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Quantifying the expected value of uncertain management choices for over-abundant Greylag Geese

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ABSTRACT

In many parts of the world, conservation successes or global anthropogenic changes have led to increasing native species populations that then compete with human resource use. In the Orkney Islands, Scotland, a 60-fold increase in Greylag Goose *Anser anser* numbers over 24 years has led to agricultural damages and culling attempts that have failed to prevent population increase. To address uncertainty about why populations have increased, we combined empirical modelling of possible drivers of Greylag Goose population change with expert-elicited benefits of alternative management actions to identify whether to learn versus act immediately to reduce damages by geese. We built linear mixed-effects models relating annual goose densities on farms to land-use and environmental covariates and estimated AICc model weights to indicate relative support for six hypotheses of change. We elicited from experts the expected likelihood that one of six actions would achieve an objective of halting goose population growth, given each hypothesis for population change. Model weights and expected effects of actions were combined in Value of Information analysis (VoI) to quantify the utility of resolving uncertainty in each hypothesis through adaptive management and monitoring. The action with the highest expected value under existing uncertainty was to increase the extent of low quality habitats, whereas assuming equal hypothesis weights changed the best action to culling. VoI analysis showed that the value of learning to resolve uncertainty in any individual hypothesis for goose population change was low, due to high support for a single hypothesis of change. Our study demonstrates a two-step framework that learns about the most likely drivers of change for an over-abundant species, and uses this knowledge to weight the utility of alternative management actions. Our approach helps inform which strategies might best be implemented to resolve uncertainty when there are competing hypotheses for change and competing management choices.

1. Introduction

Land-use changes due to agricultural intensification and altered farming practices are major drivers of biodiversity declines (Chamberlain et al., 2000; Kleijn et al., 2009). However, not all native fauna decline in response to land-use change. Species that have increased in highly human-modified landscapes such as urban and agricultural areas include egrets and storks (order Ciconiiformes) in Europe (Mendelssohn and Yom-Tov, 1999), kangaroos in Australia (Edwards et al., 1995) and Canada geese *Branta canadensis* in North America (Washburn and Seamans, 2012). Over-abundant native species can lead to competition that impacts resources valued by humans such as damage to crops or reduction in game species (Fox et al., 2017; Redpath et al., 2004; Washburn and Seamans, 2012). Often the response is to cull populations to protect economic livelihoods (Treves and Naughton-Treves, 2005). This might reduce problems temporarily but, because it addresses the proximate outcome rather than the ultimate driver of the issue, may not result in long-term success (Berger, 2006). How to effectively manage biodiversity in farming landscapes remains a key knowledge gap for policy-makers and scientists (Sutherland et al., 2006).

One native species that is increasing in population size in agricultural areas is the Greylag Goose *Anser anser*, a bird with both migratory and resident populations in the United Kingdom (Mitchell et al., 2012). Both the migrant and resident Greylag Goose populations overwinter in Scotland, and their combined numbers have steadily increased from around a thousand birds in the 1990s to more than sixty thousand in 2013, reversing a downward trend prior to this (Trinder,

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2010). In the past 20 years, there has been a marked northward shift in the wintering distribution of the migratory population which breeds predominantly in Iceland, with 60% of the population now recorded in Orkney where previously few migrant birds wintered (Meek, 2008). The population increase and shift in overwintering distribution has been blamed for damage to crops and decreased local farm productivity in the northern Orkney Islands where agriculture is the main industry. In addition to damage, grazing by Greylag Geese on agricultural land may restrict the availability of some crops and grasses that are important food sources for other bird species with which they compete (Madsen and Mortensen, 1987; Mulder and Ruess, 2001; van der Wal et al., 1998). Although a culling project was initiated in 2012 to manage Orkney goose populations particularly in the summer when most crop damage occurs (Churchill and Younie, 2013), populations continue to increase (Mitchell et al., 2012). Strategic management is needed to reduce crop production damage whilst maintaining goose populations, as the species is recovering from near-extinction during the twentieth century (Voslamber et al., 2010).

Multiple hypotheses have been proposed to explain increasing native species populations in modified human-use environments. Changes in migratory behaviour such as over-wintering without returning to breeding grounds have been attributed to climate change (e.g., Miller-Rushing et al., 2008). On a local scale, increasing bird populations have been linked to urbanization and agricultural intensification, which provides more food resources, particularly in winter when many species traditionally would have moved to exploit higher productivity in warmer areas (Partecke and Gwinner, 2007; Visser et al., 2009). Other explanations include protected area expansion and reduced hunting or egg-taking in response to harvest policies (e.g. 1954 Wild Birds Act, 1981 Wildlife & Countryside Act, the EU Birds Directive). In the case of the Greylag Goose, hunting impacts have been reduced primarily as a result of the northern shift in bird distribution away from heavy shooting pressure further south in Scotland (Trinder, 2010). All over Britain including Orkney, domestic livestock numbers fluctuate across time and space because of changes to subsidy and support systems (Fuller and Gough, 1999; Hanley et al., 2008). Changes to grazing intensities of livestock such as sheep *Ovis aries* or the area of unstocked natural vegetation are likely to affect native species, such as geese, by altering food resources (Gregory and Marchant, 1996) and habitat quality (e.g., Fuller and Gough, 1999). In the past decade, efforts by conservation agencies to restore farmland and reduce grazing intensities to benefit threatened native species (e.g. the hen harrier *Circus cyaneus* and its prey, the endemic Orkney vole *Microtus arvalis orcadensis*) has further affected natural and modified grassland availability (Amar et al., 2011; Evans et al., 2006), which could have in turn affected goose numbers if their preferred habitat changed in distribution or extent. A range of possible management actions are available to address each of these hypotheses for increasing or over-abundant native species populations, but as most have never been trialled, no empirical data are available to inform the likely outcomes of each. To make informed decisions in a changing policy and land-use landscape we need an approach that assesses firstly which hypotheses best explain goose population change over time, and secondly resolves uncertainty about which actions might best reduce goose population growth and associated damage to agriculture.

Conservation and land management research efforts are increasingly combining expert opinion and scientific data to allow for more rapid and adaptable decision making in the face of multiple uncertainties (Burgman et al., 2011; Firn et al., 2015). Examples include assessing the cost-effectiveness of strategies to assist decision making to save threatened species and other ecological assets (Chadès et al., 2015; Firn et al., 2015), or informing the expected value of alternative conservation actions (Maxwell et al., 2015; Runge et al., 2011). In most conservation decision contexts, there are multiple actions to choose from, and for each action, there are multiple possible probabilistic outcomes due to uncertainty in an ecological asset's state or trends or drivers. In decision theory, and in particular when making choices under uncertainty, the expected value (EV) or utility of an action is the weighted average of all the expected outcomes from taking a particular action (Neumann and Morgenstern, 1953). To determine the benefits of alternative actions for managing a population under existing uncertainty, managers can calculate EV based on individual estimates from experts of how each action would affect the population of interest; the actions that maximise EV are the best management actions to take under uncertainty (Regan et al., 2005).

When there is uncertainty in the underlying drivers of change, managers may want to reduce uncertainty about the likely outcomes of different actions by experimenting with alternative actions in an adaptive management and monitoring framework (Walters, 1986). Active adaptive management pursues reduction of uncertainty through actively monitoring and adjusting management interventions, whereas passive adaptive management focuses on achieving conservation objectives, with learning a useful but unintended by-product (Walters, 1986). Adaptive management experiments can be time-consuming and expensive, so it can be beneficial to assess the likely benefits of resolving uncertainties prior to commencing adaptive management experiments. Some uncertainties may affect the expected performance of management, but do not affect which management action is preferred, and we would take no different action if the uncertainty were resolved. Other uncertainties affect which management action is preferred, and can be reduced through monitoring and/or adaptive management (Runge et al., 2011). One approach for evaluating the expected management benefits of resolving uncertainty and determining which uncertainty to reduce is Value of Information (VoI) analysis (Raiffa and Schlaifer, 1961). Value of Information analysis can be used to quantify how collecting additional information (e.g. through adaptive management) may improve management outcomes, and can be calculated in different ways (Canessa et al., 2015). The expected value of perfect information (EVPI) is a calculation of the expected improvement in management outcomes that would result from access to perfect knowledge (i.e. zero uncertainty in the proposed hypotheses), and provides a useful measure of the maximum possible benefit of resolving all uncertainty (Runge et al., 2011). EVPI can also be estimated for individual parameters (or groups of parameters), termed partial EVPI or expected value of partial perfect information (EVPPI). EVPPI considers particular elements of the decision problem (e.g. which hypotheses might be resolved given alternative management actions) in order to direct and focus learning towards specific areas where the elimination of uncertainty has the most value (Canessa et al., 2015; Maxwell et al., 2015; Williams and Johnson, 2015; Yokota and Thompson, 2004).

In this study, we investigate how managers might use EV and VoI to choose between possible actions for managing over-abundant Greylag Goose populations in the Orkney Islands, where population trends have been monitored over time but there is no empirical data on the effects of alternative actions. Our objective is to minimise goose damage by setting the growth rate to one (i.e. maintaining a stable goose population). We use statistical modelling to learn which of a range of hypotheses might explain spatiotemporal trends in Greylag Goose Orkney populations over the past 20 years. We hypothesise that if small-scale changes in land use have occurred, Greylag Goose populations may have changed at different rates across space and time as a direct or indirect result of land-use changes (Mitchell et al., 2012). Because there are numerous hypotheses for change in Greylag Goose populations, we combine modelling results with expert elicitation to identify management actions with the highest EV for halting goose population growth under existing uncertainty. We then apply VoI analysis to evaluate the expected improvement in management outcomes that would result from resolving all uncertainty (EVPI), and to suggest promising hypotheses for adaptive management (informed through EVPPI), i.e. the hypotheses that, if tested experimentally, would resolve the greatest uncertainty in Greylag Goose population change.

2. Materials and methods

2.1. Study area and species data

The Orkney Islands consist of approximately 70 islands in the north-east of Scotland, of which 20 are inhabited. The main land use is agriculture, predominantly domestic sheep grazing on highly-modified grasslands (51% of the land area), with approximately 10% remaining in natural habitats (mostly moorland and woodland) in 2013. The Orkney Islands are an important non-breeding and breeding area for Greylag Geese in the UK. Greylag Geese in Orkney represent individuals from two populations: Icelandic (migratory) and British (mostly resident).

We used annual winter population census data from the Icelandic-Breeding Goose Census (IGC), a monitoring program and database maintained by the Wildfowl and Wetlands Trust (WWT) in the United Kingdom (see Appendix A1 for details). The IGC is a coordinated survey of all Greylag Geese in October and November each year (i.e. winter) across multiple sites in the Orkney Islands. All counts from 1990 (1039 birds) to 2013 (67,540 birds) were assigned to one of 12 Scottish Agricultural Census Parishes in the Orkney Islands (487 data points). Parishes roughly correspond to each island, with some Parishes overlapping multiple smaller islands (Fig. 1). Although damages occur in both summer and winter, only winter populations have been monitored long-term. Because multiple counts were undertaken in most years to account for variable arrival times between years, when there were multiple survey sites within a given Parish we summed goose numbers across each census date and used monitoring site data from the census with the maximum summed count during that winter.

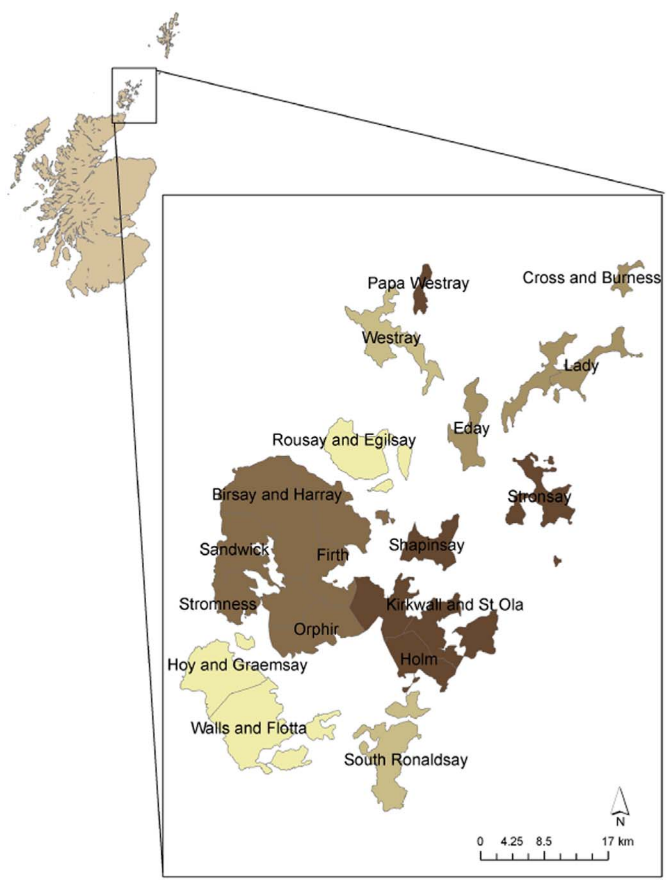

Fig. 1. Location of study area of the Orkney Islands and associated Agricultural Parishes relative to Scotland, showing the relative difference in densities of Greylag Geese on farmland in winter 2012 across the different islands (names labelled). Darker colours in the inset indicate higher densities than lighter colours (range in density per hectare of farmland = 0.28–2.28). Note that for analyses and to be consistent with the scale of Greylag Goose monitoring, the districts of Stromness, Sandwick, Birsay and Harray, Firth and Orphir were aggregated into a West Mainland population, and the districts of Kirkwall and St Ola, and Holm, represented the East Mainland population.

2.2. Land use and temperature data

We linked a spatial dataset of the location and area of Agricultural Parishes in Orkney (Civil Parish Boundaries) with data provided by the Scottish Government for the annual June Scottish Agricultural Census. For each parish and each year, we recorded the total land area, farm area under intensive pasture (improved grassland grazed with domestic livestock), cropping or rough grazing (low quality pasture), area of the Parish not on farm (excluding all agricultural land uses including rested pasture, grazed pasture and cropping) and total number of sheep (see Table S1). Because sheep only occur on farmland on islands, we calculated farm densities of sheep by dividing sheep count data by the area of each island on farm, resulting in a value representing sheep per-hectare of farmland. Parish-specific data were not available for historic temperature change, so environmental data were the mean winter temperature across all of Orkney for each year (UK Meteorological Office, 2014).

2.3. Linear models

We devised six hypotheses for spatiotemporal drivers of goose population change based on information in the scientific and grey literature (Table 1). We hypothesised that populations might be regulated by (i) time since reduction of recreational hunting impacts (correlated with the species' northward distribution shift), (ii) competition from other grazers (sheep), (iii) preferred food availability (i.e. grassland), (iv) preference for and avoidance of certain habitat types, (v) food quality, or (vi) climatic conditions such as temperature that might affect bird survival, reproductive rates and distribution. For each hypothesis, we developed a linear mixed effects model (LMM) with the same model structure but a different covariate (Table 1). We selected the following random-effect structure from alternative possible model structures after checking for correlated variances and normality of residuals:

$$\mathrm{Log}(y)_{it} = \beta_0 + \beta_1 t + \beta_2 t^2 + \beta_3 Y + (Z_{0i} + Z_1 t + \varepsilon_{it}), \tag{1}$$

where y is the response variable at Parish i in year t, and β's and Z's are fixed and random coefficients respectively. Log(y) is a function of a fixed intercept β_0, a fixed slope that depends on a quadratic effect of time t, a random intercept based on Parish (N(0,var(Z_{0i}))) and a random slope based on Year (N(0,var(Z_1t))), plus a Parish- and Year-specific (normally distributed) error term ε_{it}. A quadratic effect of time was included to account for possible threshold effects of density over time due to populations reaching carrying capacity. Y is a covariate related specifically to a hypothesis (e.g. sheep density is related to the hypothesis that competition from sheep grazing controls goose densities; Table 1). The response variable was goose density per hectare of farmland (the total goose count for the Parish divided by the area of all agricultural land in the Parish). We chose density per hectare of farmland because geese prefer to use agricultural land and very few are ever detected in the natural habitats (e.g. moorland, woodland) (Mitchell et al., 2012).

Models were fit with lmer in the lme4 package (ver. 1.4) in R (Bates et al., 2015) using restricted maximum likelihood (REML). Predictor variables were log-transformed to ensure they were normally distributed, and the response variable was also log-transformed to account for unequal variances in the error terms. Covariates were checked for collinearity using Pearson's product-moment correlation, to ensure that multi-variate models did not include correlated terms. High quality food and improved grassland were positively correlated ($r = 0.99$; $P < 0.01$) due to the latter being a subset of the former, and were not included in the same model. We compared LMMs representing each

Table 1
Hypotheses for increased goose densities change over time and space. Models predicting goose population change over time were derived from these hypotheses and are listed in Table S2. See Table S1 for variable definitions and data sources.

Hypothesis	Supporting background literature	Variables added to basic model structure (Eq. (1))
1. *Reduction in hunting pressure*: all islands are increasing equally since the species shifted northward	The migratory population of Greylag Goose shifted northward in the 1990s, away from greatest hunting pressure in the south of Scotland (Trinder, 2010).	No additional variables (year only)
2. *Removal of competition*: islands and years with lower densities of sheep due to destocking have higher goose densities by removing competitive constraints	Incentives destocking livestock have removed competition of geese with sheep for food resources (e.g., Baldi et al., 2001; Edwards et al., 1995).	Sheep density (per ha of farmland)
3. *Resource availability and food provisioning*: geese are food-limited, so islands with more preferred food have higher goose densities	Geese rely predominantly on modified pastures for food (Mitchell et al., 2012), and congregate on the islands with the most grassland available (Fox et al., 2017).	Improved grassland
4. *Habitat preferences and space limitation*: goose habitat preferences regulate densities, so islands with more low-quality habitat have fewer geese	Geese avoid natural habitats and low quality grassland (Mitchell et al., 2012). In response to conservation incentives converting farmland to natural habitat, and grassland to low-quality rough grazing habitats, geese may avoid islands with these less-preferred habitats, resulting in denser congregations on islands with more preferred grassland.	Low quality habitat (rough grazing and non-farm areas)
5. *Improved food quality*: islands with higher quality food have higher goose densities	Climate change or added nutrients or changed land use practices or different crops have improved the food quality for geese (Fox et al., 2017; Jefferies et al., 2003)	High quality food (cropping + improved grassland)
6. *Climatic suitability*: geese are climate-limited, so years with more physiologically suitable temperatures have higher goose densities	Changed winter temperatures have led to increased numbers of many migratory species in non-breeding areas (Partecke and Gwinner, 2007; Visser et al., 2009)	Mean winter temperature

hypothesis using AICc, and calculated Akaike weights from the AICc to determine the relative likelihood of each model across all tested models (Burnham and Anderson, 2002). We calculated confidence intervals around the fixed covariate estimates to assess model precision and significance of effect sizes.

2.4. Value of information

We explored how the results of our LMMs might be used to inform management of Greylag Geese. From a set of potential management responses, we calculated the expected value of each management response, to determine the action with the highest expected utility given current knowledge of which hypotheses best explain goose population response over time and space. We used this information in a VoI analysis to determine the expected value of perfect information (EVPI; Canessa et al., 2015; Maxwell et al., 2015; Runge et al., 2011). We then calculated the expected value of partial perfect information (EVPPI) to determine which hypotheses would benefit most from additional learning (such as through adaptive management) to better inform whether these were drivers of population change. The steps in calculating the EV for each action and associated VoI were:

2.4.1. Determine objective

We set a management objective of minimising goose damage on crops within the next five years whilst ensuring that the population does not begin to decline. The metric we determined to measure this objective was the probability of halting goose population growth (and maintaining as stable) without decline. Whilst this objective does not explicitly minimise farm damage by geese, it ensures that numbers are maintained at current levels and do not increase further nor decline.

2.4.2. Elicit hypotheses and determine weights

We used the hypotheses outlined in Table 1 to explain potential reasons for the increase in Greylag Geese and associated damages on farms. Each hypothesis was assigned a proportional weighting (out of 1) that reflected the amount of support for this hypothesis, with a value closer to 1 indicating that a hypothesis is a more important driver of change. As each hypothesis was represented by a single model, we used the AICc weight from LMMs that included the hypothesis-related driver (e.g. the model including "sheep density" contributed the model weight for hypothesis 2; Table 1).

2.4.3. Determine management actions and consequences for each of the selected hypotheses

We selected six possible management responses (i.e. one for each of the hypotheses), although many more are possible. The six actions were: 1 - cull geese in high density areas identified from predictive modelling; 2 - increase competition by restocking sheep; 3 - supplementary food provisioning for geese in improved grassland to reduce pressure in cropping land; 4 - increase total farm grassland area; 5 - increase area of natural habitats that may be less preferred by geese; 6 - do nothing to geese but pay damage compensation to farmers in warm years (this action assumes that geese are temporary residents, and that climate change will move geese north when it becomes too hot).

We used a version of the Delphi process modified for email interaction to elicit the consequences of these alternative management actions given different hypotheses of goose population change (Chadès et al., 2015; Runge et al., 2011). Experts were emailed a spreadsheet (see Appendix A2) with descriptions of the six management actions and hypotheses, and asked to predict the expected effect, if a given hypothesis were true, of each of the management actions on achieving the management objective. Experts were selected to participate only if they had research or management expertise with Greylag Geese (Burgman et al., 2011), and three out of seven responded. Whilst low, the small number of experts is typical for applied management questions where expert elicitation must ensure expert accuracy (i.e. quality of information) is prioritised over quantity of information (Chadès et al., 2015). For each action by hypothesis combination, experts estimated the expected likelihood that this action would achieve an objective of maintaining a goose population growth rate of 1 (neither increasing nor decreasing) in the Orkney Islands, if that hypothesis were the driver of population change over time. For example, an estimate of 0 for action 1 given hypothesis 1 indicates that action 1 would have no impact on halting population growth if hypothesis 1 were true. An estimate of 1 for action 1 given hypothesis 1 indicates that the expert predicts that action 1 would certainly (i.e. 100% chance) halt population growth if hypothesis 1 were true. These estimates need not sum to 1, as each action by hypothesis combination is independent of the other. Expert predictions were averaged and experts were allowed to refine their predictions in a second round of elicitation after initial feedback on the averaged results of all experts. There was high agreement between experts across all action and hypotheses, and as no experts changed their predictions the elicitation process stopped after two rounds. The Delphi methodology allows for additional rounds if consensus or stability of results has not been achieved after two rounds.

2.4.4. Calculate EV, EVPI and EVPPI

We first calculated the maximum expected value (maximised over all management strategies) under current uncertainty, using the equation:

$$EV = \max_{a} E_s[U(a,s)], \quad (2)$$

where E_s denotes the expectation operator applied over all hypotheses, i.e. $E_s[U(a,s)] = \sum_s U(a,s)p(s)$; s is a hypothesis for goose increase, a is the management strategy taken, $p(s)$ is the probability that hypothesis s is the true hypothesis (i.e. the weight of hypothesis s), and $U(a,s)$ is the utility after taking strategy a under hypothesis s (Runge et al., 2011; Yokota and Thompson, 2004), i.e. the probability of the goose population growth rate remaining stable and the population neither increasing nor decreasing.

We then computed the expected value of perfect information (EVPI) using:

$$EVPI = E_s[\max_{a} U(a,s)] - \max_{a} E_s[U(a,s)], \quad (3)$$

The first term in Eq. (3) represents the expected value once uncertainty has been resolved, because the optimal action is chosen after knowing which model best describes the system. The second term in Eq. (3) represents the maximum expected value in the face of uncertainty (EV).

We also explored the value of reducing uncertainty in a particular hypothesis through 'learning by doing', or adaptive monitoring and management. To do this, we calculated the expected value of partial information (EVPPI; Williams and Johnson, 2015; Yokota and Thompson, 2004) using:

$$EVPPI(s_i) = p(s_i)\max_{a}[U(a,s_i)] + (1-p(s_i))\max_{a} E_{s_i^c}[U(a,s_i^c)] - \max_{a} E_s[U(a,s)], \quad (4)$$

where s_i is a subset of the uncertainty (say, one of our six hypothesis-driven models), and s_i^c its complement. $p(s_i)$ is the probability that hypothesis s_i is the true hypothesis (i.e. the weight of hypothesis s_i). The EVPPI tells the manager how much the performance is expected to increase by resolving a particular hypothesis s_i about goose population change. Because our consequences are in terms of probability that the growth rate equals 1, VoI gives the increase in probability resulting from eliminating/reducing uncertainty, and is therefore a readily understood metric. We ranked actions first by their expected value under current uncertainty (EV) to determine which strategy has the highest utility in terms of maintaining a stable goose population. We used EVPI to determine the value of reducing all uncertainty in the system (for the proposed hypotheses), then used EVPPI to find which hypotheses and associated actions might best be placed into an adaptive management framework. An Excel macro for this analysis is included in the Supporting material.

We compared the results of our VoI including expert-elicited utilities and model-driven hypothesis weights, with a VoI that included expert-elicited utilities of actions but weighted each of the six hypotheses equally, to determine whether weighting hypotheses using empirical modelling changed the optimal action and adaptive monitoring strategy (i.e. monitoring to learn about a hypothesis whilst managing).

3. Results

3.1. Evaluating hypotheses for goose population change

The best-supported hypothesis explaining goose population change across space and time was the hypothesis for habitat preferences and space limitation (Table 2). Goose densities decreased as the proportion of the Parish covered by low quality habitat (such as rough grazing and natural woodlands) increased (effect size = −0.14 ± 0.04 S.E.; Figs. 2 and 3). The AICc weight of this model (0.97) ranked it above other models representing alternative hypotheses for change (Table 2). The random slopes of the 12 Parishes explained 91.2% of the variance over years (var(Z_{0i}) = 0.32), with residual variance (var(Z_1t) = 0.03) explaining only 8.8%. Four of the twelve island populations (Shapinsay, Stronsay, Papa Westray, and East Mainland, see Fig. 1) contributed the most to increase in goose densities over time in Orkney (see Table S3 for random slope coefficients associated with Parishes).

3.2. Value of information

Model-weighted expected value analysis indicated that the optimal action under existing uncertainty was to increase area of natural habitats (rough grazing and natural habitats, action 5, EV = 0.56, Table 3). The expected value of resolving all uncertainty about hypotheses (EVPI) was 0.01, with an expected percentage increase in performance that could be gained by resolving uncertainty of ∼2%. EV analysis assuming equal hypothesis weights changed the best action to culling (action 1, Table S4), with an EVPI of 0.11 and expected percentage increase in performance if uncertainty was resolved of 21%. In both scenarios of weighted and unweighted hypotheses, the second best action was to reduce goose densities by increasing sheep competition through localised high density stocking of sheep (action 2, EV = 0.50 and 0.36 respectively, Tables 3 and S4), despite only marginal support for the hypothesis of sheep competition from spatiotemporal models (Table 2).

The EVPPI analysis indicated that the most value of information comes from resolving the hypothesis of goose increase due to reduction in hunting pressure, regardless of whether hypotheses were weighted according to modelling results (EVPPI = 0.005; achieves 50% of the EVPI; Table 3) or unweighted (EVPPI = 0.075; achieves 68% of the EVPI; Table S4). The EVPPI values for these hypotheses were driven by high expected benefits if these hypotheses could be confirmed – if reduction in hunting pressure were the true hypothesis, then culling (action 1) could be implemented with a high relative utility (Tables 3 and S4). The weighted VoI indicated that the hypothesis of habitat preferences and space limitation (goose avoidance of low quality habitats) would have the next highest value for resolving uncertainty (EVPPI = 0.004). When hypotheses were weighted equally the EVPPI rankings of all other hypotheses changed, with removal of competition with sheep the second best hypothesis to resolve (Table S4).

4. Discussion

Our study demonstrates how a Value of Information analysis combining empirical modelling with expert elicitation can be used to explore which management strategies might be applied when managers are faced with multiple uncertainties and choices of action. Our results support the hypothesis that land-use changes in Orkney related to conservation incentives that increased natural grassland habitats have led to increased goose densities in remaining farmland areas. Limited support for alternative competing hypotheses suggests that attempting to resolve uncertainty in alternative drivers through adaptive management would not lead to substantial increases in utility: simply applying management actions with the highest expected value under existing uncertainty provides similar returns to those expected from resolving uncertainty via adaptive management. Our study provides a way forward for managers faced with uncertainty in both the drivers of wildlife population changes and the effectiveness of potential management actions, through the use of a decision-support tool that can be parameterised using a combination of empirical modelling and expert elicitation.

Our results indicate that hypothesis-driven predictions of population drivers could represent a crucial first step in deciding where and

Table 2
Results of model selection for all models representing hypotheses about drivers of change in Greylag Goose densities across different Orkney Islands and years. All models were linear functions with year as a random slope and island random intercepts. Table shows parameters included in model and Akaike weights derived from the second order information criterion (AICc), which represent the relative likelihood of a model. See Fig. 2 and Table S2 for effect sizes of covariates.

Hypothesis	Model covariates	AICc	ΔAICc	AICc model weight
4. Habitat preferences and space limitation	Year + Year^2 + Low quality habitat	− 55.29	0	0.974
2. Removal of competition (sheep)	Year + Year^2 + Sheep density	− 45.55	9.73	0.007
1. Reduction in hunting pressure	Year + Year^2	− 45.40	9.89	0.070
5. Improved food quality	Year + Year^2 + High quality food	− 44.60	10.69	0.005
3. Resource availability and food provisioning	Year + Year^2 + Preferred grassland	− 44.47	10.82	0.004
6. Climatic suitability	Year + Year^2 + Winter temperature	− 43.73	11.55	0.003

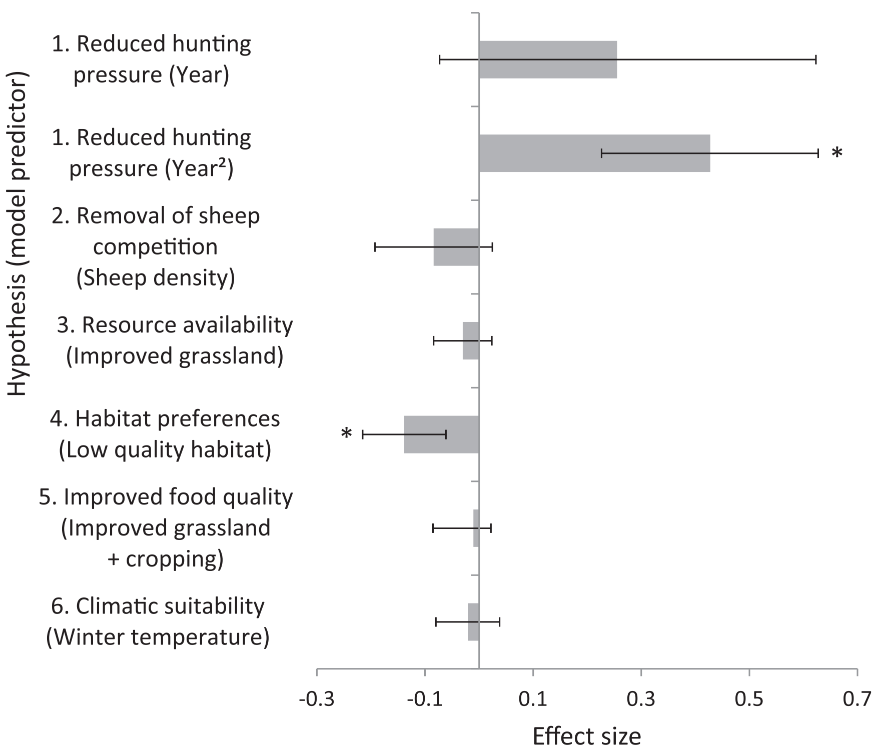

Fig. 2. Effect sizes from covariates in linear mixed-effects models relating goose density changes over time and space in the Orkney islands to one of six hypotheses of drivers (see Table 1). Showing model estimate of parameter slope ± 95% confidence interval. *Indicates significant effect size (95% confidence interval does not cross zero). See Table S2 for parameter estimates.

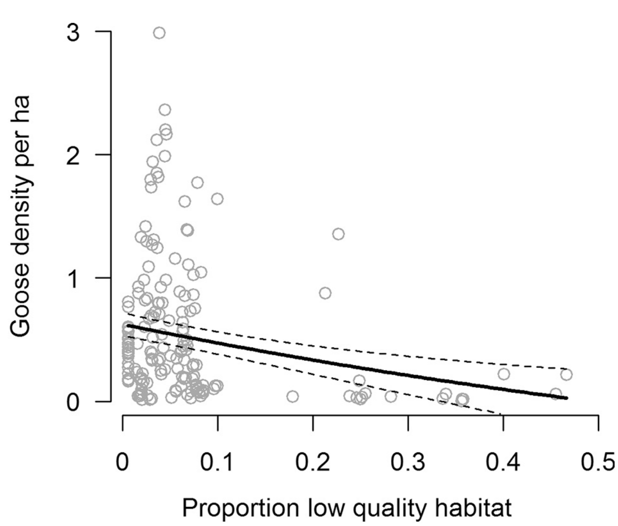

Fig. 3. Results of best model for goose population change, showing the relationship between goose densities and hypothesis 4 in Table 1 for habitat preferences and space limitation, i.e. proportion of the Parish (usually an island) covered by low quality grazing habitat. Mean (dark line) and 95% confidence intervals (dotted lines) are shown with raw data (open grey circles).

how to manage wildlife conservation in conflict with human resource use. We teased apart differences across space and time in population growth of Greylag Geese to identify the Parishes that have contributed most to the entire Orkney population (Appendix A1). By modelling changes in goose densities that might result in damage to crops on farms, we explored for the first time whether goose damage is likely to be occurring uniformly, finding that goose density (and likely associated damage) is heavily biased towards particular islands (Fig. 1, Table S3). Adding management-related covariates such as human land-use change and resource availability (Table 1), allowed us to determine which hypotheses about changes in agricultural dynamics (which vary across islands) were best supported by goose monitoring data over time. Models indicate that goose densities are higher in areas with fewer natural habitats (hypothesis 4: habitat preferences and space limitation, Table 2, Fig. 2), due to these low quality habitats being less preferred in comparison with high quality grassland (Mitchell et al., 2012).

We used VoI analysis to evaluate the benefits of further learning about each hypothesis for goose population growth, and to inform us, given the current state of knowledge, which actions might best be incorporated into an adaptive management program for Greylag Geese in Orkney. We set a single objective of halting goose population growth, although many other alternative objectives are possible. By calculating the level of support for different models of spatiotemporal variability in goose densities, we were able to incorporate evidence for several alternative hypotheses as drivers of population change over time and

Table 3
Final weighted results for expert-predicted effects of actions on achieving objective of goose damage reduction through preventing further population increase. Table shows hypothesis weights derived from linear mixed-effects models, expected value of perfect information (EVPI) and expected value of partial information (EVPPI).

Hypotheses	Model weights[a]	Action and effect on objective criteria[b]						EVPPI
		1	2	3	4	5	6	
1. Reduction in hunting pressure	0.007	0.800	0.070	0.030	0.030	0.050	0.030	0.005
2. Removal of competition (sheep)	0.007	0.330	0.600	0.100	0.150	0.400	0.200	0.001
3. Resource availability and food provisioning	0.004	0.330	0.370	0.230	0.050	0.370	0.200	0
4. Habitat preferences and space limitation	0.974	0.330	0.500	0.080	0.270	0.570	0.200	0.004
5. Improved food quality	0.005	0.330	0.300	0.170	0.080	0.470	0.280	0
6. Climatic suitability	0.003	0.330	0.330	0.030	0.030	0.320	0.200	0
Expected value of action (utility)		0.333	0.496	0.081	0.265	0.563	0.199	
Perfect information	0.570							
EVPI = 0.570–0.563	0.007							

[a] Weight derived from AICc weight of model relating hypothesis-related driver of spatio-temporal change to goose monitoring data (see Tables 1 and 2).
[b] 1 - cull geese in high density areas; 2 - increase competition by sheep restocking; 3 - supplementary food provisioning; 4 - increase total farm grassland area; 5 - increase area of natural (low quality) habitats; 6 - do nothing (assume climate change will move geese north when it becomes too hot).

space (Table 2). Crucially, empirical evidence-based weighting of hypotheses changed the EVs of actions. Based on expert advice alone (i.e. when hypotheses were equally weighted), goose culling was the optimal management action (Table S4), whereas model-weighting of hypotheses in addition to expert elicitation indicated that the best action under current uncertainty was to change the availability of natural habitat types (Table 3). EV analysis also indicated the management actions with the lowest utility, suggesting that strategies of supplementary food provisioning, increasing total farm area, and doing nothing would not achieve the objective of halting goose population growth (Table 3); results that were supported even when all hypotheses were assigned equal weights (Table S4).

Pursuing rewards indicated from EV analysis is tempting, but decision-makers need to consider that hypotheses may prove false, which would require an additional study to confirm or refute a different hypothesis. The best action in this study only gave a 56% change that the population size would stabilise, despite overwhelming support for one hypothesis of goose population change. Disproving a hypothesis often slightly increases the overall expected benefit (one hypothesis has been ruled out so the total uncertainty decreases), but the large returns of confirming the most promising hypothesis would not be realised. Decision makers need to balance expected benefits of obtaining immediate outcomes by making decisions under existing uncertainty (informed through EV) with potential gains that could be made by learning (Johnson and Williams, 2015). In this study, VoI analysis (EVPPI) suggested that determining whether experimental goose culling leads to reduced farm damage would provide the highest gains for learning through additional data collection relative to testing other hypotheses, however these gains were unlikely to be very large compared with taking immediate action (Table 3). Using AIC weights to inform our VoI meant that 97.4% of the weight was applied to a single hypothesis; thus there did not appear to be much uncertainty to resolve, as EVPI is highest when model weights are intermediate between extremes of 0 and 1.

Because of the support for one hypothesis over others in this study, the empirical modelling results played a strong role in determining the optimal management action. In other contexts of high uncertainty between hypotheses and modelling that does not resolve this uncertainty, decision makers will be faced with more evenly weighted hypotheses in the VoI (such as in our sensitivity analysis). In these cases, the expert elicitation process is vital to gaining good information on expected utility of alternative actions, and decision-makers have different options for both eliciting and incorporating these data in our approach. We took a risk-neutral approach to incorporating the expert-elicited data into EV by averaging values. Decision makers are typically risk averse (Tulloch et al., 2015), and our approach can be modified to account for risk aversion by incorporating the minimum rather than average elicited response from experts (see Table S7 in Supporting material). Such a pessimistic approach to expected value might be important to explore if there are likely to be high losses from the wrong management choice, for example for recovering critically endangered species. If taken, we recommend that (a) experts are informed a priori that their provided information might be used in this way, (b) experts are allowed to provide feedback on results both of other experts and on the EV analyses, and (c) a risk-neutral EV is also explored to evaluate how risk aversion by decision-makers could have affected management choices (Tulloch et al., 2015). Our expert elicitation process used feedback to experts to improve performance, but other contexts could employ additional methods to reduce bias, over-confidence or risk aversion in answers through ensuring that a wider set of experiences and skills are involved, and that experts be made accountable through specific testing and training questions that measure objectively their knowledge (Burgman et al., 2011). To reduce expert fatigue in cases where there are many more than six hypotheses of change, an important step in VoI is to reduce the number of proposed hypotheses to a management set (Runge et al., 2011), and this can be done by experts or through the modelling process itself (removing any hypotheses with zero support from the expert elicitation).

The models and VoI analysis in this study were constrained by several limitations. Our VoI analysis did not include costs of management actions, as a more detailed island-by-island exploration of costs and benefits of each action is recommended. We only incorporated information on over-wintering geese populations, as only a single summer census had been carried out at the time of our analyses (Mitchell, 2010). Adding summer population data to the modelling process would allow us to examine whether populations are affected by seasonal factors. For example, this might be particularly important if climate change leads to more geese over-summering in Orkney. Although we lacked sufficient models of species associations at different locations to apply it to this case study, the VoI process can be repeated to include additional locations or objectives. For Greylag Goose population management, additional objectives and associated hypotheses could be derived for different locations in the migratory cycle, such as breeding areas in Iceland (Nicol et al., 2015), or for changes in another coexisting plant or animal species of conservation interest (Evans et al., 2006; Madsen and Mortensen, 1987), or if particular factors such as land use or market drivers change in the future. For instance, the Orkney vole could be negatively impacted by management options such as restocking sheep if actions occur on preferred vole habitat (Evans et al., 2006). Conservation incentives to destock sheep and reduce farmland area were initially implemented with the goal of restoring native habitat of threatened Orkney voles and raptors (Amar et al., 2011). Our best-supported management action under current uncertainty of increasing rough grazing and natural habitats would benefit voles that are more abundant in these vegetation types (Evans et al., 2006). Expanding the spatiotemporal models to include interactions with other species, and expanding the VoI to include objectives specifically targeted at the persistence of voles, would allow managers to explore trade-offs between multiple objectives and expected utilities of different actions for maintaining coexisting species. Finally, an adaptive management framework that incorporates monitoring of action effectiveness on geese and other species would determine whether different islands might need to be managed in different ways to balance human socio-economic needs with the needs of different species of conservation concern.

Species' responses to changes in land cover are indirect responses to economic, social or policy-related drivers. A major driver of agricultural land-use change is incentive funding provided by agri-environment schemes (e.g. payments per hectare to restore natural vegetation or reduce stocking rates). We were not able to gather data on spatio-temporal variability in monetary value per ha offered for incentive programs across Orkney due to unsystematic collection of these valuable socio-economic data, so we used surrogate information on these changes in the form of change in either the area of low quality habitat (which increased over time as restoration of farmland and conversion of pastures increased) and sheep density (which declined over time as destocking increased) (Amar et al., 2011; Evans et al., 2006). Changes in sheep numbers or farm area are supply-chain responses to market or policy (e.g. conservation incentive) mechanisms. Livestock values at Orkney Auction Mart rose during 2000–2010, perhaps as a consequence of falling livestock numbers across Scotland generally. Livestock has continued to trade at, or near, the levels of 2009 Orkney Islands Council, 2013, which suggests that the second-best action in our VoI of restocking pastures, could help leverage losses of crop production that could occur if farmers restore cropland to rough grazing and natural habitats to reduce geese numbers. We recommend further research into the socio-economic drivers for land use change, including social surveys and collation of data pertaining to the amount of money invested in private land conservation incentives (e.g. subsidies to reduce stocking rates) over time (Fox et al., 2017; Hanley et al., 2008). VoI could also be applied directly to these drivers. For example, linking the value of crop damage to market drivers, to explore whether economic indicators might be used in place of costly and time-consuming surveys of the wildlife causing damage. Analysing the link between socio-economic drivers and crop damage could also help re-evaluate policies to ensure that perverse outcomes of conservation or economy are reduced.

Understanding the drivers behind change in the behaviour or abundance of native species can help discover early warning signs, learn which sites are the main contributors to change, identify where future change might also occur, and inform choices about which management actions might be most effective to manage populations (Clements et al., 2015). Given the vast uncertainties inherent in managing threatened species, and the lack of resources available to gain information to inform decision-making, natural resource management stands to benefit substantially from VoI analysis. We provide a relatively simple tool for canvassing management options and communicating the best choices to decision- and policy-makers for conservation or resource management problems where underlying data (e.g. population monitoring) about the state and variability of a system or population exist and can be modelled to understand drivers of change, but few data exist on how management might alter the current state. We propose that combining expert elicitation with empirical modelling enables the best possible information to be used in management decision-making. Our study provides a way to integrate basic understanding of the drivers behind wildlife population changes with approaches such as expected values analysis, which informs decisions about what actions could provide the highest immediate benefits for achieving a particular management objective, and Value of Information analysis, which identifies actions and hypotheses that might be incorporated into an adaptive management experiment.

Authors' contributions

Analyses were performed by AT under the direction of NB (modelling) and SN (VOI). All authors contributed to study design, writing and editing the manuscript.

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Appendix A. Supplementary data

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References

Amar, A., Davies, J., Meek, E., Williams, J., Knight, A., Redpath, S., 2011. Long-term impact of changes in sheep *Ovis aries* densities on the breeding output of the hen harrier *Circus cyaneus*. J. Appl. Ecol. 48, 220–227.

Baldi, R., Albon, S., Elston, D., 2001. Guanacos and sheep: evidence for continuing competition in arid Patagonia. Oecologia 129, 561–570.

Bates, D., Maechler, M., Bolker, B., Walker, S., 2015. Fitting linear mixed-effects models using lme4. J. Stat. Softw. 67, 1–48.

Berger, K.M., 2006. Carnivore-livestock conflicts: effects of subsidized predator control and economic correlates on the sheep industry. Conserv. Biol. 20, 751–761.

Burgman, M., Carr, A., Godden, L., Gregory, R., McBride, M., Flander, L., Maguire, L., 2011. Redefining expertise and improving ecological judgment. Conserv. Lett. 4, 81–87.

Burnham, K.P., Anderson, D.R., 2002. Model Selection and Multimodel Inference: A Practical Information-theoretic Approach. Springer, New York.

Canessa, S., Guillera-Arroita, G., Lahoz-Monfort, J.J., Southwell, D.M., Armstrong, D.P., Chadès, I., Lacy, R.C., Converse, S.J., 2015. When do we need more data? A primer on calculating the value of information for applied ecologists. Methods Ecol. Evol. 6, 1219–1228.

Chadès, I., Nicol, S., van Leeuwen, S., Walters, B., Firn, J., Reeson, A., Martin, T.G., Carwardine, J., 2015. Benefits of integrating complementarity into priority threat management. Conserv. Biol. 29, 525–536.

Chamberlain, D.E., Fuller, R.J., Bunce, R.G.H., Duckworth, J.C., Shrubb, M., 2000. Changes in the abundance of farmland birds in relation to the timing of agricultural intensification in England and Wales. J. Appl. Ecol. 37, 771–788.

Churchill, G., Younie, A., 2013. Orkney resident Greylag goose adaptive management pilot 2012 to 2015. In: Annual Report for 2012 Season. Report by the Orkney Greylag Goose Management Group.

Clements, C.F., Drake, J.M., Griffiths, J.I., Ozgul, A., Egbert, H.v.N., Susan, K., 2015. Factors influencing the detectability of early warning signals of population collapse. Am. Nat. 186, 50–58.

Edwards, G.P., Dawson, T.J., Croft, D.B., 1995. The dietary overlap between red kangaroos (*Macropus rufus*) and sheep (*Ovis aries*) in the arid rangelands of Australia. Aust. J. Ecol. 20, 324–334.

Evans, D.M., Redpath, S.M., Elston, D.A., Evans, S.A., Mitchell, R.J., Dennis, P., 2006. To graze or not to graze? Sheep, voles, forestry and nature conservation in the British uplands. J. Appl. Ecol. 43, 499–505.

Firn, J., Maggini, R., Chades, I., Nicol, S., Walters, B., Reeson, A., Martin, T.G., Possingham, H.P., Pichancourt, J.B., Ponce-Reyes, R., Carwardine, J., 2015. Priority threat management of invasive animals to protect biodiversity under climate change. Glob. Chang. Biol. 21, 3917–3930.

Fox, A.D., Elmberg, J., Tombre, I.M., Hessel, R., 2017. Agriculture and herbivorous waterfowl: a review of the scientific basis for improved management. Biol. Rev. 92, 854–877.

Fuller, R.J., Gough, S.J., 1999. Changes in sheep numbers in Britain: implications for bird populations. Biol. Conserv. 91, 73–89.

Gregory, R., Marchant, J., 1996. Population trends of jays, magpies, jackdaws and carrion crows in the United Kingdom. Bird Stud. 43, 28–37.

Hanley, N., Davies, A., Angelopoulos, K., Hamilton, A., Ross, A., Tinch, D., Watson, F., 2008. Economic determinants of biodiversity change over a 400-year period in the Scottish uplands. J. Appl. Ecol. 45, 1557–1565.

Jefferies, R.L., Rockwell, R.F., Abraham, K.F., 2003. The embarrassment of riches: agricultural food subsidies, high goose numbers, and loss of Arctic wetlands – a

continuing saga. Environ. Rev. 11, 193–232.
Johnson, F.A., Williams, B.K., 2015. A decision-analytic approach to adaptive resource management. In: Allen, C.R., Garmestani, A.S. (Eds.), Adaptive Management of Social-ecological Systems. Springer Netherlands, pp. 61–84.
Kleijn, D., Kohler, F., Báldi, A., Batáry, P., Concepción, E.D., Clough, Y., Díaz, M., Gabriel, D., Holzschuh, A., Knop, E., Kovács, A., Marshall, E.J.P., Tscharntke, T., Verhulst, J., 2009. On the relationship between farmland biodiversity and land-use intensity in Europe. Proc. R. Soc. B Biol. Sci. 276, 903–909.
Madsen, J., Mortensen, C.E., 1987. Habitat exploitation and interspecific competition of moulting geese in East Greenland. Ibis 129, 25–44.
Maxwell, S.L., Rhodes, J.R., Runge, M.C., Possingham, H.P., Ng, C.F., McDonald-Madden, E., 2015. How much is new information worth? Evaluating the financial benefit of resolving management uncertainty. J. Appl. Ecol. 52, 12–20.
Meek, E., 2008. The latest status of greylag geese in Orkney. Goose News 7, 6–7.
Mendelssohn, H., Yom-Tov, Y., 1999. A report of birds and mammals which have increased their distribution and abundance in Israel due to human activity. Isr. J. Zool. 45, 35–47.
Miller-Rushing, A.J., Lloyd-Evans, T.L., Primack, R.B., Satzinger, P., 2008. Bird migration times, climate change, and changing population sizes. Glob. Chang. Biol. 14, 1959–1972.
Mitchell, C., 2010. Status and Distribution of Icelandic-breeding Geese: Results of the 2009 International Census. Wildfowl & amp; Wetlands Trust/Joint Nature Conservation Committee Report, Slimbridge.
Mitchell, C., Leitch, A.J., Brides, K., Meek, E., 2012. The Abundance and Distribution of British Greylag Geese on Orkney, August 2012. Wildfowl & Wetlands Trust Report, Slimbridge.
Mulder, C.P.H., Ruess, R.W., 2001. Long-term effects of changes in goose grazing intensity on arrowgrass populations: a spatially explicit model. J. Ecol. 89, 406–417.
Neumann, J.v., Morgenstern, O., 1953. Theory of Games and Economic Behavior. Princeton University Press, Princeton, NJ.
Nicol, S., Fuller, R.A., Iwamura, T., Chadès, I., 2015. Adapting environmental management to uncertain but inevitable change. Proc. R. Soc. Lond. B Biol. Sci. 282.
Orkney Islands Council, 2013. Orkney Economic Review 2012-13. Orkney Islands Council Report, Kirkwall.
Partecke, J., Gwinner, E., 2007. Increased sedentariness in European blackbirds following urbanization: a consequence of local adaptation? Ecology 88, 882–890.
Raiffa, H., Schlaifer, R., 1961. Applied Statistical Decision Theory. Clinton Press Inc., Boston.
Redpath, S.A., Arroyo, B.E., Leckie, E.M., Bacon, P., Bayfield, N., Gutierrez, R.J., Thirgood, S.J., 2004. Using decision modeling with stakeholders to reduce human-wildlife conflict: a Raptor-Grouse case study. Conserv. Biol. 18, 350–359.
Regan, H.M., Ben-Haim, Y., Langford, B., Wilson, W.G., Lundberg, P., Andelman, S.J., Burgman, M.A., 2005. Robust decision-making under severe uncertainty for conservation management. Ecol. Appl. 15, 1471–1477.
Runge, M.C., Converse, S.J., Lyons, J.E., 2011. Which uncertainty? Using expert elicitation and expected value of information to design an adaptive program. Biol. Conserv. 144, 1214–1223.
Sutherland, W.J., Armstrong-Brown, S., Armsworth, P.R., Tom, B., Brickland, J., Campbell, C.D., Chamberlain, D.E., Cooke, A.I., Dulvy, N.K., Dusic, N.R., Fitton, M., Freckleton, R.P., Godfray, H.C.J., Grout, N., Harvey, H.J., Hedley, C., Hopkins, J.J., Kift, N.B., Kirby, J., Kunin, W.E., Macdonald, D.W., Marker, B., Naura, M., Neale, A.R., Oliver, T.O.M., Osborn, D.A.N., Pullin, A.S., Shardlow, M.E.A., Showler, D.A., Smith, P.L., Smithers, R.J., Solandt, J.-L., Spencer, J., Spray, C.J., Thomas, C.D., Thompson, J.I.M., Webb, S.E., Yalden, D.W., Watkinson, A.R., 2006. The identification of 100 ecological questions of high policy relevance in the UK. J. Appl. Ecol. 43, 617–627.
Treves, A., Naughton-Treves, L., 2005. Evaluating lethal control in the management of human-wildlife conflict. In: Woodroffe, R., Thirgood, S.J., Rabinowitz, A. (Eds.), People and Wildlife, Conflict or Co-existence? Cambridge University Press, Cambridge, pp. 86.
Trinder, M., 2010. Status and Population Viability of Icelandic Greylag Geese in Scotland. Scottish Natural Heritage Commissioned Report No. 366.
Tulloch, A.I., Maloney, R.F., Joseph, L.N., Bennett, J.R., Di Fonzo, M.M., Probert, W.J., O'Connor, S.M., Densem, J.P., Possingham, H.P., 2015. Effect of risk aversion on prioritizing conservation projects. Conserv. Biol. 29, 513–524.
UK Meteorological Office, 2014. Scotland Mean Temperature (Degrees C) Areal series. (. http://www.metoffice.gov.uk/climate/uk/summaries/datasets).
van der Wal, R., Kunst, P., Drent, R., 1998. Interactions between hare and brent goose in a salt marsh system; evidence for food competition? Oecologia 117, 227–234.
Visser, M.E., Perdeck, A.C., Van Balen, J.H., Both, C., 2009. Climate change leads to decreasing bird migration distances. Glob. Chang. Biol. 15, 1859–1865.
Voslamber, B., Knecht, E., Kleijn, D., 2010. Dutch Greylag Geese *Anser anser*: migrants or residents. Ornis Svecica 20, 207–214.
Walters, C.J., 1986. Adaptive Management of Renewable Resources. Macmillan, New York, New York, USA.
Washburn, B.E., Seamans, T.W., 2012. Foraging preferences of Canada geese among turfgrasses: implications for reducing human–goose conflicts. J. Wildl. Manag. 76, 600–607.
Williams, B.K., Johnson, F.A., 2015. Value of information in natural resource management: technical developments and application to pink-footed geese. Ecol. Evol. 5, 466–474.
Yokota, F., Thompson, K.M., 2004. Value of information analysis in environmental health risk management decisions: past, present, and future. Risk Anal. 24, 635–650.