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A robust optimization approach for solving problems in conservation planning

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ABSTRACT

In conservation planning, the data related to size, growth and diffusion of populations is sparse, hard to collect and unreliable at best. If and when the data is readily available, it is not of sufficient quantity to construct a probability distribution. In such a scenario, applying deterministic or stochastic approaches to the problems in conservation planning either ignores the uncertainty completely or assumes a distribution that does not accurately describe the nature of uncertainty. To overcome these drawbacks, we propose a robust optimization approach to problems in conservation planning that considers the uncertainty in data without making any assumption about its probability distribution. We explore two of the basic formulations in conservation planning related to reserve selection and invasive species control to show the value of the proposed robust optimization. Several novel techniques are developed to compare the results produced by the proposed robust optimization approach and the existing deterministic approach. For the case when the robust optimization approach fails to find a feasible solution, a novel bi-objective optimization technique is developed to handle infeasibility by modifying the level of uncertainty. Some numerical experiments are conducted to demonstrate the efficacy of our proposed approach in finding more applicable conservation planning strategies.

1. Introduction

Conservation Planning concerns itself with the issues related to maintaining and increasing biodiversity. Preserving biodiversity is crucial to human societies and the future of planet Earth. Hence its slow erosion constitutes a threat as consequential as that posed by the climate change (Billionnet, 2013). According the International Union for Conservation of Nature (2017), about 24,000 species out of the 91,000 listed are threatened with extinction. Two of the key issues, among others, resulting in the loss of biodiversity, as identified by the Convention on Biological Diversity (CBD), are land fragmentation and invasive predators. The alteration and loss of the habitats for many species is caused by rampant deforestation, overpopulation, agriculture and other economically beneficial land use alternatives (Polasky et al., 2008).

There is an abundant body of knowledge prescribing the creation of land reserves, geographic regions designated for the preservation of biodiversity, as a way to slow the process of habitat destruction and to protect threatened species from the processes that threaten their existence (Rodrigues et al., 2004). Due to limited monetary and land resources available for conservation and the difficulty of reversing land use decisions in the long term, it is imperative that the reserve selection decision to be based on sound scientific evidence. There is a long history of using optimization methods for reserve selection in assistance to the process of reserve selection (Haight et al., 2000; Polasky et al., 2000; Cabeza and Moilanen, 2001; ReVelle et al., 2002; Arthur et al., 2002; Costello and Polasky, 2004). More recently there has been a growing interest in solving problems of reserve design, i.e., reserve selection with constraints on size, shape, connectivity, compactness and species complementarity (Jafari et al., 2017; Beyer et al., 2016; Haight and Snyder, 2009; Williams et al., 2005; Margules and Pressey, 2000). A brief review of the reserve selection literature and the issues therein is presented in Section 3.

Another major threat to biodiversity and other ecosystem services is the introduction of invasive species (Pejchar and Mooney, 2009). For example, Doherty et al. (2016) estimated that the invasions of mammalian species such as feral cats, rodents and pigs were responsible for massive extinctions (738 vertebrate species) and may have contributed to 58% of the cases of contemporary extinctions of birds, mammals and reptiles. Once established, it is very difficult and costly to fully eliminate an invasive species. Many mathematical optimization formulations have been presented to

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manage and control the spread of invasive species. We present a brief review of these formulations in Section 3.

Conservation planning also encompasses other problems besides the two we have mentioned above. Other authors have discussed the use of mathematical optimization to solve a variety of conservation problems (Billionnet, 2013). However, one crucial aspect that has not been sufficiently considered is the issue of noisy information, for example due to imperfect detection of species during surveys (Williams et al., 2005). In their seminal work on systematic conservation planning, Margules and Pressey (2000) point out that conservation planning is riddled with uncertainty. Uncertainty pervades the use of biodiversity surrogates, the setting of conservation targets, decisions about which kinds of land tenure can be expected to contribute to targets and for which features, and decisions about how best to locate, design, implement and manage new conservation areas in the face of limited resources, competition for other uses, and incursions from surrounding areas. New developments in all the planning stages will progressively reduce, but never eliminate, these uncertainties. They recommend that planners, rather than proceeding as if certain, must learn to deal explicitly with uncertainty in ways that minimize the chances of serious mistakes.

Many problems in conservation planning require information about state variables (e.g., species abundance, occupancy), rates that pertain to the dynamic of ecological systems (e.g., population growth rate, movement rate), or conservation value of land parcels among other variables (Williams et al., 2005). Ignoring these potential sources of uncertainties may lead to bad decisions. Many studies have addressed these uncertainties with probabilistic and stochastic approaches. These approaches, although a big step up on the deterministic models, do not handle the uncertainty sufficiently. This is due to the fact that there are always certain inhibiting assumptions regarding the nature of the uncertainty in these methods. More precisely, due to sparsity of the data available, it is overly optimistic to try and over fit this data into certain probability distributions.

To deal with the issue of uncertainty and the lack of sufficient probabilistic information, there has long been a discussion of using robust optimization (see, for instance, Beyer et al., 2016). But we were not able to find any study that exploits this technique. In this paper, we propose to use robust optimization for conservation planning and optimal control of invasive species.

Since robust optimization (Bertsimas and Sim, 2004; Ben-Tal et al., 2009) accounts for the worst-case scenarios, it ensures that the problem is tractable and near optimal in the face of large uncertainty. When using the robust approach, the decision maker will know the quantum of parametric uncertainty they are protected against when they deploy the decisions and policies recommended by the robust counterpart of a formulation. In this paper, we also show another crucial value of the robust optimization. For some conservation problems, if the uncertainty is very large it may be infeasible to find a solution that meets a budget constraint. A crucial question then arises; if we are unable to address all the uncertainty using the current resources, where can we best expend these resources for improving our data gathering efforts in order to reduce the quantum of uncertainty as much as possible. We have developed a bi-objective optimization approach that addresses this question. Our approach gives managers the possibility to visualize how much uncertainty can be addressed for a given budget and provides a prescriptive set of recommendations about where to focus their data gathering efforts. As we show in Section 5, this knowledge can have profound policy implications. We come up with a novel bi-objective optimization formulation to model this approach and develop it further.

This paper is organized as follows: In Section 2, we describe the robust optimization approach that we have used. In Section 3, we review existing basic optimization formulations developed for two fundamental problems in conservation planning. In Sections 4 and 5, we introduce a robust optimization approach for the invasive control problem and the reserve selection problem, respectively, and present some numerical experiments. Finally, in Section 6, we state our concluding remarks.

2. Preliminaries: robust optimization

Robust optimization is a principal method to address data uncertainty in mathematical programming formulations. This method has been successfully applied to solve many problems (under uncertainty) when the exact distribution for the data is unknown or difficult to determine or otherwise using stochastic optimization techniques is computationally impractical. In general, robust optimization is a conservative approach that seeks to protect the decision maker against the worst realizations of outcomes. The focus of this study is the robust optimization technique developed by Bertsimas and Sim (2004) since it allows for controlling the degree of conservatism of the solution.

Let $\boldsymbol{c}$ be an n-vector, $\boldsymbol{A}$ be an $m \times n$ matrix, and $\boldsymbol{b}$ be an m-vector. The deterministic optimization formulations in this study are in the form of mixed integer linear programs, i.e.,

$$\begin{aligned} \min \quad & \boldsymbol{cx} \\ \text{s.t.} \quad & \boldsymbol{Ax} \leq \boldsymbol{b} \\ & \boldsymbol{x} \geq \boldsymbol{0} \\ & x_i \in \mathbb{Z} \quad \text{for } i = 1, \ldots, n_1, \end{aligned}$$

where $\boldsymbol{x}$ is the vector of variables containing n_1 number of integer variables, and n_2 number of continuous variables (note that $n = n_1 + n_2$). Also, all coefficients are rational, i.e., $\boldsymbol{A} \in \mathbb{Q}^{m\times n}$, $\boldsymbol{b} \in \mathbb{Q}^m$, and $\boldsymbol{c} \in \mathbb{Q}^n$. In all proposed formulations in this study, the data uncertainty affects only the elements of the matrix $\boldsymbol{A}$. To avoid any unnecessary confusion, we next explain a customized version of the robust optimization technique developed by Bertsimas and Sim (2004) that works on this specific class of optimization problems.

We do not make any assumption about the exact distribution of each entry a_{ij} of the matrix $\boldsymbol{A}$. However, it is assumed that reasonable estimates for the mean value of the coefficient $\bar{a}_{ij}$ and its range $\hat{a}_{ij}$ are available. In other words, we assume that each entry a_{ij} takes value in $[\bar{a}_{ij} - \hat{a}_{ij}, \bar{a}_{ij} + \hat{a}_{ij}]$. Note that $\hat{a}_{ij}$ can be equal to 0.

For each row $i \in \{1, \ldots, m\}$ of the matrix $\boldsymbol{A}$, we introduce a number Γ_i (defined by users) to adjust the the required level of conservatism in the proposed robust optimization formulation. This number simply imposes an upper bound on the number of entries of row i of the matrix $\boldsymbol{A}$ that can reach their worst-case values. Given that $\boldsymbol{Ax} \leq \boldsymbol{b}$ and all variables are non-negative, the worst-case value for the entry a_{ij} of the matrix $\boldsymbol{A}$ is $\bar{a}_{ij} + \hat{a}_{ij}$. So, higher the value of Γ_i, higher the degree of conservatism. The parameter Γ_i can only take values in the interval $[0, |J_i|]$ where $J_i = \{j : \hat{a}_{ij} > 0\}$. We assume that if $\Gamma_i \notin \mathbb{Z}$ then at most $\lfloor \Gamma_i \rfloor$ number of entries of row i of the matrix $\boldsymbol{A}$ can reach their worst-case values, i.e., $\bar{a}_{ij} + \hat{a}_{ij}$. One other entry r_i can reach the value of $\bar{a}_{ij} + (\Gamma_i - \lfloor \Gamma_i \rfloor)\hat{a}_{ij}$. In simpler terms, if there are one hundred entries in a row i of matrix $\boldsymbol{A}$, and the corresponding Γ_i value is 50.7, then 50 entries of row i of matrix $\boldsymbol{A}$ can reach their worst-case values of $\bar{a}_{ij} + \hat{a}_{ij}$ and one other entry will reach the value of $\bar{a}_{ij} + 0.7\hat{a}_{ij}$. The robust optimization formulation that