Decision-Making for Land Conservation: A Derivative-Free Optimization Framework with Nonlinear Inputs

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Abstract

Protected areas (PAs) are designated spaces where human activities are restricted to preserve critical habitats. Decision-makers are challenged with balancing a trade-off of financial feasibility with ecological benefit when establishing PAs. Given the long-term ramifications of these decisions and the constantly shifting environment, it is crucial that PAs are carefully selected with long-term viability in mind.

Using AI tools like simulation and optimization is common for designating PAs, but current decision models are primarily linear. In this paper, we propose a derivative-free optimization framework paired with a nonlinear component, population viability analysis (PVA). Formulated as a mixed integer nonlinear programming (MINLP) problem, our model allows for linear and nonlinear inputs. Connectivity, competition, crowding, and other similar concerns are handled by the PVA software, rather than expressed as constraints of the optimization model. In addition, we present numerical results that serve as a proof of concept, showing our models yield PAs with similar expected risk to that of preserving every parcel in a habitat, but at a significantly lower cost.

The overall goal is to promote interdisciplinary work by providing a new mathematical programming tool for conservationists that allows for nonlinear inputs and can be paired with existing ecological software. The code and data are available at https://github.com/cassiebuhler/conservation-dfo.

Introduction

As a consequence of habitat degradation due to human activities, protected areas (PAs) have been implemented for protecting vulnerable species and preserving valuable ecological processes (World Wildlife Fund 1980). In recent years, the post-2020 Global Biodiversity Framework has mandated that 30% of land and sea be established as protected areas by 2030 (Convention on Biological Diversity 2020; Executive Order No. 14,008 2021). This initiative, coined "30×30", has motivated further research on PAs and their decision frameworks.

Conservationists have cautioned that area-based goals, such as 30×30, have the potential to prioritize quantity over quality and emphasize the importance of prioritizing ecological value, such as biodiversity, in these decisions (Maxwell et al. 2020; Joppa and Pfaff 2009). However, financial support is still vital to the long-term management and efficacy of a PA (Coad et al. 2019; Rodrigues and Cazalis 2020; Watson et al. 2014; Lawler et al. 2020).

When implemented appropriately, PAs are a necessary investment for our planet (Dudley 2008). With the environment rapidly changing (e.g. climate change increasing habitat fragmentation (Costanza et al. 2020)), it is crucial that PAs are carefully selected with consideration of future conditions to reduce the risk of extinction (Williams, Rondinini, and Tilman 2022; Akasaka et al. 2017; Cruz, Santulli-Sanzo, and Ceballos 2021).

Population Viability Analysis

While there are many ways to estimate extinction risk, one of the more popular tools in conservation biology is population viability analysis (PVA), which predicts the probability of extinction for a species in a particular habitat (Akçakaya and Sjögren-Gulve 2000). Scientists use forecasts from PVA in recovery plans (Runge et al. 2017; Faust et al. 2016) and management decisions (Lacy and Breininger 2021) for threatened species.

PVA also provides insight on the persistence of a species in PAs, ultimately used to inform practitioners on improvements necessary to increase the likelihood of survival (Winton, Bishop, and Larsen 2020; Finnegan et al. 2021). In addition, PVA has been used to advise potential PA locations based on an unprotected population that is declining (Andersen, Jang, and Borzée 2023).

Researchers have noted that PVA is a valuable risk assessment, yet the necessary data required for PVA can be challenging to obtain, which often limits PVA to single-species (Rondinini and Chiozza 2010). Moreover, many PVA studies in the literature were found to lack clear documentation of parameters and assumptions (Doak et al. 2015) making it impossible to reproduce results (Morrison, Wardle, and Castley 2016) which ultimately compromises its quality and reliability (Chaudhary and Oli 2020) as code and data transparency is necessary in conservation decision-making (Morrison, Wardle, and Castley 2016).

Mathematical Programming

Establishing PAs requires balancing a trade-off of financial feasibility with ecological benefit. For decades, optimization models have aided decision-makers with such trade-offs (Alagador and Cerdeira 2022; Billionnet 2013). The first use of mathematical programming to select conservation sites was published by (Margules, Nicholls, and Pressey 1988) and (Cocks and Baird 1989). The authors proposed using integer programming (IP), with linear inputs and binary decisions, rather than existing ranking methods.

In mathematical programming models. a landscape is modeled as a raster divided into $n \times n$ pixels, where each pixel is a parcel eligible to be selected as a PA. The set of parcels is denoted as P, and the set of species is denoted as S. Let $x_p, p \in P$ be the binary decision variable denoting whether or not parcel p on a landscape is selected as a PA. The IP is defined as follows:

$$\underset{x \in \{0,1\}^{|P|}}{\text{minimize}} \quad c^T x \quad \text{subject to} \quad Ax \geq b, \tag{1}$$

where $A \in \mathbb{R}^{|S| \times |P|}$, $c \in \mathbb{R}^{|P|}$, and $b \in \mathbb{R}^{|S|}$. In the minimum set cover formulation, c_i is the cost of acquisition for parcel i, $A_{j,i}$ is the population for species j in parcel i, and b_j is a target population for species j. Following the introduction of optimization models in conservation, variations of (1) were proposed (Underhill 1994; Possingham et al. 1993; ReVelle, Williams, and Boland 2002). IPs also can represent the maximal set coverage: maximizing a species population without exceeding a budget β.

$$\underset{x \in \{0,1\}^{|P|}}{\text{maximize}} \quad \sum_{i \in P, j \in S} A_{ji} x_i \quad \text{subject to} \quad c^T x \leq \beta \tag{2}$$

Maximal set coverage is also used in many applications (Camm et al. 1996; Church, Stoms, and Davis 1996; Arthur et al. 1997; Csuti et al. 1997; Rosing, ReVelle, and Williams 2002; Rodrigues, Orestes Cerdeira, and Gaston 2000). More recently, spatial properties, such as compactness (Marianov, ReVelle, and Snyder 2008) and functional connectivity (Önal et al. 2016; Dilkina et al. 2017; Gupta et al. 2019; Costanza et al. 2020; Williams et al. 2020), have been introduced as constraints in these models.

To this day, IP is the most common optimization model used in conservation planning. This formulation limits the objective and constraints to linearity, which ultimately, limits the potential applications of the model.

Mixed Integer Linear Programming A mixed-integer linear programming problem (MIP) allows both for continuous and discrete decisions in an optimization problem with linear inputs. While MIPs are less common in conservation planning, continuous decision variables such as currency (Jafari and Hearne 2013; Jafari et al. 2017), and amount of land or number of parcels allocated to a species (Beaudry et al. 2016) have been used to decide candidate sites.

Mixed Integer Nonlinear Programming An optimization problem that simultaneously allows for nonlinear functions, continuous decisions, and discrete decisions is called a mixed integer nonlinear programming problem (MINLP).

$$\begin{aligned} \underset{x,y}{\text{minimize}} \quad & f(x,y) \\ \text{subject to} \quad & g(x,y) \leq 0 \\ & x \in X \subseteq \mathbb{Z}^p \\ & y \in Y \subseteq \mathbb{R}^n \end{aligned} \tag{3}$$

where X is the set of discrete variables, Y is the set of continuous variables, and $f : (X,Y) \mapsto \mathbb{R}$ and $g : (X,Y) \mapsto \mathbb{R}^m$ are sufficiently smooth functions.

One of the first uses of MINLPs in conservation decision-making introduced a nonlinear objective function (Ferson et al. 2000) for clustering habitats in a reserve. The same approach was also used in marine PAs (Leslie et al. 2003). (Stralberg et al. 2009) presented an MINLP which had a nonlinear objective and represented salinity in wetland restoration as a continuous variable. While formulations of MINLPs exist, researchers often linearize the nonlinear functions before solving the problem, due to reasons such as availability of modeling environments and solvers, availability of high quality linearizations, and theoretical guarantees for optimality.

The Proposed MINLP Approach As policymakers push for 30×30, we anticipate a need for more complex spatial optimization models for PAs. With the gap between theory and practitioners in implementing spatial conservation models (Sinclair et al. 2018; Ferraz et al. 2021), there is a need for interdisciplinary collaboration. Therefore, the goal of this work is to provide a new mathematical programming tool for conservationists which allows for linear and nonlinear inputs, as well as continuous and discrete variables.

Our proposed MINLP model will be structured with a "plug-and-play" feature, where a user would be able to plug in their preferred metric (and the software for computing it) to optimize over. This would allow our model to be used as a framework and provide flexibility to the ongoing advancements. In this paper, we will present a proof-of-concept by connecting the model to a PVA software to represent several nonlinear problem components. Connectivity, competition, crowding, and other similar concerns are handled by the PVA software, rather than expressed as constraints of the optimization model.

Methods

For this proof-of-concept paper, we will focus only on binary decisions. The heuristic used in the paper can solve general MINLPs, which will be handled in future research. In this paper, we will consider two forms of (3). The first is a single-objective, constrained problem formulated as follows:

$$\underset{x \in \{0,1\}^{|P|}}{\text{minimize}} \quad f(x) \quad \text{subject to} \quad g(x) \geq \tau \tag{4}$$

The second is a multi-objective problem reformulated as an unconstrained problem:

$$\underset{x \in \{0,1\}^{|P|}}{\text{minimize}} \quad \sum_{k=1}^{m} \lambda_k f_k(x) \tag{5}$$

P	Set of parcels.
B	Landscape divided into $n \times n$ parcels, each with a habitat suitability index, representing the level that a parcel can support this species. Refer to Figure 1.
X_p	Binary decision variable denoting whether or not parcel $p \in P$ is preserved. Refer to Figure 1.
Z	Resulting habitat from configuration X. For any parcel $p \in P$, $Z_p = B_p X_p$. Refer to Figure 1.
c_p	Acquisition cost of preserving parcel p
$r(Z)$	Risk of total extinction for habitat Z.
$t(Z)$	Median time to extinction for habitat Z.
$a(Z)$	Expected minimum abundance for habitat Z.
ρ	Threshold by which the solution from Z can differ from the solution given by B.
β	Budget

Table 1: Descriptions of the decision variable and parameters used in our models. Refer to the technical appendix (Buhler and Benson 2023) for illustrations of functions r, t, and a.

where m is the number of objectives and λ is a vector of penalty parameters.

In this section, we will discuss these models in further detail as applied to PVA for a metapopulation. The notation can be found in Table 1.

For our analysis, we will use the software *RAMAS GIS* (Akçakaya and Root 2013a) and *RAMAS Metapopulation* (Akçakaya and Root 2013b) as the PVA component. From this software, we opted to use the following metrics in our model: risk of total extinction, time to extinction, and expected minimum abundance. To ensure reproducibility of our results (Morrison, Wardle, and Castley 2016), we provide further descriptions of these PVA terms and more detail on implementation can be found in the technical appendix[1].

Recall that PVA is based on predictions which we obtain from repeatedly simulating a iteration. In our analysis, we set the duration to be 100 years and generate 1000 iterations for each simulation. The statistics are reported using a 95% confidence interval based on the Kolmogorov-Smirnov test statistic. The width of the confidence interval is a function of number of iterations, and to limit the variance in risk we chose the maximum value allowed by the software.

Median Time to Extinction In *RAMAS*, the time to quasi-extinction is the number of years until a metapopulation abundance drops below a given threshold. In our case, we set this threshold as 0 and refer to it as time to extinction.

In each of the 1000 iterations, the time to extinction is recorded. The median is then computed over these iterations. We report this value and refer to it as the median time to extinction.

If a habitat does not reach extinction in at least 500 iterations, a median is not reported. For such cases, the median time to extinction would be recorded as > 100. That is, in our time frame of 100 years, the population did not go extinct in at least half of the iterations.

Risk of Extinction The terminal extinction risk is the probability that a metapopulation abundance will be below a certain threshold at the end of 100 years. The risk of extinction is the terminal extinction risk when the threshold is chosen to be 0.

Expected Minimum Abundance For each iteration in the simulation, the abundance of every metapopulation is totaled for each year, and the smallest abundance level over the 100 years is recorded. The expected minimum abundance is the average over 1000 iterations. This metric is useful to evaluate iterations where the metapopulation may not be close to extinction.

Many conservation models use functional and structural connectivity as constraints. For our proposed model, both types of connectivity are considered implicitly through expected minimum abundance, since model parameters that impact abundance (such as carrying capacity, relative survival, relative fecundity) are functions of total habitat suitability (THS). Larger patches have higher THS, so maximizing or constraining to higher values of expected minimum abundance imposes connectivity.

We also experimented with average habitat suitability, and found that this encouraged small patches of high habitat suitability that were fragmented. This area could be explored further, as smaller patches are also beneficial and have shown to have higher biodiversity (Fahrig 2020).

Model with Constraints

The baseline scenario entails preserving every parcel in the landscape B. Then, our optimization model with constraints (adapted from (4)) aims to obtain the cheapest solution that yields a median time to extinction, risk of extinction, and expected minimum abundance within a pre-defined gap of the corresponding metric for the baseline. The resulting constrained MINLP is as follows:

$$
\begin{aligned}
\underset{X \in \{0,1\}^{|P|}}{\text{minimize}} \quad & \sum_{p \in P} c_p X_p \\
\text{subject to} \quad & r(Z) - (\rho_r + r(B)) && \leq \quad 0 \\
& t(Z) - \rho_t t(B) && \geq \quad 0 \\
& a(Z) - \rho_B a(B) && \geq \quad 0 \\
& Z_p = B_p X_p && \forall \quad p \in P \\
& X_p \in \{0, 1\} && \forall \quad p \in P
\end{aligned}
\tag{6}
$$

The risk of extinction is a probability, so the gap is integrated additively into the model (i.e. risk of extinction for

[1]An extended version of our paper with the technical appendix is available online (Buhler and Benson 2023).

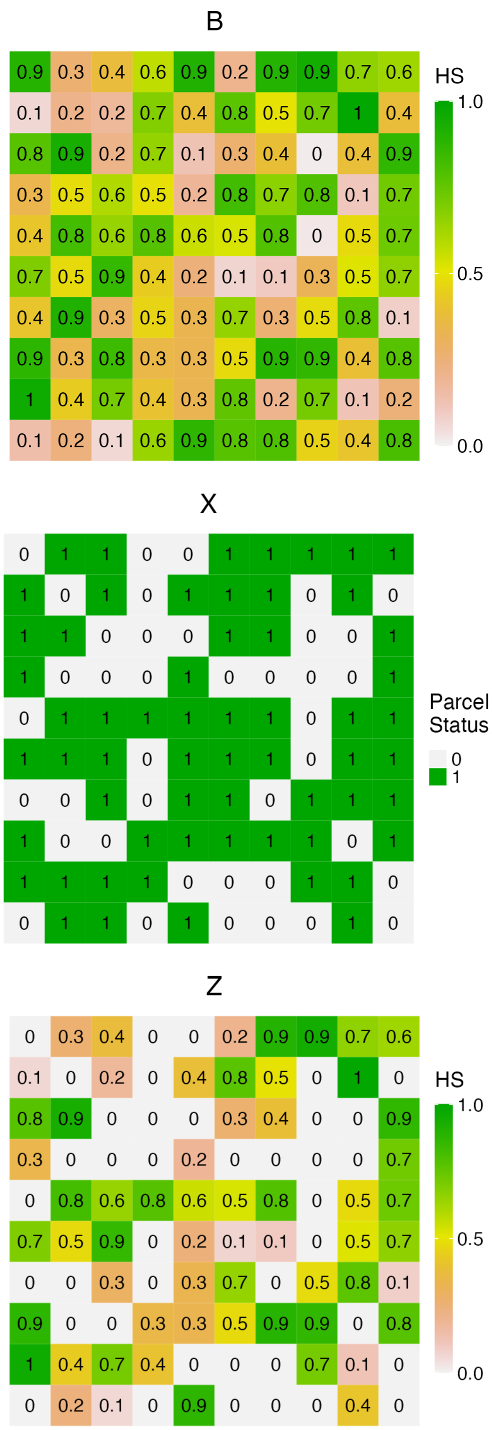

Figure 1: This figure illustrates the process of obtaining the habitat map Z. Only the parcels selected by X, which is the solution from (6) or (8), are retained from the full habitat map B. The maps B and Z display the habitat suitability (HS) for each parcel.

Algorithm 1: Black-Box Optimization Framework

Input: Landscape B
Parameters: Model type, ρ, λ
Output: X^*

```
if Model type is Constrained then
    Obtain baseline PVA metrics r(B), t(B), a(B) for B
    Formulate and solve (6) using Ant Colony Optimization, obtain X*
else if Model type is Multi-Objective then
    Formulate and solve (8) using Ant Colony Optimization, obtain X*
end if
return X*
```

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the preserved habitat should be within a small percentage of the baseline risk). Note that in this model, we have a linear objective, discrete decisions, and nonlinear constraints for the PVA metrics obtained from RAMAS, which is invoked as a black-box.

Multi-Objective Model

Re-interpreting the cost and the PVA metrics as priorities, we can also formulate a multi-objective model. Let

$$f(X) = \left[\sum_{p \in P} c_p X_p, r(Z), t(Z), a(Z) \right] \tag{7}$$

be the vector of objective functions, and let $\lambda = [\lambda_1, \ldots, \lambda_4]$ be a vector of weights. We use weighted decomposition to convert this n objective problem into a single objective:

$$\begin{aligned} \underset{X \in \{0,1\}^{|P|}}{\text{minimize}} \quad & \sum_{i=1}^{4} \lambda_i f_i(X) \\ \text{subject to} \quad & Z_p = B_p X_p \quad \forall p \in P \\ & X_p \in \{0,1\} \quad \forall p \in P \end{aligned} \tag{8}$$

Solution Heuristic

The black-box nature of (6) and (8) yields a MINLP where the underlying nonlinear functions are not well-defined and the overall problems are nonconvex. Therefore, we propose to use a heuristic to solve these problems. Specifically, we have chosen to use Ant Colony Optimization as our solution method.

Numerical Testing

Software & Hardware

The machine used has an Intel(R) Core(TM) i5-3470S CPU @ 2.90GHz processor, 12 GB of installed RAM, and operates on a Windows 10 64-bit. This machine was accessed using a remote desktop on a macOS 13.4.1 with a 3.6 GHz 10-Core Intel Core i9 processor.

The code uses a combination of Python (Version 3.10.9), R (Version 4.3.1), *RAMAS GIS: Spatial Data* (Version 6.0), *RAMAS GIS: Habitat Dynamics* (Version 6.0), and *RAMAS Metapopulation* (Version 6.0). The R package used for generating the data was *raster* (version 3.6-20). The optimization models were solved using *pygmo* (Version 2.18.0).

Data

The input data B is a randomly generated raster where each pixel has a value that is uniformly distributed from $[0, 1]$ to represent the habitat suitability.

To establish groups of parcels that will contain metapopulations, we set a habitat threshold to 0.5, where only parcels of higher than the threshold are habitable. A collection of contiguous habitable parcels is denoted as a patch. Refer to Figure 2.

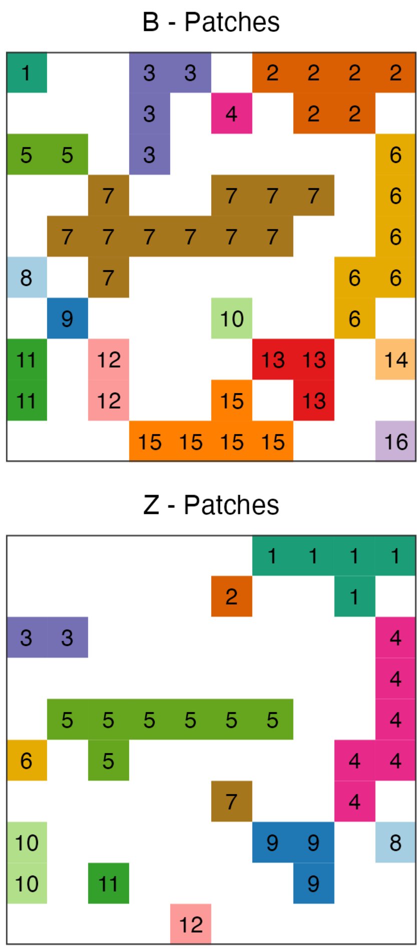

Figure 2: This figure displays the patch structure of B and Z from Figure 1. We see that Z did not preserve patches 1, 3, 9, or 16 from B and it reduced patches 2, 7, 12, and 15. Out of the 48 habitable parcels, 37 are preserved.

Testing

The following process is outlined in Algorithm 1 and further detailed in the technical appendix (Buhler and Benson 2023).

Depending on the model type, either (6) or (8) is solved using Extended Ant Colony Optimization (ACO) as described in (Schlüter, Egea, and Banga 2009) and implemented in the Python package, *pygmo*. (The parameters used in ACO are outlined in the technical appendix.) This heuristic is state-of-the-art and it was chosen because the MINLPs are nonconvex nonlinear problems with black-box function evaluations. In each iteration of the ACO, we create a habitat map Z and the simulation in *RAMAS* runs for 100 years and repeats 1000 times to obtain the PVA metrics.

To create a habitat map Z, we begin with the full habitat map B and consider the preserved parcels as indicated by X. For parcels that are not preserved, the habitat suitability level decreases such that it is no longer habitable. This is shown in Figure 1.

We present two landscape sizes: 10×10 and 20×20. For each landscape, we solve (6) and (8) and report the metrics and those from the baseline scenario in Table 2.

Results

The median time to extinction for each solution was identical to that of the baseline. This indicates that at least half of the simulations did not end in extinction.

The constrained model for both sizes and the multi-objective model for $n = 20$ also have the same risk of extinction as the baseline. Whereas, the risk of extinction has a marginal increase with the multi-objective model for $n = 10$. Recall the 95% confidence interval is based on the Kolmogorov-Smirnov test statistic, thus has a width of $\pm 3\%$ given 1000 replications. Considering this, a 0.017% risk of extinction is quite similar to B's risk of 0%.

For the expected minimum abundance, we begin to see a reflection of patch size on the population level. Habitats with smaller patches will have less abundance. Thus, the habitats with the most abundance are the most expensive.

The constrained model used $\rho = [0.1, 0.9, 0.8]$, thus the constraints are $r(Z) \leq 0.1$, $t(Z) \geq 90.9$, and $a(Z) \geq 61.4$ for $n = 10$ and $r(Z) \leq 0.1$, $t(Z) \geq 90.9$, and $a(Z) \geq 271.88$. for $n = 20$. ACO does not guarantee feasibility, thus the optimal solution is one which has the minimal constraint violation. We see the risk and time constraint are satisfied, while the abundance is not.

Comparing the abundance and cost to the multi-objective model, we find that abundance is much higher for the constrained model. This is due to abundance being a constraint, rather than an objective, as satisfying the constraints are prioritized by the solution heuristic.

It follows that the costs of the multi-objective solutions are the cheapest. The weights $\lambda = [0.35, 0.15, 0.15, 0.35]$ valued cost and abundance the same and higher than risk and time. These parameters were selected to reflect the difficulty of obtaining feasible abundance.

The corresponding habitat map for the 10×10 case of Z_c^* is presented in Figure 1, along with the patches in Figure 2. Additional figures from Table 2 are in the technical appendix (Buhler and Benson 2023).

	Z_c^*	Z_m^*	B
10×10			
Total Cost	340	199	577
Risk	0	0.017	0
Time	> 100	> 100	> 100
Abundance	33.5	12.1	61.4
20×20			
Total Cost	1134	874	2137
Risk	0	0	0
Time	> 100	> 100	> 100
Abundance	135.2	69.4	339.6

Table 2: Let Z_c^* and Z_m^* be the landscape given from X^* in (6) and (8), respectively. B is the case if every parcel were preserved. *Risk* is the risk to total extinction. *Time* is the median time to extinction. *Abundance* is the expected minimum abundance.

Discussion

Limitations Due to our selected PVA software, we were unable to solve using parallel computing, which drastically impacted the runtime. For this reason, we needed to limit the size of the landscape and the number of ACO generations, as these have the biggest impact on runtime.

Let g denote the number of generations, the number of iterations are then

$$\text{Iterations} = (n^2 + 1) * (g + 1)$$

Without parallel computation, the problem scales by a factor of n^2. This is significant considering that each iteration requires around 31 and 36 seconds for $n = 10$ and $n = 20$, respectively.

Ideally, the PVA component (or other selected software) would need to allow parallelization when working with larger landscape sizes. While long-term conservation decisions do not necessarily need to be made in a short window, parallelization can speed up the numerical testing and model refinement process.

Additionally, the MINLP with black-box functions limits us to using solution heuristics, which lack theoretical optimality guarantees.

Still, heuristics can offer computational advantages and are not unusual in conservation settings. MARXAN (Ball, Possingham, and Watts 2009), a population conservation planning software, uses simulated annealing. Even with explicitly defined convex formulations in optimization models, heuristics can be preferred for their interpretability and ability to scale up through parallelization.

Lastly, this framework is intended as a starting point to further multidisciplinary research. AI should aid conservationists, not replace them. The tools that are helpful for decision-makers must have the ability to tackle complex scenarios and integrate their software and models seamlessly.

Future Directions There are a few avenues to explore in future work. We have already indicated that parallelization of the optimization method will be a priority. We can also incorporate methods from derivate-free optimization literature, such as using surrogate functions for the PVA metrics.

The testing in this paper used randomly generated data. While this does not impact the mechanisms of the framework, the overall goal is to use real data that reflect real-world problems. Species distribution models produce range maps depicting the geographic locations where a species may occur and are often used in spatial optimization models. Applying such methods would provide more validity to the results.

Finally, another area of exploration would be incorporating metrics that allow for multiple species. This implementation would increase problem size, as every species would add another dimension to the model. It would also increase opportunities and motivation for parallelization of the optimization method.

Ethical Statement

Historically, protected areas have been used as a tool for colonization under the guise of conservation, largely impacting the Indigenous Peoples (West, Igoe, and Brockington 2006; Stevens 2014). Optimization models in conservation planning have potential to yield inequitable decisions, particularly in the context of transnational conservation initiatives such as 30×30 (Chapman et al. 2021), thus it is imperative that this framework–and others like it–are used with discretion.

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