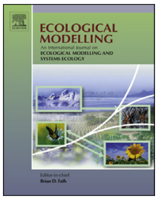
Ecological Modelling 273 (2014) 186–199

Contents lists available at ScienceDirect

Ecological Modelling

journal homepage: www.elsevier.com/locate/ecolmodel



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

Fred A. Johnson[a,*], Gitte H. Jensen[b], Jesper Madsen[b], Byron K. Williams[c]

[a] Southeast Ecological Science Center, U.S. Geological Survey, 7920 NW 71 Street, Gainesville, FL 32653, USA
[b] Department of Bioscience, Arctic Research Centre, Aarhus University, Building 1110, DK-8000 Aarhus C, Denmark
[c] The Wildlife Society, 541 Grosvenor Lane, Suite 200, Bethesda, MD 20814, USA

ARTICLE INFO

Article history:
Received 24 March 2013
Received in revised form 23 October 2013
Accepted 25 October 2013
Available online 5 December 2013

Keywords:
Adaptive management
Value of information
Optimization
Pink-footed goose
Robustness
Uncertainty

ABSTRACT

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

---

* Corresponding author. Tel.: +1 352 264 3488.
E-mail address: fjohnson@usgs.gov (F.A. Johnson).

0304-3800/$ – see front matter. Published by Elsevier B.V.
http://dx.doi.org/10.1016/j.ecolmodel.2013.10.031

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

1. Introduction

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

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

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

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

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

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

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

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