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Simulating Demography, Monitoring, and Management Decisions to Evaluate Adaptive Management Strategies for Endangered Species

Stefano Canessa[1,2,3] | Sarah J. Converse[4] | Lynn Adams[5] | Doug P. Armstrong[6] | Troy Makan[7] | Mhairi McCready[8] | Kevin A. Parker[8,9] | Elizabeth H. Parlato[6] | Hannah A. Sipe[10] | John G. Ewen[3]

[1]Dipartimento di Scienze e Politiche Ambientali, Università degli Studi di Milano, Milan, Italy | [2]Division of Conservation Biology, Institute of Ecology and Evolution, University of Bern, Bern, Switzerland | [3]Institute of Zoology, Zoological Society of London, London, UK | [4]U.S. Geological Survey, Washington Cooperative Fish and Wildlife Research Unit, School of Environmental and Forest Sciences & School of Aquatic and Fishery Sciences, University of Washington, Seattle, Washington, USA | [5]Department of Conservation—Te Papa Atawhai, Christchurch, New Zealand | [6]Zoology and Ecology Group, Massey University, Palmerston North, New Zealand | [7]Department of Conservation—Te Papa Atawhai, Rotorua, New Zealand | [8]Hihi Conservation Charitable Trust, Wellington, New Zealand | [9]Parker Conservation Ltd, Nelson, New Zealand | [10]Washington Cooperative Fish and Wildlife Research Unit, School of Environmental and Forest Sciences, University of Washington, Seattle, Washington, USA

Correspondence: Stefano Canessa (stefano.canessa@unimi.it)

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ABSTRACT

Adaptive management (AM) remains underused in conservation, partly because optimization-based approaches require real-world problems to be substantially simplified. We present an approach to AM based in management strategy evaluation, a method used largely in fisheries. Managers define objectives and nominate alternative adaptive strategies, whose future performance is simulated by integrating ecological, learning and decision processes. We applied this approach to conservation of hihi (*Notiomystis cincta*) across Aotearoa-New Zealand. For multiple extant and prospective hihi populations, we jointly simulated demographic trends, monitoring, estimation, and decisions including translocations and supplementary feeding. Results confirmed that food supplementation assisted recovery, but was more intensive and expensive. Over 20 years, actively pursuing learning, for example by removing food from populations, provided little benefit. Recovery group members supported continuing current management or increasing priority on existing populations before reintroducing new populations. Our simulation-based approach can complement formal optimization-based approaches and improve AM uptake, particularly for programs involving many complex and coordinated decisions.

1 | Introduction

Conservation managers must typically implement actions in the face of uncertainty. Given this reality, it is common to advocate for adaptive management (AM; Holling 1978), that is, management that seeks to build knowledge, which then improves subsequent decisions to achieve desired outcomes. Generally, learning by doing involves a trade-off: in species recovery plans, experiments that compare multiple actions could accelerate learning and reduce long-term extinction risks, but also entail short-term risks,

because during the experiment some individuals will be allocated to sub-optimal treatments (Canessa et al. 2016). Adaptive management seeks the optimal solution to this learning-doing trade-off (Williams 1996).

Despite this intuitive appeal, many programs that identify as AM do not clearly state objectives, do not make explicit predictions, do not use and update models, and do not focus monitoring on key uncertainties (Westgate et al. 2013). These gaps leave programs vulnerable to poor decision-making and uninformative monitoring (Runge 2011). Real-world endangered species management often involves complex problems with many actions and decisions across space and time, and such problems are extremely difficult to solve optimally for AM ("curse of dimensionality"; Chadès et al. 2017; but see Chapman et al. 2023), Therefore, most conservation AM examples are necessarily simplified (e.g. Bragg et al. 2020; Canessa et al. 2016; Rout et al. 2009). Simplification encourages clarity, but can also make models less credible or relevant to decision-makers (Addison et al. 2013).

On the other hand, species management is often informed by simulation-based tools like population viability analysis, which could be expanded to simulate learning and AM (Lacy 2019). In fisheries, management strategy evaluation (MSE; Punt et al. 2016) is used to assess harvest rules under uncertainty, simulating dynamic management strategies that use different methods for data collection and analysis, and comparing their expected outcomes (Punt et al. 2016). The potential for MSE to incorporate AM has been only partially explored (Punt et al. 2016), and MSE remains underused in conservation (Bunnefeld et al. 2011).

In this study, we used a simulation combining elements of AM and MSE to help develop an adaptive recovery plan for an endangered species. Under this approach, managers nominated several alternative strategies, each consisting of different decision rules, reflecting different attitudes to risk and adaptive learning. We then predicted those strategies' performance using simulations that integrated demography, monitoring, and decision-making. We then identified the strategy that was expected to provide the best outcomes across multiple objectives, based on managers' preferences.

2 | Methods

2.1 | Case Study and Decision Context

The hihi (*Notiomystis cincta*) is an endemic passerine of Aotearoa-New Zealand. Following habitat destruction and predation by invasive mammals, it declined to a single population by the late 1800s and is now considered Vulnerable (IUCN 2020). Recovery of the species is coordinated by the Department of Conservation's (government) Hihi Recovery Group (HRG), which includes representation from community conservation groups and other specialists. Management primarily involves reintroduction to forested sites free of invasive mammalian predators throughout its historical range. Such sites are progressively becoming available through forest regeneration and predator eradication. However, available evidence indicates that populations reintroduced to these sites require supplementary feeding (Armstrong et al. 2007; Doerr et al. 2017). The HRG wants populations to persist without intensive management, but the viability of unfed reintroduced populations is uncertain. The HRG has long implemented structured decision-making and AM (Armstrong et al. 2007; Ewen et al. 2018). However, until now structured decisions have concerned individual sites or pairs of sites, for example to decide whether to supplement food (Ewen et al. 2014). Our study sought to help transition hihi recovery toward a national AM program, embracing both additional opportunities for cross-site learning and the added complexity of coordinated decisions.

We evaluated alternative strategies across sites over the next 20 years against the HRG's five fundamental objectives, previously agreed by the group (Ewen et al. 2018): maximizing number of birds and number of populations (both measured at year 20), minimizing management costs (total over 20 years), minimizing human intervention ("naturalness", measured by the number of fed sites over 20 years), and maximizing advocacy (measured by total site visitors over 20 years). Our study included 7 sites with extant populations in 2020 (4 islands and 3 predator-exclusion-fenced mainland sites), and another 6 sites currently unoccupied but identified by the HRG as suitable for translocations (5 islands and 1 fenced mainland site).

Working with the HRG, we defined seven alternative strategies (Table 1; see also Supplementary Information). Strategies included quantitative decision rules about how many birds to take from and release to each site, and whether to provide supplementary food, based on annual estimates of carrying capacity and population sizes. Each strategy was adaptive in the sense that actions would change based on available knowledge; different strategies encompassed different approaches to learning and managing. Some favored safer management, for example by releasing only at sites with high expected carrying capacities or always feeding populations (e.g. *Status quo*, *Sequential* and *Reinforcement* in Table 1). Other strategies sought learning more actively, possibly incurring greater risks: for example, removing food to learn whether sites could support unfed populations, or attempting releases at sites with lower expected carrying capacities to learn about those estimates (e.g. *New learning*, *Visitor*, *Responsive)*. The aim of our analysis was to identify the strategy with the best expected results across the fundamental objectives.

2.2 | Adaptive Management Simulation

We simulated each strategy as a three-step cycle: demography, learning and decision-making (Figure 1; details and code in Supplementary Information). For every annual step, we simulated how each population grew (demographic model), how many birds would be counted and what demographic estimates would be obtained from those data (learning model), which decisions (actions within the strategy) would be applied based on the estimated parameters, and what effect those decisions would have on parameters for the following year. We incorporated parametric uncertainty around carrying capacities (with and without supplementary feeding), expected population growth rates, postrelease survival, and detection probability. Based on available data, we incorporated demographic stochasticity and random variation in detection probability (by year and

TABLE 1 | Summary of alternative strategies. Each strategy consists of rules for harvesting, releasing, and feeding each year based on current population sizes and estimated carrying capacities. Releases cease when failure is declared ($N_f \leq 3$), when estimated population size exceeds unfed carrying capacity, or after a set number of years (two for *Status quo*, four for all other strategies). "Learning" indicates whether a strategy prioritized acting based on current knowledge (*conservative*), accelerating learning by, for example, removing food from populations (*risky*), or somewhere in between (*balanced*). For a complete description, see Supplementary Information.

Learning rationale	Harvest	Release	Feeding
1. Status quo			
Conservative (rationale: current management in 2020)	Current source, high threshold ($N > 60$)	Empty sites only One site at a time, ranked by highest capacity	All sites: ad libitum
2. Sequential			
Balanced (rationale: prioritize islands and differentiate feeding between islands and mainland)	Current source, high threshold ($N > 60$) Any other site, medium threshold ($N > 40$)	Empty or occupied sites Multiple releases, ranked by: 1. highest expected capacity 2. smallest current population	Original sites: ad libitum New sites: 1. Mainland: only release years 2. Islands: never Rescue feeding: yes
3. Seasonal			
Balanced (rationale: status quo for original sites, support releases at new sites)	Any site, medium threshold ($N > 40$)	Empty or occupied sites Multiple releases, ranked by: 1. highest expected capacity 2. smallest current population	Original sites: ad libitum New sites: only release years Rescue feeding: yes
4. New learning			
Risky (rationale: status quo for original sites, multiple releases at new sites but no support)	Any site, medium threshold ($N > 40$)	Empty or occupied sites Multiple releases, ranked by: 1. highest expected capacity 2. smallest current population	Original sites: ad libitum New sites: never Rescue feeding: no
5. Visitor			
Risky (rationale: deliberate removal of food at any site where it is acceptable)	Any site, medium threshold ($N > 40$)	Empty or occupied sites Multiple releases, ranked by: 1. highest expected capacity 2. smallest current population	Original sites: never New sites: only release years Rescue feeding: yes

(Continues)

TABLE 1 | (Continued)

Learning rationale	Harvest	Release	Feeding
6. Responsive			
Balanced (rationale: aim to remove feeding at new sites, but support during releases and restart if needed)	Any site, medium threshold (N > 40)	Empty or occupied sites Multiple releases, ranked by: 1. highest expected capacity 2. smallest current population	Original sites: ad libitum New sites: only release years Rescue feeding: yes
7. Reinforcement			
Conservative (rationale: prioritize existing populations before opening new sites)	Any site, medium threshold (N > 40)	Empty or occupied sites Multiple releases, ranked by: 1. Original sites first 2. Ongoing releases 3. Empty sites	Original sites: ad libitum New sites: only release years Rescue feeding: yes

site), visitor numbers (by year and site), and inflation rates (by year).

All parameters were expressed using full probability distributions (priors), which were used in two ways. First, we used the priors to draw the "true" values driving demographic and observation processes, generating sets of parameters once at the beginning of each simulation (time-independent, e.g. carrying capacity) or every year during each simulation (time-dependent, e.g. growth rate and detection probability). Therefore, the "true" parameter distributions were the same within and across simulations, but the actual values used changed. Second, we used the priors to represent the initial knowledge of parameters at the start of the 20 years. These "estimated" distributions were then updated annually by the learning model and therefore changed as information was collected. Parameter distributions were based on existing data where available (Table 2; Supplementary Information). We formally elicited estimates of carrying capacity from seven HRG experts using the IDEA protocol (Hemming et al. 2018).

For each strategy, we ran 100 simulations, tracking numbers of birds, occupied sites, harvests, releases, and feeding interventions. We tracked learning performance using the proportional change in the coefficient of variation around carrying capacity between years 1 and 20 ($\Delta CV = (CV_{t=20} - CV_{t=1}) / CV_{t=1}$, repeated for fed and unfed K). For each simulation run, based on these outcomes we calculated management costs and advocacy potential (Supplementary Information). We thus obtained 100 sets of simulated outcomes (one for each fundamental objective) under each strategy.

2.3 | Decision-Making

After obtaining the simulation results, we assessed which strategy best met the HRG's objectives, and whether it differed from what the group would have chosen without the simulation's support. First, to identify a priori preferences, we asked HRG members to (re)read the verbal description of strategies and choose their preferred one. Second, to explore how members traded off objectives implicitly, we gave them verbal and visual summaries of simulation results and asked them to confirm or change their previous choice. Third, to identify the best multi-criteria decisions, we asked HRG members to look at simulation results and express their preferences for the different objectives as weights, using swing-weighting (Clemen and Reilly 2001). We rescaled the simulated outcomes for each strategy on a 0–1 scale and multiplied them by each respondent's weights, to obtain a distribution of aggregate scores and strategies' ranking. We used scenario planning to assess whether weights were robust to parametric uncertainty and stochasticity (Supplementary Information). In total, 20 HRG members expressed their preference weights, and 12 of them went through all three phases of assessment, allowing us to compare the pre- and postsimulation choices. All results were then fed back to the HRG for evaluation and decision-making (ongoing as of July 2024).

TABLE 2 | Starting population sizes and parameters used in the simulation. Parameters marked as "imputed" were randomly drawn from distributions of values for other sites. Parameters marked as "not required" for Te-Hauturu-o-Toi were not used in the simulation. K_u and K_f were formally elicited from experts; R_{max} was calculated from published information (Armstrong et al. 2007; Armstrong et al. 2002; Doerr et al. 2017) using the method described by Dillingham et al. (2016); other parameters were derived from existing population models (Parlato et al. 2021). K_u carrying capacity without feeding, K_f carrying capacity with feeding, N_f estimated number of females in 2020, P_{mean} probability of detection (logit scale), P_{sd} annual variability in probability of detection, α_{COR}, β_{COR} and T_{COR} parameters for postrelease increase in mortality (Armstrong et al. 2017), R_{max} maximum growth rate (identical across sites).

Site	Parameter								
	K_u	K_f	N_f	P_{mean}	P_{sd}	α_{COR}	β_{COR}	T_{COR}	R_{max}
Te-Hauturu-o-Toi	981.1 ± 413.2	977.7 ± 412.9	not required						0.34 ± 0.066
Bushy Park	13.3 ± 6.7	73 ± 21.3	13.5 ± 3.3	0.03 ± 0.13	0.63 ± 0.1	−0.06 ± 0.37	−2.41 ± 0.86	0.5 ± 0	
Repanga/Cuvier	14.6 ± 8.7	14.5 ± 8.7	0	imputed					
Kapiti	11.0 ± 4.3	109.9 ± 21.8	35.4 ± 5.5	1.46 ± 0.25	1.01 ± 0.23	imputed			
Karori/Zealandia	9.0 ± 4.3	94.6 ± 21.8	25.3 ± 5.9	0.66 ± 0.17	0.80 ± 0.14	−0.43 ± 0.16	−1.05 ± 0.84	0.27 ± 0	
Maungatautari	174.4 ± 112.3	622.0 ± 332.1	42.8 ± 18.4	0.12 ± 0.65	0.52 ± 0.27	0.34 ± 0.24	−1.39 ± 0.33	0.58 ± 0	
Mokoia	2.0 ± 1.7	33.8 ± 10.9	0	imputed					
Rotokare	27.3 ± 13	135.1 ± 38.3	22.3 ± 3.5	1.24 ± 0.27	1.53 ± 0.29	−0.03 ± 0.36	−2.0 ± 0.89	0.22 ± 0.03	
Rotoroa	0 ± 1	4 ± 2.2	0	imputed					
Shakespear	11.7 ± 3.4	60.1 ± 12.8	0						
Taranga/Hen	64.3 ± 42.9	64.8 ± 42.2	0						
Tāwharanui	7.5 ± 5	86.9 ± 20.2	0						
Tiritiri Matangi	5.7 ± 3.6	101.7 ± 14.2	92.9 ± 5.3	1.18 ± 0.19	1.31 ± 0.17	0.64 ± 0.08	−10.07 ± 1.55	0.07 ± 0	

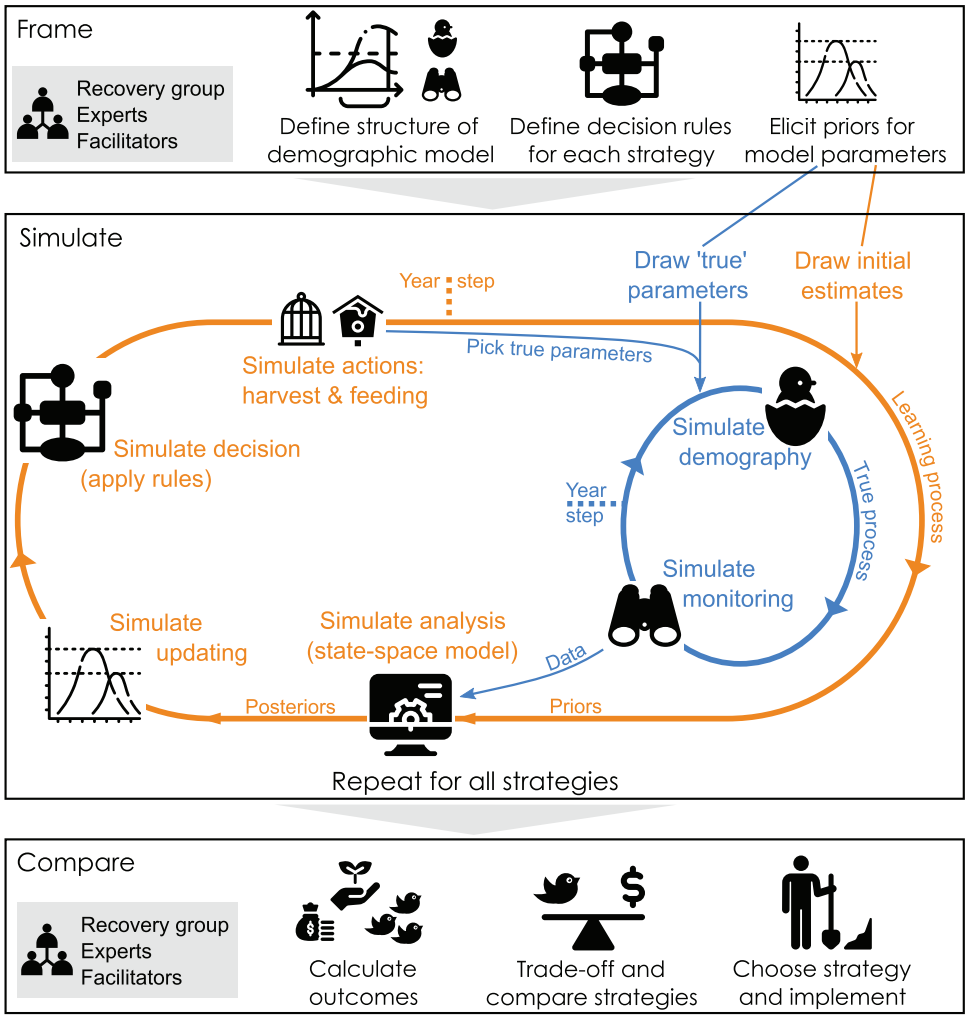

FIGURE 1 | Illustration of our planning process. First, we worked with the recovery group, experts and stakeholders to frame the problem and define alternative strategies, model structures and priors. Second, we simulated each strategy multiple times, drawing the "true" parameters for each simulation from the priors. We simulated the annual true demographic and observation processes, and the learning and decision-making processes; decisions then influenced next year's true process, changing population sizes and carrying capacities through harvest and feeding, respectively. Third, we provided the expected outcomes of each strategy from simulation results to the Recovery Group, who expressed their preferences and made a final decision. Icons made by Freepik from www.flaticon.com.

3 | Results

At the end of the 20-year simulation, strategy *Status quo*, where all sites were always fed, had the largest total population size on average across simulations; strategy *Visitor*, where food was removed from all populations above a given population size, had the smallest population size (Figure 2A). *Status quo* created the most populations, followed by *Sequential* and *Reinforcement*. *Status quo* was most expensive over the 20 years and *Visitor* cheapest (Figure 2C). Feeding intensity was lowest for *Visitor* and highest for *Status quo* (Figure 2D). Advocacy potential, measured as number of site visitors, was generally greater for strategies that allowed more populations (Figure 2E). The strategy rankings for the different objectives were generally constant across different values of fed or unfed carrying capacity (Supplementary Information).

Most strategies reached their maximum number of populations within 5–7 years, except *Reinforcement*, which took the entire period (Figure 2A). Total population size grew similarly for most strategies, approaching carrying capacity at the end of the 20 years, except for strategy *Visitor*, which began to stabilize after 10 years (Figure 3B). Costs grew similarly for all strategies, although with different final outcomes (Figure 3C). After the first 5–6 years, feeding intensity usually remained constant (Figure 3D). Strategies involving more active learning were slightly better at reducing uncertainty about unfed carrying capacity (e.g., ΔCV for K_{unfed} was ~0% for *Status quo*, −12% for *Seasonal*, −16% for *Visitor*, and −14% for *Reinforcement*; Supplementary Information). Conversely, conservative strategies that involved more releases supported by feeding allowed slightly better learning about fed carrying capacity (e.g., ΔCV for K_{fed} was −31% for *Status quo*, −25% for *Seasonal*, −20% for *Visitor*, and −24% for *Reinforcement*). Learning was often limited more by site characteristics than by strategy: at sites with high variability, carrying capacities were over- or underestimated consistently across strategies (Supplementary Information).

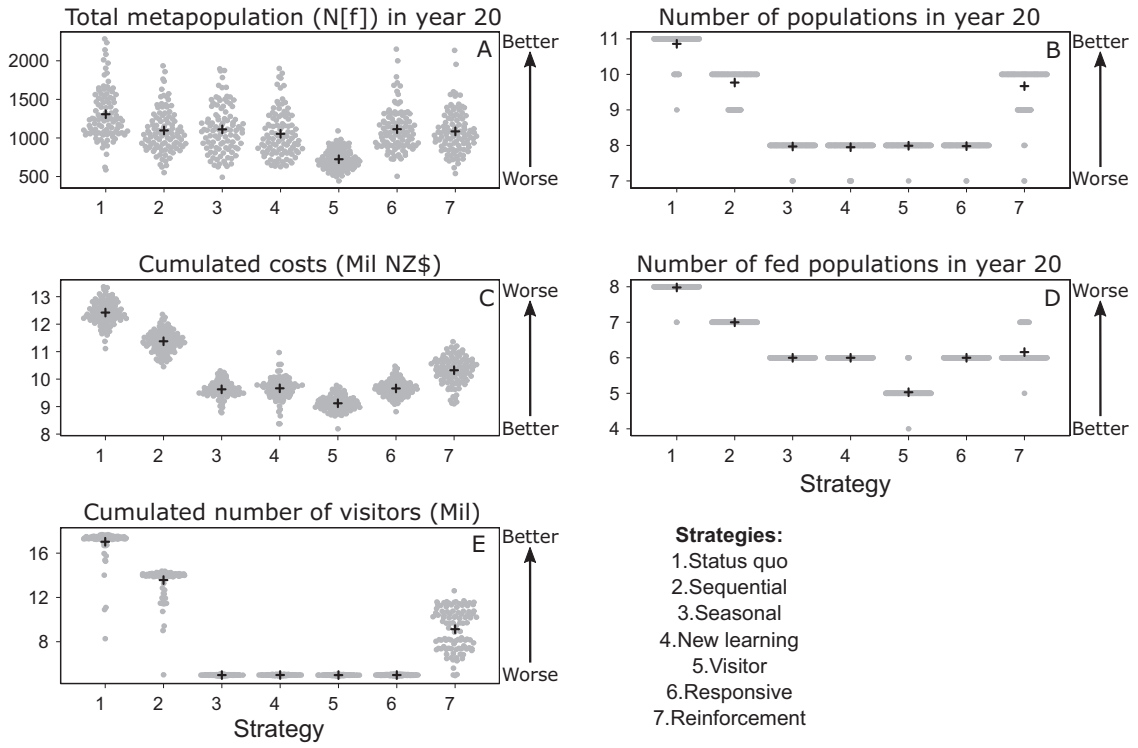

FIGURE 2 | Performance of alternative adaptive management strategies against the five fundamental objectives. Points indicate the outcomes of 100 simulation runs for each strategy (randomly offset on the *x*-axis to reflect density), crosses indicate mean outcomes across simulations. Note *y*-axis limits differ to match the range of results. Numbers indicate strategies (refer to Table 1).

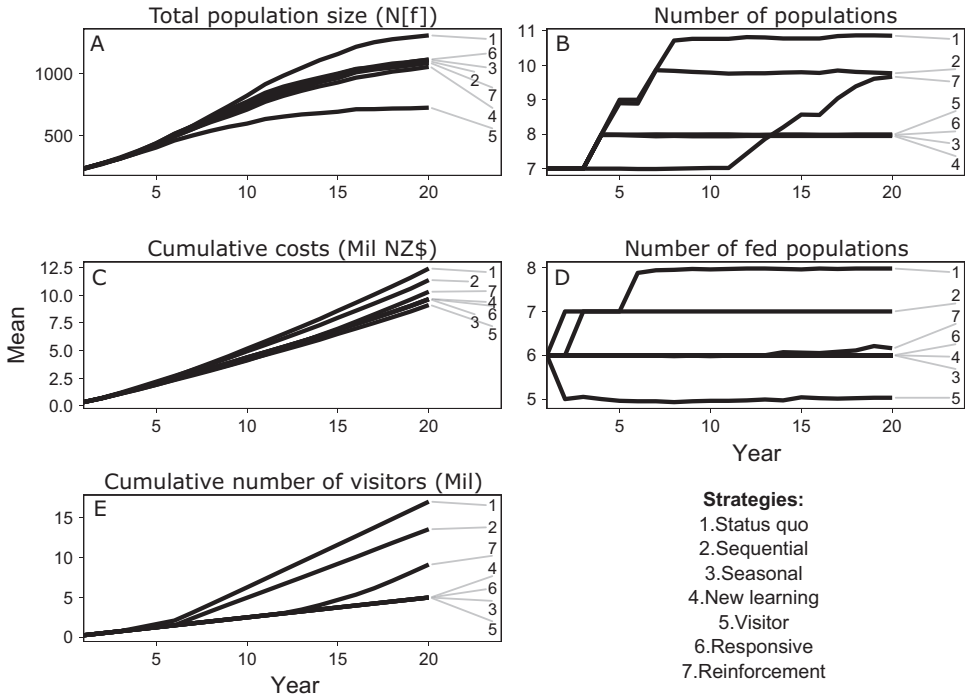

FIGURE 3 | Accumulation of outcomes for individual strategies over time. Black lines indicate mean outcomes across 100 simulation runs for each strategy (uncertainty not shown for clarity—refer to Figure 2). Numbers indicate strategies (refer to Table 1).

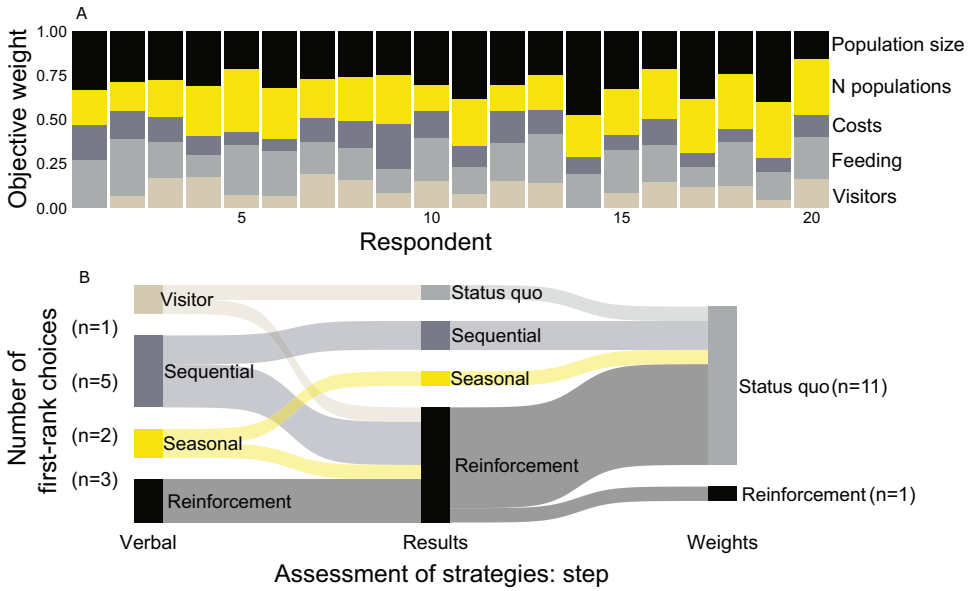

FIGURE 4 | **(A)** normalized preference weights expressed by recovery group members ($n = 20$) when looking at average predicted outcomes across strategies (for weights in worst- and best-case scenarios, see Supplementary Information). **(B)** top-ranked strategy by individual group members ($n = 12$) when looking at (1) verbal descriptions of strategies, (2) visual and statistical summaries of simulation results, and (3) aggregate scores from multi-criteria decision analysis based on objective weights in **A**. Hihi color palette from R package Manu (Thomson 2022).

Before seeing results, 9/12 respondents preferred learning-oriented strategies (*Sequential*, *Seasonal*, and *Visitor*), only 2/12 chose *Reinforcement* and none chose *Status quo* (Figure 4B). After seeing results, 6/12 changed to a more conservative strategy (*Reinforcement* or *Status quo*; Figure 4B). Based on elicited objective weights, 11/12 would choose either *Status quo* and 1/12 *Reinforcement* (Figure 4B). The ranking was driven mostly by objective weights and was generally robust to parametric uncertainty (Supplementary Information). Total population size was mostly ranked as the first or second most important objective (13/20 and 5/20 respectively), as was number of populations (first for 5/20 and second for 10/20), and naturalness (feeding) was the third most important objective (17/20 ranked within the first three objectives).

4 | Discussion

Our results illustrate some well-known dynamics of adaptive management, as well as the advantages and limitations of our simulation-based approach. As expected, more conservative strategies led to more and larger populations but also to increased cost and human interventions. However, the range of outcomes and trade-offs across strategies was smaller than expected, and the benefits of riskier learning did not offset its short-term costs. Hereafter, we reflect on how these results may reflect real constraints to learning, the composition of our working group, and the attitude of HRG members.

The trade-off between the benefits and costs of learning depended on prior knowledge, but also on our ability to learn about hihi and to adjust management (Canessa et al. 2015). We also incorporated multiple stochastic processes both in demography and learning, which limited learning so that some strategies consistently under- or overestimated carrying capacities, particularly in early years. Over shorter periods, AM is less effective since there is less time to reap the benefit of improved management (Hauser and Possingham 2008). The 20-year time frame set by the HRG was relatively short even for a fast-maturing short-lived species like the hihi, but provided a realistic assessment of the potential for learning, which is often limited in the short-term management of small populations (Canessa et al. 2019).

Our group composition likely also influenced our results. First, our strategies, although different, remained within the group's comfort zone. Candidate new sites were those considered broadly suitable by the HRG, and most strategies involved fail-safe response to local declines by restoring feeding or reinforcement releases. Second, prior knowledge limited the ranges of the "true" parameters, constraining the possible outcomes. The long-term hihi program provides high-quality data to inform simulations, but the accumulated experience and interactions might have constrained the experts' thinking. Riskier learning might involve releases at sites with lower estimated carrying capacities, or not responding to local declines, to accelerate learning even at the cost of local failure. In practice, however, trade-offs may be complex. For example, by releasing at sites with lower carrying capacities, or removing food, we could learn about carrying capacities to establish more populations or at least avoid unnecessary feeding (lowering costs and increasing naturalness). However, where carrying capacities turned out to be lower than expected, the benefits of learning were offset by fail-safe responses, locking in more intensive management and disrupting learning about unfed *K*. In future iterations, we might include such high-risk strategies directly in the model, to help understand the potential for learning or, at the other extreme, the consequences of no learning, for example by abandoning monitoring completely. Such strategies could be added directly by facilitators or elicited from another expert group external to hihi. Similarly, uncertainty could be added by allowing true

parameters to randomly fall outside the priors defined by experts, encouraging the same experts to specify broader priors, constructing a range of optimistic and pessimistic scenarios with specific a priori combinations of parameters rather than drawing from the entire parameter space, or including external input to add diverse knowledge and stimulate discussion in the elicitation. Such creative thinking can be uncomfortable, but it will help fully exploit the realism provided by the simulation-based approach.

Once confronted with the limited trade-offs found in the simulation results, most HRG partners revised their original motivation to shift to more active learning strategies. The agreement among group members became greater than initially expressed during discussions and was robust to uncertainty in the key parameters. The eventual choice of maintaining a relatively conservative strategy was thus a rational, transparent one, rather than a biased preference for the status quo (Ritov and Baron 1992). Even simply defining and coding the strategies highlighted logical pitfalls. For example, we initially chose release sites based on their fed carrying capacity. However, this was a poor criterion if we expected feeding to eventually stop, because removing feeding from sites that have overshot their non-fed carrying capacity can lead to population crashes. Formalizing strategies also forced us to clearly specify decision rules, for example, how to split ties between candidate release sites. Such issues might seem obvious in hindsight, but only surfaced because AM requires explicit rules, unlike vague trial-and-error (Runge 2011).

This study was possible because the HRG already implements a structured decision-making approach, of which AM is a special case (Runge 2011). The group already had clearly defined objectives with measurable attributes, a model for quantitative predictions, and experience in solving trade-offs by expressing preference weights (Ewen et al. 2014). These steps are also recommended for MSE (Punt et al. 2016). Building on this basis, we could address the AM problem of whether and how learning would improve outcomes for the fundamental objectives. We did not seek to know exactly how many birds to harvest or which site to feed for a given state of uncertainty, but to find the best rules for making that decision in whatever uncertainty state the future may bring. Comparing strategies, we sought the best way to learn and adapt, although this best solution was limited to the predefined set of strategies and not mathematically optimal (Chadès et al. 2017; Walters 1986).

The complexity of the hihi recovery plan, with many populations, objectives, actions, and uncertain parameters across space and time, would likely make it intractable for AM optimization, although emerging approaches may address this limitation (Chapman et al. 2023). The before-after comparison of strategy rankings by HRG members suggests this problem is also too complex to solve by intuition alone. Our simulation-based approach provides an alternative approach: it is more deliberative than a non-adaptive solution and more realistic than some extreme simplifications needed for optimization-based AM. Managers and scientists must work together to find the right degree of simplification; our simulation-based approach provides an additional, flexible tool to support AM for species recovery programs that involve complex decisions across multiple dimensions.

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Data Availability Statement

All data used in this study are provided in the text and in supplementary information. Code and data are also available from https://github.com/canessas/Hihi_AdaptiveMgt_2024_SupMat.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.