

Research

Intervene or wait? A model evaluating the timing of intervention in conservation conflicts adaptive management under uncertainty

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ABSTRACT. The timing of biodiversity managers' interventions can be critical to the success of conservation, especially in situations of conflict between conservation objectives and human livelihood, i.e., conservation conflicts. Given the uncertainty associated with complex social-ecological systems and the potentially irreversible consequences of delayed action for biodiversity and livelihoods, managers tend to simply intervene as soon as possible by precaution. However, refraining from intervening when the situation allows can be beneficial, notably by saving critical management resources. We introduce a strategy for managers to decide, based on monitoring, whether intervention is required or if waiting is possible. This study evaluates the performance of this waiting strategy compared to a strategy of unconditional intervention at every opportunity. We built an individual-based model of conservation conflict between a manager aiming to conserve an animal population and farmers aiming to maximize yield by protecting their crop from wildlife damage. We then simulated a budget-constrained adaptive management over time applying each strategy, while accounting for uncertainty around population dynamics and around decision making of managers and farmers. Our results showed that when the decision for the manager to intervene was based on a prediction of population trajectory, the waiting strategy performed at least as well as unconditional intervention while also allowing managers to save resources by avoiding unnecessary interventions. Under difficult budgetary constraints on managers, this waiting strategy ensured as high yields as unconditional intervention while significantly improving conservation outcomes by compensating managers' lack of resources with the benefits accrued over waiting periods. This suggests that waiting strategies are worth considering in conservation conflicts because they can facilitate equitable management with a more efficient use of management resources, which are often limiting in biodiversity conservation.

RÉSUMÉ. Le timing d'intervention des gestionnaires de biodiversité peut être déterminant dans le succès d'un programme de conservation, tout particulièrement quand leurs objectifs sont incompatibles avec des activités humaines (conflits de conservation). Mais l'incertitude associée aux systèmes socio-écologiques, ainsi que l'irréversibilité potentielle des conséquences d'un retard d'action peut pousser les gestionnaires à simplement intervenir dès que possible. Pourtant, y renoncer quand la situation le permet peut être bénéfique, notamment en mettant efficacement à profit les ressources non-utilisées. Nous proposons ici une stratégie basée sur le monitoring pour choisir si une intervention est nécessaire ou si attendre est préférable. Cette étude évalue la capacité de cette stratégie à satisfaire à la fois les objectifs de conservation et ceux des activités humaines en comparaison avec une stratégie d'intervention systématique et inconditionnelle. Pour ce faire, nous avons développé un modèle individu-centré de conflit de conservation entre des gestionnaires cherchant à conserver une population animale et des agriculteurs cherchant à en minimiser l'impact sur leurs cultures. Nous avons ensuite simulé une gestion adaptative du conflit sous contrainte budgétaire pour chaque stratégie, tout en prenant en compte l'incertitude associée à la dynamique de la population et à la prise de décision des parties prenantes. Quand la décision était basée sur une prédiction de la trajectoire de la taille de la population, notre stratégie était au moins aussi performante qu'une intervention inconditionnelle et permettait aux gestionnaires d'économiser des ressources en évitant des interventions non nécessaires. Lorsqu'un budget trop faible rendait la gestion difficile, notre stratégie a considérablement amélioré les résultats relatifs à la conservation en compensant le manque de ressources par les bénéfices accumulés au cours des périodes sans intervention. Ces résultats montrent que notre stratégie devrait être envisagée car elle peut assurer une gestion équitable du conflit tout en permettant une utilisation plus efficace des ressources de gestion, souvent limitantes en conservation de la biodiversité.

Key Words: *adaptive management; conservation conflicts; decision-making modeling; individual-based modeling; management strategy evaluation; timing of intervention; uncertainty*

INTRODUCTION

With a growing human population and rising standards of living, the amount of Earth's surface used for human activities is increasingly large and often overlaps with the ranges of species of conservation concern. A conservation conflict can arise when such a species is strictly protected but also has an impact on human livelihood, potentially leading to a clash of interests over management decisions (Redpath et al. 2013, 2015). Diverging objectives can lead land users to defect from policies by ignoring or subverting them and engage in illegal activities often hindering conservation objectives (Bunnefeld et al. 2013, Bainbridge 2017,

Glynatsi et al. 2018, Rakotonarivo et al. 2020). These conflicts are especially serious when conservation and protection interferes with essential livelihood activities such as agriculture (Behr et al. 2017, Mason et al. 2017). Conservation policies must therefore be in line with land users' interests to ensure compliance and maximize conservation success while minimizing the impact on food security and/or farmers' income. Moreover, because conservation conflicts form complex systems with multiple biological, environmental, geographical, and social components, the response to change in these interlinked social-ecological systems (SES) is difficult to anticipate (van Wilgen and Biggs

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2011, Game et al. 2013, Mason et al. 2018). To avoid unforeseen perturbations that might jeopardize biodiversity conservation or human livelihood, management should also embrace the uncertainty around ecological processes and human behavior (Fryxell et al. 2010, Bunnefeld et al. 2011, Schlüter et al. 2012, Cusack et al. 2020).

A practical way to deal with uncertainty challenges and complex systems is adaptive management, a technique seeking to improve management iteratively by learning from its outcomes (Williams et al. 1996, Hicks et al. 2009, Keith et al. 2011). It is particularly well adapted to conservation conflicts management because regular monitoring and policy updates enhance the ability to trade-off between opposing interests (Redpath et al. 2013, Wam et al. 2016, Mason et al. 2018, Richardson et al. 2020). Adaptive management thus tailors the conservation policy as closely as possible to the system's variations, however, when and why to update the policy can be key to better management of SES and conservation conflicts (Pérez et al. 2019). Because the consequences of mismanagement can be detrimental and even sometimes irreversible (e.g., crop losses and/or animal population extinction; Kaswamila et al. 2007), conventional wisdom might suggest that reacting as often as possible with updated policy will maximize conservation success. But waiting can ultimately lead to better management results when well planned, because it can bring a variety of benefits, including enhancing knowledge through monitoring or research (Walters 1986, Gregory et al. 2006, Nicol et al. 2018). For example, Sims and Finnoff (2013) modeled the progression of the slow and predictable spread of an invasive species and showed that, due to the knowledge acquired during the period of waiting, a delayed time of first intervention was more efficient in reducing both the spread and damages on the focal ecosystem than intervention immediately after detection of the invasion. In contrast, a delayed intervention when the invasion was fast and erratic caused a loss of control over the species progression, eventually leading to a state in which any intervention became pointless. In an adaptive management context, Iacona et al. (2017) modeled national parks' bird diversity protection schemes and showed that waiting and saving conservation funds to accrue interest before spending it progressively on protection achieved a higher number of protected species and a quicker recovery of the extinction debt than front-load spending. Because financial and human resources for management are often limited (Hughey et al. 2003, McDonald-Madden et al. 2008), waiting when the benefits outweigh the risks can avoid unnecessary spending, provided that constraints on conservation funding allocation allow it (Ruiz-Miranda et al. 2020, Wu et al. 2020). This trade-off between instances of intervention and waiting in an adaptive management process has not yet, to our knowledge, been explored in the context of conservation conflicts. We hypothesize that by refraining from intervening when conflicting stakeholder interests are already aligned, managers could save resources and use them to enhance impact when intervention will be most needed to deliver conservation and/or land users' objectives. We predict that it is likely to be especially relevant in situations in which a manager's lack of resources could be compensated for by benefits accumulated over a period of waiting.

To investigate the effect of the timing of intervention on management quality while accounting for the different sources of

uncertainty associated with conservation conflicts, we used generalized management strategy evaluation framework (GMSE; Duthie et al. 2018). Generalized management strategy evaluation framework builds on management strategy evaluation (MSE) framework, which explores the possible outcomes of alternative management scenarios to assess their adequacy to managers' objectives (Smith et al. 1999). Management strategy evaluation, first developed in fisheries and later used for terrestrial species, decomposes the process of natural resources adaptive management over time with sub-models of population dynamics, monitoring, management decision-making and harvesting activities, which inform and influence each other. This structure helps to isolate different components of uncertainty associated with each process when evaluating a scenario (Bunnefeld et al. 2011). Generalized management strategy evaluation framework uses an individual-based approach for all four sub-models, simulating uncertainty intrinsically (Grimm 1999, DeAngelis and Grimm 2014), and includes a decision-making sub-model simulating goal-oriented behavior for manager and farmer agents, with the possibility of sub-optimal choices (genetic algorithm; Hamblin 2012, Duthie et al. 2018). Furthermore, by generating differences between agents, individual-based models (IBMs) can model another potential source of conflict: the inequitable distribution of costs and benefits among stakeholders. Rakotonarivo et al. (2020, 2021) showed that a higher perceived equity in conservation measures among farmers increased the propensity to choose pro-conservation options. Among-user equity is thus important to model and monitor during conservation conflicts management. Knowing this, we further develop and apply GMSE to evaluate the efficiency of alternative management timing strategies against unconditional intervention and determine whether and how a profitable timing trade-off can be found for conservation conflict management under uncertainty.

We modeled a budget-constrained adaptive management of a conservation conflict in which a wildlife animal population of conservation concern has a negative impact on agricultural activities, and farmers can respond by culling to minimize yield loss. We propose two novel timing strategies for the manager to determine whether the situation warrants intervention when the resources saved by waiting generate long-term benefits. Through simulations with GMSE, we assessed how each timing strategy affected the quality of management regarding the conflict between biodiversity conservation and agricultural production objectives. We thereby determined for which conditions our alternative strategies resulted in better management than intervening at every opportunity.

METHODS

Model overview

Model case

To simulate conservation conflict management over time, we develop an individual-based model with a population of wildlife animals (referred to as "population"), farmers, and a manager, all interacting on an agricultural landscape. The landscape is divided into discrete cells, each of which produces an agricultural yield and can hold any number of animals. Each farmer owns a contiguous block of cells that forms their "land," and the sum of

its cells' productivity determines the farmer's yield. Animals consume agricultural resources from landscape cells to survive and reproduce, which consequently reduces the farmers' yield. Farmers can cull animals that are on their own land to reduce yield loss. The manager attempts to avoid extinction by maintaining the population around a predefined target size (T_N), as previously done in, e.g., the management of conflict between mountain nyala antelope conservation and trophy hunting in Ethiopia (Bunnfeld et al. 2013), or between farming and migrating bird protection in Scotland or Sweden (Bainbridge 2017, Mason et al. 2017, Nilsson et al. 2021). This target was chosen to be high enough to prevent extinction, but low enough to ensure a satisfactory yield to farmers. The manager's method is to implement a policy incentivizing or disincentivizing culling as appropriate to get the population size closer to T_N . Hence, following an adaptive management process, the manager updates this policy according to the monitoring of the population size (N_t) at each time step t .

Manager policymaking

The manager receives a fixed, non-cumulative budget (B_M) at the beginning of each time step, which we interpret to reflect the total time, energy, or money available to the manager to implement a change of policy and enforce culling restrictions. The policy is modeled as a cost that farmers must pay to cull an animal on their land. The manager can draw into B_M to raise this cost to discourage farmers from culling and favor population growth and can decrease it to facilitate culling and favor a population decrease. To model the budget needed to enforce a restricting policy, every increase of 1 in the culling cost requires an investment of 10 budget units (b.u.) from the manager. Conversely, as the manager does not need to incentivize farmers to remove animals when the policy allows high culling rates, they do not need to spend budget to decrease the cost. The amount by which the manager changes the culling cost is computed by GMSE's evolutionary algorithm according to their goal, which was modeled as minimizing the distance between N_t and T_N given farmers' cull rate in response to the previous cost.

Timing strategies

We explored three timing strategies that determine whether a manager intervenes and updates the policy or waits and leaves it as is. The control strategy (CTL) was the null model in this study. It corresponds to unconditional intervention at every opportunity and was modeled as the manager updating the policy at every time step. With the adaptive timing of intervention strategy (ATI), we define a permissive range (P_T) around T_N in the form of $T_N \pm P_T$. Within this range, the manager considers N_t close enough to T_N , and consequently, decides that the current policy results in a sustainable culling rate for the population. Hence, the manager will update the policy if and only if the population is monitored outside $T_N \pm P_T$. The trajectory strategy (TRJ) is the same as the ATI strategy, except that when N_t is inside $T_N \pm P_T$, the manager makes a prediction on next time step's population size in the form of a linear extrapolation based on the current and preceding monitoring results. If this prediction falls inside $T_N \pm P_T$, the manager leaves the policy unchanged; otherwise, they update it. In both ATI and TRJ strategies, after a time step without updating the policy, the manager receives an additional proportion (budget bonus B_b) of their initial budget to model the benefits associated with waiting. This bonus can be accumulated over several

consecutive time steps of waiting but is lost as soon as the manager draws into their budget to raise the level of restrictions again (modeling details in Appendix 1).

Farmers action planning

At the beginning of each time step, each farmer receives a fixed, non-cumulative budget (B_F), which they allocate to culling a certain number of animals on the land that they own at the cost set by the manager's policy. A minimum cost of 10 b.u. models the baseline budget needed for a farmer to cull an animal. The number of animals culled is independently computed for each farmer using GMSE's evolutionary algorithm, meaning that each farmer makes an independent decision for how to act according to their goal: maximizing their own yield.

Simulations with generalized management strategy evaluation framework (GMSE)

To simulate conservation conflict adaptive management with different timing strategies under uncertainty, we used the R package GMSE (Duthie et al. 2018). See Appendix 1 for further details on modeling, parameter choices, and simulations.

Initial parameters

We modeled the landscape as a grid of 40 equally sized rectangular pieces of land, each individually owned by a farmer. We modeled a population that is stable in absence of culling, but under the threat of extinction for a high culling rate. We defined the population dynamics model parameters such that an equilibrium size was reached quickly and steadily. The farmers were provided with an initial budget high enough to cull up to the expected number of animals on their land when the population is at equilibrium ($B_F = 1000$ b.u.), so the population went extinct if the conflict was left unmanaged. At first, the manager's initial budget was set equal to the farmers' ($B_M = B_F = 1000$ b.u.) and manager's target was set at half the equilibrium size ($T_N = 2000$ animals). The initial population size was set at $N_0 = 1000$ animals, which is sufficiently low for the population to be under immediate threat of extinction and justify the initial involvement of a manager. We chose these parameters for the control strategy to produce adequate management while also leaving room for improvement and to determine the extent to which alternative strategies can generate better results.

Population dynamics sub-model

Generalized management strategy evaluation's population dynamics model features a population of N animals, each of which has an age and a position on the landscape. In each time step, each animal moves from its current cell to a random cell within a defined range. Upon arrival, the animal consumes a proportion of 0.5 of the cell's remaining yield. All animals move 12 times during a single time step in a random order. After all movement and feeding, animals asexually produce one offspring for every five resource units consumed, which are added to the population as new individuals. Next, animals that have consumed over four and three-quarters resource units and have an age \leq five time steps survive, the others are removed from the population. This consumption criterion leads to density-dependent intra-specific competition for resources, and modeling life events discretely generates inter-individual variability as well as geographical and demographic stochasticity, therefore accounting for several sources of uncertainty around population dynamics.

Monitoring sub-model

We assumed that the manager makes no errors during monitoring, thus N_t represents the exact population size at each time step. This assumption avoided modeled stochastic monitoring errors that would have challenged a full understanding of management dynamics.

Decision-making sub-model

In each time step, manager and farmer decision making is independently modeled using evolutionary algorithms, allowing the emergence of a conflict when agents' goals are opposed. This approach computes practical but not necessarily optimal decisions, recognizing that most people cannot think of every single possibility to choose the optimal one, but can choose the best option among those they could conceive (Hamblin 2012, Duthie et al. 2018), generating uncertainty around stakeholders' individual decision making.

Experimental plan

Systematic parameter exploration

To assess management quality of ATI and TRJ in terms of population dynamics and farmers yield, we varied the permissiveness P_T and budget bonus B_b across a range of values for each strategy and compared the outcomes with those of CTL. P_T ranged from 0% of the manager's target T_N (unconditional update at every time step, i.e., CTL) to 100% of T_N (update only in the extreme situations in which the population is extinct or close to natural equilibrium in absence of culling) by 10% increments. B_b ranged from 0% of the manager's initial budget B_M (no bonus following a time step of waiting) to 100% of B_M by 10% increments. For each unique combination of P_T and B_b , we ran 100 independent simulation replicates of management over a period of 20 time steps under identical initial conditions.

Management outcomes

We defined the most desirable outcomes as when management prevents the population from going extinct (1), while keeping it as close as possible to target (2) and ensuring the highest yield to farmers (3) with the lowest inequity among them (4). For a particular combination of parameters, extinction risk (1) was assessed as the frequency of extinction events over all replicates, denoted as f_{ext} . We measured how close to target the population was (2) with the difference between the population size (N_t) and the manager's target (T_N) weighted by T_N at the end of a simulation averaged over all replicates, denoted d_T in % of T_N . Farmers' total yield (3) was calculated as the ratio of the sum of all cell's yield at the end of a simulation over the maximum yield the landscape can provide in the absence of animal consumption (40,000 yield units) averaged over all replicates and denoted Y_{end} in % of the landscape's maximum productivity. The among-farmer inequity (4) was measured as the difference between the lowest and highest farmer's yields weighted by the highest yield at the end of a simulation, averaged over all replicates, denoted Y_{ineq} in % of the highest yield. Finally, we computed the proportion of time steps without manager's intervention over the time length of a simulation and averaged it over all replicates, denoted t_w ($1-t_w$ is thus the proportion of policy updates). We computed 95% bootstrapped confidence interval around each average (Manly 2007). The between-stakeholder equity was assessed by systematically confronting the conservation and the agricultural outcomes to detect unbalanced repartition of costs and benefits.

Sensitivity to manager's budget

We hypothesized that the effect of the budget bonus amount (B_b) on management quality would be stronger in situations of higher budget constraint on the manager. To test for this, we selected the permissiveness of 50%, in which outcomes with TRJ were not different from CTL but with a weak B_b effect. We decreased the manager's initial budget (B_M) from 1000 to 500 b.u. by 100 b.u. increments. For each B_M , we varied B_b from 0 to 100% of B_M by 10% increments in 100 replicates and measured the same outcome proxies as the previous section to investigate the effect of B_b amount on management quality according to B_M . We also simulated management with CTL for each B_M value to check how well the waiting strategies performed in comparison.

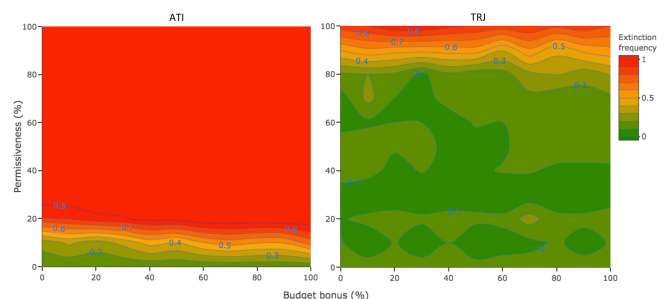
RESULTS

Adaptive timing of intervention strategy

Conservation outcomes

When applying the adaptive timing of intervention (ATI) strategy, increasing the permissiveness value caused the extinction risk to increase and the final population size to decrease below target with no marked effect of the budget bonus (B_b ; Fig. 1 and Appendix 2, Fig. A2.1). No combination of permissiveness and bonus amount resulted in equivalent or lower extinction risk than CTL strategy ($f_{ext} = 0.15$ with [0.08; 0.22] 95% confidence interval). No parameter combination of ATI strategy resulted in the population being closer nor equally close to target as CTL strategy ($d_T = -24.90\%$ [-33.78; -16.26]) either, which is not surprising given that extinction was almost certain for most combinations ($f_{ext} > 0.9$ for $P_T > 20\%$).

Fig. 1. Extinction frequency (f_{ext}) according to the permissiveness (P_T) and budget bonus (B_b) combinations in an individual-based model simulating the management of a population under conditions of conservation conflict. The greener, the lower the risk of extinction. The band formed by $P_T = 0$ and the corresponding B_b values are the f_{ext} obtained with the control strategy (CTL). With adaptive timing of intervention strategy (ATI; left panel), there was no combination of P_T and B_b parameters resulting in as low a f_{ext} as control strategy (CTL; 0.15 [0.08; 0.22] 95% CI), and population extinction was almost certain in most cases, with a weak positive effect of B_b regardless of the permissive range size. With the trajectory strategy (TRJ; right panel), most areas are as green as or greener than CTL's f_{ext} value, meaning TRJ performed at least as well as CTL regarding extinction risk. The effect of B_b on f_{ext} was weak to absent.



Agricultural outcomes

Increasing permissiveness caused the farmers' final yield to increase, and among-farmer yield inequity to decrease with no effect of the budget bonus amount (Appendix 2, Figs. A2.2 and A2.3). Farmers' final yield was > 90% of the maximum for all ATI parameter combinations, which was slightly more than CTL ($Y_{end} = 89.64\%$ [88.04; 90.90]). The among-farmer inequity was slightly lower than CTL results ($Y_{ineq} = 5.68\%$ [4.97; 6.34]). Indeed, as permissiveness increased, there were fewer animals feeding on farmers' land so the impact on yield was lower, and the farmers' yield got closer to maximum. Also, the highest yields attained the maximum value while the lowest kept increasing, which reduced inequity.

Mechanisms underlying the outcomes

With ATI, most extinction events occurred when the population was monitored to exceed the permissive range, and in response, the manager lowered the level of culling restrictions to favor a population decrease down to target. A problem arose when, in the following time step, the population was monitored inside the permissive range because it caused the manager to leave the policy unchanged. Farmers then continued to cull at a low cost, driving the population to extinction at the next time step (Fig. 2, ATI panel). Consequently, the larger the permissive range around target, the more likely this was to happen, thereby explaining why the extinction frequency and deviation from target increased with permissiveness values. This misinterpretation from the manager regularly occurred in the ATI parameter areas with very high extinction frequency (Fig. 1), in which the population deviation from target at the time step preceding extinction was within the manager's permissive range (Appendix 2, Fig. A2.4). Hence, the most effective strategy for avoiding population extinction here was to intervene unconditionally in every time step, at the expense of slightly decreasing farmers' final yield.

Trajectory strategy

Conservation outcomes

When applying TRJ, the extinction frequency and deviation from target were at least as close to 0 as CTL for permissiveness values up to 80%, without the manager intervening up to 40% of the time (Fig. 1; Appendix 3, Figs. A3.1 and A3.2). The budget bonus value had either no effect or a weak effect on the outcomes. Several combinations resulted in an extinction frequency under 0.1, even 0 sometimes, while $f_{ext} = 0.15$ [0.08; 0.22] with CTL. The effect of bonus amount was slightly stronger in the 40 and 50% permissiveness range (Appendix 3, Fig. A3.2), where bonus values between 20 and 50% resulted in the population being closer to target than CTL ($d_T = -24.90\%$ [-33.78; -16.26]). We chose the 50% parameter area for the experiment on sensitivity to manager's initial budget to test whether this weak effect could amplify when applying stronger budget constraints on the manager.

Agricultural outcomes

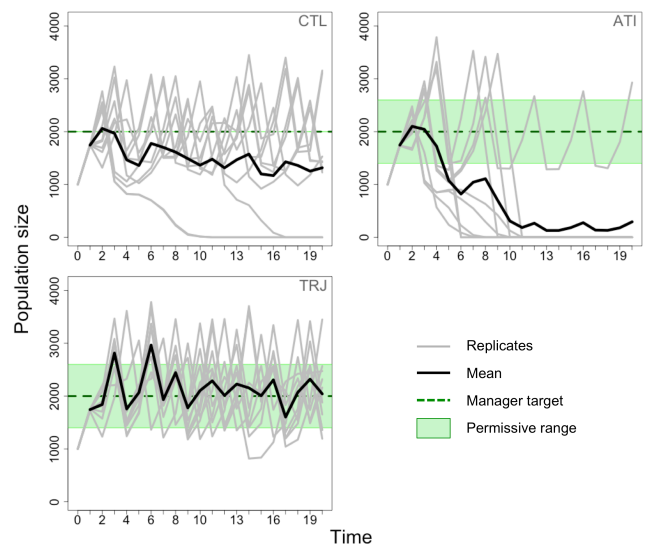
With TRJ, the farmers' final yield was as close to the maximum landscape production capacity as the CTL strategy regardless of the permissiveness and budget bonus values (Appendix 3, Fig. A3.3). Similarly, the among-farmer yield inequity was as low as CTL regardless of the permissiveness and budget bonus values (Appendix 3, Fig. A3.4).

Fig. 2. Average population size over time of 10 simulation replicates with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict.

Upper left: when manager intervenes unconditionally (control strategy, CTL). The extinctions happened when the population got too far below target size (T_N) between two consecutive time steps for the manager to be able to rectify by increasing restrictions.

Upper right: when applying the adaptive timing of intervention strategy (ATI; permissiveness (P_T) = 30%, Budget bonus (B_b) = 10%). Most extinctions happened when population size was over the permissive range, then was monitored into it the following time step. Thus, managers did not update the policy, allowing farmers to continue culling at a low cost, frequently driving the population to extinction at the following time step. Note: in the replicate that did not result in extinction, the population was never monitored into the permissive range during a decrease, causing the manager to update the costs and control the situation with better timing.

Lower left: when applying the trajectory strategy (TRJ; T_N = 30%, B_b = 0%). The TRJ strategy avoided some extinction events.



Mechanisms underlying the outcomes

The rare extinction events with CTL seem to have occurred when population was over target and the manager decreased the level of restrictions by too much, or when farmers happened to cull more than expected, which caused the population to decrease beyond reparation (Fig. 2, CTL panel). The TRJ strategy may have avoided this imprecision by offering managers the possibility not to intervene at these moments where the population is in the upper permissive range and keep the population closer to target (Fig. 2, TRJ panel). The absence of effect from the budget bonus

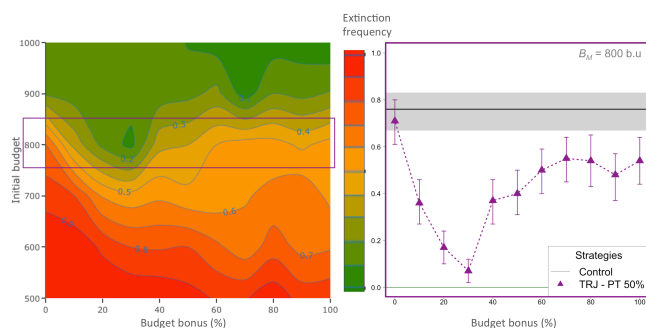
amount was most likely caused by the manager initial budget alone often being enough to efficiently ensure both population maintenance and farmers' yield given our initial parameter values, leaving no room for improvement due to a bonus. Thus, TRJ achieved similarly good management outcomes to CTL without managers having to intervene at every time step and regardless of the amount of benefit obtained from waiting periods.

Sensitivity to manager's initial budget

Conservation outcomes

The extinction frequency increased, and the final population size decreased below target, with decreasing manager's initial budgets (Fig. 3). But for $B_M = 800$ b.u., the extinction frequency steadily decreased from 0.71 [0.61; 0.80] without budget bonus, to 0.07 [0.02; 0.12] for a bonus of 30% of B_M (Fig. 3), which is significantly closer to zero than CTL for the same initial budget ($f_{ext} = 0.76$ [0.67; 0.83]). At higher bonuses, the extinction frequency increased again between 0.3-0.6, which is lower than CTL, although still a high extinction risk. The same trend was observed in the distance to target, which rose from -78.4% of T_N [84.9; -70.9] without budget bonus, to -11.4% [-21.4; -2.1] for the same bonus of 30% of B_M (Appendix 4, Fig. A4.1); CTL being -83.7% [-88.7; -78.0;] (Appendix 4, Fig. A4.1).

Fig. 3. Extinction frequency when applying the trajectory strategy (TRJ); permissiveness (P_T) = 50%, according to manager's initial budget (B_M) and budget bonus amount (B_b) in an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the lower the extinction frequency. For $B_M = 800$ b.u. (violet square, detail on the right panel), a pit forms along increasing B_b values, meaning that low to intermediate values for B_b markedly lowered the extinction risk. Error bars show 95% bootstrapped confidence intervals. The black line is the f_{ext} with control strategy for the same initial budget and the gray shaded area the 95% confidence interval around it.



Agricultural outcomes

The farmers' final yield increased, and the among-farmer inequity decreased with decreasing manager's initial budget (B_M) because of the positive effect on extinction risk and the positive effect on population size (Appendix 4, Figs. A4.3 and A4.4). In the $B_M = 800$ b.u. area, the farmers' final yield was between 85% and 100% (for the highest extinction frequency) without varying markedly with the bonus amount. With the bonus of 30% that critically improved conservation outcomes, the final yield was 89.20%

[87.47; 90.76] instead of 97.18% [96.14; 99] with the CTL strategy for the same manager's budget (at the expense of a very high extinction risk). The inequity was 5.94% [5.23; 6.68] instead of 2.11% [1.65; 2.6] with CTL, which is still relatively low.

Mechanisms underlying the outcomes

For the manager's initial budget value that maximized the budget bonus' negative effect on extinction risk and positive effect on population size ($B_M = 800$ b.u.), if the manager intervened at every time step or used TRJ but without getting any benefit from the waiting periods, extinctions occurred when the population fell to too low a population size. It was then challenging for the manager to rectify the population trajectory with only their initial budget because the culling cost was always too low to efficiently reduce farmers' culling rate (Fig. 4, CTL). If, in this situation, the manager accumulated budget bonus from previous waiting period (s), they had enough power to enforce higher restrictions on farmers as soon as the population did, or was predicted to, fall under the manager's permissive range. Intermediate bonus amounts ensured that when the latter happened, the population could increase closer to the manager's target (Fig. 4, TRJ). The TRJ thus appeared to be more efficient than CTL in situations of stronger budget constraint on the manager. In such situations, the role of the budget bonus was critical in decreasing the extinction risk, while maintaining a high and equitable yield to farmers and allowing the manager to save 20 to 30% of their interventions (Appendix 4, Fig. A4.2).

DISCUSSION

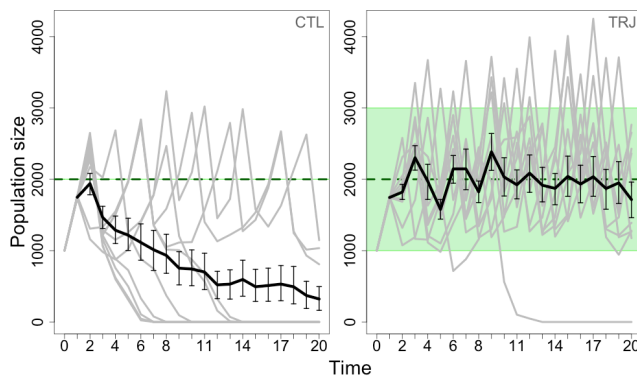
Summary of the study

When adaptively managing a conservation conflict in a social-ecological system, our modeling of strategies dynamically alternating between intervention and waiting found that management outcomes were better when the decision to intervene was made based on a prediction of the system's response than when based on the latest monitoring results alone. With prediction-based decisions, conservation and agricultural outcomes were at least as good as intervening unconditionally, while allowing the manager to save management resources and avoid unnecessary, potentially harmful interventions. When a low budget limited a manager's ability to effectively manage the conservation conflict, the benefits accrued during waiting periods were applied when intervention was most critical and greatly improved conservation outcomes with only a weak impact on farmers' yields and equity. Naturally, the main risk with waiting strategies is to decide to wait when intervention is needed, or to intervene when waiting is preferable. Basing intervention only on current monitoring should be avoided because when population density is monitored inside the permissive range during a sharp increase or decrease, managers can mistakenly conclude that the policy is adequate when, in fact, keeping the same policy running again can lead to extinction or critical yield loss. Basing intervention on population trajectory instead also includes a risk of inaccurately predicting the population density to be within the permissive range causing the managers to wait while the policy is inadequate to align conservation and agricultural objectives. Nevertheless, the consequences for yield loss or population decline were reversible when using an adequate permissive range.

Fig. 4. Population size over time averaged over 50 replicates (thick black line, error bars being the 95% confidence intervals) plotted on 10 replicates (thin gray lines) with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict and an initial budget of 800 b.u. The green dotted line shows manager's target (T_N), and the green area represents the permissive range $T_N \pm P_T$.

Left panel: when applying the control strategy (CTL). Extinctions happened when the population got too far below the manager's target (green dotted line) between two consecutive time steps for the manager to be able to rectify with their initial budget only.

Right panel: when applying the trajectory strategy (TRJ; $P_T = 50\%$, $B_b = 30\%$). Thanks to the benefits accumulated over waiting periods, the manager was able to raise the culling cost high enough to maintain farmers' culling rate at a sustainable value. The replicate that resulted in extinction was caused by a strong misprediction of time step 10's population size, causing the manager to wait while intervention was needed.



Importance of budget and monitoring in waiting strategy's efficiency

The superiority of our trajectory strategy over unconditional intervention depended on the manager's budget. When the budget was high enough to manage the situation efficiently, the outcomes with the trajectory strategy were at least as good as unconditional updates regardless of the budget bonus amount. This suggests that interventions when the population was monitored within the permissive range and predicted to stay in it (i.e., oscillating close to target) were less useful. Because the initial budget was sufficient for satisfactory management, the benefits reaped during waiting periods with the trajectory strategy could not further improve the management outcomes. This is relevant because human, financial, and time resources are limited in conservation and there is a constant competition for their allocation to cases (Hughey et al. 2003, McDonald-Madden et al. 2008, Jachowski and Kesler 2009, Ruiz-Miranda et al. 2020). It is also increasingly recognized that different species can impact human livelihood in different ways and at different times within the same geographical area, which should be considered in management (Pozo et al. 2020,

2021). Intervention in one conflict could thus be a priority for a time and then deprioritized when another requires intervention more urgently. Therefore, resources unused during periods of waiting in a well-funded case could instead be allocated to other, potentially less well-funded and/or more pressing cases and improve overall conservation benefits (Wu et al. 2020). Our trajectory strategy can thus help a dynamic allocation of management resources to cases that need them the most at a given instance.

When a limited budget made management more challenging, the resources saved when not intervening using the trajectory strategy could generate enough benefits to compensate for the lack of resources. We emphasize that the prediction based on population trajectory is a means for managers to reduce the risk of misjudging the timing of intervention; what improved management here was better access to the benefits accumulated over waiting periods. This result supports previous modeling results in Iacona et al. (2017), in which national park managers did not have enough budget to put every endangered bird species under protection at once but could maximize success by waiting and saving their funds to gradually enhance their monetary power. Importantly, this is only possible if unused management resources are not revoked or reallocated when less needed. A review of exit-strategies in conservation by Ruiz-Miranda et al. (2020) found that withdrawing funds when objectives are attained is very uncommon in adaptive management (but should be more considered and carefully planned). The present study suggests that the budget saved during waiting periods should be reallocated if the management resources are not limiting but invested in improving future interventions if they are.

To isolate the effect of various timing strategies on management quality, we assumed that the manager had perfect knowledge of population size. But real-world monitoring involves uncertainty that plays an important role in the success of conservation (Bunnefeld et al. 2011, Nuno et al. 2013). Monitoring uncertainty will cause errors in estimating population density and therefore errors in deciding if the situation requires intervention. This will decrease the efficiency of both unconditional intervention and trajectory strategies, but the latter might be more impacted because errors will influence both monitoring and trajectory prediction, therefore mitigating the advantage over unconditional intervention. Indeed, the efficacy of trajectory strategy might rely on more regular and accurate monitoring, which might not always be possible or affordable. Testing the effect of observation accuracy or cost on management quality is beyond the scope of this study, but it is an important aspect to consider when applying timing strategies (McDonald-Madden et al. 2011, Milner-Gulland 2011, Wu et al. 2020).

Because our focus is on management strategy and not on control measures, we limited farmers' options to culling for the sake of simplicity and ease of model interpretation. We did not model indirect measures such as fencing, widespread in the management of conservation conflicts over land use (Nyhus 2016, Pooley et al. 2017) because these measures are rather permanent constructions that are not always fitted to the regular changes and updates of our adaptive management process. Nevertheless, future modeling might usefully consider a range of alternative options for population management.

Modeling novelties for adaptive management

The ongoing 6th mass extinction under a rapidly changing climate (Ceballos et al. 2017) and the consequences of land-use conflicts between agriculture and wildlife protection on food security often put conservation managers under urgency (Du Toit 2010). Our results suggest that the urgency to act should not mean systematic, unconditional intervention and stress the importance of acquiring information to choose wisely how and when to intervene. As with software such as ISIS-fish (Mahévas and Pelletier 2004) or FLR (Kell et al. 2007) in fisheries management, the method developed here can inform managers' policymaking. Parameterizing GMSE with empirical data from a conflict between farming and common cranes in Sweden has previously permitted the evaluation of subsidy levels that best balanced culling and scaring to maintain both birds' population and farmers' income (Nilsson et al. 2021). Likewise, targeted parameterization of our model can give managers information to decide how permissive they should be and how much gain they should expect from waiting periods for our strategy to be useful regarding conservation and land-users' objectives and management resources allocation efficiency.

The individual-based nature of our model and the modularity of GMSE framework accounts for several sources of uncertainty around population dynamics and stakeholders' individual decision making. Our mechanistic model simulates population dynamics with intrinsic demographical uncertainty (inter-individual variability in the realization of life events) and geographical uncertainty (animals' movement is stochastic; Uchmański and Grimm 1996, Stillman et al. 2015). Future work could also include explicit modeling of environmental uncertainty, potentially in the form of stochastic extreme events impacting both population dynamics and farmers' yields. Currently, our results are robust even if population dynamics are uncertain and if spatial distribution can induce inequity by having the animals sometimes being more numerous on one farmer's land than another. Rakotonarivo et al. (2020, 2021) showed that the perceived equity in the balance of costs and benefits of conservation actions between and among stakeholders' groups plays an important role in land-users' propensity to choose pro-conservation strategies. However, the aspect of equity in conservation conflicts has scarcely been incorporated in modeling results. For example, Wam et al. (2016) used a measure of monetary equity between different stakeholder groups in their management model balancing logging, livestock grazing, and game hunting activities in a boreal forest. Our method also controls between-stakeholder equity by systematically confronting the population dynamics and the farmers' yield. In addition, we used a new indicator parameter for among-stakeholder equity by measuring the success of our strategies against the difference between the lowest and highest farmers' yields. Among-stakeholder equity, to our knowledge, has not been modeled before in conservation conflicts, and modeling stakeholders individually like the present study offers a direct measure of equity among members of the same group, thus allowing its monitoring as an important outcome of management.

The lack of dynamic stakeholder behavior modeling has been identified as a major cause of failure in conservation (Schlüter et al. 2012). Previous studies have addressed this by modeling decision making using game theory (Colyvan et al. 2011, Glynasti et al. 2018). Nevertheless, a game-theoretic framework can have

limitations when applied to management decision making, including fixed behavior rules, finite sets of actions (e.g., cooperate or defect), and the assumption that players are perfectly rational and aware of the best options for them (Myerson 1997). In this model, we use evolutionary algorithms, a form of artificial intelligence, for managers and farmers to make decisions, which we show offers a heuristic to find practical solutions when the panel of options is too large for game theoretic problems (Hamblin 2012). We combined the evolutionary algorithms with an individual-based approach and model decision making independently for each stakeholder with the possibility for sub-optimal choices along a continuum of possible actions (see also Kamra et al. 2018, Cusack et al. 2020, Nilsson et al. 2021). Simulating these different sources of uncertainty in our experiments allowed us to conclude that the strategy we proposed is relevant even if managers do not always make the most efficient policies and if farmers do not always behave as they were expected to.

CONCLUSION

We use an uncertainty-robust modeling tool to compare the management quality of waiting strategies against unconditional intervention regarding conservation and agricultural objectives and discuss which strategy to use according to cases of conservation conflicts. We propose a strategy for managers to dynamically alternate between intervening and waiting informed by population monitoring. When the decision to intervene or wait is based on a prediction of population trajectory, our strategy can result in a better, more equitable management of conservation conflicts, especially in situations of limiting budget. By saving time, energy and/or money when intervention is not necessary, it can also ensure a more efficient use of management resources.

Responses to this article can be read online at:

<https://www.ecologyandsociety.org/issues/responses.php/13341>

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Data Availability:

The data/code that support the findings of this study are openly available on GitHub at <https://github.com/AdrianBachl> EcologyAndSocietyArticle-data-code. Ethical approval for this research study was granted by the University of Stirling (approval number EC 2018_19 342).

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Appendix 1.

Modelling details.

Model overview

Model case.

To simulate conservation conflict management over time, we develop an individual-based model with a population of discrete animals, discrete farmers, and a biodiversity manager, all interacting on an agricultural landscape. The landscape is divided into discrete cells, each of which produces an agricultural yield and can hold any number of animals. Each farmer owns a contiguous block of cells that forms their ‘land’, and the sum of its cells’ productivity determines the farmer’s yield. Each animal’s reproduction and survival depend on the amount of agricultural resources it consumes from landscape cells, which consequently reduces the farmers’ yield. Farmers can cull animals that are on their own land to reduce yield loss. We chose population parameter values to ensure that unrestricted culling consistently drove the animal population to extinction (see the ‘initial parameters’ section below). The manager attempts to avoid extinction by maintaining the population around a predefined target size (T_N). This target was chosen to be high enough to prevent extinction, but low enough to ensure a satisfactory yield to farmers. The manager’s method is to implement a policy incentivizing or disincentivizing culling as appropriate to increase or decrease population size to be closer to T_N . Hence, following an adaptive management process, the manager updates this policy according to the monitoring of the population size (N_t) at each time step t . Farmers’ and manager’s actions are constrained by finite budgets (respectively B_F and B_M), which we interpret to reflect the total time, energy or money that a farmer can allocate to realize culling actions, or the manager to implement a change of policy and enforce culling restrictions at each time step. Furthermore, a conservation conflict will arise when the policy enforced by the manager prevents the farmers from culling as many animals as they want to minimize yield loss. Our case’s conflict dynamics are therefore affected by both the ecology of the population and the flexible, goal-oriented decision-making of the manager and farmers.

Manager policymaking.

To maintain the population as close as possible to T_N , the manager receives a fixed, non-cumulative budget B_M at the beginning of each time step (i.e., it is completely lost if unused at the end of the time step). They can allocate it into setting a cost that farmers must pay to cull an animal on their land. A minimum cost of 10 budget units (b.u.) models the baseline budget needed for a farmer to cull an animal. The manager can draw into B_M to raise this cost to discourage farmers from culling and favor population growth and can decrease it to facilitate culling and favor a population decrease. To model the budget needed to enforce a policy

restricting culling, a raise of 1 in the culling cost requires an investment of 10 b.u. from the manager. Conversely, as the manager does not need to incentivize farmers to remove animals when the policy allows high culling rates, they do not need to spend budget to decrease the cost. The amount by which the manager changes the culling cost is computed according to their goal (see the ‘decision-making sub-model’ section below), i.e., keeping the population as close as possible to target. Manager’s goal was modelled as minimizing the distance between the monitored population size N_t and T_N .

Timing strategies.

We included three timing strategies that determine whether a manager intervenes and updates the policy or waits and leaves it as is. The Control strategy (CTL) was the null model in this study. It corresponds to unconditional intervention at every opportunity and was modelled as the manager simply updating the policy at every time step. With the Adaptive Timing of Intervention strategy (ATI), the manager dynamically alternates between intervening and waiting based on the distance between N_t and T_N . ATI defines a permissive range P_T around T_N in the form of $T_N \pm P_T$. Within this range, the manager considers N_t close enough to T_N , and consequently, that the current policy results in a sustainable culling rate for the population. Hence, at a given time step, the manager will update the policy if and only if the population is monitored outside this $T_N \pm P_T$ range. The Trajectory (TRJ) strategy is the same as the ATI strategy, except that when N_t is into $T_N \pm P_T$, the manager makes a prediction on next time step’s population size based on the current and preceding monitoring results. If this prediction falls into the $T_N \pm P_T$ range, the manager assumes that the policy is effective and leaves it unchanged; otherwise, they update it. In both ATI and TRJ strategies, after a time step without updating the policy, the manager receives an additional proportion B_b of B_M to model the benefits associated with waiting (e.g., the money, time or energy saved by not engaging in the process of updating the policy and enforce the change on farmers, or the interests gained from putting up the money saved). This bonus can be accumulated over several consecutive time steps of waiting but is lost as soon as the manager draws into their budget to raise the level of restrictions again.

Farmers' action planning.

At the beginning of each time step, each farmer receives a fixed, non-cumulative budget B_F , which they allocate into culling a certain number of animals on the land that they own at the cost set by the manager’s policy. The number of animal culled is independently computed for each farmer using GMSE’s evolutionary algorithm (see the ‘decision-making sub-model’ section below), meaning that each farmer makes an independent decision for how to act according to their goal: maximizing their own yield. We used this model case to investigate how different timing strategies for a biodiversity manager’s intervention can affect the outcomes of an adaptively managed conservation conflict.

Simulations with GMSE

To simulate a conservation conflict management with different strategies under uncertainty, we used the R package ‘GMSE’ (Duthie et al. 2018). GMSE is a flexible modelling tool to simulate key aspects of natural resource management over time and address adaptive management questions *in silico* (Cusack et al. 2020, Nilsson et al. 2021). GMSE offers a range of parameters to simulate resource variations and management policy options with individual-based models of population dynamics, monitoring, manager decision-making and farmer decision-making.

Initial parameters.

We modelled a spatially explicit landscape with a grid of 200 by 200 cells, divided into 40 equally sized rectangular pieces of land, each individually owned by one of 40 farmers. For the animals, we wanted to model a population that is stable in absence of culling, but under an important threat of extinction under a high culling rate. We defined the population dynamics model parameters such that, under constraint of density-dependent intra-specific resource competition only, an equilibrium was reached quickly and steadily, as a stable natural population would. The size at equilibrium (K) was sought such that the expected number of animals per farmer’s land was about a hundred on average (i.e., around 4000 individuals on the landscape). The farmers were provided with an initial budget high enough to cull up to the expected number of animals on their land at the baseline cost (i.e., 1000 b.u), and at first, the manager’s initial budget was set equal to the farmers’ one. We set T_N at half the equilibrium size, which was low enough to maintain farmers’ yield over 90% of their maximum yield, but high enough to ensure a relatively low extinction risk of around 15% with the Control strategy (c.f. Management outcomes and Results sections in main document). We intentionally chose these parameters for the Control strategy to produce adequate management while also leaving room for improvement in order to determine the extent to which alternative strategies can generate better results. We set the initial population size $N_0 = 1000$, which is sufficiently far below K for the population to be under extinction threat and justify the initial involvement of a manager.

Population dynamics sub-model.

GMSE’s population dynamics model features a population of N animals, each of which has an age as well as an x and y landscape position, all initialized at random (integers sampled with equal probabilities along the range of possible values). In each time step, each animal moves from its current cell to a random cell within a defined range of cells in any direction (including the original cell). After arriving at a cell, the animal feeds and consumes a proportion of 0.5 of the cell’s remaining yield. All animals move 12 times during a single

time step, but individual movement across all animals occurs in a random order to avoid having a subset of animals complete all their moving and feeding before the others have started. After all movement and feeding has occurred, the animals asexually produce one offspring for every 5 resource units consumed (e.g., if an animal has consumed 12 resource units it produces 2 offspring). The offspring are added to the population as new individuals of age 0 on the cell on which they were produced. Next, animals that have consumed over 4.75 resource units and have an age under or equal to 5 time steps survive to the next one. Animals that do not survive are removed from the population. This consumption criteria lead to density-dependent intra-specific competition for resource, and modelling life events discretely and probabilistically generates inter-individual variability, as well as geographical and demographic stochasticity, therefore accounting for several sources of uncertainty around population dynamics.

Monitoring sub-model.

We assumed that the manager makes no errors during monitoring, thus N_t represents the exact population size at each time step. This assumption avoided modelled stochastic monitoring errors that would have challenged a full understanding of management dynamics.

Decision-making sub-model.

Manager and farmer decision-making is modelled in GMSE using evolutionary algorithms (Hamblin 2012). Each time an agent makes a decision, the GMSE evolutionary algorithm generates a set of random possible policies for managers (culling costs) or action plans for farmers (number of culls), and then allows this set to evolve on its own self-contained timescale. Policies or action plans that are better aligned to an agent's goal have a relatively high fitness, and the fittest ones are selected to be the agent's policy/action plan when the conditions for the algorithm termination are met (see supporting information S1 in Duthie et al. 2018, and GMSE documentation for further details). Our model thereby computes a practical but not necessarily optimal decision, recognizing that most people cannot think of every single possibility to choose the optimal one, but can choose the best option among those they could conceive. This process generates inter-individual variability, errors, and stochasticity in agents' decision-making, therefore simulating several sources of uncertainty around human behavior.

Timing strategies implementation.

CTL is the default strategy in GMSE: at each time step t , the evolutionary algorithm calculates an appropriate cost of culling (most likely a raise in the cost when $N_t < T_N$ and a decrease when $N_t > T_N$). In contrast, when applying ATI, the manager updates the policy only if N_t is out of the permissive range ($T_N \pm P_T$). Hence, the evolutionary algorithm is called only if

$$\left| \frac{N_t}{T_N} - 1 \right| > P_T$$

Otherwise, the cost is left the same as the previous time step. Lastly, when applying TRJ, the process is the same as ATI, except that the decision to update is based on a prediction of next time step's population size \hat{N}_{t+1} instead of N_t . We chose as a predicting function a simple linear extrapolation based on the current (N_t) and previous (N_{t-1}) population sizes that has the advantage of including the influence of the active policy on population variation in a simple way. Hence, with TRJ the condition for calling the evolutionary algorithm is

$$\left| \frac{\hat{N}_{t+1}}{T_N} - 1 \right| > P_T ,$$

$$\text{With } \hat{N}_{t+1} = N_t + (N_t - N_{t-1}).$$

Otherwise, the cost stays the same as previous time step. After a time step without calling the evolutionary algorithm, the manager starts the next one with an addition of a proportion B_b of B_M b.u. to their regular budget B_M . (See Fig. A5 for a flowchart of the different strategies.)

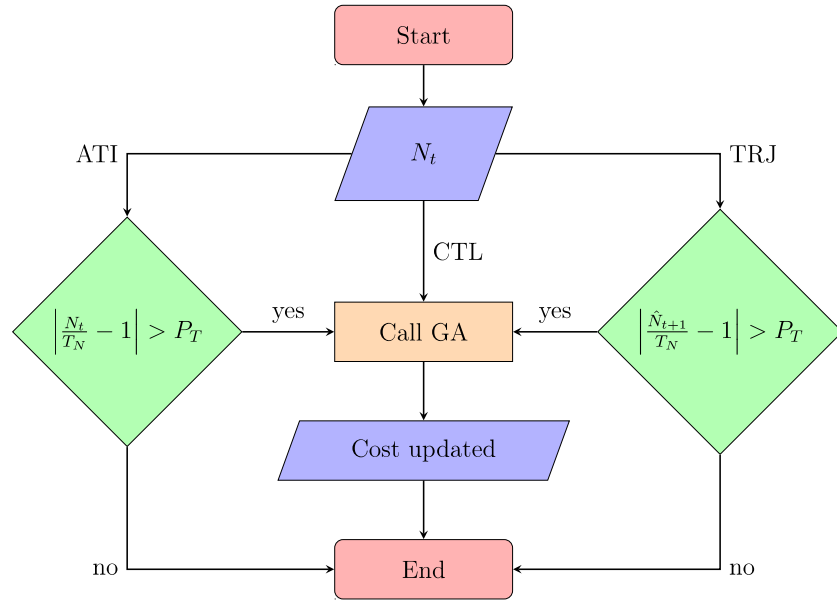


Fig. A1. Flowchart of the three timing strategies.

Table A1.1. Summary of useful symbols.

| Symbol | Status | Description | Unit |
|------------|----------|--|---------------------------------|
| t_{max} | constant | max simulation time | times steps |
| T_N | constant | manager's target for population size | nb. of individuals |
| N_0 | constant | initial population size | nb. of individuals |
| N_t | variable | population size monitored at time step t | nb. of individuals |
| P_T | variable | permissiveness around T_N | % of T_N |
| B_M | variable | manager's initial budget | b.u. |
| B_b | variable | budget bonus amount | % of B_M |
| f_{ext} | outcome | extinction frequency over a set of replicates | % of replicates |
| Y_{end} | outcome | average farmers' yield at the end of a simulation. | % of landscape max productivity |
| Y_{ineq} | outcome | average differential between lowest and highest farmers' yields at the end of a simulation | % of highest yield |
| d_T | outcome | Average distance between N_t and T_N at the end of a simulation | % of T_N |
| t_w | outcome | Average proportion of time steps without intervention | % of simulation time |

Table A1.2. GMSE parameter values. Parameters not mentioned here were set to default (as in <https://confoobio.github.io/gmse/articles/SI3.html>).

| Parameter | Value | Description |
|----------------|-------|--|
| time_max | 20 | Maximum time steps in simulation |
| land_dim1 | 200 | Width of landscape (horizontal cells) |
| land_dim2 | 200 | Length of landscape |
| res_death_type | 0 | Rules affecting resource death (consumption-based) |
| res_birth_type | 0 | Rules affecting resource birth (consumption-based) |
| observe_type | 3 | Type of resource observation (transect observation) |
| res_move_obs | FALSE | Resource move during transect observation |
| res_consume | 0.5 | Pr. of a landscape cell's value reduced by the presence of a resource in a time step |
| max_ages | 5 | The maximum number of time steps a resource can persist before it is removed |
| minimumcost | 10 | The minimum cost of a farmer performing culling |
| user_budget | 1000 | A farmer's budget per time step for performing any number of actions |

| | | |
|----------------|------|--|
| manager_budget | 1000 | A manager's budget per time step for setting policy |
| manage_target | 2000 | The manager's target resource abundance |
| RESOURCE_init | 1000 | The initial abundance of resources |
| culling | TRUE | Resource culling (removes a resource entirely) is a policy option |
| stakeholders | 40 | Number of farmers in the simulation |
| landownership | TRUE | farmers own land and increase utility indirectly from landscape instead of resource use |
| manager_sense | 0.15 | A metric of managers accuracy in predicting change in stakeholder behaviour given a change in cost |
| consume_surv | 4.75 | Amount of cell value for a resource to eventually survive until the next time step |
| consume_repr | 5 | Amount of cell value for a resource to eventually produce offspring |
| times_feeding | 12 | Maximum number of times a resource consumes landscape value per time step |

Appendix 2.

Additional figures of the adaptive timing of intervention strategy experiment results.

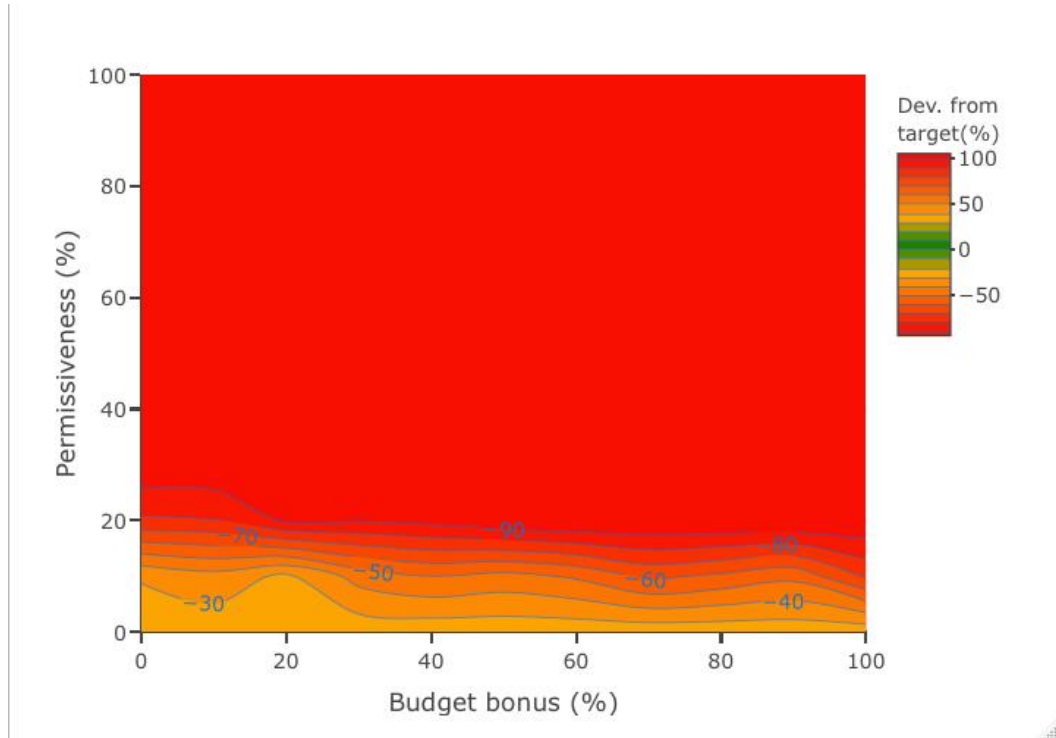


Figure A2.1. Population's average deviation from target (d_T) at the final time step of simulation according to permissiveness (P_T) and budget bonus (B_b) values when applying the Adaptive Timing of Intervention strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the closer the population to manager's target (T_N). Given the numerous extinctions (see Fig.1), the population very often ended at a size of 0, meaning a -100% deviation from target, hence the large red area. With Control strategy, the population was under target by -30 to -20% . Expectedly, this reflects the same tendency as the extinction frequency f_{ext} .

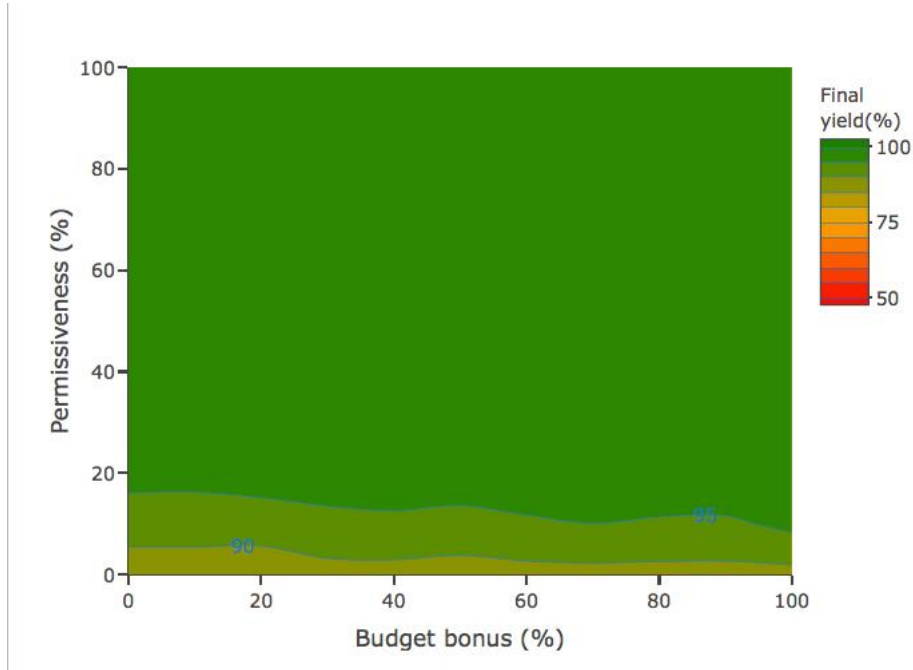


Figure A2.2. Average farmers' yield (Y_{end}) at the final time step of simulation according to permissiveness (P_T) and budget bonus (B_b) values when applying the Adaptive Timing of Intervention strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the closer the farmers' yield to landscape maximal productivity. Given the numerous extinctions (see Fig.1), farmers very often reach their maximal yield, hence the large green area. With control strategy, farmers got between 85 and 90% of their maximal yield on average because the population was more efficiently managed and thus larger.

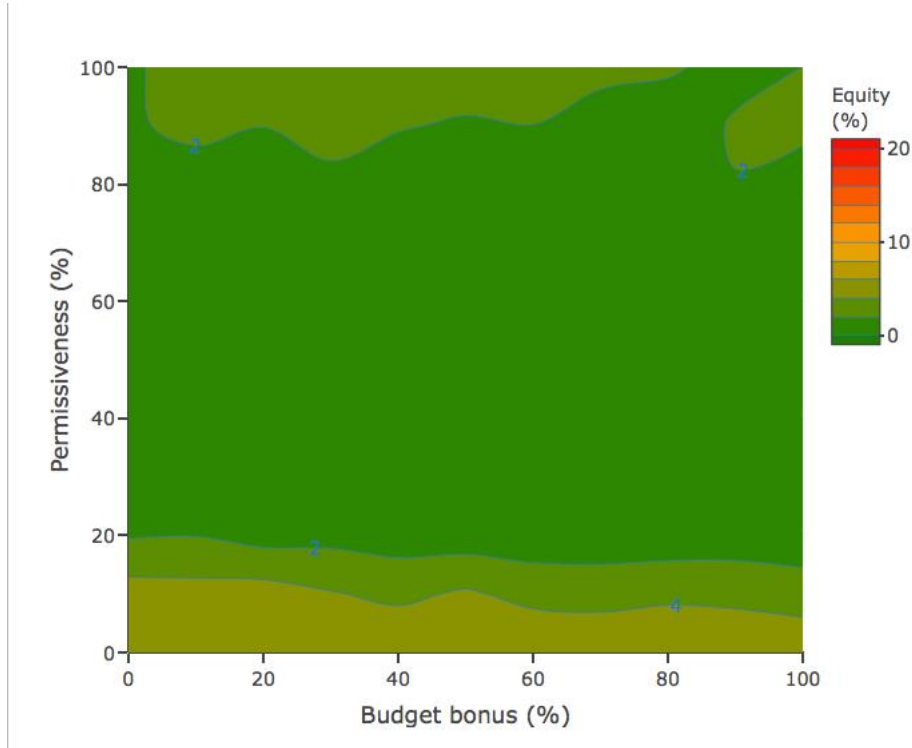


Figure A2.3. Average farmers' yield inequity (Y_{ineq}) at the final time step of simulation according to permissiveness (P_T) and budget bonus (B_b) values when applying the Adaptive Timing of Intervention strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the smaller the difference between the highest and lowest farmer's yields. Given the numerous extinctions (see Fig.1), farmers very often reach their maximal yield while the lower yields were higher than with control strategy, hence the very low inequity.

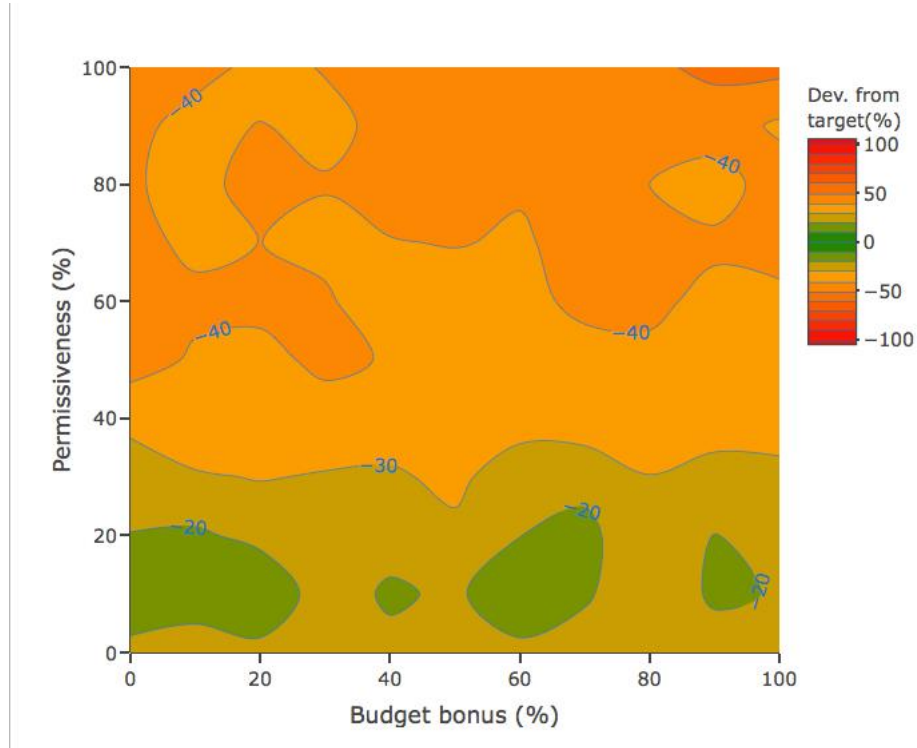


Figure A2.4. Population's average deviation from target (d_T) at the time step before the end of simulation (t_{max} or extinction) according to permissiveness (P_T) and budget bonus (B_b) values. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the closer the population to manager's target (T_N). Note that in most areas of high extinction risk (red areas in Fig.1), the population size was monitored into the corresponding permissive range in the time step preceding extinction, causing the manager to wait when intervention was urgent.

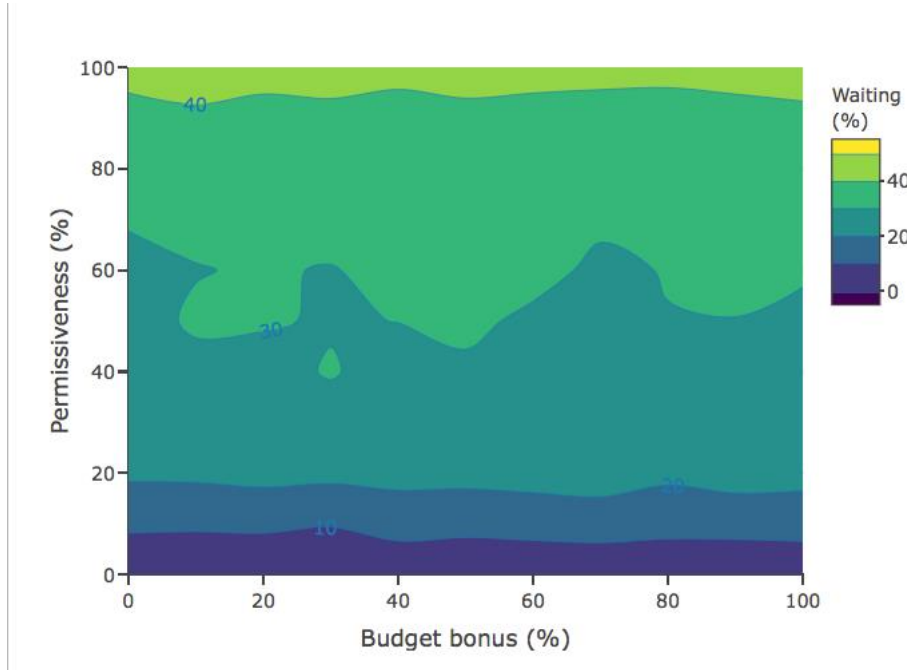


Figure A2.5. Average proportion of time steps without manager's intervention (t_w) during a simulation according to permissiveness (P_T) and budget bonus (B_b) values when applying the adaptive timing of intervention strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The lighter, the larger the number of time steps without intervention.

Appendix 3.

Additional figures of the trajectory strategy experiment results.

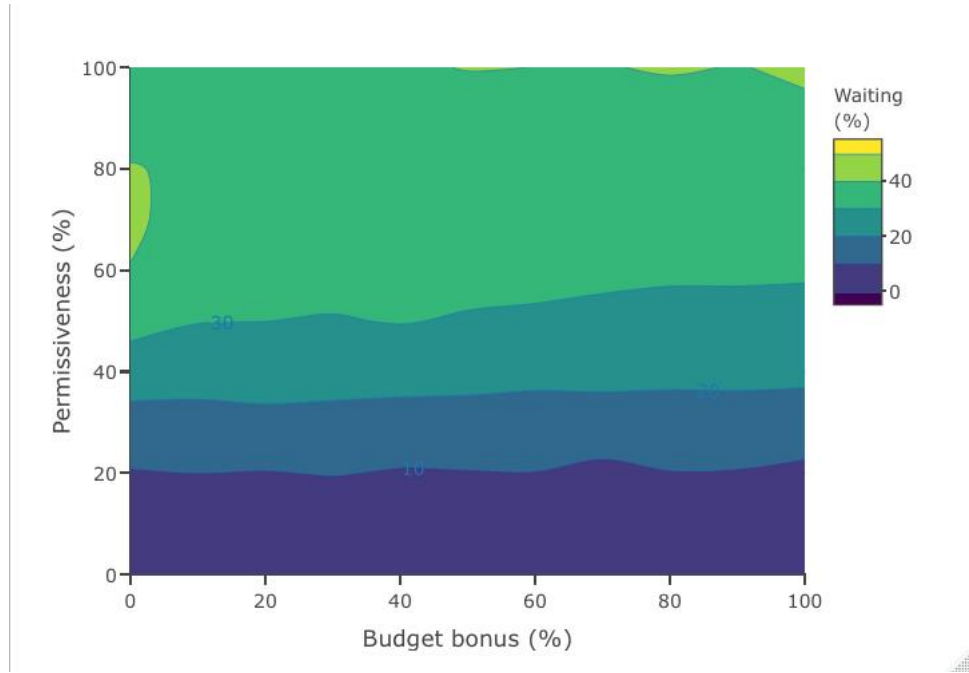


Figure A3.1. Average proportion of time steps without manager's intervention (t_w) during a simulation according to permissiveness (P_T) and budget bonus (B_b) values when applying the Trajectory strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The lighter, the larger the number of time steps without intervention. In the 30% P_T parameter area, the manager could save between 10 and 20% of their interventions.

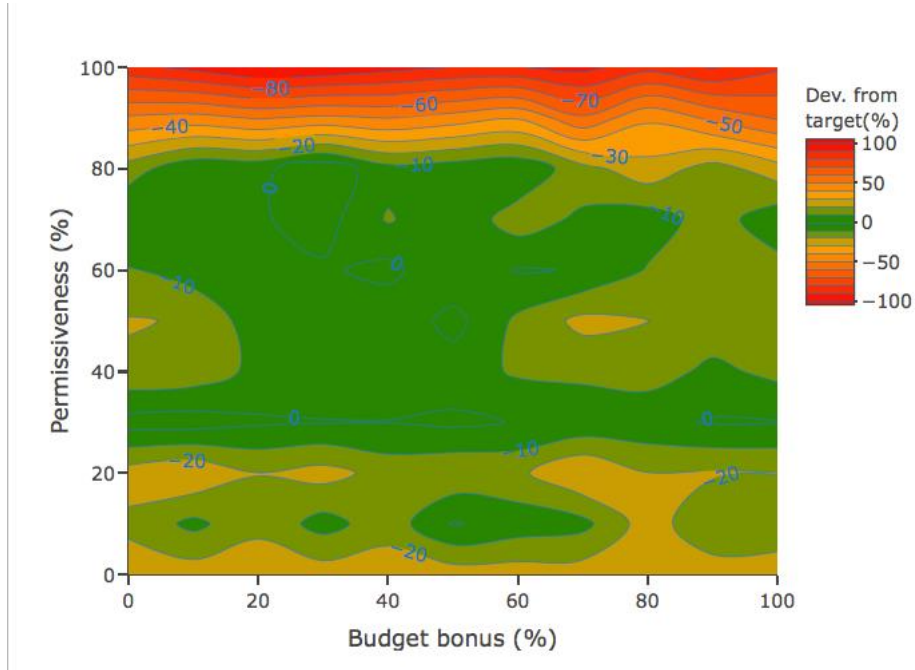


Figure A3.2. Population's average deviation from target (d_T) at the final time step of simulation according to permissiveness (P_T) and budget bonus (B_b) values when applying the Trajectory strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the closer the population to manager's target (T_N). Most areas are greener than the control strategy ($P_T = 0$ band) meaning that the trajectory strategy maintained the population closer to target. Note that in the $P_T = 30$ parameter area, d_T is the closest to 0 for every B_b values.

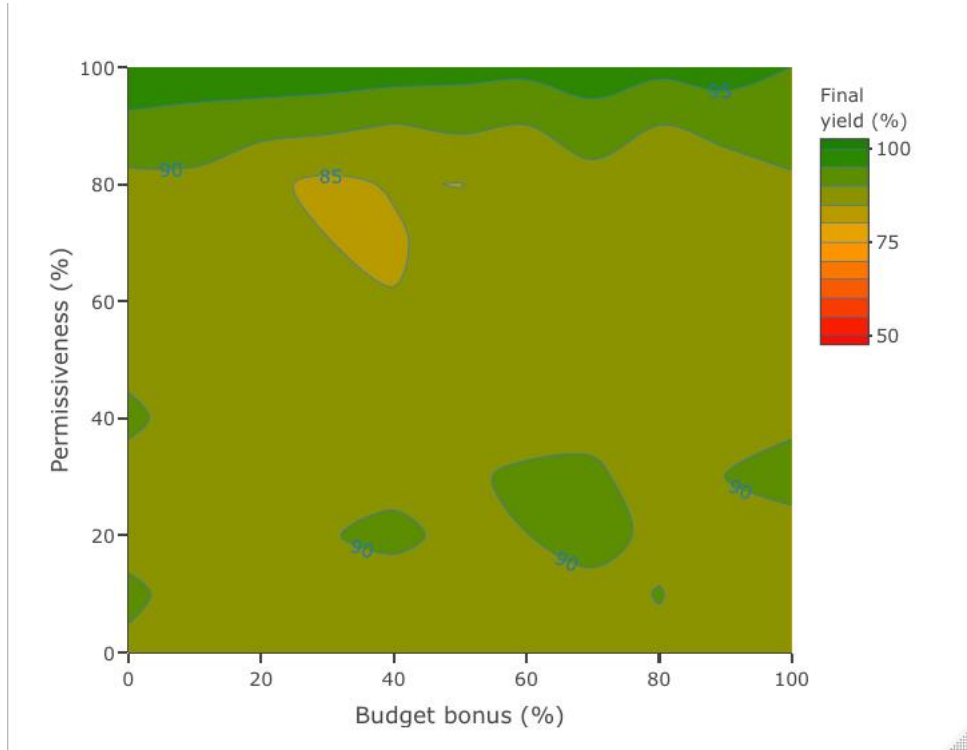


Figure A3.3. Average farmers' yield (Y_{end}) at the final time step of simulation according to permissiveness (P_T) and budget bonus (B_b) values when applying the Trajectory strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the closer the farmers' yield to landscape maximal productivity. Most areas are as green as control strategy, with a final farmers' yield over 85% of their maximum.

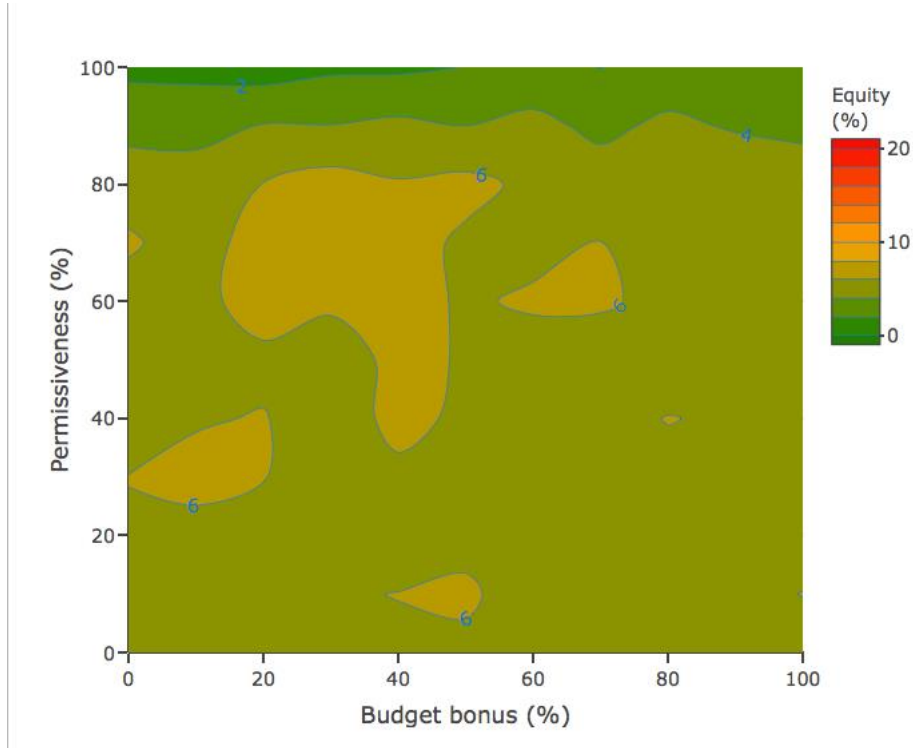


Figure A3.4. Average farmers' yield inequity (Y_{ineq}) at the final time step of simulation according to permissiveness (P_T) and budget bonus (B_b) values when applying the trajectory strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the smaller the difference between the highest and lowest farmer's yields. Most areas are as equitable, or slightly less equitable than control strategy.

Appendix 4.

Additional figures of the sensitivity to manager's initial budget experiment results.

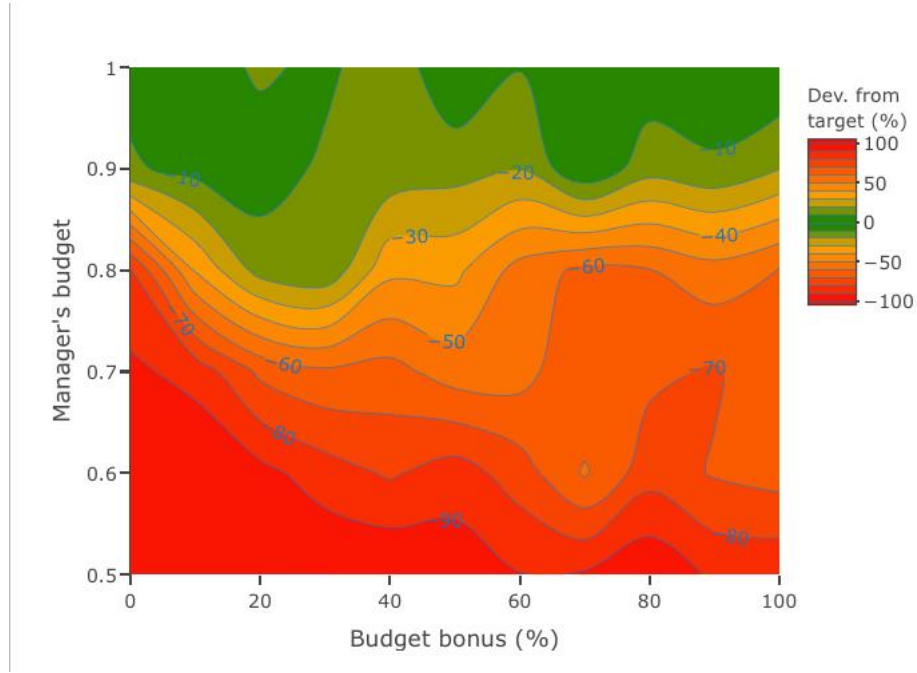


Figure A4.1. Population's average deviation from target (d_T) at the final time step of simulation according to manager's initial budget (B_M) and budget bonus (B_b) values when applying the Trajectory strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the closer the population to manager's target (T_N).

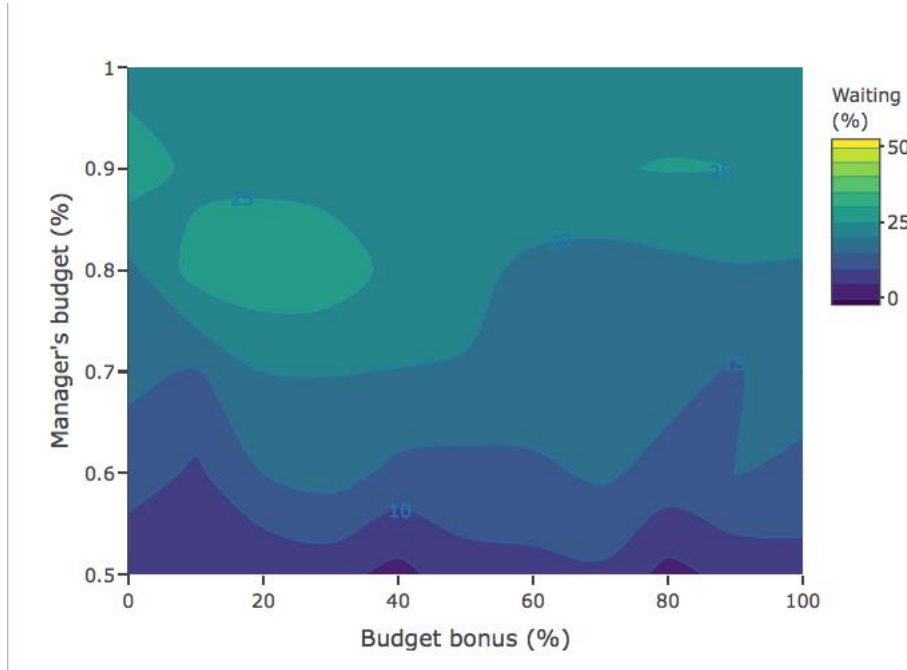


Figure A4.2. Average proportion of time steps without manager's intervention (t_w) during a simulation according to manager's initial budget (B_M) and budget bonus (B_b) values when applying the Trajectory strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The lighter, the larger the number of time steps without intervention. The $B_M = 800$ b.u. and 20-30% B_b parameter area was also the one where the manager needed to intervene less, another sign that the population is often close enough to target not to need an intervention.

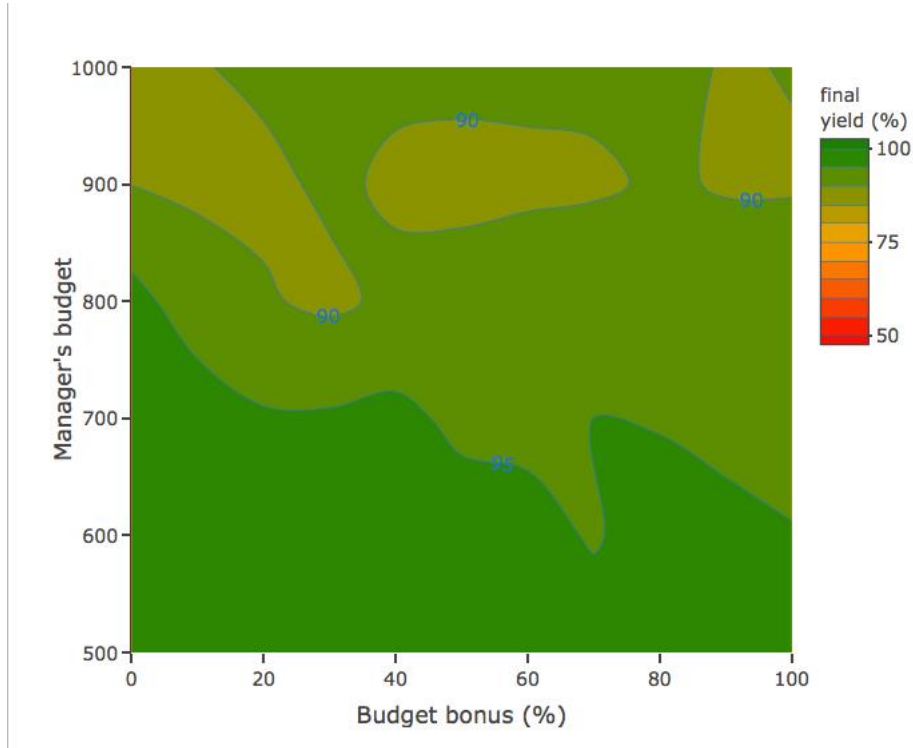


Figure A4.3. Average farmers' yield (Y_{end}) at the final time step of simulation according to manager's initial budget (B_M) and budget bonus (B_b) values when applying the Trajectory strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the closer the farmers' yield to landscape maximal productivity. In the areas where the extinction frequency is acceptable, the farmers' final yield is over 85% of their maximum, which is comparable to the previous experiments.

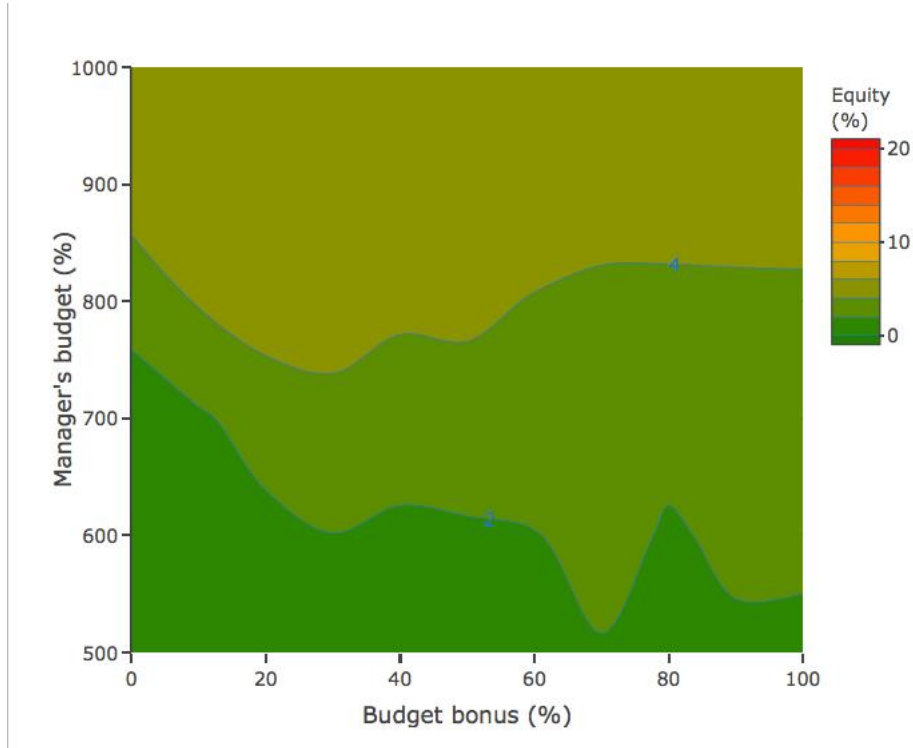


Figure A4.4. Average farmers' yield inequity (Y_{ineq}) at the final time step of simulation according to manager's initial budget (B_M) and budget bonus (B_b) values when applying the trajectory strategy. Results from simulations with an individual-based model simulating the adaptive management of a population under conditions of conservation conflict. The greener, the smaller the difference between the highest and lowest farmer's yields. In the areas where the extinction frequency is acceptable, the inequity is between 4 and 6% which is comparable to the previous experiments.