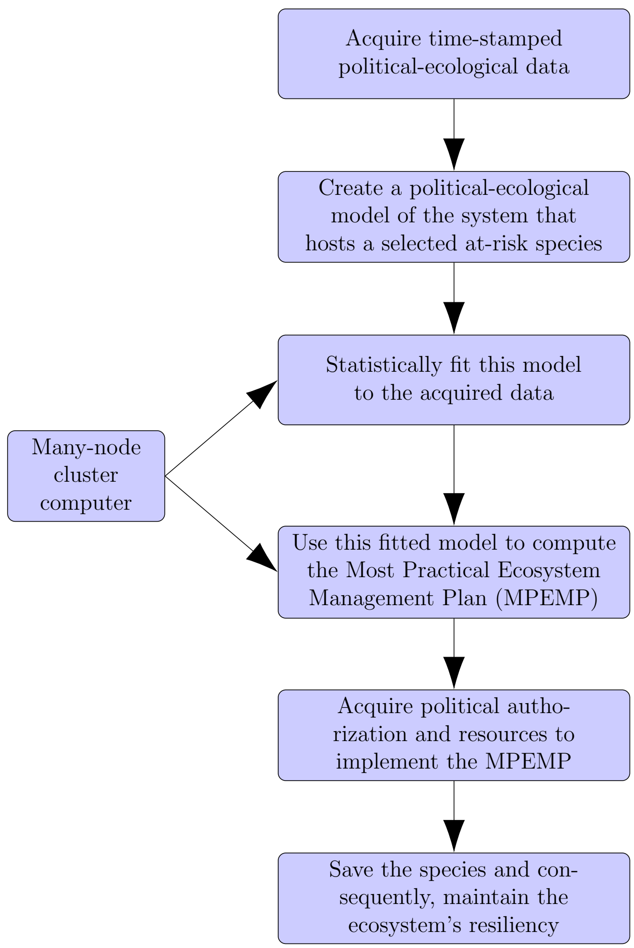
Graphical Abstract

Using Political-Ecological Models to Sustain Biodiversity

Timothy C. Haas[a,b,c]



Highlights

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- A first of its kind toolkit finds feasible and effective ecosystem management plans.
- This toolkit is applied to the conservation of the East African cheetah.
- To support the toolkit, a new optimization algorithm is developed.
- The statistical estimation of political-ecological model parameters is now possible.
- This algorithm also makes ecosystem management plan computations possible.

Using Political-Ecological Models to Sustain Biodiversity

Timothy C. Haas[a,b,c]

[a]*Lubar College of Business, University of Wisconsin-Milwaukee, 3202 N. Maryland Ave., Milwaukee, 53201, WI, United States*
[b]*UCLA Department of Computer Science, Los Angeles, CA, United States*
[c]*Profitable Biodiversity, Los Angeles, CA, United States*

Abstract

Because of the irreversibility of a species' global extinction, the chances of future extinction events need to driven to zero across a wide range species, both flora and fauna. A necessary step towards reducing these chances is to find and implement politically feasible ecosystem management plans that can head off extinction events. This article's first contribution is a first of its kind software toolkit that implements one way to find these plans. This toolkit provides an organization the means to (1) build a political-ecological model; (2) fit this model to a political-ecological data set; and finally, (3) use this model to compute the *most practical ecosystem management plan* (MPEMP). This model-based approach to first understanding the political issues surrounding the conservation of a selected endangered species and then second, finding a conservation plan that works with these political realities – is hamstrung by the challenging and expensive computations needed to first, fit a political-ecological model to data and then second, compute the MPEMP from this fitted model. Therefore, this article's second contribution is a new optimization algorithm that overcomes this challenge when it is run on a cluster computer. This new algorithm finds the global solution to an optimization problem characterized by constraints and a black-box, stochastic objective function that may have multiple extrema and jump discontinuities. This toolkit is illustrated by finding the MPEMP for conserving the cheetah (*Acinonyx jubatus*) population across Kenya and Tanzania.

Email address: `haas@uwm.edu` (Timothy C. Haas[a,b,c])
URL: `https://profitablebiodiversity.com` (Timothy C. Haas[a,b,c])

Keywords: extinction crisis, biodiversity conservation, political-ecological models, model credibility, ecosystem management, robust statistical estimators, optimization algorithms, high performance computing

Abbreviations:

CA: Consistency Analysis
HJ: Hooke and Jeeves optimization algorithm
IBM: Individual Based Model
MDAS: Multiple Dimensions Ahead Search
MPEMP: Most Practical Ecosystem Management Plan
NGO: Nongovernmental Organization
PACSA: Parallel Asynchronous Coupled Simulated Annealing
SA: Simulated Annealing
SA-MDAS: Simulated Annealing – Multiple Dimensions Ahead Search
SDE: Stochastic Differential Equation
TSCC: Triton Shared Computing Cluster

1. Introduction

Earth is in the midst of an extinction crisis (Torres-Romero et al., 2024), (Garber et al., 2024) with many species becoming globally extinct every year (Verones et al., 2022). Global extinction of a species is irreversible. Assuming that the end goal of environmental and ecological conservation efforts is to sustain ecosystems in states that are close to those circa 2025, it can be argued that conservation efforts that directly contribute to stemming irreversible ecosystem state changes should be given the highest priority both politically and financially. To support these efforts, this article delivers a toolkit that can help to (a) develop *political-ecological* models that can credibly gauge likelihoods of global extinction events; and (b) develop ecosystem management plans based on these models that can reduce these likelihoods.

Specifically, this article makes two contributions to the challenge of *global biodiversity conservation*. The first is to make available a free and publically accessible toolkit for modeling political-ecological systems that host one or more species that are at risk of global extinction. Refer to such a species as being *at-risk*. This toolkit can be used to find politically feasible and ecologically effective ecosystem management plans. Here, an ecologically effective ecosystem management plan is one that predicts a viable population of the at-risk species over the planning horizon.

Based on the urgency of the global extinction crisis, this article's toolkit or a similar one needs to be used immediately by many research groups to find implementable and effective ecosystem management plans that can stem the negative trends in abundance currently being exhibited by many of the earth's species.

This toolkit is apparently new because a literature search failed to find another toolkit that (a) supports the statistical estimation of a political-ecological model followed by (b) the use of that fitted model to find an ecosystem management plan that is both politically feasible and ecologically effective.

The article's second contribution is a new optimization algorithm that makes practical, the use of cluster computers to statistically fit these political-ecological models to data sets composed of both political actions executed by groups that impact the ecosystem that hosts an at-risk species – and observations on ecological variables such as that species' abundance through time. This second contribution is critical for the successful application of this article's toolkit.

To use this toolkit, an organization first, statistically estimates the parameter values of a political-ecological model. They then use this fitted model to compute the *most practical ecosystem management plan* (MPEMP) (Haas, 2011, Chapter 4). Accordingly, this toolkit is referred to here as the *MPEMP Constructor*.

This article takes a broad view of what constitutes biodiversity to include species that may not have any commercial value but are listed as Vulnerable or Endangered on the IUCN Red List (Panwar et al., 2023), (Testa et al., 2025), (Tobias et al., 2025). Such species include many terrestrial mammals, marine mammals, fish, and many plants.

The private sector, although paying lip service to the conservation of such species, actually has a strong economic interest in biodiversity conservation that is focused mainly on the preservation of potentially profitable genetic resources. The commercial value of these resources was approximately USD44 trillion in 2022 (Medlong et al., 2022). The total budget of NGOs engaged in preserving endangered species by comparison, is in the neighborhood of USD12 billion (Wan, 2023). The efforts of the many professionals engaged in work to curb biodiversity loss, although laudable, is dwarfed by the efforts in the private sector to profit from biodiversity resources. In other words, the big money is being spent on preserving species that have high commercial potential rather than on species that, in-part, define the word, "wild."

Some efforts are being made, however, to encourage more private sector spending on species who have no commercial value but do have (1) *existence value*, (2) *bequest value*, or (3) *ecosystem function value*, i.e., the species performs important ecosystem-support functions. Existence value is the perceived value of knowing that a species exists, and bequest value is the perceived value of conserving a species for future generations (Ressurreição et al., 2012).

Beverdam et al. (2025) for example, call for a "blending" of private and public sector funds to conserve species that are not commercially valuable. An example of this type of financing mentioned by these authors is the so-called "Rhino Bond" that targets the conservation of the commercially valueless black rhinocerous (*Diceros bicornis*) in Africa.

1.1. The way forward

The concept that this article is offering a realization of, is a toolkit that can find conservation plans that are ecologically effective and politically feasible to implement. After describing how this concept is realized in software, this article gives a proof of this concept by finding a management plan for the East African cheetah that requires minimal changes to the political beliefs of those groups surrounding this biodiversity conservation challenge while predicting that the cheetah population will remain viable through the planning horizon.

As an example of this article's approach to biodiversity conservation, Haas and Ferreira (2017) build an agent/individual based model of the political-ecological system that surrounds rhinoceros (*Ceratotherium simum*) poaching in South Africa. These authors simulate several management options and predict that under current management policies, rhinos in South Africa will become extinct around the year 2036.

Such models, however, are in their infancy but need to quickly mature because at present extinction rates, many species including most large mammals will be globally extinct by about 2055 (Ceballos et al. , 2015). In other words, if present trends continue, a significant proportion of the earth's species will soon be gone due mainly to the activities of the most recent (circa 2025) several generations of humans.

This article gives a tested toolkit, namely, the MPEMP Constructor that can be used to (a) model such political-ecological systems; and (b) based on such models, compute ecosystem management plans that, when implemented, fend off species extinction events. The MPEMP Constructor toolkit streamlines the construction of an integrated model composed of agent-based submodels of political processes that interact with a hybrid individual-based population dynamics submodel of the at-risk species that has been selected for conservation.

What mechanisms of biodiversity loss would such models represent? Habitat loss is often pointed to as the principal driver of global biodiversity loss (Hanski, 2011). But recently, one study could find no statistical difference between loss of habitat and *direct exploitation*, i.e., intentional harvesting of wildlife either legally or illegally (Jaureguiberry et al., 2022). Illegal harvesting and illegal trading of wildlife is referred to as *wildlife trafficking*. The scale of exploitation-curbing biodiversity conservation projects that is needed to slow the globe's ongoing biodiversity losses, is much larger than the sum total of currently active projects. To help address this disparity, the MPEMP Constructor is engineered to focus on the modeling of direct exploitation drivers of biodiversity loss.

Recently, the literature has called for a more holistic view of biodiversity conservation rather than a focus on single species preservation (Tobias et al., 2025). This view, called "process-based" by Tobias et al. (2025) argues that maintaining ecological processes that drive critical ecosystem functioning, should be the primary goal of biodiversity conservation initiatives. These processes include adaptation, gene flow, dispersal, and trophic interactions.

Acknowledging that the goal of avoiding the extinction of species that have evolved over millions of years is not to be abandoned, Tobias et al. (2025) call for a synthesis of species-centric and process-based approaches to biodiversity conservation:

> "We advocate integration and communication across the two primary cultures of conservation—species-centric and process-based—as the most effective progress will occur when these two missions operate in tandem and synergistically ((Tobias et al., 2025))."

Process-based approaches to biodiversity conservation, however, have yet to wrestle with direct exploitation effects on an ecosystem's functioning.

Such integration is straightforward within the methods detailed in this article. For instance, *functional diversity* (FD) is one way to describe the healthy functioning of an ecosystem. FD can be quantified from remotely-sensed NDVI data (Li et al., 2025). And, *trophic transfer* between predators and their prey can be quantified with the *AB ratio* reviewed in Carroll et al. (2019). These two metrics can easily be added to the species abundance objective function employed in this article to arrive at an analysis and planning workflow that integrates species-centric goals and process-based goals.

The MPEMP maximally increases the probability of a species' survival while requiring the least change in the beliefs held by identifiable groups of humans in those countries that host a selected at-risk species. Indeed, according to Haas (2024c), any project that is intended to sustain biodiversity needs to have its MPEMP computed so that the conservation project can either be modified to enhance its conservation effectiveness – or abandoned altogether and replaced by a project that implements the MPEMP. MPEMP Constructor guides the user through this MPEMP computation.

An organization would use the MPEMP Constructor to complete the following five steps.

1. Acquire a data set that pertains to the political-ecological system that hosts a selected at-risk species.
2. Create a political-ecological model of this system.
3. Compute statistical estimates of this model's parameters.
4. Display and assess the political-ecological actions generated by this fitted model.
5. Compute the MPEMP from this fitted model and implement it.

This five-step procedure has application in a business-oriented approach to conserving a selected at-risk species (Haas, 2022), (Haas, 2024c). Briefly, revenue from a commercial *offering* funds a *biodiversity project*. This project operationalizes the MPEMP that has been computed for that species and the political-ecological system that hosts it.

This article proceeds as follows. A description is given in Section 2 of this *interacting influence diagrams* modelling architecture (Haas, 2011, Chapter 2). Then, as an example, this architecture is used to build a model of the political-ecological system that hosts the East African cheetah (*Acinonyx jubatus*) population. A new cluster computer-based optimization algorithm is presented in Section 3 that has developed out of proposals advanced by Haas (2024). The above model is fitted via this new algorithm to a *political-ecological actions history* data set in Section 4. Statistical estimates of this model's parameter values found via Consistency Analysis (CA) (Haas, 2011, Chapter 3) are computed by running the new optimization algorithm on the Triton Shared Computing Cluster (TSCC) at the San Diego Supercomputer Center (San Diego Supercomputer Center, 2025). In Section 5, this statistically estimated model is used to compute the associated MPEMP. Section 6 contains a list of institutional challenges that need to be overcome before such models can be widely used to identify extinction-avoiding management plans. Some conclusions are reached in Section 7.

2. An Integrated Political-Ecological Model

2.1. Why do submodels need to be integrated?

Given a model composed of political submodels and an ecosystem submodel, if actions that are generated by political submodels do not impact the ecosystem submodel at model-generated time points – and ecosystem submodels actions do not in turn, affect these political submodels, then feedback loops between political processes and ecological processes cannot emerge.

For instance, if a climate model is exogenously set to a schedule of reductions in carbon emissions forcing, there is no mechanism for modelling the vicissitudes of political support for climate policy. Such vicissitude might take the form of a sequence of governmental administrations alternately supporting and then not supporting climate change mitigation policies. The jagged time series of carbon emissions that results from this support-nonsupport policy record cannot be realistically simulated unless this sequence of different administrations and the effects of their actions on earth's climate is represented in the simulation model. Hence, there needs to be an *integrated* model of political processes interacting with ecological processes. In this article, the main ecological process that needs to be modeled is the population dynamics of an at-risk species.

2.2. Advantages of an individual-based model of an at-risk species

As Netz et al. (2022) note,

> "To allow for mathematical analysis, models of predator–prey coevolution are often coarse-grained, focussing on population-level processes and largely neglecting individual-level behaviour. As selection is acting on individual-level properties, we here present a more mechanistic approach: an individual-based simulation model for the coevolution of predators and prey on a fine-grained resource landscape, where features relevant for ecology (like changes in local densities) and evolution (like differences in survival and reproduction) emerge naturally from interactions between individuals" (Netz et al., 2022).

2.3. Example: The East African cheetah population

The cheetah is listed as Vulnerable on the IUCN Red list and as Endangered by the Namibian government (Milloway, 2025). Countries that host cheetah populations include Kenya and Tanzania (Durant et al., 2022). These two countries share a border and hence have the potential of interacting with each other politically. Therefore, as an example, a political-ecological model is built of the cheetah-hosting political-ecological system enclosed by these two countries. This model consists of submodels of several groups that affect the cheetah population, and an ecosystem submodel of East African cheetah population dynamics. All of these submodels interact with each other through time.

This agent/individual-based political-ecological model of the cheetah-hosting ecosystem contained within Kenya and Tanzania, is new.

2.3.1. *Submodels interact through a bulletin board*

At each time step, each group submodel and the ecosystem submodel read actions directed against themselves from a bulletin board. Conditional on a read-in input action, a group submodel computes the expected value of *overall goal attainment* that they believe they will receive if they implement a particular action-target combination. After making this computation for all action-target combinations in their repertoire, they post to the bulletin board the combination that has the highest expected overall goal attainment. The Ecosystem Management Actions Taxonomy (EMAT) (Haas, 2024b) dictates what actions a submodel recognizes and what it holds in its repertoire of output actions.

The ecosystem submodel reacts to actions directed against it by adjusting its output of cheetah and prey abundance across time. For instance, if at a particular time point during the simulation, this submodel reads in a poaching action, it will immediately reduce cheetah abundance by some amount.

2.3.2. *Group submodels*

Submodels represent Kenya's presidential office, the Kenya Wildlife Service, the rural residents of Kenya, and the pastoralists of Kenya. Similar submodels are constructed for Tanzania. A ninth group submodel is constructed of a conservation-focused nongovernmental organization (NGO) that runs conservation projects in both of these countries.

Haas (2011, Chapter 2), Haas and Ferreira (2017), and Haas (2025) detail the cognitive theory and causal flow that these submodels use to decide what action to implement based on (a) their beliefs; and (b) those actions that have been directed against them (called *input actions*). Specifically, these group decision making submodels make decisions that they believe will further their own set of goals without regard to the goals of other groups and, except for the wildlife protection agency groups, without regard to what effects their actions might have on the ecosystem or the abundance of any particular species.

2.3.3. Cheetah-hosting ecosystem submodel

The ecosystem submodel tracks the dynamics of the trans-Kenya-Tanzania cheetah population (abundance through time). This submodel interacts with the above rural resident and pastoralist group submodels. Cheetah are individually modeled following the individual-based model (IBM) paradigm. For simplicity, however, this IBM interacts with a stochastic differential equation (SDE) submodel of cheetah prey such as Thomson's gazelle (*Gazella thomsoni*) (Fitzgibbon, 1990). Both the cheetah IBM and the herbivore SDE represent population dynamics stochastically.

This synthetic predator-prey submodel is new and extends a model described in Kimbrell and Holt (2005).

Parameterization of this submodel follows a set of data-based values reported in Kelly et al. (1998):

> "Data are presented on the demography and reproductive success of cheetahs living on the Serengeti Plains, Tanzania over a 25-year period. Average age at independence was 17.1 months, females gave birth to their first litter at approximately 2.4 years old, interbirth interval was 20.1 months, and average litter size at independence was 2.1 cubs. Females who survived to independence lived on average 6.2 years while minimum male average longevity was 2.8 years for those born in the study area and 5.3 years for immigrants" (Kelly et al., 1998).

Working from this information, Table 1 contains the parameter values used in the cheetah IBM and the prey SDE.

Using the constants in Table 1, The cheetah abundance submodel produces 963 cheetah at the end of the 2020-2025 time span assuming a poaching rate of one cheetah per week. If all cheetah poaching is turned off, the submodel produces 1565 cheetah at the end of 2025.

Parameter	Value
Cheetah	
Initial (2020) abundance	1744
Female life expectancy	6.2
Male life expectancy	2.8
Age at maturity	1.42
Female sexual maturity	2.4
Interbirth interval	1.675
Herbivores	
Initial abundance (minor poaching)	2250
(moderate poaching)	4500
(severe poaching)	8750
Birth rate − death rate (minor poaching)	-0.003
(moderate poaching)	-0.014
(severe poaching)	-0.017
White noise multiplier (minor poaching)	0.001
(moderate poaching)	0.001
(severe poaching)	0.001

Table 1: Ecosystem submodel parameter hypothesis values. Initial cheetah abundance is from Durant et al. (2022) (see below). Cheetah IBM parameter values are derived from Kelly et al. (1998). The temporal unit is *years*. Submodel output of herbivore abundance depicts a negative trend through time that is influenced by the amount of herbivore poaching.

3. A New Optimization Algorithm

To make the use of political-ecological models practical for purposes of giving input into biodiversity conservation planning, an optimization algorithm is needed that can solve the CA and MPEMP optimization problems. These optimization problems have objective functions that are (a) bound-constrained, (b) stochastic, and (c) expensive to evaluate. These objective functions also contain multiple extrema and jump discontinuities. A literature search failed to uncover any optimization algorithm that is designed to find the global extremum of such functions. Therefore, to address this need, a new optimization algorithm is introduced herein that combines Simulated Annealing (SA) (Corana et al., 1987) and Multiple Dimensions Ahead Search (MDAS) (Haas, 2020). This new algorithm is called Constrained Stochastic

Synchronous Coupled Simulated Annealing – MDAS (SA-MDAS).

3.1. Background

Consider an optimization problem wherein an objective function in n dimensions (hereafter, *variables*) is to be *minimized.* A *black-box optimization algorithm* can handle all types of deterministic objective functions without assuming anything about their smoothness or presence of discontinuities. To-date, however, there has been little work on the development of algorithms that can optimize a noisy (hereafter, *stochastic*) black-box objective function.

As reviewed in Haas (2024), one algorithm that is capable of finding the *global* solution to a deterministic black-box objective function is Parallel Asynchronous Coupled Simulated Annealing (PACSA) of Gonçalves-e-Silva et al. (2018). This algorithm however, does not recognize constraints and is not designed for stochastic objective functions.

In addition, when the cooling schedule of Aarts and Korst (1989) is employed within PACSA, computational experience has shown that the use of equation (1) in Gonçalves-e-Silva et al. (2018) causes the maximum accepted function value term to become large as iterations increase. This happens because some of the performers begin to return poor (large) objective function values when their solution chains enter suboptimal subspaces of the solution space. This increased value of the maximum-function term causes the acceptance probability to become small – causing progress towards an optimal solution to essentially stop. For this reason, the asynchronous inter-performer coupling scheme developed in Gonçalves-e-Silva et al. (2018) is not used in SA-MDAS.

Regarding stochastic objective functions, Haas (2024) proposes for future work, the development of an optimization algorithm capable of computing statistical estimates of the parameters of a political-ecological model. This envisioned algorithm would handle (a) *bound constraints*; and (b) stochastic objective functions using the procedure of Branke et al. (2008). Bouttier and Gavra (2019) in contrast to Branke et al. (2008), however, provide a convergence proof for their approach to handling stochastic objective functions within an SA optimization algorithm. For this reason, the Bouttier and Gavra (2019) approach to handling stochastic objective functions is employed in SA-MDAS rather than the approach taken by Branke et al. (2008).

One final background note: In the eighteenth century, the person who organized an opera production was referred to as an *impresario*. The individuals who performed the opera be they singers, dancers, instrumentalists or conductors, were (and are) referred to as *performers* (Holmes, 1994). These terms are used here to refer to different roles given by an optimization algorithm to different compute nodes who collectively, make up a cluster computer (Werstein et al., 2006).

3.2. The algorithm's intended runtime environment

In SA-MDAS, an impresario posts tasks to a *JavaSpace* (Haas, 2020) for performers to take and complete. Once completed, a performer posts a task's results back to the JavaSpace. The impresario then takes these results from the JavaSpace and uses them to decide where next to search. Here, a JavaSpace is implemented via the *GigaSpaces* XAP (Ciatto et al., 2020). SA-MDAS is implemented in the Java$^{\mathrm{TM}}$ language because Java is (a) computationally efficient; (b) easily parallelized; and (c) easy to read and hence, easy to maintain (Haas, 2020).

3.3. Algorithm summary

SA-MDAS uses both SA and MDAS to solve an optimization problem that has a (possibly) stochastic black box objective function and continuous variables that are bound-constrained. Implicit constraints are also accommodated. To ensure finite-time convergence, SA-MDAS employs the cooling schedule of Aarts and Korst (1989, chapter 4).

SA-MDAS employs many performers to both increase the chance that a global solution is found, and to reduce the *wall clock time* (Jiang and Singh, 2010) that it takes to find it. This is accomplished in-part through a new method developed herein called Multiple Periodic Exchange (MPE) – a scheme similar to the class of parallel SA algorithms dubbed *periodic exchange schemes* by Lee and Lee (1996).

A well-known characteristic of SA is its slow rate of convergence (Guilmeau et al., 2021). This drawback is addressed in SA-MDAS by switching the search algorithm from a parallel SA algorithm to a parallel Hooke and Jeeves (HJ) algorithm namely, MDAS.

The result of this *two-phase* architecture (Ferreiro et al., 2019) is an algorithm that takes advantage of SA's global search capability enhanced through cluster computing – but that avoids SA's proclivity for slow convergence by switching to an efficient local search algorithm (MDAS) that also leverages a cluster computing environment. The switch happens only after significant effort has been directed towards finding a subspace that has a high likelihood of containing the global minimum. Specifically, this switch is delayed until the SA step length along any variable becomes so small that the likelihood of a move into a radically different subspace also becomes small.

3.4. Algorithm

1. Global search phase:
    - (a) Set values for n_s (see Appendix), and the chain length. Also, find initial values for each variable's step length, and the control parameter t ("temperature"). Initialize this latter parameter so that the percentage of moves accepted is between 70 and 90. Run this task on the impresario compute node alone.
    - (b) Within SA's inner loop, start each of m performer nodes at the same initial solution.
    - (c) Run these performers simultaneously but independently over one Markov chain.
    - (d) Always accept solutions that deliver a score value that is smaller than *current_value*. Accept other solutions with probability

$$\exp\left\{-(trial\_value - current\_value)/t\right\}. \tag{1}$$

    - (e) Block until all performers have finished their respective chains.
    - (f) Update the sample size used to compute the average value of a stochastic objective function. Also update each variable's step length.
    - (g) Update t via the rule developed in Aarts and Korst (1989, Chapter 4).
    - (h) Return if a solution has been found such that the score function has been reduced to 90% of its initial value. Otherwise, continue to Step *i*.

(i) Execute MPE by reinitializing every performer with the solution that gave the current smallest score value.

(j) Go to Step *c*.

2. Local search phase:

(a) After the SA subalgorithm has returned, use the returned solution as the starting solution in an MDAS run. Set the MDAS algorithm to search forward three variables at a time.

(b) Run MDAS to convergence and then stop. The convergence criterion is the relative change in the objective function between two successive reductions in the objective function's value (Wright et al., 2009):

$$|f(\mathbf{x}_k - f(\mathbf{x}_{k-1})|/f(\mathbf{x}_{k-1}) \leq \epsilon \tag{2}$$

where $f(.)$ is the negative of the CA objective function. This criterion begins to be evaluated only after the algorithm has computed its first 500 function evaluations.

3.4.1. Convergence properties of SA-MDAS

Given a bound-constrained, continuous function, Lewis and Torczon (1999) prove that the HJ algorithm converges to a local extremum (see also Polak and Wetter (2003)). Because MDAS is an extension of HJ, MDAS enjoys at least the convergence properties of the well-understood HJ algorithm.

As mentioned above, SA is known to be capable of finding the global extremum. And MDAS is known to be able to find the closest local extremum. Therefore, the convergence properties of SA-MDAS are known for the case where both phases are allowed to converge.

The Appendix contains details of how SA-MDAS handles continuous variables and stochastic objective functions. Details are also given on (a) the overhead that the algorithm incurs from its need to pass messages between compute nodes; (b) how it performs on standard test functions; and (c) how it compares to other optimization algorithms.

3.5. Algorithm performance on a relevant objective function

To see if SA-MDAS can solve real-world CA and MPEMP optimization problems, it is used here to optimize an interpretable objective function that is similar to those found in both the CA and MPEMP. This test function consists of a (smooth) quadratic polynomial component, one jump discontinuity, and a stochastic component as follows.

$$f(x,y) = \begin{cases} -(x^2-1)^2 - (x^2y - x - 1)^2 & \\ \quad + 0.1Z, & x \in (-1.5,\ 0),\ y \in (-0.5,\ 2.5) \\ -(x^2-1)^2 - (x^2y - x - 1)^2 & \\ \quad + 10.0 + 0.1Z, & x \in (0,\ 1.5),\ y \in (-0.5,\ 2.5) \\ -1.0, & \text{otherwise} \end{cases} \tag{3}$$

where $Z \sim N(0,\ 1)$. There are two extrema: A smaller one at $(-1,\ 0)$ and a larger (global) one at $(1,\ 2)$. This function is adapted from Cook (2017).

The use of a noisy quadratic polynomial to represent CA's simulated Hellinger distance component (Haas, 2011, Chapter 11) is justified as follows. First, Wu and Karunamuni (2012) show that for many density functions, the Minimum Hellinger Distance (MHD) estimator is smooth in the parameters being estimated. Second, the test function's additive noise mimics the stochasticity of simulated Hellinger distance (SMHD). As an aside, SMHD is known to be a consistent estimator (Luong and Bilodeau, 2017).

SA-MDAS is started at $(-1.2,\ -0.4)$. This point is close to the smaller, non-global extremum and is chosen in order to see if SA-MDAS can find the global extremum when started close to a non-global one. After 1759 function evaluations, the SA component converged. Then, after 4320 more function evaluations, the MDAS component converged to the global extremum. The stochastic sample size was initialized at three. During the course of the search, this value was increased to first, eight, and then 36. Based on this test, it appears that SA-MDAS is capable of solving CA and MPEMP optimization problems.

4. Statistical Estimation of a Political-Ecological Model

4.1. Overview of the CA estimator

The CA estimator of Haas (2011, Chapter 3) produces a set of *consistent* parameter values such that model output balances agreement with data versus agreement with cognitive theories of decision making. To do this, an objective function is defined to be the priority-weighted sum of standardized measures of the agreement with a data set (g_S), and the agreement with the model's joint probability distribution across its stochastic nodes (hereafter, *distribution*) under *hypothesis* parameter values (g_H). The value of $ch \in (0,\ 1)$ is the relative priority given to having the *consistent* (estimated) model's distribution agree with the one specified by the hypothesis parameter values – versus agreeing with the data (here, an observed actions history): $g_{CA} = (ch)g_H + (1 - ch)g_S$. The distribution that emerges when the parameters of all submodels are set at their CA-estimated values, is called the *consistent distribution*.

When ch is 0, CA becomes a frequentist statistical estimator. When ch is 1, CA finds parameter values that result in the model maximally agreeing with both decision making theory and with ecological theory that collectively, dictate how the political-ecological system is expected to behave through time.

CA fits a model in two stages. Stage I consists of finding parameter values that cause the model to match as many observed actions as possible. Then, this Stage I percentage of action-agreement matches (its *match fraction*) is computed. Next, Stage II adjusts these Stage I parameter values until the model's distribution is as close as possible to the hypothesis distribution while maintaining Stage I's match fraction. The idea behind this two-stage approach is to minimize the occurrence of *jump discontinuities* (Schober and Prestin, 2023). Such jump discontinuities can occur when one or more group submodels switch to different action-target combinations as a result of the optimization algorithm making small changes to the values of some of the model's parameters.

4.2. Objective function

Because of the above-mentioned potential for jump discontinuities, it is important to not accept any trial moves that reduce the match fraction from that achieved in Stage I. This agreement is enforced by adding a large penalty to the objective function if a move causes a reduction in the agreement with the observed actions history. Use of such a penalty function to, in-effect, represent an implicit constraint, works in SA-MDAS because numerical instabilities that might be caused by explosive numerical derivative computations cannot happen because SA-MDAS does not compute such derivatives.

Stage II uses a stochastic agreement function for g_H that is the negative of the Hellinger distance between the consistent and hypothesis distributions. Letting $P(P = i) = p_i$ (and $P(Q = i) = q_i$), for two discrete distributions, this distance is

$$H(P, Q) = \sqrt{\frac{1}{2} \sum_{i=1}^{d} (\sqrt{p_i} - \sqrt{q_i})^2} \tag{4}$$

where d is the number of discrete values that the random variable P (and Q) can take on (Suresh, 2021).

4.3. Stage I's action-matching algorithm

Stage I finds starting parameter values by executing two subalgorithms. The first subalgorithm entails the sequential matching of action-target combinations with those observed. This subalgorithm is as follows.

1. At each time point, check the match between the observed action-target combination and the one generated by the group submodel. If they do not match, replace the submodel's action-target combination with that observed.
2. If this replacement causes the overall fraction of matches to become smaller, reject this replacement.
3. If the end-time has not been reached, go to the next group submodel or next time point. Otherwise, write this *desired actions history* to a file and exit.

The second subalgorithm proceeds by adjusting submodel parameters until model output matches as many action-target combinations in the desired actions history as possible – regardless of its agreement with the hypothesis distribution.

4.4. Results

SA-MDAS is used to statistically estimate parameter values of the political-ecological model of East African cheetah trafficking as follows.

4.4.1. Actions history

Haas (2024b) describes a STAR-compliant protocol for extracting EMAT actions from online sources. Refer to this protocol as the *EMAT actions extractor*. This protocol is used to extract EMAT actions reported in online sources concerning cheetah management in Kenya and Tanzania. Doing so yields 24 actions over the period November 2018 through July 2025 (Table 2).

Date	Actor	Action	Target(s)	Location
2018.80	kenepa	translocate_animals	ecosys	Lewa_Conservancy
2018.80	kenrr	poach_for_cash	ecosys	Lewa_Conservancy
2021.37	tanepa	increase_damage_control	tanrr	Serengeti
2021.39	kenepa	positive_ecoreport	ecosys	Maasai_Mara
2021.42	kenepa	fund_education_grant	ecosys	Samburu Tsavo
2021.58	kenepa	arrest_poaching_suspects	ecosys	Meru_NP
2021.82	kenepa	positive_ecoreport	kenpres	Lewa_Conservancy
2021.84	kenepa	increase_damage_control	kenrr	Tsavo
2021.93	kenepa	translocate_animals	ecosys	Ziwa_Rhino_Sanctuary
2022.49	kenepa	translocate_animals	ecosys	Eastern
2022.49	kenrr	sell_few_rhino_horns	ecosys	Eastern
2022.59	kenepa	translocate_animals	ecosys	Mount_Kenya
2022.62	kenepa	increase_anti-poaching	kenrr	Maasai_Mara_NP
2022.80	kenrr	poach_for_cash	ecosys	Eastern
2022.93	kenrr	poach_for_cash	ecosys	Nairobi
2023.72	kenepa	use_tech._to_find_habitat	ecosys	Narok
2023.83	kenrr	poach_for_cash	ecosys	Nairobi_NP
2024.10	kenepa	translocate_animals	ecosys	Laikipia
2024.46	kenepa	conduct_wildlife_survey	ecosys	Maasai_Mara
2024.51	kenrr	poach_for_cash	ecosys	Kilimanjaro
2024.58	tanepa	positive_ecoreport	tanpres	Ngorongoro_Reserve
2025.14	ngo	donate_dollars_to_NP	ugaepa	Pian_Upe_Reserve
2025.65	kenrr	sell_several_rhino_horns	ecosys	Nairobi
2025.66	kenepa	translocate_animals	ecosys	Nairobi

Table 2: Political-ecological actions extracted from online sources with the EMAT actions extractor

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4.4.2. EMAT actions extractor error assessment

The EMAT actions extractor includes a procedure for assessing the accuracy of the machine detection of actions from online sources. Here, a particular online source is referred to as a *story*. This detection accuracy task is similar to *inter-coder* reliability except that here, only physical actions are detected rather than the presence and/or strength of an expressed sentiment towards an action or object (Brandt and Sianan, 2025). Jalal et al. (2020) finds that detecting an action in text is a less subjective task than the task of judging the amount of sentiment being expressed in a text.

Haas (2024b) gives a procedure for estimating the types of errors that the protocol can make. These error types are as follows.

1. The protocol returns an action from a story but either a different action is present in the story or there is no action in there at all. Haas (2024b) calls this return a *spurious action*. This error is a failure of the *EMAT action parsing/lookup* algorithm.
2. The protocol fails to return any action when, in actuality, an action is indeed present in the story. This error is also a failure of the EMAT parsing/lookup algorithm.
3. The protocol fails to detect a source, actor, subject, date, country, and/or region for the action.

Here, the accuracy assessment procedure of Haas (2024b) is modified to focus only on the first of these error types. This is because

1. The EMAT action parsing/lookup algorithm depends on pre-formed verb phrases, direct object phrases, and prepositional phrases. If these preformed phrases are not comprehensive for the content domain they are applied to, errors can occur.
2. Because the protocol exhaustively searches for verb, direct object, and prepositional phrases, the likelihood that it completely misses an action contained in the story is low. Hence, this type of error is not assessed here.
3. The third error type is not caused by parsing errors but instead, is due to string-comparison failures. With comprehensive files containing the domain's actors, dates, countries, and regions, these types of errors are infrequent. Such comprehensive files have indeed been prepared for the cheetah-hosting political-ecological system that is studied herein.

The error assessment procedure is as follows. Let n_{true} be the number of human-extracted actions from a collection of story files. Let $r_{correct}$ be the fraction of n_{true} that were extracted by the algorithm. Let $r_{spurious}$ be the ratio of the number of spurious actions to n_{true}.

When the protocol executes, an *extraction assessment* file is written that contains story texts along with those actions extracted by the protocol. The values of $r_{correct}$ and $r_{spurious}$ can be computed by manually reading this extraction assessment file and noting the number of true actions; the number of extracted actions that match true actions; and the number of extracted actions that are spurious. Using these values, the protocol's accuracy is estimated with $n_{correct}/n_{true}$, and its chance of returning a spurious action is estimated with $n_{spurious}/n_{true}$.

The protocol was run on two story files containing stories from 2023 and 2024. The author read the resulting assessment file and computed $n_{true} = 25$, $n_{spurious} = 2$, $r_{spurious} = 0.08$, and $r_{correct} = 0.92$. Based on this error assessment exercise, the EMAT actions extractor appears to be at least 90% accurate, while exhibiting a low rate of spurious action detections.

4.4.3. Cheetah abundance data

Cheetah sightings data is typically collected by field ecologists running camera traps or observing cheetah spoor. Based on these data-collection methods, Durant et al. (2022, p. 7) reports that in the year 2020, there were 1744 cheetah scattered across Kenya and Tanzania (Table 3).

Country	Region	Abundance
Kenya	Serengeti/Mara/Tsavo/Laikpia	1250
Tanzania	Ruaha	184
Kenya	North	175
Tanzania	Katavi-Ugalla	55
Kenya	Maasai Steppe	47
Kenya	Turkana	33
	Total	1744

Table 3: Kenya and Tanzania cheetah abundance 2020.

A data file is created based that contains this value of 1744.

4.4.4. Model fitting

The parameters that determine how likely Kenya rural residents and Tanzania rural residents think they will be arrested after they poach cheetah for cash are adjusted so that the model's output agrees with the observed actions history while exhibiting a joint probability distribution across its nodes that maximally agrees with the distribution defined to represent theoretical propositions about these beliefs. This cognitive variable is influenced by a poacher's perception of their current economic status, and their current perception of how much trouble with the police they are already in. The economic status variable takes on the values *negligible, inadequate,* and *adequate.* The imminent-interaction-with-police variable takes on the values *will be arrested for poaching, will be evicted,* and *no interaction with police.* See Haas and Ferreira (2017) for the cognitive theory supporting this variable and its application to rhino poaching in South Africa.

Here, the hypothesis distribution values of these parameters represent the theory that a typical rural resident believes there is little chance they will have any interaction with police after they poach a cheetah for cash. Equal priority is given to agreement with the hypothesis distribution versus agreement with observations ($ch = 0.5$).

This CA is implemented as a 54-variable optimization problem. These variables are the parameters that determine the Scenario Imminent Interaction with Police (SIIWP) node in the Kenya rural resident submodel and the Tanzania rural resident submodel under the conditioning event that a rural resident decides to implement the output action, *poach cheetah for cash.* The model was run over the period January 1, 2022 through December 31, 2025.

SA-MDAS employed four performers with each performer accessing 10 *threads* when performing a parallel Monte Carlo simulation. Each such simulation required 1000 simulated realizations of a submodel's stochastic nodes. Such a simulation was run whenever a submodel received a new input action-target combination at some step in the period that the model was run over.

The wall clock time of the SA-MDAS run was 5.28 hours. Phase one converged after 213 function evaluations. And, using $\epsilon = 0.01$, phase two converged after 520 function evaluations. At its completion, the algorithm had increased the value of g_{CA} by 23.16% (Table 4).

Agreement measure	Symbol	Initial value	Consistent value	Percent increase
Agreement with observed actions history (match fraction)	$g_S^{(Grp)}$	0.563	0.625	11.01
Agreement with observed - cheetah abundance	$g_S^{(Eco)}$	0.000	0.000	0.0
Average agreement between consistent group submodels and hypothesis submodels	$g_H^{(Grp)}$	-0.480	-0.400	16.67
Overall agreement	g_{CA}	-0.359	-0.261	27.30

Table 4: CA agreement measures before and after the SA-MDAS run. Agreement between the ecological submodel's consistent distribution and its hypothesis distribution is not computed because no parameters within this submodel are being estimated.

Figure 1 displays the actions history generated by the CA-estimated model along with those observed actions that are matched by the CA-estimated model. To exhibit typical interaction patterns that are obscured in this Figure, Figure 2 exhibits a closeup of the period from 2024 to 2025.

Figure 1: Model-generated actions history from 2020 through 2025. Green crosses are observed actions matched by the the CA-estimated model. The **o** symbol denotes an observation on cheetah abundance.

Figure 2: Model-generated actions history from 2024 to 2025.

This example shows that SA-MDAS can find CA estimates of a political-ecological model's parameters in a practical amount of cluster computer wall clock time.

4.5. Sensitivity of ch assignment

The value of ch quantifies the priority of finding parameter values that causes the model's output to agree with prior hypotheses about how groups reach decisions in a political space and how the dynamics of a wildlife population unfolds – versus having model output agree with a political-ecological data set. In a highly cited article, Marler and Arora (2010) call these weights *a priori articulation weights* because they are used to express the relative priority the analyst wishes to give to each objective function in the multiobjective optimization problem. For instance, in the above CA example, the analyst wishes to give equal priority to agreement with political-ecological theory and agreement with data. To accomplish this, they set each weight to the value 0.5.

Because a priori articulation weights are analyst-specified, there is no parameter misspecification issue. There is, however, the question of whether a small change in these weights might continue to represent the analyst's priorities but yield a higher value of g_{CA} at the optimization problem's solution. To explore this possibility, the analyst would set ch to a subjectively insignificantly different value from its original value and then rerun the optimization algorithm.

As example of such a sensitivity study, starting at the above-computed solution, the SA-MDAS optimization algorithm is rerun with ch in turn, set to 0.499, and 0.501. Doing so yields g_{CA} values of -0.291, and -0.279, respectively. These values are 11%, and 6% lower than the value of -0.262 when $ch = 0.5$. These results suggest that the CA solution is not overly sensitive to 0.2% departures from $ch = 0.5$.

4.6. Over-parameterization and generalizability

The political-ecological model has more parameters than the number of actions and ecological variable observations contained in the political-ecological data set. For many models, this situation can lead to poor prediction performance (Dhingra, 2024). One well-known example is the class of high-order polynomial regression models. These models can exhibit fitted parameter values that are mostly determined by the noise component in the data set they are being fitted to. The fitting of parameter values to the group decision making submodels, and ecological submodel used herein, however, is disciplined by the need to produce parameter values that are similar to those contained in the associated submodels generated by decision making theory, and ecological theory, respectively. These *hypothesis submodels* by intention, display behaviors that are not noisy. Hence, as a result of CA, the *consistent submodels,* while agreeing with the political-ecological data set, will not be prone to having fitted parameter values that are the result of CA simply fitting to the noise in the data set.

5. Finding the MPEMP

Haas and Ferreira (2017) state that

> "A more general method of developing management policies is the *most practical ecosystem management plan* (MPEMP) of Haas (2011, Chapter 4). The MPEMP emerges from the pattern of group behaviors that results from modifying one or more group belief systems. These modifications are such that the agreement between group belief systems that are estimated from data – and the belief systems that produce group actions that cause a desired ecosystem state, is maximized. In other words, the MPEMP is the sequence of group behaviors that occur from the least change in existing group beliefs systems that still achieves ecosystem state goals" (Haas and Ferreira, 2017).

5.1. What does an MPEMP look like?

An MPEMP can consist of several politically-initiated ecosystem management actions. Actions that can be modeled with the MPEMP Constructor include the following.

- develop alternate livelihoods,
- install wildlife control fencing,
- increase antipoaching efforts,
- relocate animals,
- shoot marauding elephants,
- eradicate invasive plants,
- donate antipoaching equipment,
- plant trees,
- restore mine tailings areas,
- compensate farmers for wildlife damages,
- gazzette land into reserve patches, and
- downgrade, downsize, and degazette protected areas (PADDD) Albrecht et al. (2021).

See the file `emat.dfn` in the Supplementary Materials file, `data.zip` for a complete list of ecosystem-affecting political actions as gleaned from political-ecological data acquired using the EMAT actions extractor.

5.2. MPEMP computation

Finding the MPEMP involves solving an optimization problem. This optimization problem is constrained by the requirement that any solution needs to produce values of the ecosystem submodel's output variables that are close to the desired values at the desired point in time. This implicit constraint is incorporated into the MPEMP optimization problem as a penalty function in a manner similar to how the constraint of maintaining a maximal fraction of model-to-observed action matches is incorporated into the CA optimization problem.

Only group submodel parameters can be variables in this constrained optimization problem. CA-estimated parameter values are used as starting values for all group submodels. During the optimization's search, however, all ecosystem submodel parameters are held at their CA-estimated values. Doing so represents the assumption made in the MPEMP optimization problem that ecosystem dynamics are not under anthropogenic control but group belief systems are. Therefore, realistic ecosystem management plans should be restricted to making small modifications to human beliefs – and hence human behavior – rather than attempting to make changes to those ecological mechanisms that are represented in the ecosystem submodel.

The preferred solution to the MPEMP optimization problem is a local one rather than a global one. This is because the MPEMP is the plan that requires the least change in existing beliefs to cause human behaviors to change enough to allow the ecosystem to reach a desired state. Existing beliefs are represented by the model's consistent distribution. Hence, a solution that is close to existing beliefs needs to be found.

The objective function in an MPEMP optimization problem needs to include the ecosystem submodel. This because the effect of different sets of group actions on the ecosystem needs to be detected every time the objective function is evaluated. And, when the ecosystem submodel is stochastic as in the East African cheetah example herein, some method of handling the resulting stochastic objective function needs to be employed. Within SA-MDAS, the method of Bouttier and Gavra (2019) is used (see Appendix).

5.3. MPEMP algorithm

5.3.1. Definitions

1. The vector
$$\mathcal{B} = \left[\mathcal{B}^{(Grp)\prime}\ \mathcal{B}^{(Eco)\prime}\right]'$$
contains parameters of the group submodels, and the ecosystem submodel, respectively.
2. Let the vector, $\mathbf{Q}(\mathcal{B})$ contain the monitored ecosystem submodel variables whose values are generated by the ecosystem submodel using parameter values contained in $\mathcal{B}$.

3. Let $\mathbf{q}_d$ contain the desired ecosystem state in terms of $\mathbf{Q}(.)$ along with the time when these values are to be achieved.
4. Identify those actions that, if taken, would contribute the most towards the ecosystem submodel producing the values in $\mathbf{q}_d$. Also identify those actions that, if ceased, would raise the likelihood of the ecosystem submodel producing the values in $\mathbf{q}_d$. Collect all of these desirable and undesirable actions into a set called $\mathbf{c}_{MPEMP}$.

5.3.2. Algorithm

The following mathematical form of the MPEMP algorithm extends the one reported in Haas (2020).

1. Compute CA estimates of selected model parameters, i.e., update $\mathcal{B}_H$ to the most recent set of consistent parameter values: $\mathcal{B}_C$.
2. Compute $\mathbf{q}_H \equiv E\left[\mathbf{Q}(\mathcal{B}_H)\right]$.
3. Specify $\mathbf{q}_d$ and $\mathbf{c}_{MPEMP}$.
4. Compute initial values for $\mathcal{B}^{(Grp)}$ with CA's **Initialize** step.
5. Compute

$$\mathcal{B}_{\mathrm{MPEMP}} = \underset{\mathcal{B}^{(Grp)}}{\arg\max} \left\{ g_H^{(Grp)}\left(\mathcal{B}\right) - \frac{||E[\mathbf{Q}(\mathcal{B})] - \mathbf{q}_d||}{||\mathbf{q}_H - \mathbf{q}_d||} \right\} \quad (5)$$

under the set of constraints specified by $\mathbf{c}_{MPEMP}$.

Note that during the search in Step 5, $\mathcal{B}_H^{(Eco)}$ is unchanged.

5.3.3. Quantifying political feasibility

The mathematical form of the MPEMP algorithm supports one way to quantify the concept of a politically feasible ecosystem management plan: Associate political feasibility with $g_H(\mathcal{B}_{\mathrm{MPEMP}}^{(Grp)}) \in (-\infty,\ 0]$ where $\mathcal{B}_{\mathrm{MPEMP}}^{(Grp)}$ contains the parameters of the decision making submodels whose values have been modified from those in $\mathcal{B}_H^{(Grp)}$ in such a way that now, the sequence of output actions taken by the different groups in the model causes a desired ecosystem state at a desired future time point ($\mathbf{q}_d$).

Therefore, A *model-based* measure of an ecosystem management plan's political feasibility can be defined as

$$\psi \equiv g_H^{(Grp)}(\mathcal{B}_{\mathrm{MPEMP}}^{(Grp)})/(|g_H^{(Grp)}(\mathcal{B}_H)| + 0.000001). \quad (6)$$

The numerator is the agreement of the MPEMP distribution with the hypothesis distribution where large negative values indicate poor agreement. The first term in the denominator is the absolute value of the agreement of the model's distribution with the hypothesis distribution – using parameter values from the hypothesis distribution itself. When approximation error is zero, this term is zero. Hence, $g_H^{(Grp)}(\mathcal{B}_{\text{MPEMP}}^{(Grp)}) \leq |g_H^{(Grp)}(\mathcal{B}_H)|$.

A plan having a value of $\psi << -1.0$ will face stiff political resistance to its implementation because significant changes to the belief systems of one or more groups needs to happen – while a plan having a value close to -1.0 should not face such strong political headwinds.

5.3.4. Avoiding conceptual circularity

A model-based measure of political feasibility can become *conceptually circular* (Prato, 2019) if its value is always the same under different sets of model parameter values. It is argued here that ψ is not a conceptually circular measure. Conceptual circularity exists when the premise of a concept contains definitions that are present in the concept's conclusion such that the concept is a truism, i.e., is always true. In other words, the concept's premises and its conclusion can be inverted without changing the outcome. An example is the concept of the legality of abortion. One way to describe this concept is with the following two statements. Premise: "Abortion is the intentional killing of a human being." Conclusion: "Because the intentional killing of a human being is illegal, abortion should be illegal." The premise implies that a fetus is a human being. In this case, because the conclusion concerns a human being, it is always true. These statements can be inverted as follows: Premise: "The intentional killing of a human being is illegal." Conclusion: "Because abortion is the intentional killing of a human being, it should be illegal."

A *political feasibility* score is developed in Peng et al. (2021). These authors form a likert scale from six metrics that have been discussed in the political economy literature. The authors use this score to measure the political feasibility of several environmental management plans under review for mitigating air pollution in India. Their concept of political feasibility is not circular because the six metrics are defined in literature that is outside of the characteristics of the proposed air pollution management plans.

Here, because ψ is defined exclusively in terms of the political submodel's parameters, it is a model-based measure of political feasibility. Given a set of parameter values that cause the model to fit a political-ecological data set well, the parameter values that are needed to compute a value of ψ may be significantly different from those that produce this good fit to the data set. Therefore, the value of ψ cannot be determined by looking at the model's structure alone (its "premise"). Rather, a political-ecological data set, a proposed ecosystem management plan, and the model are all required before the value of ψ can be known. And this value may be low or high depending on the characteristics of these three components. Therefore, although ψ is defined in terms of the model, its definition is not conceptually circular.

5.4. Results

The desired ecosystem state is 200 cheetah across Kenya and Tanzania in the year 2030. The parameters to be modified during the search for the MPEMP are those used in the above CA example with the addition of the parameters defining the node: Number of Cheetah Poached (NMPOACHED) under the proposed action of *poach cheetah for protection* for both Kenya rural residents and Tanzania rural residents.

These parameters are included in the MPEMP computation to study the feasibility of a two-pronged approach to cheetah conservation: Discouraging rural residents from poaching cheetah for cash while at the same time increasing antipoaching measures. To these ends, the SIIWP parameters are included in order to guide the amount of belief-change that would be needed to discourage rural residents from poaching cheetah for cash. And the NMPOACHED parameters are included in order to find how much antipoaching measures need to be increased in order to stop rural residents from poaching cheetahs for protection. Optimizing these two sets of parameters simultaneously results in smaller changes to these parameters relative to the changes that would be required if only one of these sets was changed without changing the other. And smaller changes give the plan greater political feasibility.

In summary, the CA computation modifies the SIIWP parameters concerning *poach cheetah for cash*. The MPEMP computation modifies the SI-

IWP parameters concerning *poach cheetah for cash* and the NMPOACHED parameters conditional on *poach cheetah for protection*.

5.4.1. MPEMP computation

To begin the optimization computation at a feasible solution, initial values of the SIIWP parameters were modified to produce the following output actions by both the Kenya rural resident group, and the Tanzania rural resident group: no *poach cheetah for cash* actions, no *poach cheetah for food* actions; but high probabilities for the actions, *poach cheetah for protection*, and *protest national park boundaries*.

The SA-MDAS optimization algorithm was run with three performers executing on 10 threads each. The run's wall clock time was 2.75 hours. The initial MPEMP objective function value was -0.5734, and the final value was -0.4962 for a 7.66% increase. Phase one converged after 77 function evaluations and phase two after 48 function evaluations.

5.4.2. The computed MPEMP

This run produces an MPEMP that is projected to allow an expected cheetah population size of 268 by 2030. This value is higher than the desired value of 200 cheetah by 2030 and avoids the near extinction event at the end of 2029 (only 53 cheetah) that is predicted by the model under the business-as-usual plan. The measure of the plan's political feasibility, ψ is computed to be -1.019.

Tables 5 and 6 show each parameter's definition, its CA value, and its MPEMP value. These parameter value changes indicate that the MPEMP is to (a) change the belief in being arrested for poaching cheetah for cash from being perceived as negligible to being perceived as likely; and (b) increase antipoaching measures to the point where Kenya and Tanzania rural residents each succeed in poaching less than five cheetah per week.

The number of cheetah poached per week by Kenya rural residents and the number of cheetah poached per week by Tanzania rural residents were not adjusted during CA estimation run. Instead, these two parameters were held at their hypothesis values. These hypothesis values are both 5.0 – below the upper bound constraint value of 6.0 that is shared by these parameters. This value represents a significant amount of poaching and aligns with the hypothesis that these rural residents do not believe they will be arrested for poaching cheetah.

Parameter	Node	CA value	MPEMP value	Change fraction	$> 10\%$ change?
1	Number_Poached	5.994	3.574	00.403??	*
2	SIIWP	00.274	00.193	00.294	*

Table 5: Kenya rural resident parameter value changes needed to produce the MPEMP. The first parameter is the average number of cheetah poached per week by Kenya rural residents. The second set of parameters define the perceived outcome by Kenya rural residents under the decision option to *poach cheetah for cash*. Perceived outcomes are *will be arrested for poaching*, *will be evicted*, and *no interaction with police*.

Parameter	Node	CA value	MPEMP value	Change fraction	$> 10\%$ change?
29	Number_Poached	5.994	5.372	00.103??	*
30	SIIWP	00.039	00.328	7.423	*

Table 6: Tanzania rural resident parameter value changes needed to produce the MPEMP. The first parameter is the average number of cheetah poached per week by Tanzania rural residents. The second set of parameters define the perceived outcome by Tanzania rural residents under the decision option to *poach cheetah for cash*. Perceived outcomes are *will be arrested for poaching*, *will be evicted*, and *no interaction with police*.

5.4.3. The MPEMP's political consequences

Because of ψ's modestly negative value, this MPEMP is expected to face moderate political resistance. A practical policy for implementing this MPEMP is to simultaneously (a) visibly increase antipoaching enforcement in both countries, and (b) communicate such increases to the rural residents of Kenya and Tanzania (Kegamba et al., 2024), (Nachihangu et al., 2022).

This fitted model and the political insights derived from it, are new.

6. Discussion

6.1. Institutional challenges

The practice of political-ecological modelling to guide conservation efforts will advance as progress is made on the following challenges.

1. Collaboration with the private sector is needed to tap their distributed autonomy; enormous reserves of talent; and enormous reserves of cash and credit (Haas, 2022), (Haas, 2024c), (Haas, 2025).
2. Better political-ecological data sets need to be acquired that, via cluster computer computations, can be used to statistically fit the parameters of these models. On the political side, observations need to be acquired on those private political agreements that often determine the fate of conservation legislation. On the ecological side, unrestricted and non-invasive monitoring of species abundance is needed. Currently, such data is often restricted because (a) owners refuse access to their properties, and/or (b) data managers fear that poachers will hack into the data's repository to locate wildlife (Lennox et al., 2020).
3. In order to make the statistical fitting of these models feasible to a wide spectrum of researchers, cluster computing resources need to be financially accessible to cash-strapped departments of ecology and departments of political science.

   One economical alternative to purchasing time on a commercial cluster computer is to organize some number of in-house computers into a cluster computer. With the JavaSpaces-based SA-MDAS algorithm, this is a straightforward four-step build:

   (a) Install on an impresario, a *dynamic domain name system* (DDNS) (mintdns, 2023) to give this computer a fixed domain name so that performers can locate its GigaSpace. A DDNS is acquired from an internet provider or from a DDNS provider. Fees can be either none; a fixed monthly charge; or a monthly, usage-based charge.
   (b) Verify that all performers can access the internet.
   (c) Install the Java Development Kit (free) and the GigaSpaces XAP (annual lease) on the impresario and all performers.
   (d) Compile and run on these computers, the Java code exercised in this article (see Supplementary Materials).
4. The credibility of political-ecological models in the eyes of their skeptics needs to be established by meeting Popperian credibility criteria that are based on frequentist statistical methods (Haas, 2024). CA as applied herein, is one such method. Communicating to the public that

extinction event predictions have been made by credible models may help the public take such messaging seriously rather than discounting such warnings as no more than *scientist activisim* (Whipple, 2024).

5. Group decision making mechanisms need to be better understood. Such newly-derived mechanisms need to be programmed into each group decision making submodel that runs within a political-ecological model. Also, computational models need to be developed that, through improved architectures, realistically integrate political and ecological processes. One such architecture employed herein is that of agent-based submodels communicating with each other and with an individual-based ecosystem submodel through a bulletin board architecture.
6. Increased financial and career support is needed for interdisciplinary research on the integration of political and ecological processes. Within academia, this support will be aided when (a) journal editors encourage the publication of high-quality manuscripts that probe this interface (Huber-Sannwald, 2025), (O'Connor et al., 2021), (Van Bael, 2025); and (b) departmental committees encourage tenure-track faculty to publish at this interface (Washbourne et al., 2024). Outside academia, funding agencies need to seek out and fund high-quality proposals to build and test models of those political-ecological systems that contain at-risk species.

7. Conclusions

For purposes of biodiversity conservation, attention needs to focus on finding politically feasible projects aimed at conserving biodiversity. Earth is running out of time to save what remains of its biodiversity. MPEMPs need to be computed and implemented as soon as possible.

The political-ecological models that will support these projects, can have their parameters statistically estimated via CA to political-ecological data sets acquired via the EMAT actions extractor. Use of CA to perform this parameter estimation, allows cognitive theories of decision making to be represented in the final fitted models. Computations then can be performed with this fitted political-ecological model to produce an MPEMP.

The CA and MPEMP optimization problems, however, are challenging to solve because they are bound constrained and have objective functions that are stochastic, possess multiple extrema, exhibit jump discontinuities, and are expensive to evaluate. SA-MDAS is currently the only optimization algorithm that can solve such problems. This algorithm makes these computations feasible by scaling on the increasing availability of cluster computers.

As per this article's title, the MPEMP is how a political-ecological model can help sustain biodiversity. This article's freely available MPEMP Constructor toolkit can be immediately used by an organization to develop and implement politically feasible and ecologically effective plans for conserving those at-risk species that they have selected to help preserve.

Given the current negative trends in biodiversity, one might conclude that conservation research is futile and hence, should be abandoned. A recent meta-analysis, however, using data from many different conservation projects, finds that actually, conservation projects have been effective at stopping or at least slowing the decline of biodiversity across the globe (Oxford, 2024). Given this evidence, there is reason to believe that research products such as the MPEMP Constructor toolkit can help build a conservation science that is capable of guiding successful efforts to curb the loss of species regardless of their commercial value.

7.1. Future work

Adding-in parameters to represent Kenya pastoralist and Tanzania pastoralist beliefs about their likelihood of being arrested for poaching is planned for future work.

The accuracy of the EMAT actions extractor will continue to be improved. The pcDE algorithm will be extended to solve both the CA and MPEMP optimization problems.

Supplementary material

All source code and input files that form the MPEMP Constructor toolkit are contained in the Supplementary Material section of this article. These files are `java_source.zip`, `scripts.zip`, and `data.zip`. The first of these files contains all Java source code for the program **id**. The second file contains all needed Linux® shell scripts and Windows® batch files. The third file contains model definition files and all of the political-ecological data analyzed in this article. These three files are available at either

> `www.profitablebiodiversity.com/software`

or Zenodo:

> `https://about.zenodo.org/policies/`:
> doi: 10.5281/zenodo.19653266 (April 19, 2026 version)
> doi: 10.5281/zenodo.19653265 (all versions resolving to the latest)

Step-by-step instructions for using the toolkit

1. Download the above three files and unzip them.
2. Install the latest Long-Term Support release of the Java Development Kit (JDK) from
   `https://www.oracle.com/java/technologies/downloads/`.
3. Install the latest version of the Gigaspaces XAP from
   `https://www.gigaspaces.com/downloads/`.
4. If on a Linux operating system, start a Linux terminal; if on a Windows operating system, start a command prompt DOS window.
5. On Linux, compile **id** with the command

   ```
   sh compile.shl Run_id.java
   ```

   On Windows, issue the command

   ```
   compile Run_id.java
   ```

6. On Linux, run the **id** interactions actions history example with the command

   ```
   sh idalone.shl kentan.id
   ```

   On Windows, run the command

   ```
   idalone kentan.id
   ```

7. To run the example's statistical estimation computation, do the following.
   (a) Edit the text file `kentan.id` so that the group of statements that make up the `estimate_nodes` **id** relation is just below the `context files` statement group as per the following.

```
report estimate
   estimate_nodes(2020.0 2026.0 2 (kenrr 1 SIIWP) (tanrr 1 SIIWP)
       .5 1000 true true true no_plots_only)

report estimate
   find_mpemp(2025.0 2031.1 2 (kenrr 2 SIIWP NMPOACHED)
      (tanrr 2 SIIWP NMPOACHED) 1000)

report evaluate
   id_interactions(2020.0 2026.1 1000)
```

   (b) Rerun the **id** command file, `kentan.id`.

8. To find the MPEMP, do the following.
   (a) Rename all `*-cons.par` files that were created by the statistical estimation run to `*-hyp.par`.
   (b) Edit `kentan.id` so that the `find_mpemp` relation is just below the `context files` group.
   (c) Rerun the **id** command file, `kentan.id`.

9. To run a parallel version of **id**, do the following. At the command prompt on a Linux cluster computer that uses SLURM (SLURM, 2026) to manage batch jobs, run the shell script `pesimpresario.shl` with the command

   ```
   sbatch pesimpresario.shl kentan.id
   ```

   Each compute node on this cluster computer needs to have its own IP address. The shell script `pesimpresario.shl` will in turn, call the shell script `pesperformer.shl` as many times as specified by the

   `nmclients=` .

   line in `pesimpresario.shl`.

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Appendix: SA-MDAS Tests, Details, and Comparisons

SA-MDAS performance on analytic objective functions

SA-MDAS is used to solve Bukin's F4 and F6 functions (Mishra, 2006). These functions have a pathological number of *non-global minima* (Hasanzadeh et al., 2022). Haas (2020) reports that MDAS correctly solves Bukin's F4 function. Using $n_s = 60$ (Corana et al., 1987), a chain length of 10, and 10 performers, SA-MDAS finds the global minimum solution to Bukin's F4 function in 12,353 objective function evaluations.

SA-MDAS, however, fails to find the global minimum solution for Bukin's F6 function. But when the global search phase of SA-MDAS is allowed to run to convergence rather than switching to its local search phase, the global minimum of this function is found after 4,716,030 function evaluations.

Based on these experiments, SA-MDAS appears to be able to (a) find solutions to real-world conservation optimization problems that have fewer modes than Bukin's F4, and (b) find the global minimum of a highly multimodal function when nearly unlimited computing power is available.

Continuous variables

All parameters in the political-ecological model studied in Section 4 are continuous. Hence, a method is needed for applying SA to continuously-valued variables. Here, the method developed in Corana et al. (1987) is used. One way to specify the length of SA's Markov chain, i.e., the number of passes through SA's inner loop, is to define it to be the size of the neighborhood surrounding the current solution point (Aarts and Korst, 1989, p. 65), i.e., the number of points reachable in one move. The number of such points can become large.

Corana et al. (1987) take a different approach. They define their n_s constant to be how many times each variable is subjected to trial moves within one pass through SA's inner loop. Each variable is subjected to these

n_s trials sequentially. Consequently, the value $n \times n_s$ becomes in-effect, their chain length. These authors do not attempt to equate their de-facto chain length definition with the number of possible points accessible in one move – and instead, simply recommend n_s be set to 20. In SA-MDAS, however, a move always consists of a possible step-change on each and every variable. Therefore, in SA-MDAS, n_s is the number of times that moves are made within one pass through SA's inner loop.

As in Corana et al. (1987), SA-MDAS recomputes each variable's step length every pass through the outer loop. Except for initialization, step length updates in SA-MDAS use equations given in (Corana et al., 1987, p. 267).

The step length's "varying criterion," Corana et al. (1987) and the step lengths themselves need to be initialized. This is accomplished by first assuming that the median is returned by the uniform random number generator on the unit interval, i.e., the value 0.5. Then, the initial median step length is initialized to be the width of the widest set of the n bound constraints divided by 50 – and then multiplied by this median value. The chain length is fixed at the value $10 \times n_s$ where $n_s = 3$.

The continuous-variable scheme of Corana et al. (1987) for SA maintains an approximately 50% acceptance rate at every temperature, t. But this is accomplished by progressively making the step length along each variable, smaller. Hence, as the temperature decreases, the chance that SA will break into a significantly more optimal subspace becomes small since, as the temperature decreases, a typical move will be close to the current point. Hence, at some temperature, the global search capability of SA will become practically nonexistent. This characteristic of SA as applied here to continuous variables is the motivation for the algorithm's switch from SA in phase one (global search) to MDAS in phase two (local search).

Stochastic objective functions

SA-MDAS can handle stochastic objective functions using a method developed by Bouttier and Gavra (2019). These authors define a "time" variable, t. To avoid confusion with this article's notation for "temperature," u is used here to refer to this variable. In the Bouttier and Gavra (2019) method, instead of evaluating the objective function once when a "score" evaluation is needed by SA, the function is evaluated n_u times at the same point in the solution space. These n_u values are then averaged and returned as the score value at that point. The size of n_u increases as u (time) increases.

The value of u is updated every pass through the outer loop with $u = u+\zeta$ where ζ is a realization from the Exponential(1.0) distribution. Because the expected value of this distribution is 1.0, this update is, on average, adding the value 1.0 to u every pass through the outer loop. Addition of this stochastic term rather than the addition of the fixed value 1.0 to u every pass through the outer loop is necessary to allow the chain of SA-generated solutions to be modeled as a continuous-time Markov process. This is the model that is assumed by Bouttier and Gavra (2019) in their proof of the method's convergence.

Their method also requires a monotone, increasing function mapping u to n_u. SA-MDAS uses the function

$$n_u = f(u) = \left\lfloor \sqrt{u/u_0} \right\rfloor \tag{7}$$

where $\lfloor . \rfloor$ is the floor function and u_0 is the starting value of u.

In contrast to Step (g) of the algorithm in Section 3.4, Bouttier and Gavra (2019) have the temperature, t decreased by some function of u such as $t = 1/u$. But doing so would have ignored the standard deviation of the objective function as estimated after each pass through SA's inner loop. Hence, SA-MDAS employs the Aarts and Korst (1989) algorithm to decrement t rather than the function used by Bouttier and Gavra (2019).

Inter-performer coupling

By executing MPE in the algorithm's Step (i) (Section 3.4), SA-MDAS couples the performers to each other by allowing them to always begin their respective chains at the current best solution that was found across all performers during the last outer loop iteration.

Message-passing overhead

Spreading tasks across a cluster of performers as is done in SA-MDAS is known to have some amount of *latency* (Pichetti et al., 2024). Here, such latency is viewed as a minor issue because the optimization problem's objective function, being composed of interacting agent/individual stochastic submodels, is computationally expensive to evaluate. Hence, most of the compute time needed to estimate the parameters of the political-ecological model will typically be taken by objective function evaluations rather than by inter-node messaging.

To verify this conjecture, an experiment was conducted using Bukin's F4 function. This function takes very little compute time. SA-MDAS was run on a Windows$^{\mathrm{TM}}$ laptop computer with 32 GB of memory running at 1.2 GHz. Doing so resulted in SA-MDAS requiring 1.62 seconds to compute 192K evaluations of Bukin's F4 function. SA-MDAS was next run on the TSCC to perform 1,400 evaluations of this same function using two performers communicating with the impresario through a GigaSpace. Wall clock time for these evaluations was seven minutes. Almost all of this time was devoted to inter-node message-passing. These values suggest that a GigaSpaces implementation of SA-MDAS requires about 0.3 seconds to complete a *round-trip*, i.e., the posting of a task to the GigaSpace, a performer downloading the task, uploading the result, and the impresario taking the result off of the GigaSpace. Note that a round-trip does not include the objective function's evaluation.

Let x be the number of minutes needed to evaluate the objective function. Assume a 100-node cluster computer is available. Then, the break-even function evaluation time can be estimated by solving for x in:

$$192000x = 192000x/100 + 192000(0.3/60) \tag{8}$$

The left side of 8 is the time needed to compute 192K function evaluations on a single-processor computer, while the right side is the time needed to compute the same number of evaluations on a cluster computer running 100 nodes in parallel. Equation 8 can be written as $0.99x = 0.3/60$, i.e., x is approximately equal to the roundtrip time. Hence, for expensive functions, cluster computing can speed-up black-box optimization problems even when round-trip times are as large as 0.3 seconds. And further, this speed-up increases as the objective function's evaluation time increases.

In the example of Section 4.4.4, one evaluation of CA's objective function requires at least 80 seconds. Given this level of computational expense, an optimization algorithm that scales on the increasing availability of cluster computer nodes, is currently, the only feasible way to statistically fit a large political-ecological model to data.

SA-MDAS compared SA, Random Search, and HJ

The optimization problem of least sum-of-squares possesses a very smooth, unimodal objective function. Using only phase one (SA), SA-MDAS needed 3,780 evaluations to solve a 27-variable least sum-of-squares problem. Whereas an HJ algorithm (Haas, 2020) needed 1,725 evaluations, and a Random Search algorithm (Schumer and Steiglitz (1968)) needed 1,568 evaluations. These latter two algorithms are local, nonstochastic, and do not scale well as neither can make use of more than one compute node.

Similar to PACSA, SA-MDAS phase one mainly uses parallel processing to store the end result of many chains to increase the chance that it will find the global minimum point – not necessarily to speed up the solution time (Gonçalves-e-Silva et al., 2018). In other words, the focus of SA-MDAS phase one is to find the global minimum, not to speed up the solution. Even with this caveat, SA-MDAS phase one takes only about twice as long to solve a 27-variable least-squares problem as do two strictly local-search algorithms.

SA performs global search through decisions to probabilistically accept uphill moves (worse objective function values) rather than delineating a partitioning of the solution space first and then evaluating the function at some point in each partition as is done for example, in Jia et al. (2024). Such a partitioning-then-evaluation approach to global optimization results in many objective function evaluations regardless of whether they end up being uphill or downhill values. Further, there is an implicit assumption that all points within a partition have function values that are similar to the value at the single point actually evaluated in that partition.

MDAS, being more focused on local search than SA, employs many performers to

1. Perform limited global search (up to the m dimensions (variables) being searched simultaneously), and

2. Produce a speedup from the sequential HJ algorithm by evaluating the objective function at all m-dimensions-ahead search points simultaneously rather than sequentially.

Covariance Matrix Adaptation Evolutionary Strategy, Bayesian Optimization, and parallel Compact Differential Evolution

Covariance Matrix Adaptation Evolutionary Strategy (CMA-ES) assumes the objective function is continuous (Gomez-Rosero et al., 2024) and hence is not designed to solve constrained, stochastic black-box optimization problems wherein the objective function may exhibit jump discontinuities at unknown points in the search space.

Bayesian Optimization (BO) uses a kriging step to decide on its next move. Because of this gaussian-based move strategy, BO assumes that the objective function is continuous and differentiable (Tiwary, 2012). BO has been adapted to run on a cluster computer (Binois et al., 2025). These authors develop and test an algorithm that efficiently uses many compute nodes to solve an multi-objective optimization problem that consists of several continuous and differentiable objective functions. Their algorithm uses a heuristic approach to noisy objective functions (called there, *noisy simulators*. References are given to convergence proofs that apply to the case of deterministic objective functions.

Sala et al. (2025) uses feasibility regions (partitions) to extend BO to the case of objective functions that exhibit jump discontinuities. See above for issues with partitioning approaches to handle jump discontinuities.

An *evolutionary algorithm* that can solve an optimization problem by harnessing many compute nodes, is the "parallel Compact Differential Evolution" (pcDE) algorithm of Sui et al. (2020). pcDE is an extension of the Compact Genetic Algorithm (CGA). By running pcDE on multiple compute nodes, the algorithm's instability can be reduced and its efficiency improved (Sui et al., 2020). Within the algorithm, noise is added to the (possibly) noisy objective function to avoid having the solution sequence settle into a local extremum.

A proof of CGA's convergence to a local extremum is given in Rastegar et al. (2006). The classic Differential Evolution (DE) optimization algorithm lacks a proof of convergence to the global extremum. A modified version of this algorithm, however, does enjoy a proof that, given an infinite sequence of populations, the algorithm will arrive at the global extremum (Knobloch et al., 2017).

SA-MDAS compared to CMA-ES, BO, and pcDE

Based on the above, pcDE appears to have the greatest potential for solving bound-constrained optimization problems wherein the noisy objective function is multi-modal and has jump discontinuities. This evolutionary algorithm is similar to SA and could be modified so as to guarantee its convergence to a global extremum. BO would need significant research before such a statement could be made of it.

Hence, currently (circa 2026), among all known algorithms for finding on a cluster computer, the global maximum of a noisy, multi-modal function that possesses jump-discontinuities at unknown points, SA-MDAS appears to be (a) the most theoretically understood, and (b) the most free of restrictive conditions on the objective function. Therefore, SA-MDAS is advanced here as the algorithm of choice for finding the MPEMP to manage a political-ecological system with the end-goal of conserving one of its at-risk species.

The objective function of the MPEMP optimization problem makes this problem challenging. Although SA-MDAS is one of a few algorithms capable of solving this problem, (possibly) more efficient algorithms for its solution that scale on cluster computers are needed. To this end, extending pcDE to solve the MPEMP problem is planned for Future Work (see above).