = \underset{\left(H_{t} \mid N_{t}\right)}{\arg \max} \left\{ \sum_{t=1}^{\infty} \left[w\left(1 + e^{\left(\left|\left(N_{t+1} \mid N_{t}, H_{t}\right) - \alpha\right| - \beta\right)}\right)^{-1} + \left(1 - w\right) \frac{\left(H_{t} \mid N_{t}\right)}{\max\left(H_{t}\right)} \right] \right\},$$

where $0 \leq w \leq 1$ is the relative degree of emphasis on maintaining the population near its goal. The second term is the relative value of harvest, scaled by the maximum harvest under consideration. Thus, $w = 1$ represents a sole objective related to population size and $w = 0$ represents a sole objective of maximizing sustainable harvest. Values of w intermediate between 0 and 1 represent a mix of both objectives. The assignment of weights is not the purview of scientists, but of decision makers who must judge how best to balance the desires of different stakeholder interests. It will eventually be necessary to construct a utility function such as that described above before an AHM strategy can be derived for Taiga Bean Geese.

Acknowledgements

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