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Research

Integrating conflict, lobbying, and compliance to predict the sustainability of natural resource use

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ABSTRACT. Predictive models are sorely needed to guide the management of harvested natural resources worldwide, yet existing frameworks fail to integrate the dynamic and interacting governance processes driving unsustainable use. We developed a new framework in which the conflicting interests of three key stakeholders are modeled: managers seeking sustainability, users seeking increases in harvest quota, and conservationists seeking harvest restrictions. Our model allows stakeholder groups to influence management decisions and illegal harvest through flexible functions that reflect widespread lobbying and noncompliance processes. Decision making is modeled through the use of a genetic algorithm, which allows stakeholders to respond to a dynamic social-ecological environment to satisfy their goals. To provide the critical link between conceptual and empirical approaches, we compare predictions from our model against data on 206 harvested terrestrial species from the IUCN Red List. We show that, although lobbying for a ban on resource use can offset low levels of noncompliance, such bias leads to an increased risk of extinction when noncompliance (and therefore illegal harvesting) is high. Management decisions unaffected by lobbying, combined with high rule compliance, resulted in more sustainable resource use. Model predictions were strongly reflected in our analysis of harvested IUCN species, with 81% of those classified under regulated harvest and high compliance showing stable or increasing population trends. Our results highlight the fine balance between maintaining compliance and biasing decisions in the face of lobbying. They also emphasize the urgent need to quantify lobbying and compliance processes across a range of natural resources. Overall, our work provides a holistic and versatile approach to addressing complex social processes underlying the mismanagement of natural resources.

Key Words: *conservation; decision making; genetic algorithm; governance; harvest regulation; IUCN; management strategy evaluation; population target; trend; user; wildlife*

INTRODUCTION

In the midst of the sixth mass extinction (Ceballos et al. 2017), sustainable use of the world's natural resources, including wildlife, fish stocks, and timber, has become critical (Di Minin et al. 2019, Ripple et al. 2019). Key to achieving sustainability is the development of flexible quantitative models with which to evaluate the consequences of alternative harvest management scenarios, and in turn support decision making and policy implementation (Shea and the NCEAS Working Group on Population Management 1998, Schmolke et al. 2010, Bunnefeld et al. 2017). Although there is now broad consensus that such models should integrate both the social and ecological processes inherent to resource management systems (Milner-Gulland 2012, Sayles et al. 2019, Schlüter et al. 2019*a, b*), the resulting complexity remains daunting (Folke et al. 2010, Bunnefeld et al. 2017). A major challenge concerns how to best integrate governance processes and human behavior into existing management models in a way that optimizes predictive accuracy whilst minimizing complexity (Müller-Hansen et al. 2017, Schlüter et al. 2019*a*, Travers et al. 2019*a*), and improves applicability to a broad spectrum of harvesting systems.

Governance relates to the societal context and processes that shape collective decision making and action (Bevir 2012). The term governance is used very broadly across disciplines, but within the context of natural resource use it typically describes the interactive processes occurring among different stakeholders through which decisions relating to resource harvest and management are made (Lockwood et al. 2010, Cox et al. 2016). Although collective governance, sometimes referred to as comanagement, is often sought (Armitage et al. 2009), this is often impeded by conflicts occurring among stakeholders with diverging interests (Redpath et al. 2013, Orach and Schlüter 2016, Bodin 2017, Cumming 2018), such as the exploitation versus the conservation of a natural resource (Benítez-López et al. 2017). Such conflicts are widespread and pose a major threat to the sustainable use of natural resources worldwide. In spite of this, our ability to integrate the governance processes through which conflicts operate into existing sustainable management frameworks is currently very limited.

A common symptom of conflicts surrounding the use of natural resources is illegal harvesting behavior, whereby resource users do not comply with harvesting rules and regulations, e.g., quotas. Although individual economic and social drivers of noncompliance have received increased attention over the last decade (Keane et al. 2008, Gavin et al. 2010, Solomon et al. 2015, Duffy et al. 2016, Travers et al. 2019*b*), the behavior of resource users in relation to other complex and dynamic governance processes currently lacks theoretical and empirical support. One such process is lobbying, through which interest groups seek to directly influence management decision making to bias outcomes in their favor (Baumgartner et al. 2009, Lute and Gore 2014, Meng and Rode 2019). Lobbying may attempt to advance the interests of natural resource users, for example, those of commercial industries in the case of marketable natural resources (Murray 2003). It may also serve the interests of parties seeking to restrict resource use, such as conservation organizations (Mace 2014,

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Adams 2017, Baynham-Herd et al. 2018, Challender and MacMillan 2019). In this latter case, lobbying to impose restrictions on the use of a natural resource could exacerbate illegal harvesting pressure (Di Minin et al. 2016), particularly if the resource is economically valuable, e.g. rhino horn (Biggs et al. 2013) or culturally important, e.g., agarwood from *Aquilaria sinensis* (Chen et al. 2019). In turn, noncompliance with harvesting rules may trigger more intense lobbying, not only from conservation interest groups, but also from resource user groups that do harvest legally, thereby creating feedback processes affecting resource management. Yet, despite the huge potential for the combined and interlinked effects of conflict, noncompliance, and lobbying to destabilize sustainable natural resource use, no modeling frameworks, to our knowledge, have explicitly accounted for them.

State-of-the-art modeling frameworks to optimize natural resource management have been particularly well developed in the context of commercial fisheries, where harvest allocation is typically based on close monitoring of fish stocks and catches (Audzijonyte et al. 2019). One such framework, known as management strategy evaluation (MSE; Smith et al. 1999, Punt et al. 2016, Stephenson et al. 2017), enables the entire management system, including stock dynamics and monitoring, management decisions, and harvesting activities, to be simulated in search of a strategy that best addresses management objectives. A key feature of MSE is its ability to explicitly model the uncertainty surrounding individual management components (Milner-Gulland and Shea 2017), such as stock stochasticity, monitoring error, decision biases, or illegal behavior by harvesters. Using a fisheries example, Armitage et al. (2019) recently advocated the widespread integration of governance processes into MSE frameworks, highlighting in particular the existence of decision-making thresholds (Harford et al. 2016).

In contrast, the development of flexible, MSE-based frameworks encompassing more realistic processes of decision making and human behavior has been largely absent from terrestrial harvesting systems (Bunnefeld et al. 2011, Bunnefeld and Milner-Gulland 2016, Moa et al. 2017). Indeed, modeling frameworks to date have focused disproportionately on the ecological dimension of terrestrial harvesting systems (Gamelon et al. 2019), such as the development of elaborate population and community response models, e.g. to trophy hunting (Whitman et al. 2007, Loveridge et al. 2016) or the assessment of harvest-induced evolution (Kuparinen and Festa-Bianchet 2017). Although often presented within an adaptive management framework (Kolbe et al. 2017, Andrén et al. 2020), these approaches tend to overlook how the implementation of management decisions can be perturbed by conflicts of interest. Predictive models that can include these governance processes are now sorely needed to guide the management of terrestrial harvesting systems (Bunnefeld et al. 2011, 2017, Dobson et al. 2019), in which mismanagement and overharvesting have become widespread (Díaz et al. 2019).

In this study, we develop a flexible and widely applicable form of MSE model in which the interests of three different stakeholders are considered: managers seeking sustainability, users seeking increases in quota, and conservationists seeking harvest restrictions. All stakeholder groups are able to influence management decisions and users can harvest illegally through the implementation of flexible and dynamic functions that govern lobbying and noncompliance processes. Unlike typical MSE models that represent human behavior through scenario-based and static actions, we optimize decision making through the use of a genetic algorithm, which allows stakeholders to respond to a dynamic social-ecological environment to satisfy their (potentially divergent) goals. Using this modeling framework, we first derive general predictions regarding natural resource management sustainability in the presence of stakeholder conflicts. We then demonstrate the ability of our model to predict population trend patterns observed across a range of harvested vertebrate species from terrestrial systems. By combining existing aspects of MSE models with functions describing governance processes driven by conflicting stakeholder goals, our framework enables comparison of management strategies within a more realistic and dynamic social-ecological setting.

METHODS

Modeling framework

Management strategy evaluation models typically comprise four submodels, each representing one component of the management system (Fig. 1a; Bunnefeld et al. 2011, Punt et al. 2016). In most cases, a population submodel, which simulates the dynamics of the natural resource population under harvest, produces a “true” value of resource abundance at time step t. A monitoring submodel subsequently simulates an observation process through which an estimate of resource abundance, along with associated uncertainty, is obtained. This estimate is then passed on to a manager submodel, whose role is to turn the observation into a harvesting policy that is aligned with the manager’s objective (also called a performance metric). The resulting policy is then acted on by a harvesting submodel, which determines the final off-take from the resource population. This cycle can be repeated over a desired number of time steps, thus enabling dynamic processes to be considered when predicting management outcomes over both short and long time frames.

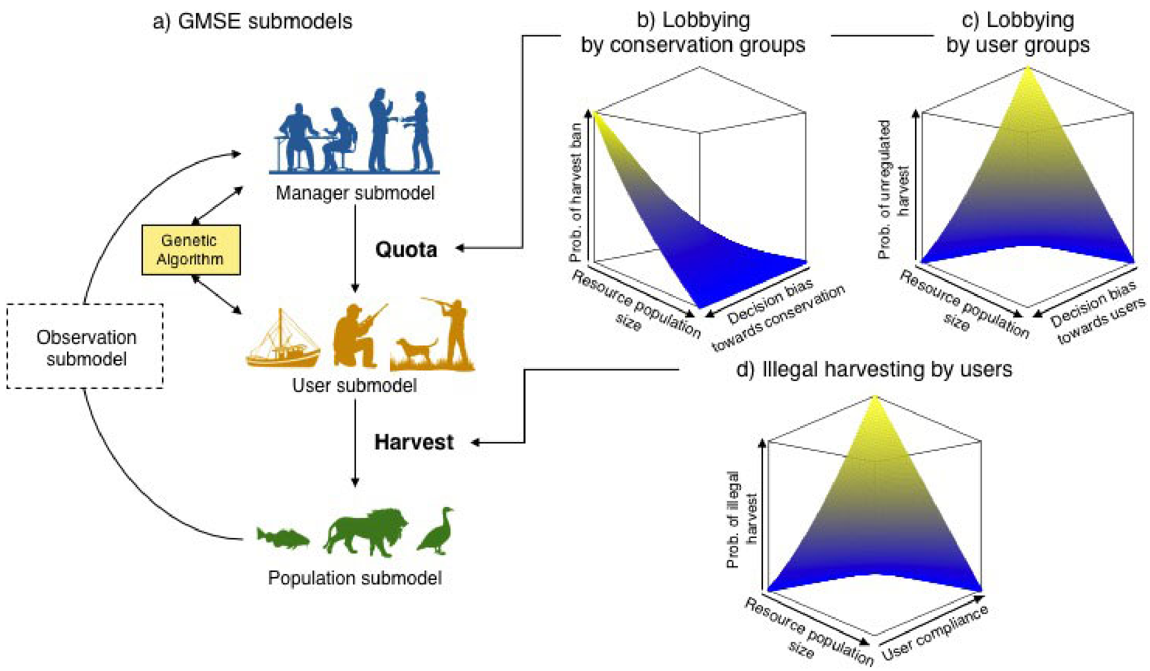
For the purpose of this study, the population submodel consists of a simple discrete logistic resource growth model of the form,

$$N(t+1) = \frac{N(t)Ke^{r(t)}}{K + N(t)(e^{r(t)} - 1)} - H(t) \qquad (1)$$

in which $N(t)$ is the resource population size at time t, K its carrying capacity, $r(t)$ its growth rate at t, and $H(t)$ the total harvest at t (combining legal and illegal off-takes, see below). Stochasticity is included in the model by sampling from a normal distribution with mean r (the intrinsic growth rate of the population) and standard deviation σ. We further assume that the observation process as implemented within the observation submodel bears no error, i.e., the resource population size is estimated perfectly by the manager.

The observed resource population size $N(t)$ is passed on to the manager submodel, whose role is to enact a harvesting quota $Q(t)$ that best minimizes deviations from the manager-specific target abundance (N_M). We choose here to focus on resource abundance as a performance metric because it is a common benchmark in the management of harvested species (Sanderson 2006, Serrouya et al. 2011, Blanchard et al. 2014), but also because it facilitates understanding of our model. Choice of harvest quota

Fig. 1. Overview of the generalized management strategy evaluation (GMSE) approach used in this study.



by the manager is implemented using a genetic algorithm that finds an adaptive, but not necessarily optimal, policy, thereby mimicking a goal-oriented process prone to human error (see Duthie et al. 2018 for more details). The resulting quota is then transferred to the harvest submodel, which also calls a genetic algorithm to determine a harvest that minimizes deviation from a user-specific target abundance (N_U) whilst taking into account varying levels of user budget (Appendix 1, Fig. A1.1).

Simulating conflict

Conflict within our MSE model can be conceptualized as assigning different objectives between manager and users with respect to $N(t)$, which the relevant submodels then attempt to optimize. To increase realism, however, we also include another key actor, conservation groups, whose primary interest in management scenarios is often to promote protection of the resource by restricting harvest. In particular, such groups may impose considerable pressure on decision makers in the form of lobbying (Sandbrook 2017). More specifically, we assume that (i) managers aim to maintain a sustainable population of a given natural resource over the period of management, i.e., achieve an average growth rate of zero, (ii) user groups seek unregulated harvest of the resource, prioritizing year on year versus long-term harvest, and (iii) conservation groups seek to ban harvesting altogether (Aryal et al. 2018), enabling the resource population to grow to carrying capacity. The objectives of users and conservationists represent opposed extremes, which is useful for conceptualizing conflicts related to natural resource use (Redpath et al. 2013). We note, however, that these can be adapted to any scenario at hand.

In the following sections, we detail how stakeholders in our model attempt to meet their respective objectives. To do this, we define two metrics that underlie levels of lobbying and illegal harvesting. The first is decision-making bias, defined as whether management decisions are biased in favor of user or conservation interests. The second is user compliance with harvesting rules, which governs the level of illegal harvesting. We note that our approach does not distinguish between the different drivers of user compliance, such as increased enforcement or monetary incentives (Cooney et al. 2017), but instead serves as a general model of behavioral change.

Lobbying function

In the model, decision making by the manager can be affected by a lobbying process representing pressure from either conservation or user interest groups (Fig. 1b and c, respectively). Lobbying pressure at time t represents the probability that the manager will disregard the original, unbiased quota derived from the genetic algorithm, i.e., $Q(t)$, and instead allow either unregulated harvesting (under user lobbying) or ban harvesting altogether (under conservationist lobbying). For simplicity, decision-making biases as a result of user and conservationist lobbying are simulated separately.

For conservationists, the probability of successful lobbying for a harvesting ban is modeled as a function of how far the observed resource abundance is from the stated conservation target (N_C) and of fixed levels of decision-making bias (I_C) toward conservation interests. I_C can be varied between $I_C = 0$ (manager completely biased) and $I_C = 1$ (manager completely unbiased). We further assume that lobbying pressure is nonexistent when $N(t) \geq N_C$, but expect it to increase exponentially as the resource population approaches extinction ($N(t) \rightarrow 0$). Thus, the probability of successful lobbying for a harvesting ban by conservation groups is defined as follows,

$$\phi_{conservation}(t) = \left[(2 - I_C)^{\frac{N_C - N(t)}{N_C}}\right] - 1 \quad (2)$$

$Q'(t)$, which represents $Q(t)$ postlobbying, is then determined using a single Bernouilli trial $X(t) \sim B(1, \Phi_{Conservation}(t))$ such that if $X(t) = 0$, $Q'(t) = Q(t)$, and if $X(t) = 1$, $Q'(t) = 0$.

For users, the probability of successful lobbying for unregulated harvest is modeled as a function of how far the observed resource abundance is from the stated user target (N_U) and, similarly to conservation lobbying, decision-making bias toward user interests (denoted as I_U). We further assume that lobbying pressure is nonexistent when $N(t) \leq N_U$, but expect it to increase exponentially as the resource population approaches carrying capacity ($N(t) \to K$). Thus, the probability of successful lobbying for unregulated harvest by user groups is defined as,

$$\phi_{User}(t) = \left[(2 - I_U)^{\frac{N(t) - N_U}{K - N_U}}\right] - 1 \quad (3)$$

As above, $Q'(t)$ is then determined with a Bernouilli trial $X(t) \sim B(1, \Phi_{User}(t))$, such that if $X(t) = 0$, $Q'(t) = Q(t)$, and if $X(t) = 1$ then $Q'(t) = H_{max}(t)$, where $H_{max}(t)$ is the maximum number of individual resources that can be harvested at time t given the user budget $B_U(t)$ and minimum cost of a harvest c_{min}, i.e.,

$$H_{max}(t) = \frac{B_U(t)}{c_{min}} \quad (4)$$

$Q'(t)$ subsequently determines how many units of the resource population the user can harvest legally. Both N_C and N_U can be varied between zero and K, the resource population carrying capacity.

Illegal harvesting function

The user can then choose to either implement the legal quota or harvest illegally, depending on which option maximizes harvest (Fig. 1d). In a similar way to lobbying, illegal harvesting pressure represents the probability that the user will successfully remove one unit from the resource population, and is defined as,

$$\Psi(t) = \left[(2 - E)^{\frac{N(t) - N_U}{K - N_U}}\right] - 1 \quad (5)$$

E is user compliance with harvesting rules and is varied in simulations from $E = 0$ (no compliance) and $E = 1$ (complete compliance). A hypothetical illegal harvest, $Y(t)$, is then derived from a Bernouilli trial $Y(t) \sim B(H_{max}, \Psi(t))$. The user then implements a final harvest $H(t)$, defined as the maximum of either $Q'(t)$ or $Y(t)$.

Simulation and statistical analysis

Model simulations were carried out in R (version 3.4.3) using the package GMSE (version 0.4.0.11; Duthie et al. 2018). The R code used to produce simulations is provided in Appendix 2, and the definition and values for set and derived parameters are presented in Appendix 3, Table A3.1. Resource population size at $t = 0$ was set to 1000 units and the carrying capacity at 2000. We ran simulations for three values of r—0.1, 0.2, and 0.3 (with $\sigma = r/10$ in all cases)—because these represented a range of commonly measured intrinsic growth rates in the harvested species considered in our empirical analysis (see below; Sibly and Hone 2002). We varied decision-making bias (I, separately for conservation and user groups) and user compliance levels (E) to control lobbying and illegal harvesting levels during each time step, respectively. For each combination, we ran 100 management iterations, each lasting 10 time-steps, i.e. years. We chose to carry out simulations over 10 time steps because this was representative of real-world management plans. In all simulations, the minimum cost of a harvest (c_{min}) was set to 10, the manager budget to 10,000, and the user budget was varied between 5000 and 10,000 (see Appendix 1, Fig. A1.1). Management effectiveness was assessed as the mean resource population growth at time step 10 across iterations. We then modeled management effectiveness as a function of decision-making bias and user compliance using generalized additive models (GAMs) with tensor product smooths (R package mgcv). We present our findings in the form of 2-dimensional contour surfaces.

As a control, we ensured that in the absence of disagreement among manager, user, and conservation objectives, the simulated resource population is managed effectively regardless of decision-making bias and user compliance levels. This was done by setting user, conservationist, and manager targets to 1000 resource units.

Application to harvested species

We compared predictions from our model against data on 206 terrestrial harvested species from the International Union for the Conservation of Nature's (IUCN) Red List of Threatened Species. We considered species belonging to the orders Anseriformes (geese and ducks, $N = 37$), Cetartiodactyla (even-toed ungulates, $N = 90$) and Carnivora (carnivores, $N = 79$) because these are commonly targeted by subsistence, recreational, and trophy hunting activities globally (Di Minin et al. 2019, Hill et al. 2019).

Using the "advanced search" option on the IUCN Red List web site (https://www.iucnredlist.org/), we filtered species by criteria relating to Taxonomy ("Anseriformes," "Cetartiodactyla," and "Carnivora"), Red List Category ("NT or LR/nt" and "LC or LR/lc"), and Threats ("Intentional use (species is the target)"). We only considered species listed as Least Concern or Near Threatened so as to minimize confounding factors associated with threat status. Filtering resulted in a total of 206 species to which the classification of decision-making bias and user compliance shown in Appendix 4 (Fig. A4.1) was applied. More specifically, we classified each species according to (1) its stated population trend at the latest assessment (decreasing, stable, or increasing), (2) the type of harvesting it was most commonly under (unregulated, regulated, or banned), and (3) the level of illegal harvest most commonly reported for a population (low, medium, or high). We then used population trend as a measure of management outcome, harvesting type as a measure of decision-making bias (with unregulated and banned taken to reflect pro-user and pro-conservation biases), and illegal harvest level as a measure of user compliance. Classifications were carried out by two of the authors and subsequently compared to ensure consistency.

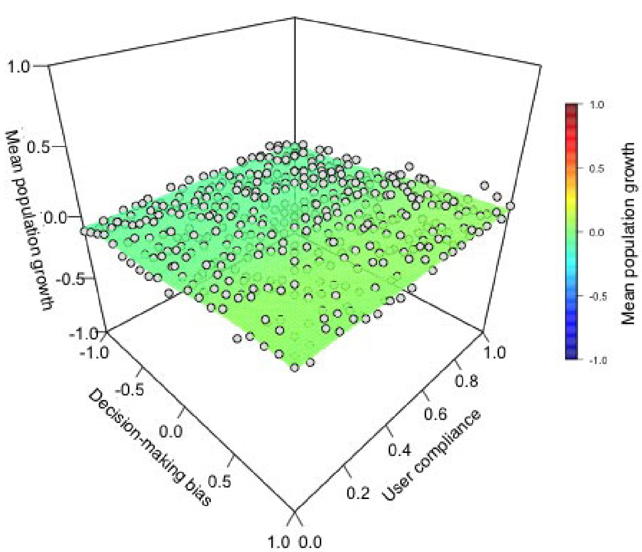
We derived the proportion of species showing a decreasing, stable, and increasing population trend for each of the different combinations of decision-making bias and user compliance. We also modeled population trend as a function of the interaction between decision-making bias and user compliance using a generalized additive model with Gaussian error structure and tensor product smooth. This resulted in an interpolated surface showing mean population trajectory (from -1 to 1) as a function of decision-making bias and user compliance classifications.

RESULTS

Model predictions

When simulated manager, user, and conservation objectives were identical, reflecting perfect agreement on target abundance for the harvested resource, mean population growth remained stable and on target over the course of 10 management years (Fig. 2). This parameterization is important because it verifies that the genetic algorithm is operating as intended by producing expected results of optimal (or near-optimal) harvest decisions over both short and long time frames. It also reflects a null model of effective management in the absence of conflicting stakeholder objectives, against which the effect of lobbying and illegal harvesting can be compared.

Fig. 2. Mean population growth over a 10-year management period as a function of decision-making bias and user compliance when manager, users, and conservationists agree on the management target. Decision-making bias ranges from entirely pro-user (-1, harvest is always unregulated) to pro-conservation (+1, harvest is always banned), with 0 representing a scenario in which manager quota decisions cannot be lobbied. When user compliance is 0, users will always partake in illegal harvesting while a value of 1 ensures users will fully comply with the quota put forward by the manager (postlobbying). Each point represents the mean population growth across 100 iterations. The surface represents predictions from a generalized additive model with decision-making bias and user compliance specified as tensor product smooths. Overall, the management target of maintaining a stable population trend is achieved for all combinations of decision-making bias and user compliance.



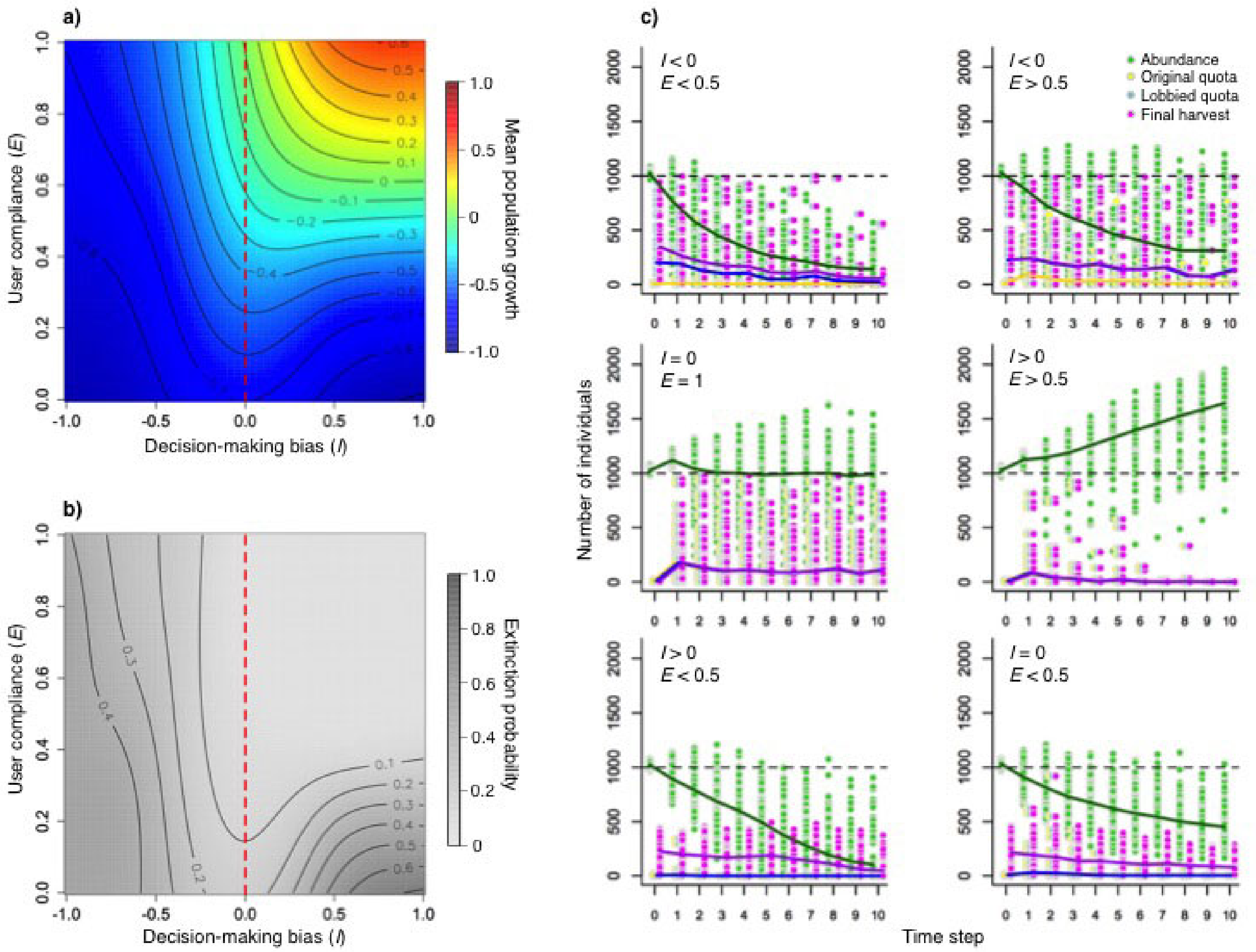
In the presence of conflicting stakeholder objectives, we find that management outcome is shaped by the interaction between decision-making bias and user compliance levels (Fig. 3). We make five predictions from our model. First, when lobbying has no effect on management decisions, a stable resource abundance is only achieved at high levels of user compliance (Fig. 3; $I = 0$ and $E = 1$). Second, as compliance decreases from high to moderate levels, i.e., increasing illegal harvest, stable and increasing resource population trends are possible to maintain if decision making by the manager is biased toward conservation objectives (Fig. 3; $I > 0$ and $E > 0.5$). Third, the combination of bias toward conservation objectives and low user compliance leads to both an increased risk of negative population growth rates and an increased probability of extinction (Fig. 3; $I > 0$ and $E < 0.5$). This arises because such decision making leads to a higher likelihood of harvesting being banned and consequently higher resource abundance, to which users respond by increasing illegal harvesting pressure when compliance is low. Fourth, as user compliance tends toward minimum levels, negative growth rates occur regardless of bias in decision making, although they are less severe if decision making is unaffected by lobbying (Fig. 3; cases when $E < 0.5$). Last, when management decisions are biased toward user interests, population abundance declines over the course of the management period (Fig. 3; cases when $I < 0$). In this case, compliance has little effect because lobbying already satisfies user interests. Importantly, these predicted patterns of management outcome were not sensitive to choice of resource population growth rate (Appendix 5, Fig. A5.1).

Application to harvested species

Of the 206 species considered, 26 (12.6%) showed an increasing population trend, while 61 (29.6%) and 119 (57.8%) exhibited stable and decreasing trends, respectively. The proportion of species showing a stable population trend was highest when user compliance was high (Fig. 4a-c, Appendix 6, Table A6.1), and particularly when harvest was regulated (47% stable trends), a finding that is consistent with our model results (Fig. 3). Species showing increasing population trends were most strongly associated with high compliance (23 out of 26 species), and either regulated (16 out of 23 species) or banned (5 out of 23 species) harvesting. Eighty-one percent of the species classified under regulated harvest and high compliance showed stable or increasing population trends.

In contrast, species populations were overwhelmingly decreasing when compliance with harvesting rules was low, regardless of decision-making bias (Fig. 4g-i). This mirrors the dominant effect of changes in illegal harvesting over lobbying in driving resource mismanagement, which our model also predicts. As user compliance decreased from high to low, however, species were more likely to exhibit stable and increasing population trends when harvest was characterized as regulated rather than unregulated or banned. Overall, predictions from our theoretical model were strongly correlated with those obtained from empirical data (Pearson's correlation corrected for autocorrelation: = 0.897, $P < 0.05$ for a simulated intrinsic growth rate of $r_{max} = 0.1$; = 0.853, $P < 0.05$ for $r_{max} = 0.2$; and = 0.821, $P < 0.05$ for $r_{max} = 0.3$, respectively; Appendix 7, Fig. A7.1).

Fig. 3. Mean population growth (a) and extinction probability (b) over a 10-year management period as a function of management decision-making bias and user compliance with harvesting rules. Panels in (c) relate to different areas of the model prediction surfaces, and illustrate time series of resource abundance, original quota put forward by the manager, modified quota as a result of lobbying, and final harvest including legal and illegal off takes for different combinations of decision-making bias and user compliance. Decision-making bias ranges from entirely pro-user (-1, harvest is always unregulated) to pro-conservation (+1, harvest is always banned), with 0 representing a scenario in which manager quota decisions cannot be lobbied (red dashed line). When user compliance is 0, users will always partake in illegal harvesting, while a value of 1 ensures users will fully comply with the quota put forward by the manager (postlobbying). The 2D contour surfaces were obtained from generalized additive models with decision-making bias and user compliance specified as tensor product smooths. Results are shown for a simulation in which the intrinsic growth rate of the harvested population was 0.2 and the carrying capacity was 2000 individuals.



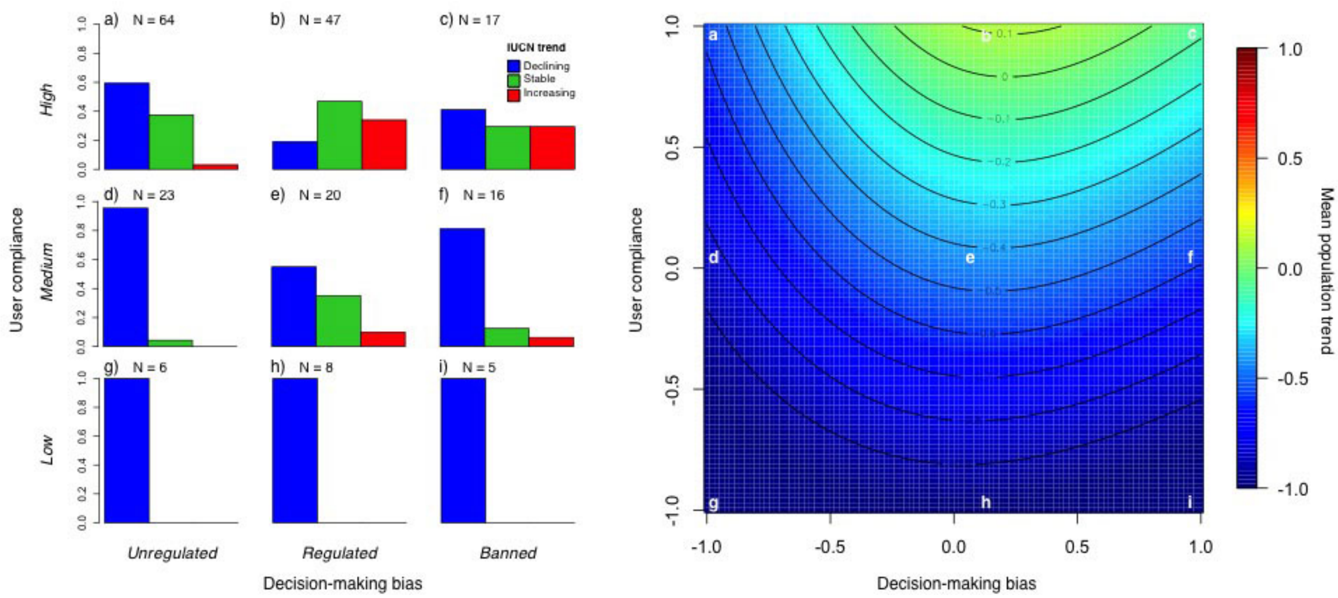
DISCUSSION

Modeling dynamic governance processes

Our work provides a holistic and versatile resource management framework that accounts for dynamic governance processes such as conflict, lobbying, and rule compliance. It highlights the complex interaction between lobbying and compliance in the presence of conflicts, and its substantial influence on the sustainability of natural resource use. Most notably, we find that lobbying for management decisions that favor conservation interests can offset medium levels of user noncompliance. Yet this comes at a risk of increased sensitivity to further reductions in user compliance, which results in higher probabilities of resource extinction relative to scenarios in which management decision making is unbiased. These theoretical predictions are well supported in real-world systems. Indeed, there is increasing evidence in the scientific literature that outright harvest bans can lead to increased levels of illegal harvest (Di Minin et al. 2016, Raithel et al. 2017). For example, bans on trophy hunting imports and activities without provision of viable land-use alternatives can lead to a rise in unregulated killing of wildlife (Lindsey et al. 2017, Dickman et al. 2019).

We also demonstrate the critical effect of changes in user compliance on sustainable resource use. Both our theoretical modeling and empirical analysis show that, when management

Fig. 4. Proportion of harvested IUCN Red List species with declining, stable, or increasing population trends for different combinations of decision-making bias and user compliance (panels a-i). N indicates the sample size for each combination. The 2D contour surface represents the interpolated mean population trend across harvested species (-1 = decreasing, 0 = stable, 1 = increasing) for varying levels of decision-making bias and user compliance, and was obtained from a generalized additive model with decision-making bias and user compliance specified as tensor product smooths. The location of letters placed on the prediction surface relate to data shown in panels (a) to (i).



decisions are unbiased, stable resource trends are most likely to be achieved when compliance is high. This finding may seem obvious, but broad consensus between conceptual models and empirical approaches that encompass a range of species and incorporate the link with lobbying has been lacking (Travers et al. 2019*b*). The pattern we observe arises because user actions have a direct effect on the resource population, whereas lobbying targets decision making by the manager. In other words, users have the "final say" on what harvest will be implemented in a given time step (Eriksen et al. 2018, Shirley and Gore 2019), thus emphasizing their potential power to drive resource populations trends. Increasing user compliance with harvesting rules should therefore be a priority when seeking to sustainably manage natural resource use. This could be achieved through increased enforcement or by reducing demand (Holden et al. 2019) and implementing bottom-up approaches to management (Duffy et al. 2016, Cooney et al. 2017), such as the development of comanagement plans that bring together all parties in search of an agreement on management targets prior to actions being carried out (Armitage et al. 2009, Young et al. 2016, Redpath et al. 2017). Our model parameterization in which all parties agree on a population target demonstrates the value of compromise in achieving sustainable natural resource use.

Application to real-world harvesting systems

Our theoretical predictions provided a strong quantitative match to those obtained from our analysis of IUCN red list data, thus demonstrating the broad applicability of our approach. Yet the importance of considering the interaction between decision-making bias and user compliance can also be emphasized through a more qualitative assessment of real-world case studies. Many ungulate and carnivore species are killed illegally in response to crop damage or livestock depredation, respectively, leading to declining populations despite high levels of international and national protection (Soofi et al. 2019). For example, Suutarinen and Kojola (2017) show how the illegal hunting of protected grey wolves (*Canis lupus*) in Finland increases with population size and strongly regulates population trends, despite the existence of "exceptional permits" to hunt wolves that cause damage to livestock. Here, strong protection laws that have enabled the wolf population to grow may have also influenced rates of illegal harvesting. In this case, our model could help highlight the damaging effect of conflict on sustainable management, and adjust legal harvest quotas based on quantified or expected rates of illegal harvesting, i.e., compliance.

Similarly, many species of herbivorous waterfowl in Europe and North America have experienced exponential increases in population size partly because of pro-conservation, protective legislation and high user compliance, yet this trend has started to occur at the detriment of agricultural crop production on which these species have become reliant (Lefebvre et al. 2017, Cusack et al. 2019). On the island of Islay in Scotland, legal harvesting of the wintering Greenland Barnacle Goose (*Branta leucopsis*) population, a species protected under EU law, has now been enforced because of lobbying pressure from agricultural interest groups, whose livelihoods are affected by goose grazing and damage to livestock pastures (McKenzie and Shaw 2017). However, the lack of evidence-based decision making relating to hunting quotas has been criticized by conservation organizations, which have brought forth lawsuits in an attempt to minimize culling. Although recent work has been used to derive more sustainable harvesting quotas based on the GMSE approach (Bunnefeld et al. 2020), it remains unclear how lobbying by both conservation and agricultural interests will affect manager decision making. Our approach could contribute to evidence-based decision making to minimize the risk of conflict escalation and dangerous tipping points in goose population trends due to overharvesting.

The relevance of our model goes beyond the orders considered in our IUCN analysis. The management of populations of birds of prey, for example, is also prone to conflict and governance issues. In the UK, the Hen Harrier (*Circus cyaneus*) is of high conservation concern and, although strictly protected, its population continues to be heavily impacted by illegal killing (Ludwig et al. 2017). Hen Harriers prey on Red Grouse (*Lagopus lagopus scotica*), a species whose populations and moorland habitat are intensively managed for shooting. The protection of the Hen Harrier is viewed as a threat to the Red Grouse shooting industry, resulting in widespread illegal killing of the raptor species on grouse moors (Murgatroyd et al. 2019). Here, our model could help explore how a healthy Hen Harrier population could be achieved despite conflicting stakeholder population targets, low compliance, and strong conservation pressure to ban legal harvesting (Redpath and Thirgood 2009).

Model assumptions and limitations

Our approach aims to portray the functioning of complex and dynamic harvesting systems often characterized by high levels of uncertainty (Bunnefeld et al. 2011). In doing so, we have made a number of assumptions about the ecological and social components of these systems. In a first instance, we have implemented a simple logistic population growth model to define the general trajectory of resource abundance. Such a model provides a heuristic platform on which to evaluate population trends whilst minimizing biological complexity (Milner-Gulland 2011). We stress that the GMSE approach used in this study also enables the application of more elaborate resource growth models (see Duthie et al. 2018), which may be better suited to particular case studies, such as a population of a species in a given area, or be parameterized to include more or less demographic and environmental stochasticity (Fryxell et al. 2010, Milner-Gulland 2011). Like the assumption of perfect observation, an unlikely characterization of real-world systems, the simplicity of our population model allows us to isolate the effect of governance processes above and beyond structural and measurement uncertainties (Bunnefeld et al. 2011).

Our approach employs a genetic algorithm to optimize goal-oriented quota decision making, which provides a more rapid alternative to a trial and error method whereby a range of quota levels are tested sequentially (Duthie et al. 2018). Although the resulting quotas are derived with a level of variation that is realistic of management decisions, this variation remains random and we do not explicitly model the mechanisms driving decision making for a given manager, e.g., inherent biases. Similarly, subsequent lobbying actions, i.e., external pressures, affect the decision provided by the genetic algorithm, but not the simulated selection process itself. Even though our goal-oriented decision makers in the model do not reflect the entire complexity of people in the real world, our approach represents an important step forward compared to error-free and static decisions used in more standard harvesting models (Dobson et al. 2019).

Despite their evident potential for influencing sustainable use, reliable measures of decision-making bias and its relationship with lobbying pressure, as well as of user compliance, are sorely lacking for most harvested species. For instance, the link between social norms and illegal behavior has received little attention in the literature (Nyborg et al. 2016). Although the simulations presented here assume both lobbying pressure and illegal harvesting increase exponentially as resource abundance deviates from a stakeholder's goal, these functions should be modified and parameterized based on available real-world data or more detailed qualitative assessments of social norms and values. Last, our approach makes the key assumption that resource user behavior is driven by a desire to maximize harvest in the short term given a resource abundance goal, i.e., economic gain. Although this extreme is used to illustrate the breadth of our approach, we acknowledge that many factors, such as cultural norms and traditions, can promote self-sustaining harvesting systems (Ostrom 2009, Struebig et al. 2018). We note that, as a start, our approach can accommodate social norms by allowing the goal of resource users to be greater than population extinction, indicating a desire to maintain abundance in the long term.

CONCLUSION

Although MSE models are often tailored to specific case studies, our analysis reveals general patterns across theoretical and empirical analyses. Specifically, although lower compliance may be offset by increased decision bias toward conservation goals, extinction risk increases when high levels of such bias are combined with low user compliance. In addition, management decisions free from any influence of lobbying can only successfully achieve sustainable harvesting given low levels of illegal harvesting and thus buy-in from stakeholders. Given this balancing act, there is an urgent need for management approaches that address the underlying social conflicts over the sustainable use of biodiversity. Such approaches should seek where possible to promote consensus between stakeholders on population targets, for instance by investing in detailed assessments of the views and needs of each interest group, and their overlap. In cases where consensus proves challenging to achieve, our modeling approach could help simulate and predict how the resulting governance processes through which divergence is expressed could affect the sustainability of harvested populations. In turn, this would allow management decisions to anticipate the effects of potential lobbying and noncompliance. Importantly, use of the proposed approach need not be restricted to natural resource management. Indeed, individual responses (including compliance) to conflict, policy, and lobbying are of high relevance to issues such as climate change mitigation (Chakra et al. 2018) and sustainable wildlife trade (Nuno et al. 2018), in which the power of consumers (of carbon and wildlife, respectively) is likely to be high.

Responses to this article can be read online at:
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Data Availability Statement:

The data and code are available in the manuscript supporting information.

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Appendix 1

Manager and user budget choice

The observed resource population size is passed on to the manager sub-model, whose role is to enact a harvesting quota that best minimizes deviations from the manager-specific target abundance. Choice of harvest quota by the manager is implemented using a genetic algorithm that finds an adaptive – but not necessarily optimal – policy, thereby mimicking a goal-oriented process prone to human error (see Duthie et al. 2018 for more details). The resulting quota is then transferred to the harvest sub-model, which also calls a genetic algorithm to determine a harvest that minimizes deviation from an user-specific target abundance whilst taking into account varying levels of user budget/

In the GMSE framework, both manager and user actions are constrained by their respective budgets (Duthie et al. 2018). A high budget for the manager increases the range of quotas they can set, and therefore enables them to exert more control on population management. In contrast, the user budget defines the maximum harvest that can be obtained by the user in the absence of management. When the user budget is high but the manager budget is low, the user is able to remove more animals from the population as the manager is unable to set a high enough quota.

Although interesting in their own right, scenarios in which the manager is unable to control the user, or in which the user is unable to fulfil the quotas set by the manager, would consistently lead to over- or under-exploitation of the wildlife population, respectively. Our focus in this study is to instead consider scenarios in which both manager and user possess the means to effectively manage the wildlife population. This enables us to focus on quantifying how, and to what extent, conflicting objectives prevent the attainment of management targets that would otherwise be met. This requires selecting values for manager and user budgets that enable a given target to be met in the absence of perturbations caused by potential disagreements.

To evaluate the influence of manager and user budgets on management outcomes, we carried out simulations in which both budgets were varied between 0 and 10,000. For each budget combination we ran 10 management time steps and recorded wildlife population size at the final time step. Simulations were carried out with μ set to 0.2, K to 2000, and population target to 1000 individuals.

When user budget is low, the wildlife population grows beyond the population target to carrying capacity regardless of manager budget (Fig A1.1). This reflects a situation in which even the maximum possible harvesting capacity is insufficient to prevent a managed population from growing. In contrast, when manager budget is low and the ability of the user to affect the wildlife population increases, extinction becomes more likely. This illustrates a situation in which a manager cannot control a highly effective harvesting strategy. This could occur, for example, if the manager repeatedly under-estimated harvesting power.

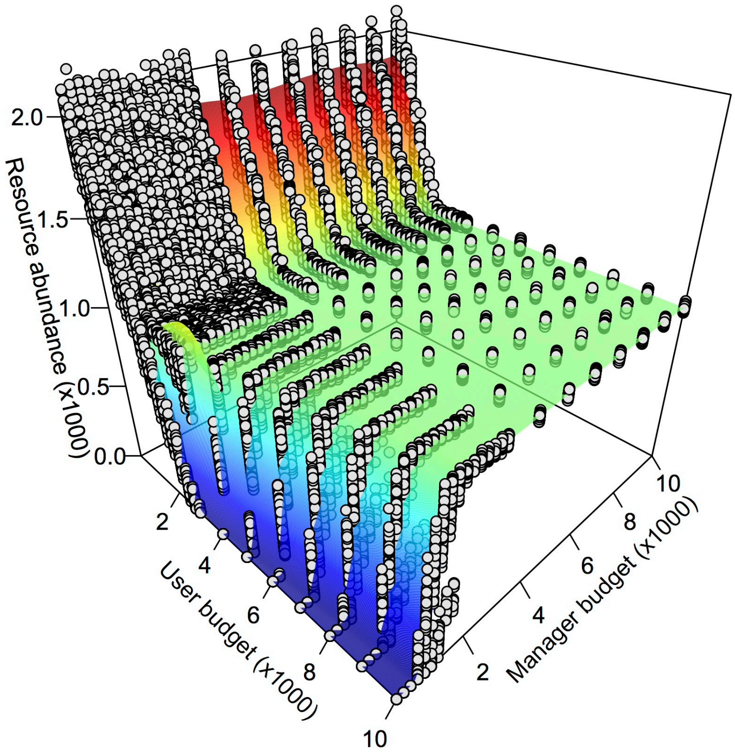

Fig. A1.1. Natural resource abundance observed as a function of user and manager budgets in the absence of conflict over management objectives. Dots denote resource abundance during the final management time step for each iteration of a user and manager budget combination. The fitted surface was obtained from a Poisson generalized additive model with a smooth tensor product representing the interaction between user and manager budgets. The surface colours are indicative of natural resource abundance (red = under-exploitation; green = target; blue = over-exploitation). The management target remained constant at 1000 individuals across the different combinations of user and manager budget. The natural resource population followed a logistic growth with an intrinsic growth rate of 0.2 and a carrying capacity of 2000 individuals.

Most importantly, we find that the management target can be achieved only for a subset of all manager and user budget combinations. In theory, any combination belonging to this subset will result in effective management in the absence of external perturbations. Based on these results, we chose to vary user budget each management year between 5,000 and 10,000, while maintaining the manager budget at 10,000. This accounts for stochastic fluctuations in user budget that may affect harvesting capacity.

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Appendix 2

R code to simulate natural resource management in the presence of conflict, lobbying and non-compliance.

Below we provide an annotated R script that can be used to replicate the simulations presented in this study.

The only R package required to run a simulation is *GMSE* (Duthie et al. 2018).

```
require('GMSE')
```

The following values can be varied to test the effect of target, budget, decision-making bias and user compliance on management outcome:

```
M.TGT = 1000                    # Manager target
U.TGT = 0                       # User target
C.TGT = 2000                    # Conservationist target

MB = 10000                      # Manager budget

decision.bias = 0               # Decision bias level
user.compliance = 0             # User compliance level

nsteps = 10                     # Number of time steps
minc = 10                       # Minimum cost of an action
```

The following functions define the population growth model, the observation model, lobbying pressure by users and conservationists, and illegal harvesting pressure by users.

```
### Population growth model

pop_model <- function(X,
```

```
                      K,
                      ig){
  Xn <-
round((X*K*exp(rnorm(1,ig,ig/10)))/(K+X*(exp(rnorm(1,ig,ig/10))-1)))
  return(Xn)
}

### Observation model

obs_model <- function(resource_vector){
      X_obs <- resource_vector
      return(X_obs)
}

### Conservation lobbying function

ClobbyingF <- function(bias_level,
                       conservation_target,
                       population_size){
  if (population_size > conservation_target){
    res <- 0
  }
  else{
    res <- (((1-
bias_level)+1)^(1/conservation_target))^(conservation_target-
population_size))-1
  }
  return(res)
}

### User lobbying function

UlobbyingF <- function(bias_level,
                       user_target,
                       population_size,
                       carrying_capacity){
  if (population_size < user_target){
    res <- 0
  }
  else{
    res <- ((((1-bias_level)+1)^(1/(carrying_capacity-
user_target)))^(population_size-user_target))-1
  }
  return(res)
}

### Illegal offtake function

IllegalHarvestF <- function(compliance_level,
                            user_target,
                            population_size,
                            carrying_capacity){
  if (population_size < user_target){
    res <- 0
  }
  else{
```

```
    res <- ((((1-compliance_level)+1)^(1/(carrying_capacity-
user_target)))^(population_size-user_target))-1
  }
  return(res)
}
```

Population parameters are set to:

```
Kk = 2000                    # Wildlife population carrying capacity
rmax = 0.2                   # Wildlife population intrinsic growth
rate
```

The code below runs one management iteration of `nsteps` time steps under user lobbying for given values of `M.TGT`, `U.TGT`, `C.TGT`, `MB`, `decision.bias`, `user.compliance` and `minc` specified above. All other values appearing in the calls to gmse_apply not defined above are default values as described in [1].

```
# Sample user budget for the set of time steps

UB <- sample(5000:10000,
             size=nsteps,
             replace=T)

# Run initial gmse_apply (the manager calls the genetic algorithm)

sim1 <- gmse_apply(res_mod = pop_model,
                   obs_mod = obs_model,
                   K = Kk,
                   ig = rmax,
                   X = 1000,
                   user_budget = UB[1],
                   minimum_cost = minc,
                   manager_budget = MB,
                   manage_target = M.TGT,
                   scaring = F,
                   culling = T,
                   castration = F,
                   feeding = F,
                   stakeholders = 1,
                   manage_freq = 1,
                   manager_sense = 1,
                   public_land = 0,
                   land_ownership = F,
                   group_think = F,
                   ga_mingen = 200,
                   get_res = "Full")
```

```
# Extract resource abundance

Nt <- sim1$resource_vector

# Extract cost

c.t <- sim1$manager_vector

# Derive quota

q.t <- floor(UB[1]/c.t)

# Maximum possible quota given user budget

max.q <- floor(UB[1]/minc)

# Slight correction to Kk in the case that stochasticity overshoots
the
# carrying capacity

CC <- ifelse(Nt>Kk,Nt+1,Kk)

# Derive probability of unregulated harvest

phi.t <- UlobbyingF(bias_level = decision.bias,
                    user_target = U.TGT,
                    population_size = Nt,
                    carrying_capacity = CC)

# Is harvest unregulated?

P.t <- rbinom(n=1,size=1,prob=phi.t)

# If P(t)=0

if (P.t == 0){
  q.prime.t <- q.t
}

# Otherwise...

if (P.t==1){

  # The new quota is then derived as

  q.prime.t <- max.q

}

# Derive maximum possible harvest at minimum cost

max.h.t <- floor(UB[1]/minc)

# If the maximum possible harvest is smaller or equal to the lobbied
quota
# No need to poach as harvesting is unregulated
```

```
if (max.h.t <= q.prime.t){
  h.t <- max.h.t
}

else{

  # Slight correction to Kk in the case that stochasticity overshoots
the
  # carrying capacity

  CC <- ifelse(Nt>Kk,Nt+1,Kk)

  # Derive probability of illegal harvest

  psi.t <- IllegalHarvestF(compliance_level = user.compliance,
                            user_target = U.TGT,
                            population_size = Nt,
                            carrying_capacity = CC)

  # Derive illegal harvest based on max harvest and probability

  Y.t <- sum(rbinom(n=max.h.t,size=1,prob=psi.t))

  if (Y.t==q.prime.t){
    h.t <- q.prime.t
  }

  else{
    h.t <- max(c(q.prime.t,Y.t))
  }

}

# Create results data.frame

results   <- matrix(dat = NA, nrow = nsteps, ncol = 9)

results[1,1] <- sim1$resource_vector;                 # Number of
resources
results[1,2] <- sim1$observation_vector;     # Observed number of
resources
results[1,3] <- q.t                      # Harvesting quota before
lobbying
results[1,4] <- q.prime.t                 # Harvesting quota after
lobbying
results[1,5] <- h.t                         # Harvest after illegal
offtake
results[1,6] <- decision.bias                           # Manager
bias level
results[1,7] <- user.compliance                    # User compliance
level
results[1,8] <- 1                                                #
Time step
results[1,9] <- UB[1]                                         # User
budget

# Apply harvest
```

```
sim1$X <- sim1$resource_vector-h.t

#####################################
### Run through rest of time steps ##
#####################################

for (time_step in 2:nsteps){

  # Run gmse_apply

  sim_new <- tryCatch(gmse_apply(old_list = sim1,
                                 res_mod = pop_model,
                                 obs_mod = obs_model,
                                 get_res = "Full",
                                 user_budget = UB[time_step]),
                      error=function(err) NA)

  if (is.na(sim_new)==T){     # If the resource goes extinct

    # Add results to data.frame

    results[time_step:nsteps,1] <- 0
    results[time_step:nsteps,2] <- 0
    results[time_step:nsteps,3] <- NA
    results[time_step:nsteps,4] <- NA
    results[time_step:nsteps,5] <- NA
    results[time_step:nsteps,6] <- decision.bias
    results[time_step:nsteps,7] <- user.compliance
    results[time_step:nsteps,8] <- time_step:nsteps
    results[time_step:nsteps,9] <- NA

    print("Extinction")

    break

  }

  if (class(sim_new)=="list"){     # If the resource does not go
extinct

    # Extract resource abundance

    Nt <- sim_new$resource_vector

    # Extract cost

    c.t <- sim_new$manager_vector

    # Derive quota

    q.t <- floor(UB[time_step]/c.t)

    # Maximum possible quota given user budget

    max.q <- floor(UB[time_step]/minc)
```

```
    # Slight correction to Kk in the case that stochasticity
overshoots the
    # carrying capacity

    CC <- ifelse(Nt>Kk,Nt+1,Kk)

    # Derive probability of unregulated harvest

    phi.t <- UlobbyingF(bias_level = decision.bias,
                        user_target = U.TGT,
                        population_size = Nt,
                        carrying_capacity = CC)

    # Is harvest unregulated?

    P.t <- rbinom(n=1,size=1,prob=phi.t)

    # If P(t)=0

    if (P.t == 0){
      q.prime.t <- q.t
    }

    # Otherwise...

    if (P.t==1){

      # The new quota is then derived as

      q.prime.t <- max.q

    }

    # Derive maximum possible harvest at minimum cost

    max.h.t <- floor(UB[time_step]/minc)

    # If the maximum possible harvest is smaller or equal to lobbied
quota
    # No need to poach as harvesting is unregulated

    if (max.h.t <= q.prime.t){
      h.t <- max.h.t
    }

    else{

      # Slight correction to Kk in the case that stochasticity
overshoots
      # the carrying capacity

      CC <- ifelse(Nt>Kk,Nt+1,Kk)

      # Derive probability of illegal harvest

      psi.t <- IllegalHarvestF(compliance_level = user.compliance,
                               user_target = U.TGT,
```

```
                                population_size = Nt,
                                carrying_capacity = CC)

      # Derive illegal harvest based on max harvest and probability

      Y.t <- sum(rbinom(n=max.h.t,size=1,prob=psi.t))

      if (Y.t==q.prime.t){
        h.t <- q.prime.t
      }

      else{
        h.t <- max(c(q.prime.t,Y.t))
      }

    }

    # Add results to data frame
    results[time_step,1] <- sim_new$resource_vector;
    results[time_step,2] <- sim_new$observation_vector;
    results[time_step,3] <- q.t
    results[time_step,4] <- q.prime.t
    results[time_step,5] <- h.t
    results[time_step,6] <- decision.bias
    results[time_step,7] <- user.compliance
    results[time_step,8] <- time_step
    results[time_step,9] <- UB[time_step]

    # Apply harvest

    sim_new$X <- sim_new$resource_vector-h.t;

    sim1 <- sim_new

  }

}
```

The following code runs one management iteration of `nsteps` time steps <u>under conservationist lobbying</u> for given values of `M.TGT`, `U.TGT`, `C.TGT`, `MB`, `decision.bias`, `user.compliance` and `minc` specified above. All other values appearing in the calls to gmse_apply not defined above are default values as described in [1].

```
# Sample user budget for the set of time steps

UB <- sample(5000:10000,
             size=nsteps,
```

```
              replace=T)

# Run initial gmse_apply (the manager calls the genetic algorithm)

sim1 <- gmse_apply(res_mod = pop_model,
                   obs_mod = obs_model,
                   K = Kk,
                   ig = rmax,
                   X = 1000,
                   user_budget = UB[1],
                   minimum_cost = minc,
                   manager_budget = MB,
                   manage_target = M.TGT,
                   scaring = F,
                   culling = T,
                   castration = F,
                   feeding = F,
                   stakeholders = 1,
                   manage_freq = 1,
                   manager_sense = 1,
                   public_land = 0,
                   land_ownership = F,
                   group_think = F,
                   ga_mingen = 200,
                   get_res = "Full")

# Extract resource abundance

Nt <- sim1$resource_vector

# Extract cost

c.t <- sim1$manager_vector

# Derive quota

q.t <- floor(UB[1]/c.t)

# Minimum possible quota

min.q <- 0

# Derive probability of harvest ban

phi.t <- ClobbyingF(bias_level = decision.bias,
                    conservation_target = C.TGT,
                    population_size = Nt)

# Is harvest banned?

P.t <- rbinom(n=1,size=1,prob=phi.t)

# If P(t)=0

if (P.t == 0){
  q.prime.t <- q.t
}
```

```
# Otherwise...

if (P.t==1){

  # The new quota is then derived as

  q.prime.t <- min.q

}

# Derive maximum possible harvest at minimum cost

max.h.t <- floor(UB[1]/minc)

# If the maximum possible harvest is smaller or equal to the lobbied
quota
# No need to poach as harvesting is unregulated

if (max.h.t <= q.prime.t){
  h.t <- max.h.t
}

else{

  # Slight correction to Kk in the case that stochasticity overshoots
the
  # carrying capacity

  CC <- ifelse(Nt>Kk,Nt+1,Kk)

  # Derive probability of illegal harvest

  psi.t <- IllegalHarvestF(compliance_level = user.compliance,
                           user_target = U.TGT,
                           population_size = Nt,
                           carrying_capacity = CC)

  # Derive illegal harvest based on max harvest and probability

  Y.t <- sum(rbinom(n=max.h.t,size=1,prob=psi.t))

  if (Y.t==q.prime.t){
    h.t <- q.prime.t
  }

  else{
    h.t <- max(c(q.prime.t,Y.t))
  }

}

# Create results data.frame

results   <- matrix(dat = NA, nrow = nsteps, ncol = 9)
```

```
results[1,1] <- sim1$resource_vector;                 # Number of
resources
results[1,2] <- sim1$observation_vector;     # Observed number of
resources
results[1,3] <- q.t                      # Harvesting quota before
lobbying
results[1,4] <- q.prime.t                 # Harvesting quota after
lobbying
results[1,5] <- h.t                         # Harvest after illegal
offtake
results[1,6] <- manager.bias                           # Manager bias
level
results[1,7] <- user.compliance                     # User compliance
level
results[1,8] <- 1                                               #
Time step
results[1,9] <- UB[1]                                         # User
budget

# Apply harvest

sim1$X <- sim1$resource_vector-h.t

#####################################
### Run through rest of time steps ##
#####################################

for (time_step in 2:nsteps){

  # Run gmse_apply

  sim_new <- tryCatch(gmse_apply(old_list = sim1,
                                 res_mod = pop_model,
                                 obs_mod = obs_model,
                                 get_res = "Full",
                                 user_budget = UB[time_step]),
                      error=function(err) NA)

  if (is.na(sim_new)==T){     # If the resource goes extinct

    # Add results to data.frame

    results[time_step:nsteps,1] <- 0
    results[time_step:nsteps,2] <- 0
    results[time_step:nsteps,3] <- NA
    results[time_step:nsteps,4] <- NA
    results[time_step:nsteps,5] <- NA
    results[time_step:nsteps,6] <- decision.bias
    results[time_step:nsteps,7] <- user.compliance
    results[time_step:nsteps,8] <- time_step:nsteps
    results[time_step:nsteps,9] <- NA

    print("Extinction")

    break

  }
```

```
  if (class(sim_new)=="list"){     # If the resource does not go
extinct

    # Extract resource abundance

    Nt <- sim_new$resource_vector

    # Extract cost

    c.t <- sim_new$manager_vector

    # Derive quota

    q.t <- floor(UB[time_step]/c.t)

    # Minimum possible quota

    min.q <- 0

    # Derive probability of harvest ban

    phi.t <- ClobbyingF(bias_level = decision.bias,
                        conservation_target = C.TGT,
                        population_size = Nt)

    # Is harvest banned?

    P.t <- rbinom(n=1,size=1,prob=phi.t)

    # If P(t)=0

    if (P.t == 0){
      q.prime.t <- q.t
    }

    # Otherwise...

    if (P.t==1){

      # The new quota is then derived as

      q.prime.t <- min.q

    }

    # Derive maximum possible harvest at minimum cost

    max.h.t <- floor(UB[time_step]/minc)

    # If the maximum possible harvest is smaller or equal to lobbied
quota
    # No need to poach as harvesting is unregulated

    if (max.h.t <= q.prime.t){
      h.t <- max.h.t
    }
```

```
    else{

      # Slight correction to Kk in the case that stochasticity
overshoots
      # the carrying capacity

      CC <- ifelse(Nt>Kk,Nt+1,Kk)

      # Derive probability of illegal harvest

      psi.t <- IllegalHarvestF(compliance_level = user.compliance,
                               user_target = U.TGT,
                               population_size = Nt,
                               carrying_capacity = CC)

      # Derive illegal harvest based on max harvest and probability

      Y.t <- sum(rbinom(n=max.h.t,size=1,prob=psi.t))

      if (Y.t==q.prime.t){
        h.t <- q.prime.t
      }

      else{
        h.t <- max(c(q.prime.t,Y.t))
      }

    }

    # Add results to data frame
    results[time_step,1] <- sim_new$resource_vector;
    results[time_step,2] <- sim_new$observation_vector;
    results[time_step,3] <- q.t
    results[time_step,4] <- q.prime.t
    results[time_step,5] <- h.t
    results[time_step,6] <- decision.bias
    results[time_step,7] <- user.compliance
    results[time_step,8] <- time_step
    results[time_step,9] <- UB[time_step]

    # Apply harvest

    sim_new$X <- sim_new$resource_vector-h.t;

    sim1 <- sim_new

  }

}
```

Literature cited

Duthie A. B., J. J. Cusack, I. J. Jones, J. Minderman, E. B. Nilsen, R. A. Pozo, R. A., S. Rakotonarivo, B. Van Moorter, and N. Bunnefeld. 2018. GMSE: an R package for generalised management strategy evaluation. *Methods in Ecology and Evolution* 9: 2396-2401.

Appendix 3

Definition and value of set and derived parameters.

Table A3.1. Definition and value of set and derived parameters.

Parameter	Definition	Value(s) used
Set parameters		
T	Number of management years	10
N_i	Initial resource population size	1000
K	Resource population carrying capacity	2000
r	Resource population intrinsic growth rate	0.1, 0.2, 0.3
σ	Growth rate standard deviation	$r/10$
N_M	Manager target abundance	1000
N_U	User target abundance	0
N_C	Conservation target abundance	2000
B_M	Manager budget - an abstract quantity that controls the ability of the manager to set higher quotas	10000
B_U	User budget - an abstract quantity that controls the ability of the user to harvest resources	Varied between 5000 and 10000 (see Appendix 1)
I_C	Level of decision-making bias in favor of conservation objectives	Varied between 0 (no bias) and 1 (complete bias)
I_U	Level of decision-making bias in favor of user objectives	Varied between 0 (no bias) and 1 (complete bias)
c_{min}	Arbitrary quantity representing the minimum cost of harvesting a resource	10
E	Level of user compliance with harvest quota set by the manager	Varied between 0 (no compliance) and 1 (full compliance)
Derived parameters		
N	Resource population size.	See Equation 1 in main text

Q	Harvest quota set by the manager prior to lobbying	Derived from the genetic algorithm
Q'	Harvest quota set by the manager post lobbying	0, Q or H_{max} (see main text)
H_{max}	Maximum number of resources that can be harvested by the user	See Equation 4 in main text
$\Phi_{Conservation}$	Probability of successful lobbying for a harvesting ban by conservation groups	See Equation 2 in main text
Φ_{User}	Probability of successful lobbying for unregulated harvest	See Equation 3 in main text
Ψ	Probability that the user will successfully harvest one individual resource unit from the population	See Equation 5 in main text
Y	Hypothetical illegal harvest that the user compares to Q' in order to decide on final harvest	$B(H_{max}, \Psi)$
H	Final user harvest	$\max(Y, Q')$

Appendix 4

Classification protocol used to assign decision-making bias and user compliance levels to harvested IUCN Red List species.

We compared predictions from our model against data on 206 terrestrial harvested species from the International Union for the Conservation of Nature's (IUCN) Red List of Threatened Species. We considered species belonging to the orders Anseriformes (geese and ducks, N=37), Cetartiodactyla (even-toed ungulates, N=90) and Carnivora (carnivores, N=79) as these are commonly targeted by subsistence, recreational and trophy hunting activities globally (Di Minin et al. 2019, Hill et al. 2019).

Using the "advanced search" option on the IUCN Red List website (https://www.iucnredlist.org/, accessed 14th January 2019), we filtered species by criteria relating to Taxonomy ("Anseriformes", "Cetartiodactyla" and "Carnivora"), Red List Category ("NT or LR/nt" and "LC or LR/lc"), and Threats ("Intentional use (species is the target)"). We only considered species listed as Least Concern or Near Threatened so as to minimize confounding factors associated with threat status. Filtering resulted in a total of 206 species to which the classification of decision-making bias and user compliance shown in Fig. A3.1 was applied (see below). More specifically, we classified each species according to 1) its stated population trend at the latest assessment (decreasing, stable or increasing), 2) the type of harvesting it was most commonly under (unregulated, regulated or banned), and 3) the level of illegal harvest most commonly reported for a population (low, medium or high). We then used population trend as a measure of management outcome, harvesting type as a measure of decision-making bias (with unregulated and banned taken to reflect pro-user and pro-conservation biases), and illegal harvest level as a measure of user compliance. Classifications were carried out by two of the authors and subsequently compared to ensure consistency.

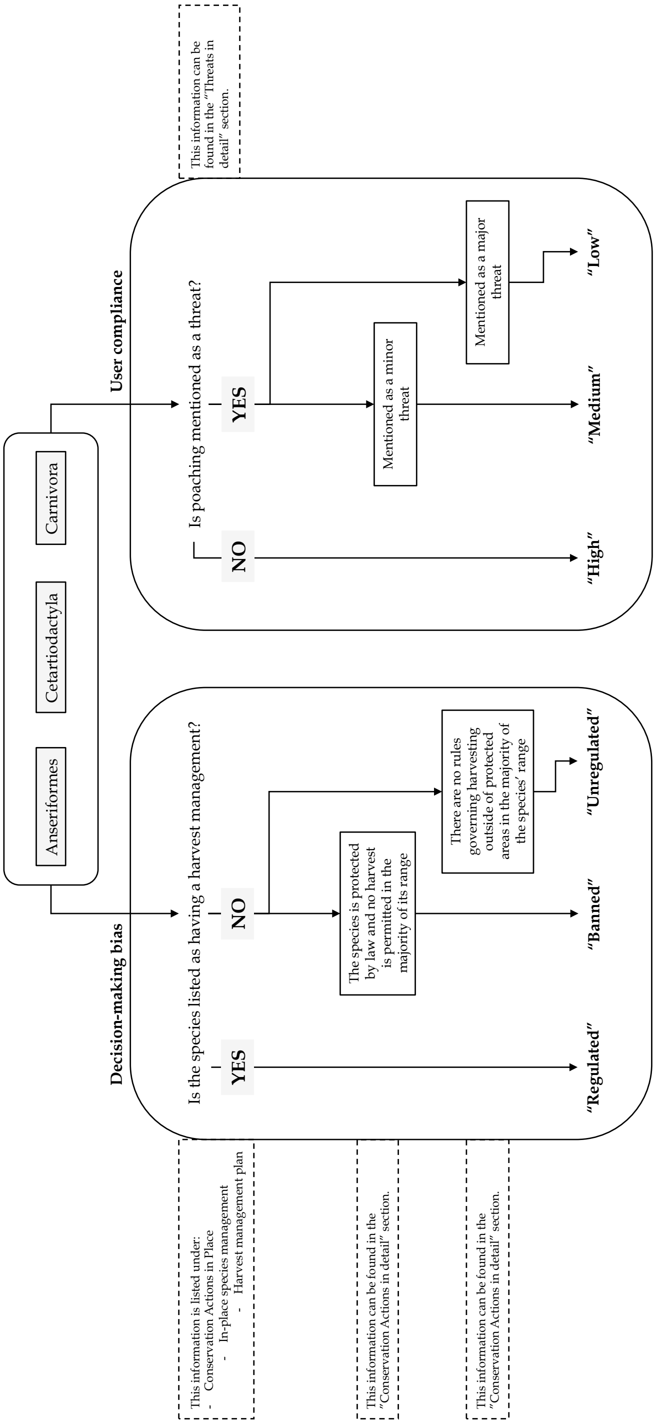

Fig. A4.1. Classification protocol used to assign decision-making bias and user compliance levels to harvested IUCN Red List species.

Appendix 5

Mean population growth and extinction probability surfaces for simulated resource population growth rates of 0.1 and 0.3.

Predicted patterns of management outcome for different combinations of management bias and user compliance are similar to those shown for a population growth rate of 0.2 in Fig. 3 in the main text. This indicates that predicted patterns are not sensitive to choice of resource population growth rate.

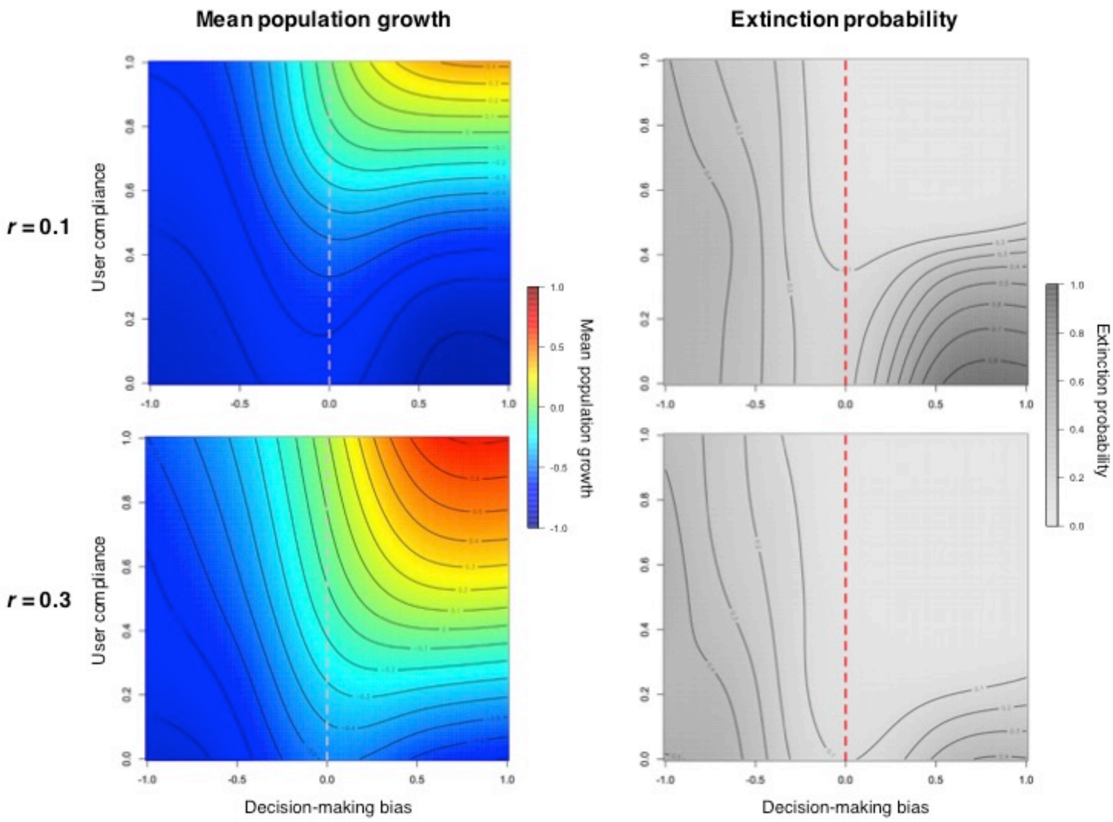

Fig. A5.1. Mean population growth and extinction probability over a 10-year management period as a function of decision-making bias and user compliance for simulated intrinsic population growth rates (*r*) of 0.1 and 0.3. Decision-making bias ranges from entirely pro-user (-1, harvest is always unregulated) to pro-conservation

(+1, harvest is always banned), with 0 representing a scenario in which manager quota decisions cannot be lobbied. When user compliance is 0, users will always partake in illegal harvesting while a value of 1 ensures users will fully comply with the quota put forward by the manager (post-lobbying). The 2D contour surfaces were obtained from generalized additive models with decision-making bias and user compliance specified as tensor product smooths. Dashed vertical lines (light grey and red) denote unbiased management decisions.

Appendix 6

Harvested IUCN Red List species.

Table A6.1. List of IUCN Red List species and associated population trend, decision-making bias and user compliance levels.

Order	Species	Scientific Name	Red List Category	Population Trend	Management Bias	User Compliance
Cetartiodactyla	Natal red duiker	*Cephalophus natalensis*	LC	Decreasing	Unregulated	High
Cetartiodactyla	Maxwell's duiker	*Philantomba maxwellii*	LC	Decreasing	Unregulated	Low
Cetartiodactyla	Common wildebeest	*Connochaetes taurinus*	LC	Stable	Unregulated	Medium
Cetartiodactyla	Waterbuck	*Kobus ellipsiprymnus*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Red flanked duiker	*Cephalophus rufilatus*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Bohor reedbuck	*Redunca redunca*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Wild boar	*Sus scrofa*	LC	Stable	Unregulated	High
Cetartiodactyla	Alpine ibex	*Capra ibex*	LC	Increasing	Regulated	High
Cetartiodactyla	Pyrenean chamois	*Rupicapra pyrenaica*	LC	Increasing	Regulated	High
Cetartiodactyla	Moose	*Alces alces*	LC	Increasing	Regulated	High
Cetartiodactyla	Tufted deer	*Elaphodus cephalophus*	NT	Decreasing	Unregulated	Medium
Cetartiodactyla	Nilgai	*Boselaphus tragocamelus*	LC	Stable	Regulated	High
Cetartiodactyla	Bongo	*Tragelaphus eurycerus*	NT	Decreasing	Regulated	Medium
Cetartiodactyla	Sitatunga	*Tragelaphus spekii*	LC	Decreasing	Regulated	High
Cetartiodactyla	Muskox	*Ovibos moschatus*	LC	Stable	Regulated	High
Cetartiodactyla	Markhor	*Capra falconeri*	NT	Decreasing	Regulated	Low
Cetartiodactyla	Himalayan goral	*Naemorhedus goral*	NT	Decreasing	Regulated	High
Cetartiodactyla	Himalayan tahr	*Hemitragus jemlahicus*	NT	Decreasing	Unregulated	Low
Cetartiodactyla	Sulawesi warty pig	*Sus celebensis*	NT	Decreasing	Unregulated	High
Cetartiodactyla	Gray brocket	*Mazama gouazoubira*	LC	Decreasing	Banned	Medium
Cetartiodactyla	Southern pudu	*Pudu puda*	NT	Decreasing	Banned	Medium
Cetartiodactyla	Blue duiker	*Philantomba monticola*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Black duiker	*Cephalophus niger*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Klipspringer	*Oreotragus oreotragus*	LC	Stable	Unregulated	High
Cetartiodactyla	Common warthog	*Phacochoerus africanus*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	European roe deer	*Capreolus capreolus*	LC	Increasing	Regulated	High
Cetartiodactyla	Japanese serow	*Capricornis crispus*	LC	Increasing	Regulated	High
Cetartiodactyla	Guanaco	*Lama guanicoe*	LC	Increasing	Regulated	High
Cetartiodactyla	Oribi	*Ourebia ourebi*	LC	Decreasing	Unregulated	High

Cetartiodactyla	Topi	*Damaliscus lunatus*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Southern lechwe	*Kobus leche*	NT	Decreasing	Unregulated	Low
Cetartiodactyla	Roan antelope	*Hippotragus equinus*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Rothschild's giraffe	*Giraffa camelopardalis*	NT	Increasing	Banned	High
Cetartiodactyla	Hartebeest	*Alcelaphus buselaphus*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Salt's dikdik	*Madoqua saltiana*	LC	Stable	Unregulated	High
Cetartiodactyla	Kirk's dikdik	*Madoqua kirkii*	LC	Stable	Unregulated	High
Cetartiodactyla	Northern red muntjac	*Muntiacus vaginalis*	LC	Decreasing	Regulated	Low
Cetartiodactyla	Sika deer	*Cervus nippon*	LC	Increasing	Regulated	High
Cetartiodactyla	Lesser kudu	*Tragelpahus imberbis*	NT	Decreasing	Regulated	Medium
Cetartiodactyla	African buffalo	*Syncerus caffer*	LC	Decreasing	Regulated	Medium
Cetartiodactyla	Bushbuck	*Tragelaphus scriptus*	LC	Stable	Unregulated	High
Cetartiodactyla	Pronghorn	*Antilocapra americana*	LC	Stable	Regulated	High
Cetartiodactyla	Peter's duiker	*Cephalophus callipygus*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Bay duiker	*Cephalophus dorsalis*	NT	Decreasing	Unregulated	Low
Cetartiodactyla	Eastern tur	*Capra cylindricornis*	NT	Decreasing	Regulated	Low
Cetartiodactyla	Reeves' muntjac	*Muntiacus reevesi*	LC	Decreasing	Unregulated	Low
Cetartiodactyla	Vicuna	*Vicugna vicugna*	LC	Increasing	Regulated	High
Cetartiodactyla	Siberian roe deer	*Capreolus pygargus*	LC	Decreasing	Regulated	Low
Cetartiodactyla	White tailed deer	*Odocoileus virginianus*	LC	Stable	Regulated	High
Cetartiodactyla	Red serow	*Capricornis rubidus*	NT	Decreasing	Banned	Low
Cetartiodactyla	Suni	*Nesotragus moschatus*	LC	Stable	Unregulated	High
Cetartiodactyla	Common duiker	*Sylvicapra grimmia*	LC	Decreasing	Unregulated	High
Cetartiodactyla	Thomson's gazelle	*Eudorcas thomsonii*	LC	Decreasing	Regulated	Medium
Cetartiodactyla	American bison	*Bison bison*	NT	Stable	Regulated	High
Cetartiodactyla	White bellied duiker	*Cephalophus leucogaster*	NT	Decreasing	Unregulated	High
Cetartiodactyla	Grant's gazelle	*Nanger granti*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Comon eland	*Tragelaphus oryx*	LC	Stable	Regulated	Medium
Cetartiodactyla	Tarim red deer	*Cervus hanglu*	LC	Increasing	Regulated	Medium
Cetartiodactyla	Argali	*Ovis ammon*	NT	Decreasing	Regulated	Low
Cetartiodactyla	Collared peccary	*Pecari tajacu*	LC	Stable	Regulated	Medium
Cetartiodactyla	Red river hog	*Potamochoerus porcus*	LC	Decreasing	Unregulated	High
Cetartiodactyla	Red deer	*Cervus elaphus*	LC	Increasing	Regulated	High
Cetartiodactyla	Mongolian gazelle	*Procapra gutturosa*	LC	Stable	Regulated	Medium
Cetartiodactyla	Wapiti	*Cervus canadensis*	LC	Increasing	Regulated	Medium
Cetartiodactyla	Chiru	*Pantholops hodgsonii*	NT	Increasing	Banned	Medium
Cetartiodactyla	Nyala	*Tragelaphus angasii*	LC	Stable	Regulated	High
Cetartiodactyla	Palawan bearded pig	*Sus ahoenobarbus*	NT	Decreasing	Banned	Low
Cetartiodactyla	Harvey's duiker	*Cephalophus harveyi*	LC	Decreasing	Unregulated	Medium

Cetartiodactyla	Mongalla gazelle	*Eudorcas albonotata*	LC	Stable	Unregulated	High
Cetartiodactyla	Greater oriental chevrotain	*Tragulus napu*	LC	Decreasing	Regulated	Low
Cetartiodactyla	Pampas deer	*Ozotoceros bezoarticus*	NT	Decreasing	Banned	High
Cetartiodactyla	Himalaya serow	*Capricornis thar*	NT	Decreasing	Banned	Low
Cetartiodactyla	Black fronted duiker	*Caphalophus nigrifrons*	LC	Decreasing	Banned	High
Cetartiodactyla	Southern red muntjac	*Muntiacus muntjak*	LC	Decreasing	Regulated	Medium
Cetartiodactyla	Blesbok	*Damaliscus pygargus*	LC	Stable	Regulated	High
Cetartiodactyla	Mountain goat	*Oreamnos americanus*	LC	Stable	Regulated	High
Cetartiodactyla	Amazonian brown brocket	*Mazama nemorivaga*	LC	Decreasing	Unregulated	High
Cetartiodactyla	Bornean yellow muntjac	*Muntiacus atherodes*	NT	Decreasing	Banned	Medium
Cetartiodactyla	Forest hog	*Hylochoerus meinertzhageni*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Ogilby's duiker	*Cephalophus ogilbyi*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Steenbok	*Raphicerus campestris*	LC	Stable	Unregulated	High
Cetartiodactyla	Cape grysbok	*Raphicerus melanotis*	LC	Stable	Regulated	High
Cetartiodactyla	Chinkara	*Gazella bennettii*	LC	Decreasing	Banned	High
Cetartiodactyla	Generuk	*Litocranius walleri*	NT	Decreasing	Unregulated	Medium
Cetartiodactyla	Tibetan gazelle	*Procapra picticaudata*	NT	Decreasing	Banned	High
Cetartiodactyla	Chinese serow	*Capricornis milneedwardsii*	NT	Decreasing	Unregulated	Medium
Cetartiodactyla	Weyn's duiker	*Cephalophus weynsi*	LC	Decreasing	Unregulated	Medium
Cetartiodactyla	Southern reedbuck	*Redunca arundinum*	LC	Stable	Unregulated	High
Cetartiodactyla	Puku	*Kobus vardonii*	NT	Decreasing	Unregulated	Low
Cetartiodactyla	Sharpe's grysbok	*Raphicerus sharpei*	LC	Stable	Unregulated	High
Anseriforme	Common goldeneye	*Bucephala clangula*	LC	Stable	Unregulated	High
Anseriforme	Garganey	*Spatual querquedula*	LC	Decreasing	Unregulated	High
Anseriforme	Harlequin duck	*Histrionicus histrionicus*	LC	Increasing	Banned	High
Anseriforme	Brown teal	*Anas chlorotis*	NT	Increasing	Banned	High
Anseriforme	Surf scoter	*Melanitta perspicillata*	LC	Decreasing	Unregulated	High
Anseriforme	Greater scaup	*Aythya marila*	LC	Decreasing	Regulated	High
Anseriforme	Ferruginous duck	*Aythya nyroca*	NT	Decreasing	Banned	Low
Anseriforme	King eider	*Somateria spectabilis*	LC	Decreasing	Unregulated	High
Anseriforme	Bean goose	*Anser fabalis*	LC	Decreasing	Regulated	Medium
Anseriforme	Northen pintail	*Anas acuta*	LC	Decreasing	Regulated	High
Anseriforme	African pygmy goose	*Nettapus auritus*	LC	Decreasing	Unregulated	High
Anseriforme	Northern shoveler	*Spatula clypeata*	LC	Decreasing	Regulated	High
Anseriforme	Greylag goose	*Anser anser*	LC	Increasing	Regulated	High
Anseriforme	Common shelduck	*Tadorna tadorna*	LC	Increasing	Banned	High
Anseriforme	Pink footed goose	*Anser brachyrhynchus*	LC	Increasing	Regulated	High
Anseriforme	Brent goose	*Branta bernicla*	LC	Increasing	Regulated	High
Anseriforme	Baikal teal	*Sibirionetta formosa*	LC	Increasing	Banned	High

Anseriforme	Barrow's goldeneye	*Bucephala islandica*	LC	Increasing	Regulated	High
Anseriforme	Red breasted merganser	*Mergus serrator*	LC	Stable	Unregulated	High
Anseriforme	Blue billed duck	*Oxyura australis*	NT	Stable	Unregulated	High
Anseriforme	Southern pochard	*Netta erythrophthalma*	LC	Decreasing	Unregulated	High
Anseriforme	American comb duck	*Sarkidiornis sylvicoal*	LC	Decreasing	Unregulated	High
Anseriforme	Fulvous whistling duck	*Dendrocygna bicolor*	LC	Decreasing	Unregulated	High
Anseriforme	African black duck	*Anas sparsa*	LC	Decreasing	Unregulated	High
Anseriforme	Orinoco goose	*Neochen jubata*	NT	Decreasing	Unregulated	High
Anseriforme	Flying steamerduck	*Tachyeres patachonicus*	LC	Decreasing	Unregulated	High
Anseriforme	Sunda teal	*Anas gibberifrons*	NT	Stable	Regulated	High
Anseriforme	Falcated duck	*Mareca falcata*	NT	Decreasing	Unregulated	High
Anseriforme	Siberian scoter	*Melanitta stejnegeri*	LC	Decreasing	Unregulated	High
Anseriforme	African comb duck	*Sarkidiornis melanotos*	LC	Decreasing	Unregulated	High
Anseriforme	Spectacled eider	*Somateria fischeri*	NT	Decreasing	Unregulated	High
Anseriforme	Barnacle goose	*Brenta leucopsis*	LC	Increasing	Regulated	High
Anseriforme	Northen screamer	*Chauna chavaria*	NT	Decreasing	Banned	Medium
Anseriforme	Hartlaub's duck	*Pteronetta hartlaubii*	LC	Decreasing	Unregulated	High
Anseriforme	Emperor goose	*Anser canagicus*	NT	Decreasing	Unregulated	High
Anseriforme	Black scoter	*Melanitta americana*	NT	Decreasing	Unregulated	High
Anseriforme	White winged scoter	*Melanitta deglandi*	LC	Decreasing	Unregulated	High
Carnivora	African clawless otter	*Aonyx capensis*	NT	Decreasing	Unregulated	High
Carnivora	Pine marten	*Martes martes*	LC	Stable	Regulated	Medium
Carnivora	Beech marten	*Martes foina*	LC	Stable	Unregulated	High
Carnivora	Northern racoon	*Procyon lotor*	LC	Increasing	Unregulated	High
Carnivora	Common palm civet	*Paradoxurus hermaphroditus*	LC	Decreasing	Regulated	Medium
Carnivora	Wolverine	*Gulo gulo*	LC	Decreasing	Regulated	Medium
Carnivora	Bengal fox	*Vulpes bengalensis*	LC	Decreasing	Banned	High
Carnivora	Margay	*Leopardus wiedii*	NT	Decreasing	Banned	Medium
Carnivora	Eurasian otter	*Lutra lutra*	NT	Decreasing	Banned	Medium
Carnivora	White nosed coati	*Nasua narica*	LC	Decreasing	Regulated	Medium
Carnivora	Striped hyaena	*Hyaena hyaena*	NT	Decreasing	Regulated	Low
Carnivora	American black bear	*Ursus americanus*	LC	Increasing	Regulated	High
Carnivora	Banded mongoose	*Mungos mungo*	LC	Stable	Unregulated	High
Carnivora	Eurasian lynx	*Lynx lynx*	LC	Stable	Regulated	High
Carnivora	Wild cat	*Felis silvestris*	LC	Decreasing	Regulated	High
Carnivora	Asiatic golden cat	*Catopuma temminckii*	NT	Decreasing	Banned	Medium
Carnivora	Brown bear	*Ursus arctos*	LC	Stable	Regulated	High
Carnivora	Spotted necked otter	*Hydrictis maculicollis*	NT	Decreasing	Unregulated	High
Carnivora	Malay civet	*Viverra tangalunga*	LC	Stable	Unregulated	High
Carnivora	Leopard cat	*Prionailurus bengalensis*	LC	Stable	Regulated	High

Carnivora	Geoffroy's cat	*Leopardus geoffroyi*	LC	Stable	Banned	High
Carnivora	Pallas's cat	*Otocolobus manul*	NT	Decreasing	Regulated	High
Carnivora	Bat eared fox	*Otocyon megalotis*	LC	Stable	Unregulated	High
Carnivora	Kinkajou	*Poto flavus*	LC	Decreasing	Unregulated	High
Carnivora	Western polecat	*Mustela putorius*	LC	Decreasing	Regulated	Low
Carnivora	South american coati	*Nasua nasua*	LC	Decreasing	Unregulated	High
Carnivora	Eurasian badger	*Meles meles*	LC	Stable	Regulated	High
Carnivora	Molina's hog nosed skunk	*Conepatus chinga*	LC	Decreasing	Unregulated	High
Carnivora	Bobcat	*Lynx rufus*	LC	Stable	Regulated	High
Carnivora	Ocelot	*Leopardus pardalis*	LC	Decreasing	Regulated	Medium
Carnivora	Pampas cat	*Leopardus colocolo*	NT	Decreasing	Banned	Medium
Carnivora	Kit fox	*Vulpes macrotis*	LC	Decreasing	Regulated	High
Carnivora	Marbled cat	*Pardofelis marmorata*	NT	Decreasing	Banned	Medium
Carnivora	Serval	*Leptailurus serval*	LC	Stable	Regulated	High
Carnivora	Pampas fox	*Lycalopex gymnocercus*	LC	Stable	Regulated	High
Carnivora	Culpeo	*Lycalopex culpaeus*	LC	Stable	Regulated	Medium
Carnivora	American marten	*Martes americana*	LC	Decreasing	Regulated	High
Carnivora	Brown palm civet	*Paradoxurus jerdoni*	LC	Stable	Unregulated	High
Carnivora	Short tailed mongoose	*Herpestes brachyurus*	NT	Decreasing	Unregulated	High
Carnivora	Spotted linsang	*Prionodon pardicolor*	LC	Decreasing	Banned	Medium
Carnivora	Aardwolf	*Proteles cristata*	LC	Stable	Unregulated	High
Carnivora	Masked palm civet	*Paguma larvata*	LC	Decreasing	Unregulated	Medium
Carnivora	Arctic fox	*Vulpes lagopus*	LC	Stable	Regulated	High
Carnivora	Honey badger	*Mellivora capensis*	LC	Decreasing	Banned	Medium
Carnivora	Banded linsang	*Prionodon linsang*	LC	Decreasing	Banned	High
Carnivora	Large indian civet	*Viverra zibetha*	LC	Decreasing	Banned	Low
Carnivora	Long nosed mongoose	*Herpestes naso*	LC	Decreasing	Unregulated	High
Carnivora	Stripe necked mongoose	*Herpestes vitticollis*	LC	Stable	Banned	High
Carnivora	Crab eating mongoose	*Procyon cancrivorus*	LC	Decreasing	Unregulated	High
Carnivora	Steppe polecat	*Mustela eversmanii*	LC	Decreasing	Banned	Medium
Carnivora	Marsh mongoose	*Atilax paludinosus*	LC	Decreasing	Unregulated	High
Carnivora	Brown mongoose	*Herpestes fuscus*	LC	Stable	Unregulated	High
Carnivora	Humboldt's hog nosed skunk	*Conepatus humboldtii*	LC	Stable	Banned	High
Carnivora	Ansorge's cusimanse	*Crossarchus ansorgei*	LC	Decreasing	Unregulated	Medium
Carnivora	Small toothed ferret badger	*Melogale moschata*	LC	Stable	Unregulated	High
Carnivora	Sable	*Martes zibellina*	LC	Increasing	Regulated	High
Carnivora	Common genet	*Genetta genetta*	LC	Stable	Banned	Medium
Carnivora	Fennec fox	*Vulpes zerda*	LC	Stable	Banned	High
Carnivora	Small toothed palm civet	*Arctogalidia trivirgata*	LC	Decreasing	Banned	High
Carnivora	American badger	*Taxidea taxus*	LC	Decreasing	Unregulated	Medium

Carnivora	Gambian mongoose	*Mungos gambianus*	LC	Stable	Unregulated	High
Carnivora	Common slender mongoose	*Herpestes sanguineus*	LC	Stable	Unregulated	High
Carnivora	Striped skunk	*Mephitis mephitis*	LC	Stable	Regulated	High
Carnivora	Hooded skunk	*Mephitis macroura*	LC	Increasing	Unregulated	High
Carnivora	Puma	*Puma concolor*	LC	Decreasing	Regulated	Medium
Carnivora	Northern hog badger	*Arctonyx albogularis*	LC	Decreasing	Unregulated	High
Carnivora	Sumatran hog badger	*Arctonyx hoevenii*	LC	Stable	Unregulated	High
Carnivora	Chilla	*Lycalopex griseus*	LC	Stable	Regulated	Medium
Carnivora	North american river otter	*Lontra canadensis*	LC	Stable	Regulated	High
Carnivora	Small indian civet	*Viverricula indica*	LC	Stable	Regulated	Medium
Carnivora	American mink	*Neovison vison*	LC	Stable	Regulated	High
Carnivora	Western spotted skunk	*Spilogale gracilis*	LC	Decreasing	Unregulated	High
Carnivora	Greater grison	*Galictis vittata*	LC	Stable	Banned	Medium
Carnivora	Black legged mongoose	*Bdeogale nigripes*	LC	Decreasing	Unregulated	High
Carnivora	Ring tailed vontsira	*Galidia elegans*	LC	Decreasing	Unregulated	Medium
Carnivora	Alexander's cusimanse	*Crossarchus alexandri*	LC	Decreasing	Unregulated	High
Carnivora	Jungle cat	*Felis chaus*	LC	Decreasing	Banned	Medium
Carnivora	Swift fox	*Vulpes velox*	LC	Stable	Banned	High
Carnivora	Canada lynx	*Lynx canadensis*	LC	Stable	Regulated	High

Appendix 7

Comparison of mean population growth predictions from generalized additive models based on theoretical simulations and empirical data.

Our classification of IUCN Red List species enabled us to derive the proportion of all species showing a decreasing, stable and increasing population trend for each of the different combinations of decision-making bias and user compliance. We then assigned numerical values to each of the three population trends (-1 for decreasing, 0 for stable and 1 for increasing) and modeled this variable as a function of the interaction between decision-making bias and user compliance using a generalized additive model with Gaussian error structure and tensor product smooth. This resulted in an interpolated surface showing mean population trajectory (from -1 to 1) as a function of decision-making bias and user compliance classifications. This surface was then compared to the theoretical surfaces obtained using growth rates of 0.1, 0.2 and 0.3 (see main text and Figure A4.1).

Figure A6.1 shows the relationship between predictions based on theoretical and empirical data for the different tested growth rates and how it compares to the x=y line (i.e. perfect match). The overall deviation from the x=y line is low for theoretical growth rates of 0.1 and 0.2 as these values are more representative of the growth rates found in the IUCN species considered (Anseriformes, Carnivore and Certatiodactlya).

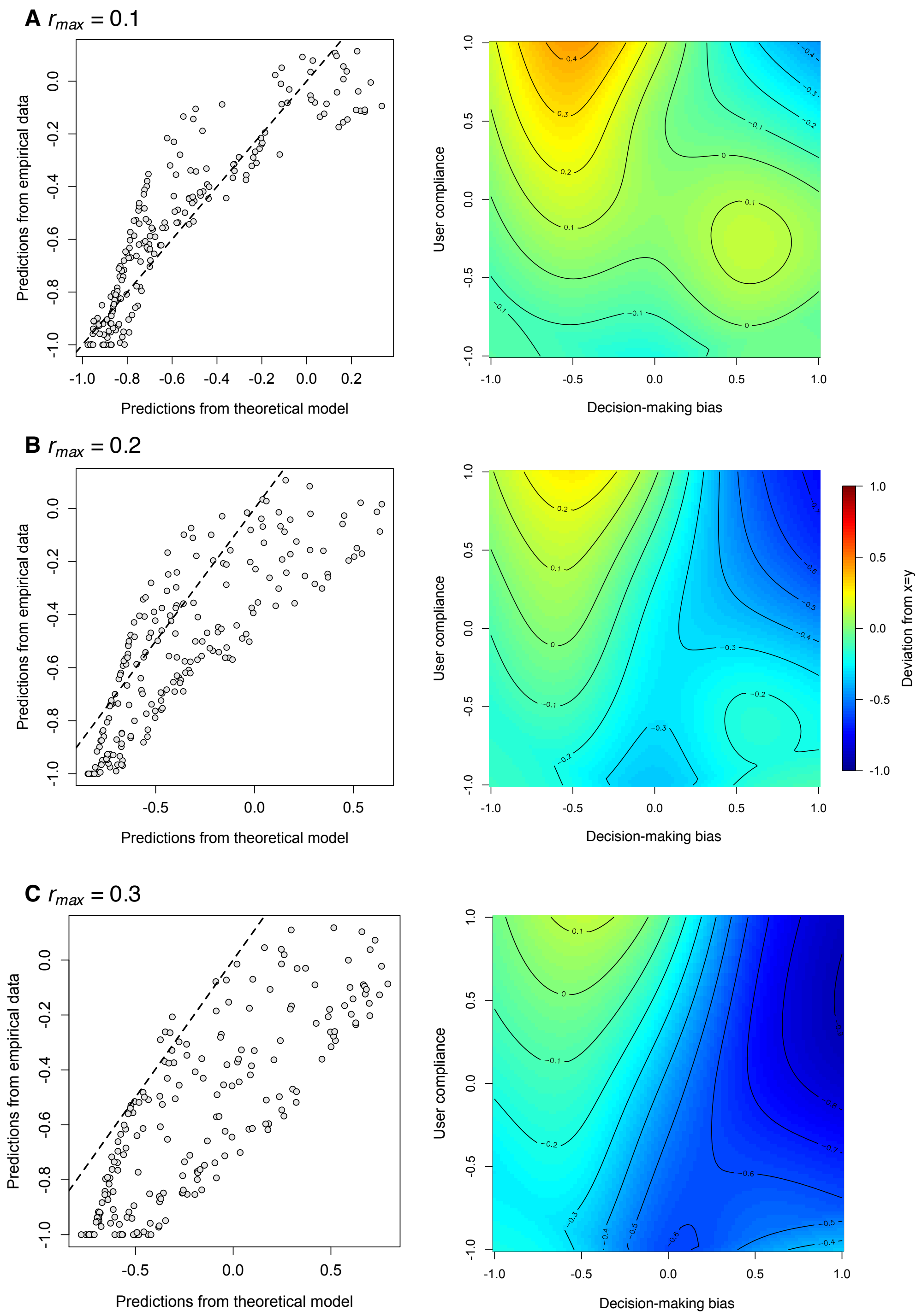

Fig. A7.1. Comparisons are shown for simulated intrinsic population growth rates of 0.1, 0.2 and 0.3. In each case, full grey circles denote a set of 200 random prediction coordinates, and the dashed line represents the x=y line. 2D contour plots show the deviation from the x=y line for varying levels of decision-making bias (-1 = pro-user interests, 0 = unbiased and +1 = pro-conservation interests) and user compliance (-1 = low compliance, 0 = medium compliance and +1 = high compliance).