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DEVELOPMENT OF AN ADAPTIVE HARVEST MANAGEMENT

PROGRAM FOR TAIGA BEAN GEESE

Development of an Adaptive Harvest Management Program for Taiga Bean Geese

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Abstract

This report describes recent progress in specifying the elements of an adaptive harvest program for taiga bean goose. It describes harvest levels appropriate for first rebuilding the population of the Central Management Unit and then maintaining it near the goal specified in the AEWA International Single Species Action Plan (ISSAP). This report also provides estimates of the length of time it would take under ideal conditions (no density dependence and no harvest) to rebuild depleted populations in the Western and Eastern Management Units. We emphasize that our estimates are a first approximation because detailed demographic information is lacking for taiga bean geese. Using allometric relationships, we estimated parameters of a theta-logistic matrix population model. The mean intrinsic rate of growth was estimated as $r = 0.150$ (90% credible interval: 0.120 – 0.182). We estimated the mean form of density dependence as $\theta = 2.361$ (90% credible interval: 0.473 – 11.778), suggesting the strongest density dependence occurs when the population is near its carrying capacity. Based on expert opinion, carrying capacity (i.e., population size expected in the absence of hunting) for the Central Management Unit was estimated as $K = 87,900$ (90% credible interval: 82,000 – 94,100). The ISSAP specifies a population goal for the Central Management Unit of 60,000 – 80,000 individuals in winter; thus, we specified a preliminary objective function as one which would minimize the difference between this goal and population size. Using the concept of stochastic dominance to explicitly account for uncertainty in demography, we determined that optimal harvest rates for 5, 10, 15, and 20-year time horizons were $h = 0.00, 0.02, 0.05,$ and 0.06, respectively. These optima represent a tradeoff between the harvest rate and the time required to achieve and maintain a population size within desired bounds. We recognize, however, that regulation of absolute harvest rather than harvest rate is more practical, but our matrix model does not permit one to calculate an exact harvest associated with a specific harvest rate. Approximate harvests for current population size in the Central Management Unit are 0, 1,200, 2,300, and

3,500 for the 5, 10, 15, and 20-year time horizons, respectively. Populations of taiga bean geese in the Western and Eastern Units would require at least 10 and 13 years, respectively, to reach their minimum goals under the most optimistic of scenarios. The presence of harvest, density dependence, or environmental variation could extend these time frames considerably. Finally, we stress that development and implementation of internationally coordinated monitoring programs will be essential to further development and implementation of an adaptive harvest management program.

Introduction

The abundance of many goose species in Europe has increased in recent decades, likely as a combination of factors including reductions in hunting pressure, favorable changes in land use, and climate change (Madsen et al. 1999). The taiga bean goose is an exception, however, declining from about 100 thousand birds in the mid-1990's to 63 thousand in 2009 (Fox et al. 2010). Signatories of the African-Eurasion Waterbird Agreement (AEWA) recently upgraded the conservation status of the taiga bean goose, requiring it to be subject to legal measures as described in the International Single Species Action Plan (ISSAP) (Marjakangas et al. 2015) (Resolution 5.6 from the AEWA MOP5, May 2012): "...*By way of exception for those populations listed in Categories 2 and 3 in Column A and which are marked by an asterisk, and those populations listed in Category 4 in Column A, hunting may continue on a sustainable use basis. This sustainable use shall be conducted within the framework of an international species action plan, through which Parties will endeavour to implement the principles of adaptive harvest management.*"

Taiga bean geese breed in Russia, Finland, Sweden, and Norway, and have a highly discontinuous winter distribution, which includes population segments in the United Kingdom and northern Denmark, in southern Sweden and southeastern Denmark, in northeastern Germany and western Poland, and in Central Asia.(Madsen et al. 1999). They are hunted principally in Russia, Sweden, southeastern Denmark, and until 2014 in Finland when a temporary moratorium went into effect. Reliable estimates of harvest are lacking, especially from Russia, but the take likely exceeded 10,000 range-wide prior to hunting restrictions in Scandanavia. The ISSAP depicts four management units of relatively discrete populations of varying status (Fig. 1). Our purpose here is to describe technical progress in developing an adaptive harvest management program (AHM) for the Central Management Unit of taiga bean geese. We were unable to conduct a similar harvest assessment for taiga bean geese in the Western and Eastern Management Units at this time, although we do briefly discuss these populations.
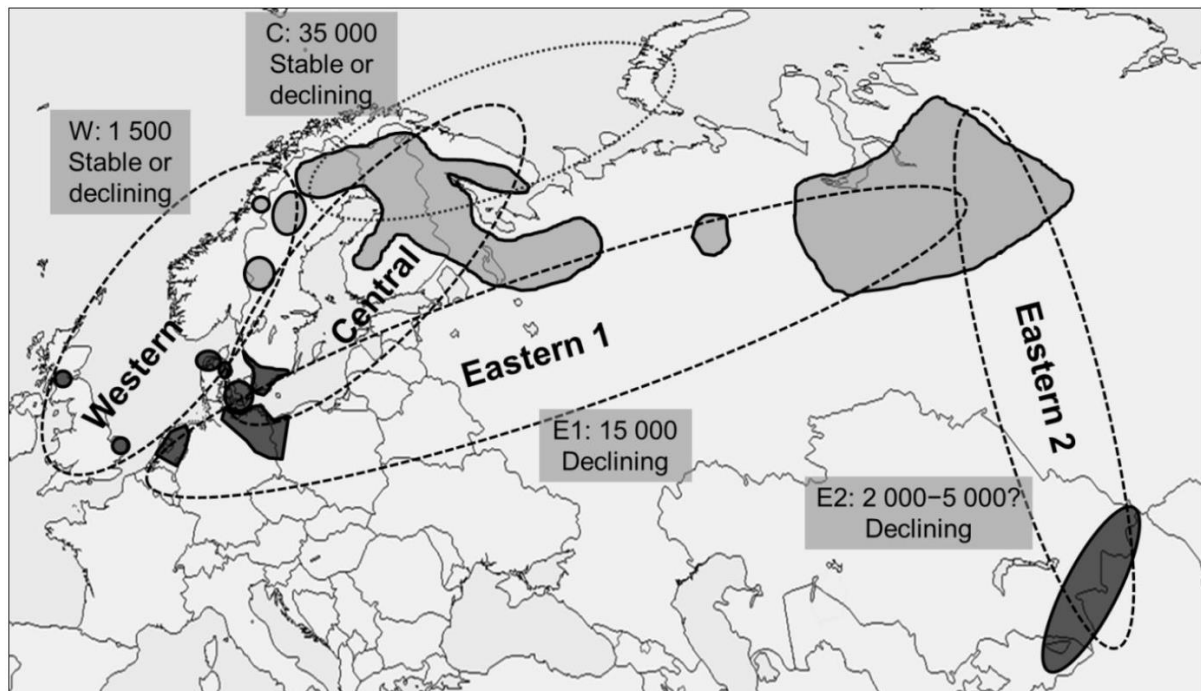
Fig. 1. Geographic representation of management units recommended for the taiga bean goose. Light and dark polygons represent breeding and wintering areas, respectively. (reproduced from the AEWA International Single Species Action Plan)

Critical elements of adaptive harvest management are: (1) quantifiable management objectives, by which alternative management strategies can be evaluated; (2) a set of alternative harvest actions (e.g., harvest quotas), from which one must be chosen (typically each year); (3) models of population dynamics, describing potential effects of harvest and other environmental drivers, as well as measures of model uncertainty; and (4) a monitoring program to assess resource status, measure management performance, and reduce uncertainty about population dynamics and the effects of harvest. This report describes recent progress in specifying these elements, and builds upon an initial assessment of sustainable harvest (Johnson 2015). We caution the reader, however, that the contents of this report are both preliminary and deliberative.

Methods

Model of population dynamics. – The harvest of renewable natural resources is predicated on the notion of reproductive surplus, and ultimately on the theory of density-dependent population growth (Hilborn et al. 1995). The theory predicts a negative relationship between the rate of population growth and population density (i.e., number of individuals per unit of limiting resource) due to intraspecific competition for resources. In a relatively stable environment, unharvested populations tend to settle around an equilibrium where births balance deaths.

Populations respond to harvest losses by increasing reproductive output or through decreased natural mortality because more resources are available per individual (density-dependent feedback). Population size eventually settles around a new equilibrium and the harvest, if not too heavy, can be sustained without destroying the breeding stock.

One of the most simple and commonly used models to determine sustainable harvests for birds is the discrete theta-logistic model (Gilpin and Ayala 1973):

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

where N is population size, r is the intrinsic rate of growth, K is carrying capacity, $\theta > 0$ is the form of density dependence, h is harvest rate, and t is time (assumed here to be in 1-year increments). The theta-logistic model lacks any age structure, however, and may not be a good approximation for geese, which typically do not breed regularly until they are three years old. Therefore, we used an age-structured analogue of the theta-logistic model for taiga bean geese. We assumed that the anniversary of the annual life cycle is in mid-winter following harvest (Fig. 2). This model assumes that survival of all age classes is identical once birds survive their first hunting season, that harvest mortality is additive to natural sources of mortality, and that young-of-the-year are twice as vulnerable to harvest as older birds.
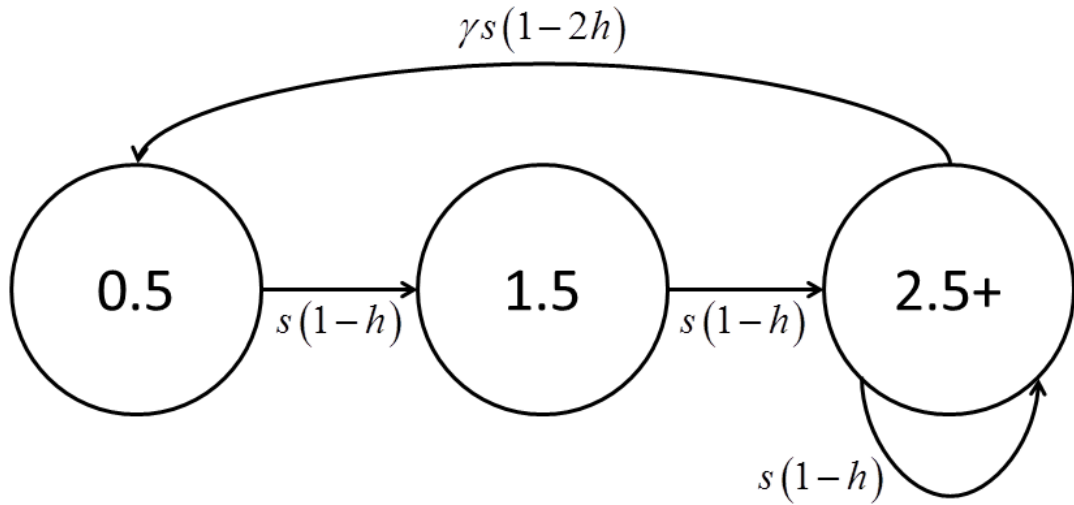
$$\gamma s (1-2h)$$

$$s(1-h) \qquad s(1-h) \qquad s(1-h)$$

Fig. 2. Proposed life cycle of taiga bean geese based on a mid-winter anniversary date. The three age classes represented are 0.5, 1.5, and ≥2.5 year olds. 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 this life cycle is:

$$
\begin{bmatrix}
n_{t+1}^{(0.5)} \\
n_{t+1}^{(1.5)} \\
n_{t+1}^{(2.5+)}
\end{bmatrix}
=
\begin{bmatrix}
0 & 0 & \gamma s(1-2h) \\
s(1-h) & 0 & 0 \\
0 & s(1-h) & s(1-h)
\end{bmatrix}
\begin{bmatrix}
n_t^{(0.5)} \\
n_t^{(1.5)} \\
n_t^{(2.5+)}
\end{bmatrix},
$$

where n represents age-class abundance and t represents year. The theta-logistic model with harvest can then be specified as:

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

where $\vec{N}$ is the vector of age-specific abundances, $\underline{M}$ is the transition matrix, $\underline{I}$ is the identity matrix, and $d\left(\vec{N}_t\right)$ is the density-dependent effect, where

$$d\left(\vec{N}_t\right) = 1 - \left(\frac{\sum \vec{N}_t}{K}\right)^{\theta},$$

with carrying capacity, K, and form of density dependence, $\theta > 0$ (Jensen 1995).

Model parameterization. –The fixed parameters of the theta-logistic model must be estimated under optimal or ideal conditions (i.e., in the absence of harvest and any density dependence). In the absence of detailed demographic information, Johnson et al. (2012) relied on detailed mortality records from 1,111 captive individuals of 23 bird species, with body masses ranging from 12 – 8663g, to estimate adult survival as:

$$s = p^{\left(\exp\left(3.22 + 0.24 \log(m) + \varepsilon\right) - a\right)^{-1}}$$

where a is age at first breeding (assumed to be 3 years in taiga bean geese), m is body mass in kg, ε is model error with $\varepsilon \sim N\left(0, \sigma^2 = 0.087\right)$, and p is the proportion of the population remaining alive at the maximum observed life span $\left(\bar{p} = 0.03, sd = 0.017\right)$. We allowed for uncertainty in p using a beta distribution: $p \sim Beta\left(3.34, 101.24\right)$. To apply this approach for taiga bean geese we used the mass of females provided by Dunning (2008) ($\bar{m} = 2.843, sd = 0.247$), and specified a gamma distribution to allow for variation in mass: $m \sim \Gamma\left(107.660, 0.026\right)$.

We used a novel method to estimate γ by relying on the demographic-invariant method developed by (Niel and Lebreton 2005):

$$r = \left[\frac{(sa - s + a + 1) + \sqrt{(s - sa - a - 1)^2 - 4sa^2}}{2a}\right] - 1,$$

where a is age at first breeding, s is adult survival, and r is the intrinsic rate of growth. We first generated 50,000 random samples of adult survival, s, using the methods described above, and then used them to generate 50,000 samples of r using Niel and Lebreton's (2005) formula. Next, we used the random samples of r to specify $(1 + r)$ (i.e., the intrinsic finite annual growth rate) as the dominant eigen value of transition matrices without harvest:

$$\underline{M}' = \begin{bmatrix} 0 & 0 & \gamma s \\ s & 0 & 0 \\ 0 & s & s \end{bmatrix}.$$

We then calculated γ numerically for each and every value of *s*, such that the dominant eigen value of $\underline{M}'$ was equal to the finite growth rate, $(1+r)$, associated with each survival, *s*.

The parameter θ in the theta-logistic model is often assumed to be equal to one, which specifies linear density dependence. However, density dependence may be non-linear depending on life history (Fowler 1981), and we were interested in whether an assumption of linear density dependence was appropriate for taiga bean geese. A negative relationship between θ and r is consistent with prevailing ecological theory (e.g., Fowler (1981)). Johnson et al. (2012) used point estimates of θ provided by Saether and Engen (2002) to fit the following model:

$$\log(\theta) = 1.129 - 1.824r + e,$$

where $e \sim \text{Normal}(0, \sigma^2 = 0.942)$. We truncated the normal distribution for the error term to the interval [-1.5 – 1.5] to keep values of theta within biologically realistic bounds. We then used the model to estimate θ and for each and every sample value of *r*.

The carrying capacity (i.e., expected population size over the long term in the absence of harvest) is difficult to estimate without a sufficiently long time series of population and harvest estimates. Lacking such data, we elicited expert judgements from those studying taiga bean geese breeding in the Keski-Pohjanmaa region of Finland. Those experts suggested that the breeding population in their study area might be 1.3 – 3 times as large in the absence of hunting, with a modal value of about 2 times as large. We in turn assumed a 90% credible interval of 1.75 – 2.25 times current population size. Extrapolating the densities of geese in Keski-Pohjanmaa to the Central Management Unit resulted in a contemporary estimate of population size of about 41,800 at the onset of the breeding season. Using this value and the 90% credible limits for the relative size of K, we fit a log-normal distribution to describe the uncertainty about the absolute value of $K \sim \log \text{N}(4.475, 0.042)$. This distribution describes carrying capacity at the onset of the breeding season; mid-winter carrying capacity was calculated as $K/\sqrt{s}$, which assumes the mid-winter carrying capacity is proportionally higher due to

approximately six months of mortality between the winter and breeding periods. Unfortunately, we were unable to obtain expert opinions about the carrying capacity of taiga bean geese in the Western and Eastern Management Units. Thus, we were unable to conduct a complete harvest assessment for those populations at this time.

We combined the i = 50,000 random samples of s^i, γ^i, K^i, and θ^i to form 50,000 transition matrices, $\underline{M}^i$, and density –dependence parameters, $d^i\left(\vec{N}_t\right)$, as a way of representing the considerable uncertainty about population dynamics of taiga bean geese in the Central Management Unit. We used these matrices and density-dependence parameters to simulate population sizes over time (see the section entitled *Optimization* below). We also examined how population size of Western and Eastern Management Unit birds might change over time in the absence of harvest and density-dependence. We used the matrices $\underline{M}^{\prime i}$, initial population sizes of 1,500 and 20,000 (15,000 in unit E1 plus 5,000 in unit E2), respectively, and the associated stable age distributions for matrices $\underline{M}^{\prime i}$. Growth rates thus derived are what they would be if the populations remained $<< 1/2$ of their respective carrying capacities and there was no harvest. Using these growth rates, we calculated the mean number of years for the Western and Eastern populations to meet their minimum goals of 5,000 and 100,000 respectively.

Management objectives. – The ISSAP call for restoring and then maintaining the Central Management Unit population of taiga bean geese at a level of 60,000 – 80,000 individuals in winter. Moreover, the stated purpose of AHM is to adjust harvest levels to reflect the status of the population such that harvest does not jeopardize future harvest opportunities (i.e., harvest is sustainable). Based on these goals, a possible objective function for harvest management is:

$$V^*\left(h,T \mid s,\gamma,K,\theta\right) = \underset{(h,T|s,\gamma,K,\theta)}{\arg\max} \frac{\sum_{t=1}^{T} U_t\left(\vec{N}_t \mid h\right)}{T},$$

where

$$U_t = \left(1 + \mathrm{e}^{\left(\left|\sum\left(\vec{N}_t|h\right)-\alpha\right|-\beta\right)}\right)^{-1},$$

and where the optimum value V of constant harvest rate, h, over time horizon, T, maximizes mean population utility, U, with a mid-winter population goal of $\alpha = 70,000$ taiga bean geese,

and inflection points $[\alpha - \beta, \alpha + \beta]$, where $\beta = 15,000$. The proposed objective 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. 3). The form of this utility curve is similar to the one used for AHM of pink-footed geese. Note that the proposed objective function does not explicitly account for the value of harvest, but rather assumes harvest is merely a tool to maintain population abundance within acceptable limits.
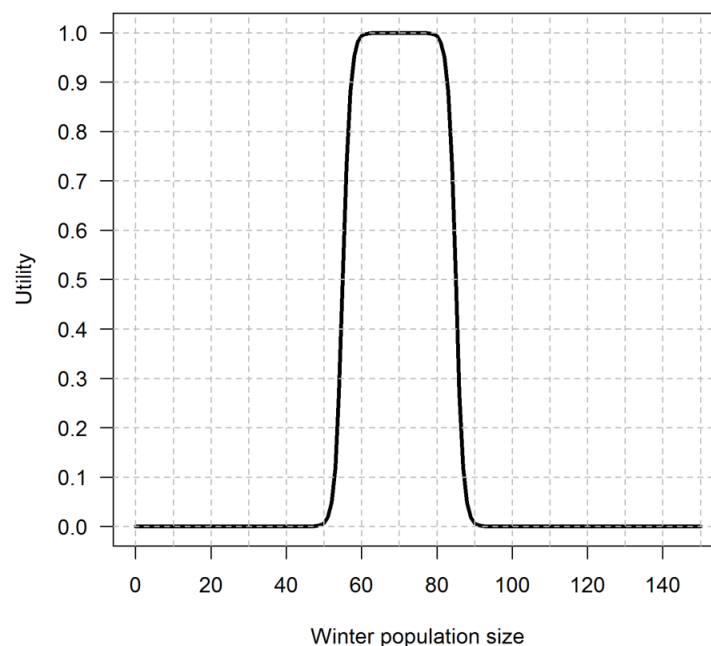

Fig. 3. Proposed utility of mid-winter population sizes of taiga bean geese in the Central Management Unit.

Alternative harvest actions. – The dangers of harvesting at a constant level are well known (Ludwig 2001), and harvest is more likely to be sustainable if a constant harvest *rate* is used (i.e., absolute harvest is changed to reflect stochastic changes in population size) (Runge et al. 2004). We thus examined possible harvest rates in the range 0 – 0.1 in increments of 0.01. Our goal was to find the constant harvest rate that best satisfies the objective function. We recognize, however, that regulation of harvest rather than harvest rate is more practical. Unfortunately, our matrix model does not permit one to calculate an exact harvest associated with a specific harvest rate. This is due largely to the fact that in practice harvest includes young of the year, which are only represented by post-harvest individuals in the matrix model. An *approximate* harvest, *H*, associated with a specific harvest rate could be calculated as:

$$H_t\left(\sum \vec{N}_t, h_t\right) = \bar{n}_t^{(2.5+)} d\left(\vec{N}_t\right) \bar{\gamma}\,\bar{s}\,2h_t + \sum \vec{N}_t d\left(\vec{N}_t\right)\bar{s}h_t ,$$

where bars over the parameters signify mean values. In the absence of information about age structure of the mid-winter population, one could rely on the stable age distribution of the matrix $d\left(\vec{N}_t\right)\cdot \underline{\bar{M}}$. We reiterate that this is only a rough approximation of harvest associated with a given population size and harvest rate. Calculation of an exact harvest would require additional assumptions about the specific timing of mortality and reproductive events during the annual cycle, and we were uncomfortable doing so given the lack of empirical data.

Optimization. –We used a simulation approach to determine the harvest rate that maximized the objective function for a specified time horizon. We examined time horizons of T = 5, 10, 15, and 20 years. For each of the i = 50,000 matrix models, we initialized population size as $\sum \vec{N}_{t=1}^i = 41,800\big/\sqrt{s^i}$, which reflects the contemporary estimate in the Keski-Pohjanmaa breeding area, inflated to produce a corresponding mid-winter estimate. Each initial population vector was parameterized using a random draw from a Dirichlet distribution with parameters equal to the stable age distribution of $\underline{M}^{\prime i}$ (in percent). This allowed for uncertain, but plausible, values of the initial age distribution for simulation purposes.

We then used the concept of stochastic dominance (Canessa et al. 2016) to explicitly account for uncertainty and risk in selecting the harvest rate, h, that maximized the objective value. For each time horizon and harvest rate, we examined the empirical cumulative distribution function (cdf) of objective values. The harvest rate associated with the lowermost cdf is the optimal choice if, and only if, it does not cross the cdf for any of the remaining harvest rates (called first-order dominance). If cdf's cross, then it is necessary to know the general risk attitude of the decision maker to identify an optimal harvest rate. We assumed a risk averse (rather than risk seeking) decision maker, so the ascending integrals of the cdf's were examined (the descending integrals would be examined for a risk-seeking decision maker). The harvest rate associated with the lowermost ascending integral is the optimal choice for a risk-averse decision maker if, and only if, it does not cross the ascending integral of any of the remaining harvest rates (called second-order dominance). We calculated ascending integrals of the cdf's using numerical integration.

All calculations were performed using the open-source computing language R (RCoreTeam 2016) (R code included as Appendix A).

Results

Using the mass-based model of Johnson et al. (2012), the mean adult survival of taiga bean geese expected under ideal conditions was estimated as $s = 0.878$ (90% credible interval: 0.799 – 0.934) (Fig. 4). Assuming age at first breeding is 3 years, and using the model of Niel and Lebreton (2005), we estimated the mean intrinsic rate of growth as 0.150 (90% credible interval: 0.120 – 0.182) (Fig. 5). We estimated the mean reproductive parameter as $\gamma = 0.567$ (credible interval: 0.285 – 1.048) (Fig. 6). We estimated the mean form of density dependence as $\theta = 2.361$ (90% credible interval: 0.473 – 11.778) (Fig. 7), suggesting the strongest density dependence occurs when the population is near its carrying capacity. We note, however, that the estimate of θ is very imprecise and the hypothesis of linear density dependence ($\theta = 1$) could not be rejected. Finally, we estimated mean carrying capacity at the onset of the breeding season as $K = 87,900$ (90% credible interval: 82,000 – 94,100) (Fig. 8). The corresponding mid-winter carrying capacity was $K = 93,700$ (90% credible interval: 86,700 – 101,700), which accounts for mortality between the winter and breeding periods.
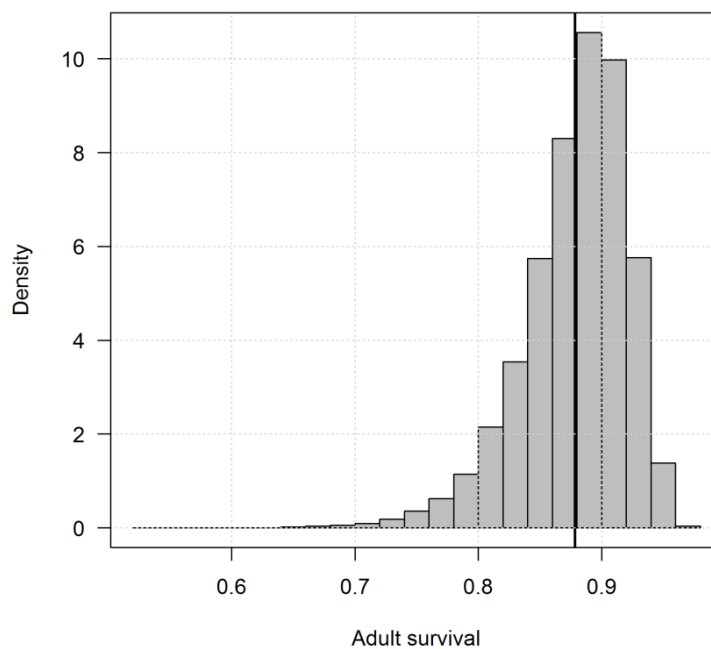

Fig. 4. Adult survival of taiga bean geese in the absence of density dependence and harvest as estimated using the method of (Johnson et al. 2012). The bold vertical line is the mean.
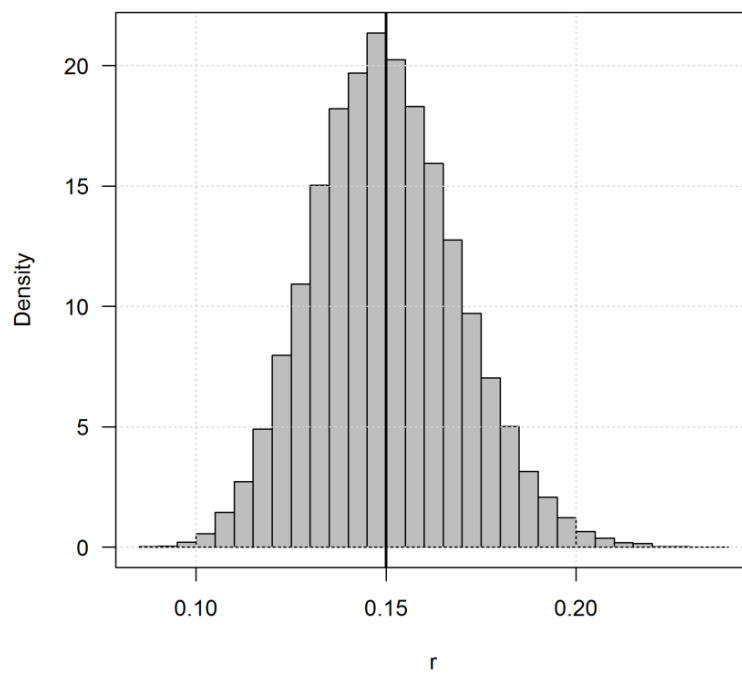
Fig. 5. The intrinsic rate of growth for taiga bean geese as estimated by the method of Niel and Lebreton (2005). The bold vertical line is the mean.
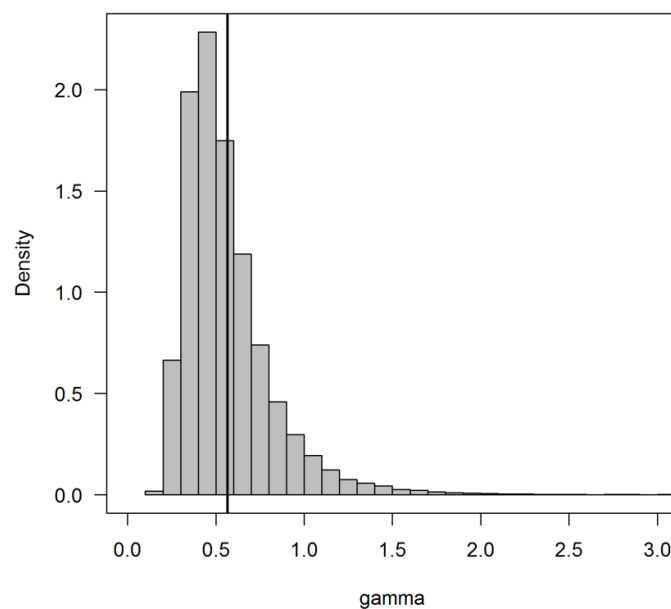

Fig. 6. Estimates of the reproductive parameter, gamma, which when combined with associated estimates of survival rate, produce finite growth rates equal to those projected by the Niel and Lebreton (2005) model based on survival alone.
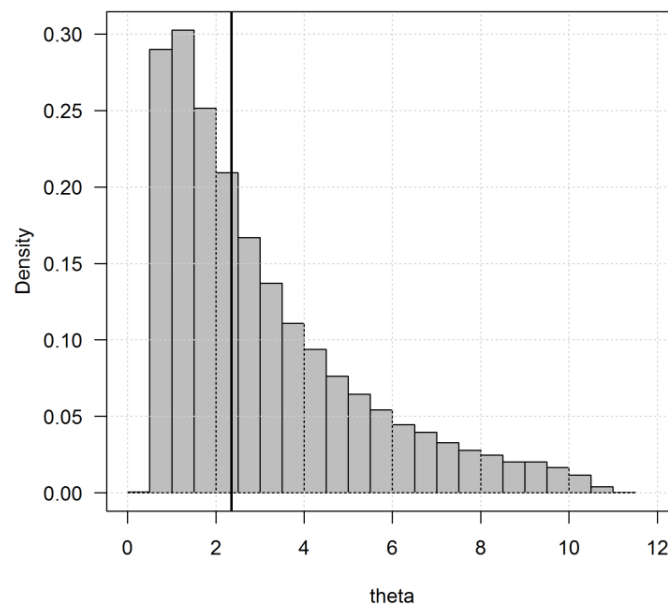
Fig. 7. Estimates of the theta parameter in the theta-logistic model using the method of (Johnson et al. 2012).
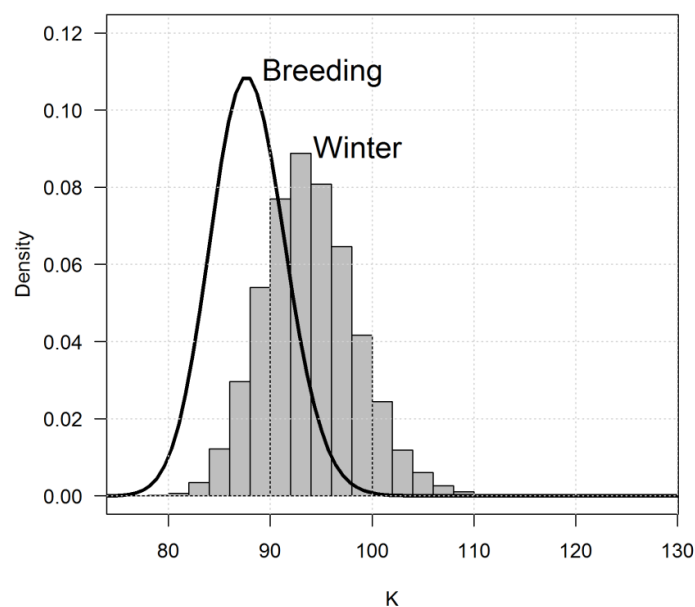

Fig. 8. Estimated carrying capacity of taiga bean geese (in thousands) in the Central Management Unit. Carrying capacity at the onset of the breeding season was based on expert opinion, and winter carrying capacity was assumed to be proportionally higher to account for mortality between the wintering and breeding periods. The histogram was based on 50,000

samples from the lognormal distribution of breeding-season carrying capacity, combined with 50,000 samples of survival rate.

The optimal harvest rate depended on the time horizon (Fig. 9). Based on the mean utility (over all transition matrices $\underline{M}^{\,i}$), the optimal harvest rates for 5, 10, 15, and 20 years were h = 0.00, 0.02, 0.05, and 0.06, respectively. We verified that these were the optimal harvest rates for a risk-neutral (first order dominance for the 5-year time horizon) or risk-averse (second order dominance for 10, 15, and 20-year time horizons) decision makers based on the concept of stochastic dominance (20-year-time horizon depicted in Fig. 10). These optima represent a tradeoff between the harvest rate (and, thus, the harvest) and the time required to achieve and maintain a population size within desired bounds (i.e., $60,000 \leq \sum \vec{N}_t \leq 80,000$ with $U_t\left(\sum \vec{N}_t\right) \geq 0.99$). For a 5-year time horizon, h = 0.00 typically approached a population size of 60,000 only in the fifth year on the average, but this was highly variable. With longer time horizons, and thus more opportunity for population growth, non-zero harvest rates were needed to keep population size within desired bounds. Approximate harvests for a range of mid-winter population sizes and harvest rates are provided in Table 1.
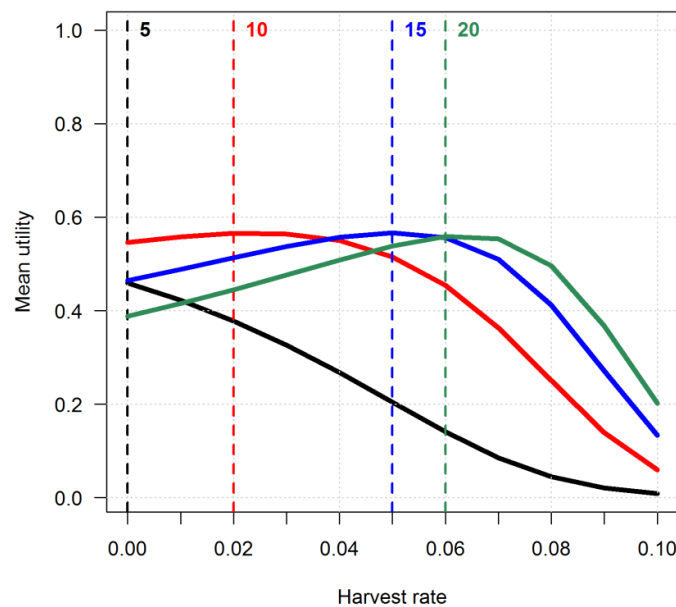

Fig. 9. Simulated mean utility over time horizons of 5, 10, 15, and 20 years (black, red, blue, and green, respectively) for a range of harvest rates of taiga bean geese in the Central Management Unit. Population sizes at the median goal of 70,000 geese have unit utility (see Fig. 3). Vertical dotted lines are the optimal harvest rates for the different time horizons.
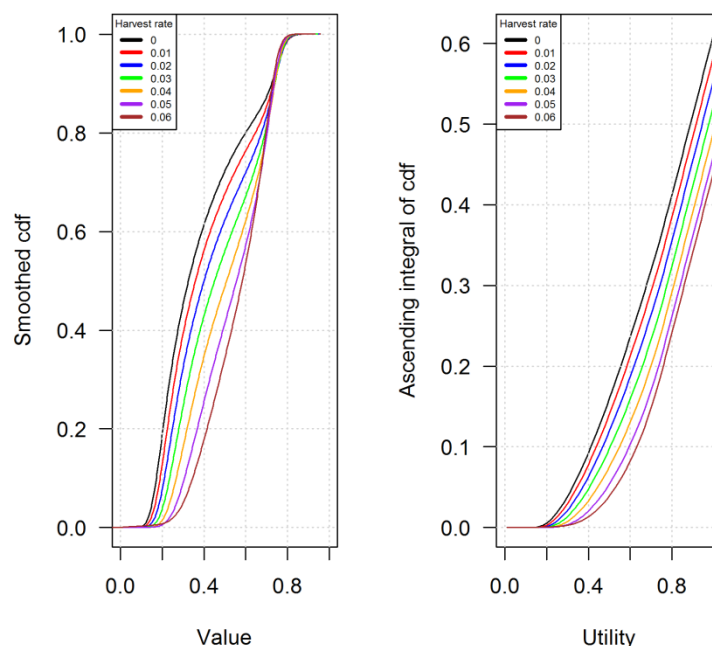
Fig. 10. Cumulative distribution function (cdf) (left panel) and the ascending integral of the cdf (right panel) of population utility based on simulation of a range of harvest rates of taiga bean geese in the Central Management Unit for a 20-year time horizon. The cumulative distribution functions in the left panel cross, meaning that a risk-averse manager must examine the right panel to determine that the ascending integral for $h = 0.06$ dominates all of the remaining integrals, suggesting it is the optimal harvest rate for a 20-year time horizon.

Populations of taiga bean geese in the Western and Eastern Units would require at least 10 and 13 years, respectively, to reach their minimum goals under the most optimistic of scenarios (i.e., no harvest and no density dependence). The presence of anthropogenic-related mortality, density dependence, or environmental variation could extend these time frames considerably, but we had no way of forecasting these conditions. Also, it may be that extant environmental conditions in these populations would not allow them to attain their maximum growth rates, even in the absence of any harvest.

Table 1. Approximate taiga bean goose harvests (in thousands) for a range of mid-winter population sizes ($\sum \vec{N}$, in thousands) and harvest rates (h) in the Central Management Unit. The approximation is based on the mean transition matrix, $\overline{\underline{M}}$, and the stable age distribution of the matrix $d\left(\vec{N}_t\right) \cdot \overline{\underline{M}}$. Note that harvest first increases with population size and then begins to decline. This is a result of density dependence operating at higher population levels, thus reducing the size of the allowable harvest.

$\sum \vec{N}$	$h = 0.01$	0.02	0.03	0.04	0.05	0.06
35	0.5	1.0	1.5	1.9	2.4	2.9
40	0.5	1.1	1.6	2.2	2.7	3.2
45	0.6	1.2	1.8	2.3	2.9	3.5
50	0.6	1.2	1.9	2.5	3.1	3.7
55	0.6	1.3	1.9	2.6	3.2	3.9
60	0.6	1.3	2.0	2.6	3.3	3.9
65	0.6	1.3	1.9	2.6	3.2	3.8
70	0.6	1.2	1.8	2.4	3.0	3.6
75	0.5	1.1	1.6	2.2	2.7	3.3
80	0.4	0.9	1.3	1.8	2.3	2.7
85	0.3	0.6	1.0	1.3	1.6	1.9

Discussion

We believe the approach presented here can provide a first approximation of allowable harvest levels when detailed demographic data are lacking. The approach can also be useful for comparing estimates of demographic parameters based on allometric relationships and expert opinion with those from empirical studies. If slightly more information were available, a more useful approach than that presented here for estimating potential population growth may be that proposed by Slade et al. (1998):

$$1 = s_a \lambda^{-1} + s_j f \lambda^{-\alpha} - s_j f s_a^{(\omega-\alpha+1)} \lambda^{-(\omega+1)}$$

where λ is the maximum finite population growth rate (i.e., $r_{\max} = \lambda - 1$), s_j and s_a are fixed survival rates of pre-reproductives and adults, respectively, f is a fixed fecundity for all reproductives, and α and ω are ages at first and last breeding, respectively. Johnson et al. 2012) provided methods for estimating f and s_j for migratory birds using published information on the components of vital rates (e.g., nest success and clutch size).

A key advantage of our approach is the ability to account for management objectives, uncertainty, and risk tolerance in a straightforward manner. Moreover, our approach does not conflate biological and management parameters as is the case with other approaches (e.g., Wade (1998)). We explicitly account for considerable demographic uncertainty in formulating the population's likely response to harvest, but then permit a decision maker to specify their management objectives and attitude toward risk (we assumed that the decision maker is not risk-seeking). The clear separation between science and policy helps decision makers understand whether disagreements about appropriate harvest levels are over predicted outcomes or how those outcomes are valued (Lee 1993). We emphasize that the management objective specified here for the Central Management Unit is preliminary, based on guidance found in the AEWA International Single Species Action Plan. It is subject to review by the International Taiga Bean Goose Working Group.

While only a first approximation to allowable harvests, we believe this analysis provides reasonable demographic values for taiga bean geese based on our comparisons of this method with more data-intensive ones for snow geese (*Anser caerulescens*), barnacle geese (*Branta leucopsis*) (Niel and Lebreton 2005), and pink-footed geese (*Anser brachyrhynchus*) (Johnson et al. 2014). Moreover, our estimates of survival and reproductive rates for taiga bean geese in the Central Management Unit are reasonably consistent with the fragmentary information provided in the International Single Species Action Plan. Also, it appears that the harvests in Finland and Sweden prior to hunting restrictions in 2014 were of sufficient magnitude to keep population size depressed near its current value (ca. 40,000).

Several cautionary notes concerning our modeling and simulation efforts are warranted, however. While our approach explicitly acknowledges that annual survival and reproductive rates are uncertain, it assumes they are fixed over time. Our simulations thus incorporate no environmental variation and, as a result, projections of population size over time may be overly optimistic. Also, we note that while our methods are reasonably robust to stochastic changes in carrying capacity, K, that is not true of stochastic changes in the intrinsic growth rate, r. We emphasize that our estimates of r are what one would expect over evolutionary (rather than ecological) time scales, and suggest that our estimates of r should be treated as theoretical maximums. Finally, we emphasize that while a constant harvest rate is robust to environmental

variation, absolute harvest is not. If environmental variation is significant (and can be specified stochastically), decision makers might consider the use of stochastic dynamic optimization methods, which provide state-dependent prescriptions for allowable harvest (Williams 1985, Possingham 1997, Johnson 2011).

Finally, we note that the management process described in this report for the Central Management Unit does not yet represent a fully adaptive strategy. Adaptation based on what is learned depends on the ability to make predictions about changes in population size that are model-specific, as well as an ability to measure, at a minimum, actual harvest and population size each year. The comparison of monitoring observations and model predictions then permits models to be improved so that better decisions can be made in the future. This report describes a simple model of population dynamics and a straightforward way to account for parameter uncertainty. As described above, however, reliable predictive models for geese may require more structure (and thus more data) than the simple model described herein. We will be exploring the potential for more complicated models and standardization of monitoring programs for all management units with the AEWA International Taiga Bean Goose Working Group in the near future.

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Appendix A. R code for estimating demographic parameters of taiga bean geese, and then simulating population size over time using a matrix analogue of the theta-logistic population model.

```
# DD Matrix Model v4.r
# caps stage classes at sad*K to prevent pathological bevavior of logistic for high abundances relative to K
setwd('C:\\Users\\fjohnson\\Documents\\PROJECTS\\Taiga Bean Geese\\Progress Report I')

#library(triangle)
library(popbio)
library(rriskDistributions)
library(gtools)
library(ggplot2)
library(popdemo)
library(akima)
library(rootSolve)
library(truncnorm)

ppi = 300

# method of moments for beta and gamma distributions
MOM.beta=function(mu,var) {
  sum_ab=(mu*(1-mu)/var)-1
  a=sum_ab*mu
  b=sum_ab*(1-mu)
  c(a,b)}

MOM.gamma = function(mean,var) {
 gamma.s = var/mean
 gamma.a = mean/gamma.s
 return(c(gamma.a,gamma.s))
 }

# utility functions
goal=70
U.fcn = function(x,goal) (x-goal)^2
x=0:150
y = U.fcn(x,goal)
ystd = (y - max(y)) / (min(y)-max(y))
plot(x,ystd,type='l',las=1,lwd=2,xlab="Population size",ylab="Utility");grid()

U.fcn2 = function(x,goal) 1 / (1 + exp(abs(x-goal)-15))
y=U.fcn2(x,goal)
tiff(file='Utility2.tif',res=ppi,width = 6*ppi, height = 6*ppi)
plot(x,y,type='l',lwd=3,xaxp=c(0,140,7),yaxp=c(0,1,10),las=1,xlab='Winter population
size',ylab='Utility');abline(v=seq(0,150,10),h=seq(0,1,.1),col='gray',lty=2)
dev.off()
```

```
# survival functions, Niel & Lebreton Eq. 15, and F function
sa.fcn = function(mass,p,alpha) p^(1/(exp(3.22+0.24*log(mass)+rnorm(z,0,sqrt(0.087)))-alpha))
getlam1=function(a,s) { ((s*a-s+a+1)+sqrt((s-s*a-a-1)^2-4*s*a^2))/(2*a) }
getF = function(f,theta,N,K)  (K*(1-(f*theta/(theta+1)))^(1/theta)-N)


################################################################################
################################################################################
z = 50000 # no. of samples

# Survival calculations
alpha = 3 # age at first breeding
mass.mean = 2.843 # female mass (Dunning 2008)
mass.sd = 0.274

# ... replicates of body mass
gamma.parm = MOM.gamma(mass.mean,mass.sd^2)
mass = rgamma(z,shape=gamma.parm[1],scale=gamma.parm[2]) # generate mass replicates

# ... replicates of proportion alive at max longevity (Johnson et al. 2012)
p = rbeta(z,3.34,101.24)

# ... replicates of adult survival (Slade et al. 1998)
sa = sa.fcn(mass,p,alpha)
mean(sa)
quantile(sa,probs=c(0.05,0.50,0.95))
tiff(file='Sa.tif',res=ppi,width = 6*ppi, height = 6*ppi)
hist(sa,col='gray',freq=F,xlab='Adult survival',main='',breaks=30,las=1);
abline(v=mean(sa),lwd=2);grid();box()
dev.off()

# lam1 is the analytical solution for Niel & Lebreton equation 15, given age at first breeding (a) and
adult survival (s)
r = log(getlam1(3,sa))
mean(r)
quantile(r,probs=c(0.05,0.50,0.95))
tiff(file='r.tif',res=ppi,width = 6*ppi, height = 6*ppi)
hist(r,col='gray',freq=F,breaks=30,las=1,main='');grid();box();abline(v=mean(r),lwd=2);
dev.off()

# generate thetas (Saether and Engen 2002)
e1=rnorm(z,0,sqrt(0.9418))
theta1 = exp(1.1286-1.8244*r+e1)
# use truncated normal for error term
e = rtruncnorm(z,a=-1.5,b=1.5,0,sqrt(0.9418))
theta = exp(1.1286-1.8244*r+e)
summary(theta1);summary(theta)
quantile(theta,probs=c(0.05,0.50,0.95))
tiff(file='theta.tif',res=ppi,width = 6*ppi, height = 6*ppi)
hist(theta,col='gray',freq=F,breaks=30,las=1,main='',xlim=c(0,12));grid();box();abline(v=median(theta
),lwd=2);
dev.off()
```

```
# Carrying capacity
#... breeding ground
curN = 41.800
(n=c(curN*1.75,curN*2.25))
par=get.lnorm.par(p=c(0.05,0.95),q=n,tol=0.001)
k = rlnorm(z,par[1],par[2])
mean(k)
quantile(k,probs=c(0.05,0.50,0.95))
#... wintering K
K = k/sqrt(sa)
mean(K)
quantile(K,probs=c(0.05,0.50,0.95))
tiff(file='K.tif',res=ppi,width = 6*ppi, height = 6*ppi)
hist(K,freq=FALSE,breaks=30,ylim=c(0,0.12),col='gray',main='',las=1);box();#abline(v=median(K),lwd=
2,lty=2)
curve(dlnorm(x,par[1],par[2]),60,130,ylab='Density',xlab='K',lwd=3,las=1,add=TRUE);grid()
abline(v=mean(k),lwd=2,lty=2)
abline(v=mean(K),lwd=1,lty=2)
text(c(88,93),c(0.11,0.09),pos=4,labels=c('Breeding','Winter'),cex=1.5)
dev.off()

# generate reproductive parameters
gamma = NULL
for (i in 1:z)
{
 gamma.fcn = function(gamma)
Re(eigen(matrix(c(0,0,(sa[i])*gamma,sa[i],0,0,0,sa[i],sa[i]),byrow=T,nrow=3))$values[1])-1-r[i]
 gamma[i] = uniroot(gamma.fcn,c(0,10))$root
}
mean(gamma)
quantile(gamma,probs=c(0.05,0.95))
tiff(file='gamma.tif',res=ppi,width = 6*ppi, height = 6*ppi)
hist(gamma,freq=FALSE,breaks=50,col='gray',main='',las=1,xlim=c(0,3));box();abline(v=mean(gamma
),lwd=2,lty=1)
dev.off()

# compile data
all = data.frame(cbind(sa,gamma,theta,K)); colnames(all) = c('sa','gamma','theta','K')
(C=round(cor(all,use='complete.obs',method='spearman'),4))

# compile matrices
classes = 3
M = stable = lambda = NULL
sad=matrix(nrow=z,ncol=classes)
for (i in 1:z)
{
 M[[i]] = matrix(c(0,0,(sa[i])*gamma[i],sa[i],0,0,0,sa[i],sa[i]),byrow=T,ncol=classes)
 lambda[i]=eigen.analysis(M[[i]])$lambda1
 sad[i,] = eigen.analysis(M[[i]])$stable.stage
}
```

```
summary(sad)

# do the r stats match?
summary(lambda-1)
summary(r)


#################################################################################
#################################################################################
#################################################################################
# conduct simulation
h = seq(0,0.10,.01) # harvest rate
I = diag(classes)
N0 = 41.8/sqrt(sa)  # intitalize pop
n = matrix(nrow=3,ncol=z)
for (j in 1:z) n[,j] = N0[j]* rdirichlet(1,sad[j,]*100)


t = 20  # time steps
# intitialize arrays for results
Pop = matrix(nrow=classes,ncol=t)
D = A = NULL
N = V = array(NA,c(z,t,length(h)))


for (k in 1:length(h))
{
 for (j in 1:z)
 {
  A[[j]] = M[[j]]
  A[[j]][1,3] = A[[j]][1,3]*(1-2*h[k])
  A[[j]][2,1] = A[[j]][2,1]*(1-h[k])
  A[[j]][3,2] = A[[j]][3,3] = A[[j]][3,2]*(1-h[k])
  Pop[,1] = n[,j]
 for (i in 2:t)
  {
  D[(i-1)] = 1 - (sum(Pop[,(i-1)])/K[j])^theta[j]
#  D = diag(c(1-Pop[1,(i-1)]/(K[j]*sad[j,1]), 1-Pop[2,(i-1)]/(K[j]*sad[j,2]), 1-Pop[3,(i-1)]/(K[j]*sad[j,3])) )
  net = D[(i-1)]*(A[[j]]-I)%*%Pop[,(i-1)]
  Pop[,i] = Pop[,(i-1)] + net
  Pop[1,i] = ifelse(Pop[1,i]<0,0,ifelse(Pop[1,i]>sad[j,1]*K[j],sad[j,1]*K[j],Pop[1,i]))
  Pop[2,i] = ifelse(Pop[2,i]<0,0,ifelse(Pop[2,i]>sad[j,2]*K[j],sad[j,2]*K[j],Pop[2,i]))
  Pop[3,i] = ifelse(Pop[3,i]<0,0,ifelse(Pop[3,i]>sad[j,3]*K[j],sad[j,3]*K[j],Pop[3,i]))
  }
 N[j, ,k] = apply(Pop,2,sum)
 V[j, ,k] = U.fcn2(N[j, ,k],goal)
 }
}
which(is.na(N)); which(is.nan(N))

# summaries by harvest rate
sumV = sumN = NULL
for (i in 1:length(h))
```

```
{
 sumV[[i]] = summary(V[,,i])
 sumN[[i]] = summary(N[,,i])
}

# store values
V20 = V
V20.mean = matrix(nrow=z,ncol=length(h))
for (i in 1:length(h)) V20.mean[,i] = apply(V20[,,i],1,mean)
V20.star = apply(V20.mean,2,mean)

# find optimal harvest rate based on mean values
opt = round(cbind(h, V5.star,V10.star,V15.star,V20.star),4)
tiff(file='TemporalOptimalv4.tif',res=ppi,width = 6*ppi, height = 6*ppi)
plot(opt[,1],opt[,2],col='black',type='l',lwd=4,ylab='Mean utility',xlab='Harvest
rate',las=1,ylim=c(min(opt[,2]),1),xaxp=c(0,0.15,15));grid()
abline(v=opt[which(opt[,2]==max(opt[,2])),1],col='black',lwd=2,lty=2)
text(0.0,1,labels=5,col='black',pos=4,font=2)
lines(opt[,1],opt[,3],col='red',type='l',lwd=4);
abline(v=opt[which(opt[,3]==max(opt[,3])),1],col='red',lwd=2,lty=2)
text(0.02,1,labels=10,col='red',pos=4,font=2)
lines(opt[,1],opt[,4],col='blue',type='l',lwd=4);
abline(v=opt[which(opt[,4]==max(opt[,4])),1],col='blue',lwd=2,lty=2)
text(0.05,1,labels=15,col='blue',pos=4,font=2)
lines(opt[,1],opt[,5],col='seagreen',type='l',lwd=4);
abline(v=opt[which(opt[,5]==max(opt[,5])),1],col='seagreen',lwd=2,lty=2)
text(0.06,1,labels=20,col='seagreen',pos=4,font=2)
dev.off()


################################################################################

# stocahstic dominance
#... cdf's for selected harvest rates
cdf=list()
for (i in 1:7) cdf[[i]] = ecdf(V20.mean[,i])

#... raw cdf's
tiff(file='StocDomV20.mean.tif',res=ppi,width = 6*ppi, height = 6*ppi)
par(mfrow=c(1,2),bg='white')
#xx = seq(0,1,.005)
#plot(xx,cdf[[1]](xx),type='l',lwd=1,ylab='Cumulative probability',xlab="Utility",main='')
#lines(xx,cdf[[2]](xx),lwd=1,col='red')
#lines(xx,cdf[[3]](xx),lwd=1,col='blue')
#lines(xx,cdf[[4]](xx),lwd=1,col='green')
#lines(xx,cdf[[5]](xx),lwd=1,col='orange')
#lines(xx,cdf[[6]](xx),lwd=1,col='purple')
#legend("topleft",title='Harvest
rate',cex=1,legend=seq(0.0,0.05,0.01),col=c('black','red','blue','green','orange','purple'),lwd=3)
#
```

25

```
# smoothed cdf's
fit1 = density(V20.mean[,1],kernel='c')
fit2 = density(V20.mean[,2],kernel='c')
fit3 = density(V20.mean[,3],kernel='c')
fit4 = density(V20.mean[,4],kernel='c')
fit5 = density(V20.mean[,5],kernel='c')
fit6 = density(V20.mean[,6],kernel='c')
fit7 = density(V20.mean[,7],kernel='c')

plot(fit1$x[-1],diff(fit1$x)*cumsum(fit1$y)[-1],type="l",lwd=1,ylab='Smoothed
cdf',xlab="Value",main='',xlim=c(0,1),las=1,col='black');grid()
lines(fit2$x[-1],diff(fit2$x)*cumsum(fit2$y)[-1],lwd=1,col='red')
lines(fit3$x[-1],diff(fit3$x)*cumsum(fit3$y)[-1],lwd=1,col='blue')
lines(fit4$x[-1],diff(fit4$x)*cumsum(fit4$y)[-1],lwd=1,col='green')
lines(fit5$x[-1],diff(fit5$x)*cumsum(fit5$y)[-1],lwd=1,col='orange')
lines(fit6$x[-1],diff(fit6$x)*cumsum(fit6$y)[-1],lwd=1,col='purple')
lines(fit7$x[-1],diff(fit7$x)*cumsum(fit7$y)[-1],lwd=1,col='brown')
legend("topleft",title='Harvest
rate',cex=0.5,legend=seq(0.0,0.06,0.01),col=c('black','red','blue','green','orange','purple','brown'),lw
d=3)


## ascending integrals
int2vec = function(x,v) integrate(ecdf(v),0,x,subdivisions=100000,rel.tol=0.001)$value
x = seq(0.01,1,.01)
y = matrix(nrow=length(x),ncol=7)
for (i in 1:length(x)) for (j in 1:7) y[i,j]=int2vec(x[i],V20.mean[,j])

plot(x,y[,1],type='l',lwd=1,xlab='Utility',ylab='Ascending integral of
cdf',las=1,col='black',xlim=c(0,1),ylim=c(0,max(y,na.rm=T)));grid()
lines(x,y[,2],lwd=1,col='red')
lines(x,y[,3],lwd=1,col='blue')
lines(x,y[,4],lwd=1,col='green')
lines(x,y[,5],lwd=1,col='orange')
lines(x,y[,6],lwd=1,col='purple')
lines(x,y[,7],lwd=1,col='brown')

legend("topleft",title='Harvest
rate',cex=0.5,legend=seq(0.0,0.06,0.01),col=c('black','red','blue','green','orange','purple','brown'),lw
d=3)
dev.off()


# Approximate harvests
n = seq(35,85,5)
h = seq(0,0.1,.01)
propY = H = matrix(nrow=length(n),ncol=length(h))
for (j in 1:length(h))
{
 for (i in 1:length(n))
 {
```

```
 d = 1 - (n[i]/mean(K))^mean(theta)
 X = matrix(c(0,0,mean(gamma)*mean(sa)*(1-2*h[j]),mean(sa)*(1-h[j]),0,0,0,mean(sa)*(1-
h[j]),mean(sa)*(1-h[j])),byrow=TRUE,nrow=3)
 A = d * X
 prop = eigen.analysis(A)$stable.stage
 propY[i,j] = n[i]*prop[3]*d*mean(gamma)*mean(sa) / n[i]*d*mean(sa)
 H[i,j] = n[i]*d*mean(sa)*h[j] + n[i]*prop[3]*d*mean(gamma)*mean(sa)*2*h[j]
 }
}

harvest.table = as.data.frame(cbind(n,H))
colnames(harvest.table)=c('N',h)
write.csv(harvest.table,'harvest.table.csv')

# West & East maximum pop growth (no harvest, no density dependence)
t = 20
E = W = matrix(nrow=classes,ncol=t)
En = Wn = matrix(nrow=z,ncol=t)

# West
for (j in 1:z)
{
 W[,1] = sad[j,]*1500
 for (i in 2:t)
 {
  W[,i] = M[[j]]%*%W[,(i-1)]
 }
 Wn[j,] = apply(W,2,sum)
}
which(is.na(Wn)); which(is.nan(Wn))
summary(Wn/1000,digits=3)

# East
for (j in 1:z)
{
 E[,1] = sad[j,]*20000
 for (i in 2:t)
 {
  E[,i] = M[[j]]%*%E[,(i-1)]
 }
 En[j,] = apply(E,2,sum)
}
which(is.na(En)); which(is.nan(En))
summary(En/1000,digits=3)

# how does D vary with N/K?
n = seq(0,1,0.05) ; cc = 1
D = matrix(nrow=z,ncol=length(n))
for (i in 1:z)
{
 for (j in 1:length(n))
```

```
 {
 D[i,j] = 1 - (n[j]/cc) ^theta[i]
 }
 }


# VOI  (not used in this report)
V.tempsum = matrix(nrow=z,ncol=length(h))
for (i in 1:length(h))
{
 V.tempsum[,i] = apply(V[,,i],1,sum)
}
(EVPI = mean(apply(V.tempsum,1,max)) - max(apply(V.tempsum,2,mean)))
(EVPIpct = EVPI / max(apply(V.tempsum,2,mean)))
```