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Highlights

- A mixed integer programming tool for multicriteria conservation planning is presented
- The tool optimizes ecological benefit and spatial fragmentation.
- A case study of the Mitchell river in northern Australia is considered.
- Obtained results show how the methodology exploits he trade-offs among criteria.
- Decision-makers can explore and analyze a broad range of conservation plans.

An integer programming method for the design of multi-criteria multi-action conservation plans

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Abstract

The design of conservation management plans is a crucial task for ensuring the preservation of ecosystems. A conservation plan is typically embodied by two types of decisions: in which areas of a given territory it will be implemented, and how actions against threats will be deployed across these areas. These decisions are usually guided by the resulting ecological benefit, their spatial effectiveness, and their implementation cost.

In this paper, we propose a multi-criteria optimization framework, for modeling and solving a mixed integer programming characterization of a multi-action and multi-species conservation management design problem. The optimization tool seeks for a management plan that maximizes ecological benefit and minimizes spatial fragmentation, simultaneously, while ensuring an implementation cost no greater than a given budget.

For showing the effectiveness of the methodology, we consider a case study corresponding to a portion of the Mitchell river catchment, located in northern Australia, where 31 freshwater fish species are affected by four threats.

The attained results show how the methodology exploits the trade-offs among the ecological, spatial and cost criteria, enabling decision-makers to explore and analyze a broad range of conservation plans. Selecting conservation plans in a more informed way allows to obtain the best outcomes from a strategic and operational point of view.

Keywords: Conservation planning; Wildlife management, Mixed integer programming; Multicriteria optimization.

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1. Introduction and motivation

A dramatic loss of biodiversity, across the whole globe, has been experienced over the last century. An indiscriminate exploitation of natural resources, the outburst of introduced species, unsustainable human population growth, and the consequences of climate change, are among the processes that have led to this lost. In July 2012, at the Rio+20 Earth Summit, the International Union for Conservation of Nature revealed that about 20,000 animal species are threatened with extinction. Among them, 4,000 are described as *critically endangered* and 6,000 as *endangered*, while more than 10,000 species are listed as *vulnerable* (IUCN, 2016). Furthermore, United

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Nations have defined biodiversity protection as one of the *Sustainable Development* goals (see United Nations, 2018; United Nations Sustainable Development Goals, 2018).

Maintaining biodiversity and ecosystemic equilibrium, is fundamental for ensuring the environmental conditions for future generations (Cardinale et al., 2012; Wilson et al., 2007). International (non-governmental) organizations, governments, academic institutions, and foundations, have devoted immense efforts in the last decades to the design and establishment of protected areas and conservation management plans, aiming at restoring and preserving landscape for wildlife. For in-depth analyses and discussion of motivations, models, cases, and challenges in the field of wildlife conservation and nature reserve planning, the reader is referred to (Gergel and Turner, 2002; Lindenmayer and Franklin, 2002; Millspaugh and Thompson, 2008).

Strategical, tactical and operational conservation decisions are usually the result of a so-called *systematic conservation planning* (SCP) process (see, e.g., Margules and Pressey, 2000; Margules et al., 2007; Wiersma and Sleep, 2016). SCP frames quantitative methodologies aiming at ensuring the long-term persistence of species by means of adequate planning and implementation of cost-effective actions. The core of most of these methodologies corresponds to modeling and solving mathematical optimization problems (Billionnet, 2013; Moilanen et al., 2009; Pressey et al., 1997; Watts et al., 2009).

The territorial design of management plans for conservation (i.e. which areas to select and respecting which spatial arrangement), is by far one of the most important aspects of conservation management plans (see Jones et al., 2016; Moilanen et al., 2009, 2011; Possingham et al., 2006; Williams et al., 2005, and the references therein). An optimized spatial distribution of a conservation plan should ensure its ecological effectiveness, as well as the efficient use of economic resources. Due to this importance, a broad body of literature has been devoted to the development of methodologies for the design, implementation and assessment of territorial aspects of natural reserves. Such tools rely, mainly, on two optimization techniques; either (mixed integer linear) mathematical programming (see, e.g., Billionnet, 2013; Beaudry et al., 2016; Church et al., 1996; Önal et al., 2016; Williams et al., 2004, 2005), or heuristics (see, e.g., Cattarino et al., 2016; Lehtomäki and Moilanen, 2013; McDonnell et al., 2002; Pressey et al., 1997). These methodologies have set the basis for developing decision-aid tools for the conservation planning and ecology community; one of the most prominent examples corresponds to MARXAN and its variants (see Ball et al., 2009; Watts et al., 2009, for further details).

The essential decisions of a conservation management plan correspond to the actions, and the corresponding level of intensity, that need to be implemented in the selected territory, i.e., the land units where the plan takes place (see Game et al., 2013). At a local scale (i.e., from the standpoint of a single land unit), such actions range from simply monitoring a given land unit to complete abatement of existing threats (the reader is refered to, e.g., Auerbach et al., 2014; Januchowski-Hartley et al., 2011; Van Teeffelen, 2007, for further discussion on this topic). The goal is to establish a territorial arrangement of actions so that we attain a maximal ecological benefit (both, at a local and aggregated level) at expenses of a minimum, or at least limited, total cost. Recently, Cattarino et al. (2015) propose a heuristic optimization approach for the spatial prioritization of multi-action planning; in their case, the goal is to find a cost-efficient conservation plan, comprised of abatement actions against threats, that ensures minimum quotas of ecological benefit for a given set of threatened species. Following that work, several approaches dealing with multi-action planning and implementation have been proposed over the last decade (see, e.g., Tulloch et al., 2016; Van Teeffelen et al., 2008), which emphasizes the importance of addressing this type of planning settings in order to achieve effective management plans.

Our contribution In this paper, we contribute to the literature devoted to multi-action (conservation) planning problems, by extending the existing work in two aspects. First, our work addresses a novel multi-species conservation planning strategy that encompasses, simultaneously, multiple actions and conflicting criteria. For such a decision-making scheme, the optimization criteria, mainly ecological, economical and functional, shall be fairly balanced in order to design effective conservation plans. This is done by defining a multicriteria mathematical optimization model, along with an algorithmic scheme for solving it. Our multicriteria approach extends previously published methods (see, e.g., Dujardin and Chadès, 2018; Klein et al., 2010; Nalle et al., 2002, 2004; Williams, 1998), as it recognizes the need of characterizing biodiversity conservation not only as a cost-efficient spatial layout design problem, but rather as a multiple action problem encoded by functional and spatial decisions and conflictive objectives associated to them. And second, following the motivations presented in the recently published work (Beyer et al., 2016), we use mixed integer linear programming (MIP) as modeling and algorithmic approach, instead of heuristic-based schemes based on MARXAN, e.g., (Cattarino et al., 2015; Hermoso et al., 2015, 2016); this allows, for real cases as we consider in this paper, a computationally efficient computation of high-quality solutions offering effective trade-offs among the different criteria.

To the best of our knowledge, this is one of the first works encoding multi-actions for the spatial management of multi-species within a multicriteria model that is tackled using MIP techniques. Therefore, our work is a further step of the operations research community towards applications emerging from the need of a sustainable impact and management of our environment.

Paper outline The paper is organized as follows. In Section 2 we describe the main methodological elements of the proposed optimization framework. The description of the case study, and extensive computational results, along with a detailed analysis, are presented in Section 3; further discussion on the attained results as well as managerial insights are provided in Section 4. Finally, in Section 5, we present concluding remarks and venues for future work.

2. A MIP framework for Multi-criteria Design of Multi-Action Conservation Plans

Following the concepts presented in the introduction, a multi-action conservation plan is encoded by the selection of a set of territorial units for systemic *monitoring*, along with *actions* against some of the threats that occur in such units, so as to maximize a multi-species conservation benefit. In this context, monitoring a unit refers to the deployment of human and/or machine-based strategies for obtaining on-site surveillance data regarding appearance and progression of threats against a specific biodiversity that we want to protect. Likewise, an *action* corresponds to an activity devoted to the partial or total eradication of a threat (e.g., in the case of tree diseases, a treatment might correspond to spraying or injecting a fungicide into the truck, branches, or soil). Hence, the conservation benefit is proportional to the reduction of the threats that occur where the target species inhabit. Besides a good ecological performance, the conservation plan is expected to be, on the one hand, functional from a spatial point of view (which is achieved by minimizing the spatial fragmentation among the selected units), and on the other, economically effective (i.e., respect a given budget). As we will show in the remainder of this article, a multi-action conservation plan that addresses these criteria and requirements is embodied by the solution of an optimization problem that we coin as bi-objective multi-action conservation planning problem (BMACP), In the following, we will present the mathematical programming model of the BMACP as well as the algorithmic scheme for solving it.

Notation and preliminaries Let I be the set of land units, so that $i \in I$ is a basic territorial division, which encompasses basic characteristics such as surface, shape, and topology. Likewise, let S be the set of species, so that, for a given unit $i \in I$, $S_i \subseteq S$ corresponds to the set of species occurring in unit $i \in I$. Similarly, let T be the set of threats, so that $T_i \subseteq T$ corresponds to the set of threats occurring in unit $i \in I$; likewise, let $T_s \subseteq T$ be the set of threats that affect species $s \in S$. In Figure 1 we show a schematic example of a territory mapped

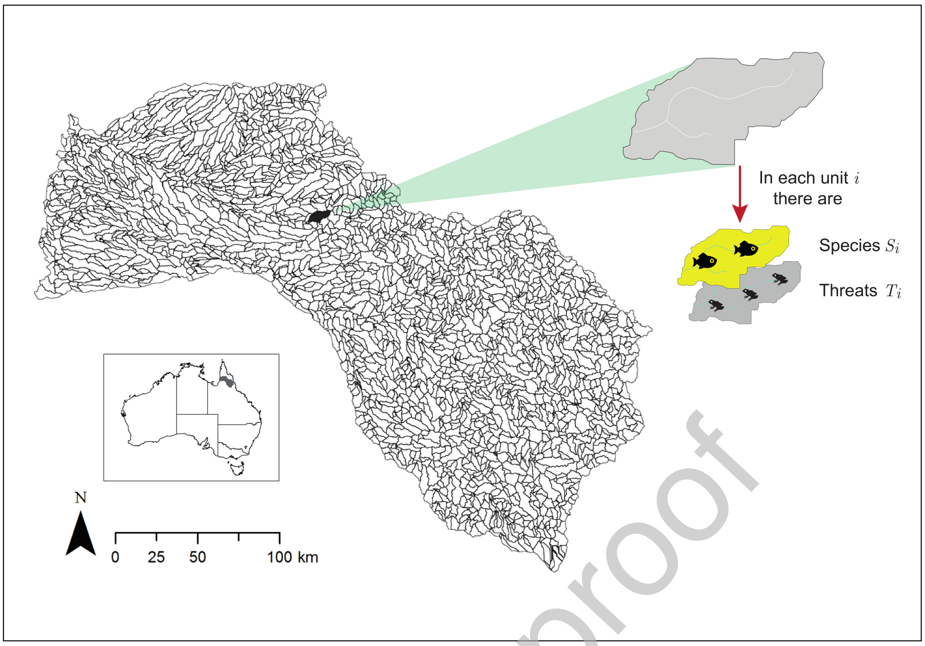


Figure 1: Schematic example of a territory mapped into a set I

into a set I and how in a particular unit $i \in I$, both species and threats can co-occur. In Section 3 we will present further details regarding the data used for the computational analysis carried out in this paper.

From an economical point of view, let $\mathbf{cf} \in \mathbb{R}^{|I|}_{\geq 0}$ be the vector of *monitoring* costs, so that cf_i is the cost of monitoring unit $i \in I$, i.e., incorporating it as part of the spatial deployment of the conservation plan; similarly, let $\mathbf{c} \in \mathbb{R}^{|I| \times |T|}_{\geq 0}$ be the matrix of *action* costs, so that c_{it} is the cost of applying an action against threat $t \in T$ in unit $i \in I$.

From a conservation point of view, the *local* benefit for a species $s \in S_i$ at a given unit $i \in I$, is *proportional* to the fraction of threats against species s for which an action is taken in i, say T_{is}, with respect to the total number of threats against s that occur in i (we assume that $|T_i \cap T_s| \neq 0$), i.e.,

$$b_{is} = \left(\frac{T_{is}}{|T_i \cap T_s|} \right)^{\nu_s}. \tag{1}$$

Since $0 \leq \frac{T_{is}}{|T_i \cap T_s|} \leq 1$, it holds that $\nu_s > 0$ allows to control how sensitive species s is with respect to a partial application of actions against all threats (see Cattarino et al., 2015). For instance, if $\nu_s = 1$ and we treat half of the threats of a species in a given unit, we achieve an ecological benefit equal to 0.5. However, if $\nu_s = 3$, then we would need to treat 80% of the threats against the same species in the same unit. Therefore, the larger the value of ν_s, for a given species s, the more effort is needed to reach higer values of ecological benefit. In this paper we assume that $\nu_s = 3$, for all $s \in S$, as done in in (Cattarino et al., 2015). If for a given pair $i \in I$, $s \in S_i$, it holds that $|T_i \cap T_s| = 0$, i.e., there are no threats for species s on unit i, then the ecological contribution for s will be 1 if unit i is taken as part of the reserve, and 0 otherwise. In this type of settings, actions against threats can be taken if and only if the corresponding unit is under the observation of managers, i.e., if the unit is part of the monitored zone. Such condition is ensured by the proposed model as it will be showed in the next section. Note that we refer to $b_{\cdot i}$ as a local measure of ecological benefit, and we do not assume further spatial synergy and functionality among intervened units. Although this is a common assumption in literature (see, ,e.g., (Billionnet, 2013; McDonnell et al., 2002; Pressey et al., 1997; Watts et al., 2009)), decision-makers must consider this when analyzing and implementing the prescribed conservation plans, as spatial interactions are likely occur in these settings an shall not be neglected. As a matter of fact, alternatives for modeling such phenomena can be found in (Albers et al., 2016; Beaudry et al., 2016; Strassburg et al., 2019) and (Thomas et al., 2004).

2.1 A MIP model for the BMACP

For the mathematical optimization models that will be presented in the following, let $\mathbf{w} \in \{0,1\}^{|I|}$ be a vector of binary variables, such that $w_i = 1$ is unit $i \in I$ is taken as part of the conservation plan (i.e., it will be, at least, monitored), and $w_i = 0$ otherwise. Likewise, let $\mathbf{x} \in \{0,1\}^{|I|\times|T|}$ be a vector of binary variables, such that $x_{it} = 1$ if an action against threat $t \in T$ is taken in unit $i \in I$, and $x_{it} = 0$ otherwise. Additionally, and for modeling purposes, let $\mathbf{z} \in \{0,1\}^{|I|\times|S|}$ be a vector of auxiliary binary variables, so that for a given $i \in I$ and a given $s \in S$, such that $|T_s \cap T_i| = 0$, $z_{is} = 1$ if land unit $i \in I$ *contributes* to the ecological benefit of species $s \in S$, and $z_{is} = 0$ otherwise.

A solution encoded by a triplet $(\mathbf{w}, \mathbf{x}, \mathbf{z})$, can be characterized by three performance measures: total ecological benefit, total spatial fragmentation, and total cost. The total ecological benefit is expressed as the sum of the local ecological benefit attained across all (intervened) units, i.e.,

$$B(\mathbf{w},\mathbf{x},\mathbf{z}) = \sum_{s\in S}\left(\sum_{i\in I_{|T_s\cap T_i|\neq\emptyset}} b_{is} + \sum_{i'\in I_{|T_s\cap T_{i'}|=0}} z_{i's}\right), \tag{2}$$

where

$$b_{is} = \left(\frac{\sum_{t\in T_s\cap T_i} x_{it}}{|T_s\cap T_i|}\right)^{\nu_s} \tag{3}$$

accounts for the local conservation benefit, induced by $(\mathbf{w}, \mathbf{x}, \mathbf{z})$, for a given species $s \in S$ in unit $i \in I$ where threats co-occur (i.e., $|T_s \cap T_i| \neq 0$).

Likewise, the second term, $\sum_{i'\in I_{|T_s\cap T_{i'}|=0}} z_{si'}$, accounts for selected units in which species $s \in S$ occurs and no threat against it co-occurs. Similarly, the fragmentation of such solution $(\mathbf{w}, \mathbf{x}, \mathbf{z})$, is given by

$$F(\mathbf{w},\mathbf{x},\mathbf{z}) = \sum_{i_1\in I}\sum_{i_2\in I|i_1\neq i_2} \frac{1}{d^2_{i_1 i_2}} w_{i_1}(1-w_{i_2}), \tag{4}$$

i.e., if a unit is selected, the neighboring units are preferred over more distant units, where $\mathbf{d} \in \mathbb{R}^{|I|\times|I|}_{\geq 0}$ is the matrix of pair-wise distances, so that d_{ij} corresponds to the up-stream distance between units $i, j \in I$. Therefore, by minimizing fragmentation function $F(\cdot)$ we maximize the spatial aggregation of the selected units. As explained in (Hermoso et al., 2011), this strategy avoids the selection of isolated planning units and forces the inclusion of closer upstream areas. On the one hand, this approach is concordant with ecological theory, as it considers the natural and roughly exponential decay of upstream influences with distance; and on the other, it accounts for the natural capacity of rivers to mitigate impacts when designing reserves (see Hermoso et al., 2013, for further details). Note that fragmentation is only measured with respect to monitored units. Nonetheless, in our setting, actions can be only applied on monitored units; hence, by minimizing function $F(\mathbf{w}, \mathbf{x}, \mathbf{z})$ we are also attempting to contribute to the spatial aggregation of actions (a similar strategy is followed by Cattarino et al., 2015). And, finally, the total cost is expressed by

$$C(\mathbf{w},\mathbf{x},\mathbf{z}) = \sum_{i\in I}\sum_{t\in T_i} c_{it}x_{it} + \sum_{i\in I} cf_i w_i, \tag{5}$$

i.e., the sum of the action costs plus the monitoring costs (note that in order to perform an action in a unit, this must be selected for monitoring in the first place). In practice, conservation agencies typically plan their territorial strategies constrained by a certain budget,which is granted according to mid- or long-term policies defined by a central administration. In other words, decision-makers typically face the task of finding a conservation plan, say $(\mathbf{w},\mathbf{x},\mathbf{z})$, fulfilling $C(\mathbf{w},\mathbf{x},\mathbf{z}) \leq C_0$, where $C_0 \geq 0$ is the budget allocated for the pursued plan.

Wrapping up all the concepts and definitions presented so far, the BMACP can be formulated as the following bi-objective optimization problem;

$$\begin{aligned}
(B^*, F^*) = &\max\ B(\mathbf{w},\mathbf{x},\mathbf{z}),\ \min\ F(\mathbf{w},\mathbf{x},\mathbf{z}) && \text{(BMACP.1)}\\
\text{s.t.}\quad & C(\mathbf{w},\mathbf{x},\mathbf{z}) \leq C_0 && \text{(BMACP.2)}\\
& \sum_{t\in T_i} x_{it} \leq |T_i| w_i,\ \forall i \in I && \text{(BMACP.3)}\\
& \sum_{s\in S_i} z_{is} \leq |S_i| w_i,\ \forall i \in I && \text{(BMACP.4)}\\
& \mathbf{w} \in \{0,1\}^{|I|},\ \mathbf{x} \in \{0,1\}^{|I|\times|T|},\ \mathbf{z} \in \{0,1\}^{|I|\times|S|}. && \text{(BMACP.5)}
\end{aligned}$$

The two objectives described before, maximization of ecological benefit and minimization of spatial fragmentation, are encoded in (BMACP.1). Constraint (BMACP.2) corresponds to the budget constraints, since it limits the total cost to be no greater than C_0. The fact that actions can be performed ($\sum_{t\in T_i} x_{it} > 0$) only on monitored units ($w_i = 1$) is ensured by constraint (BMACP.3), and (BMACP.4) follows the same arguments (but for units where no threat occurs for a given instance). Finally, constraint (BMACP.5) imposes the nature of the variables.

Note that both, the benefit $B(\mathbf{w},\mathbf{x},\mathbf{z})$ and the fragmentation $F(\mathbf{w},\mathbf{x},\mathbf{z})$ are non-linear expression, therefore, formulation (BMACP.1)-(BMACP.5) is non-linear. The non-linearity associated to function $B(\mathbf{w},\mathbf{x},\mathbf{z})$ can be handled through the use of piece-wise linear functions which require additional auxiliary binary variables and the incorporation of additional constraints (see, e.g., Belotti et al., 2013; Keha et al., 2006). In particular, we used the strategy encoded into the `IloPiecewiseLinear` function of IBM ILOG CPLEX® 12.6.3 (IBM). Likewise, the non-linearities associated to the expression $F(\mathbf{w},\mathbf{x},\mathbf{z})$, can be tackled by using the linearization that induces the so-called boolean quadratic polytope (see Padberg, 1989, for a fundamental paper on these matters). The latter technique has be been recently used, for example, within the context of conservation planning (see Beyer et al., 2016).

Note that solving (BMACP.1)-(BMACP.5) means to explore the so-called *Pareto frontier*. This frontier is comprised by the set of all points (B^*, F^*), which are induced by the solutions satisfying Pareto *optimality* (i.e., non-dominated solutions). For the case of the BMACP, a formal definition of Pareto optimality is presented below.

Definition 1. *(see, e.g., Censor, 1977) A feasible solution* $(\mathbf{w}^*,\mathbf{x}^*,\mathbf{z}^*)$ *of the BMACP is Pareto optimal, if and only if there exists no other feasible solution* $(\mathbf{w}',\mathbf{x}',\mathbf{z}')$ *such that* $B(\mathbf{w}',\mathbf{x}',\mathbf{z}') \geq B(\mathbf{w}^*,\mathbf{x}^*,\mathbf{z}^*)$ *and* $F(\mathbf{w}',\mathbf{x}',\mathbf{z}') \leq F(\mathbf{w}^*,\mathbf{x}^*,\mathbf{z}^*)$*, with at least one strict inequality. A feasible solution* $(\mathbf{w}^*,\mathbf{x}^*,\mathbf{z}^*)$ *is* weakly *Pareto optimal, if and only if there is no solution* $(\mathbf{w}',\mathbf{x}',\mathbf{z}')$*, where both inequalities are strict.*

As we will show in the following subsection, our algorithmic strategy aims at approximating the Pareto frontier, i.e., finding a collection of solutions that are *near* to the frontier. By comparing such a collection of (nearly) Pareto optimal solutions, it is possible to analyze the trade-offs between the two objectives (B and F) and how the budget on the cost sharpens such trade-offs, as well as the characteristics of the solutions. As we will show in Section 3, by means of a case study, exploiting such trade-offs allows the decision-makers to have not only one, but actually a pool of management plans, each of them offering different performances. In the following subsection, we will outline a strategy for approximating the corresponding Pareto front. As it will be detailed next, this strategy relies on iteratively solving conveniently constrained single-objective problems.

2.2 A strategy for solving the BMACP

In order to approximate the Pareto frontier associated to the BMACP, and explore nearly optimal (and non-dominated) solutions, we implemented a quite intuitive strategy, which fits with the decision-making process that it is carried by the conservation agencies. Such strategy is outlined below.

The proposed methodology relies, in the first place, on making the following question: *what would be the most beneficial conservation plan if no budget nor fragmentation constraint limits our actions?* To answer such question, it is necessary to solve the following (single objective) maximum benefit multi-action problem (MAP),

$$(\mathbf{w}', \mathbf{x}', \mathbf{z}') = \arg\max \; B(\mathbf{w}, \mathbf{x}, \mathbf{z}) \tag{MAP.1}$$

$$\text{s.t.} \qquad \text{(BMACP.3)-(BMACP.5).} \tag{MAP.2}$$

The solution of this optimization problem, $(\mathbf{w}', \mathbf{x}', \mathbf{z}')$, corresponds to a selection of units (and actions, when corresponding) that ensures the maximum conservation benefit, without any budget constraint. Let $B^* = B(\mathbf{w}', \mathbf{x}', \mathbf{z}')$, and let $F^* = F(\mathbf{w}', \mathbf{x}', \mathbf{z}')$; we then solve the following auxiliary problem

$$(\mathbf{w}^*, \mathbf{x}^*, \mathbf{z}^*) = \arg\min \; C(\mathbf{w}, \mathbf{x}, \mathbf{z}) \tag{MAP.3}$$

$$\text{s.t.} \qquad B(\mathbf{w}, \mathbf{x}, \mathbf{z}) \geq B^* \tag{MAP.4}$$

$$\text{(BMACP.3)-(BMACP.5);} \tag{MAP.5}$$

hence, $C^* = C(\mathbf{w}^*, \mathbf{x}^*, \mathbf{z}^*)$ corresponds to the minimum cost budget required to attain the maximum ecological benefit B^*. The interplay of these two problems is characterized by the following observation;

Observation 1. *If* (MAP.1)-(MAP.2) *is solved to optimality, with B^* being the corresponding objective function value, then any feasible solution of* (MAP.3)-(MAP.5) *is an optimal solution* (MAP.1)-(MAP.2)*.*

It is expected that in most real-world applications, the value of C^*, the *ideal* budget, is (much) higher than the budget that will be available. As a matter of fact, one could expect that decision-makers take decisions using a budget that it is rather a *fraction* of C^*, i.e., $C_\rho = \rho C^*$, with $\rho \in [0, 1]$ being the *budget-fraction*. Hence, for a given $\rho \in [0, 1]$, the optimization problem that must be solved is nothing but a *budget constrained* counterpart of the above presented maximum benefit multi-action problem (C-MAP), i.e.,

$$(\mathbf{w}^*_\rho, \mathbf{x}^*_\rho, \mathbf{z}^*_\rho) = \arg\max \; B(\mathbf{w}, \mathbf{x}, \mathbf{z}) \tag{C-MAP.1}$$

$$\text{s.t.} \qquad C(\mathbf{w}, \mathbf{x}, \mathbf{z}) \leq C_\rho \tag{C-MAP.2}$$

$$\text{(BMACP.3)-(BMACP.5);} \tag{C-MAP.3}$$

let B^*_ρ be the attained objective value. Evidently, if $\rho = 1$ (i.e., $C_\rho = C^*$), the obtained solution would be equivalent to that of (MAP.1)-(MAP.2) as can be concluded from Observation 1. Although the solution

$(\mathbf{w}^*_\rho, \mathbf{x}^*_\rho, \mathbf{z}^*_\rho)$ ensures an optimal use of the budget C_ρ for achieving a maximum ecological benefit, the induced fragmentation, say F^*_ρ, can be arbitrarily poor. Thereafter, and in order to address the second objective of the BMACP, we shall look for the corresponding non-dominated Pareto solution associated to B^*_ρ, i.e., find a minimum fragmentation solution that ensures (at least) the same ecological benefit B^*_ρ, and at a cost no greater than C_ρ. Such solution can be found by solving the following (single-objective) minimum fragmentation budget and benefit constrained multi-action problem (CB-MAP),

$$(\mathbf{w}^{**}_\rho, \mathbf{x}^{**}_\rho, \mathbf{z}^{**}_\rho) = \arg\min \ F(\mathbf{w}, \mathbf{x}, \mathbf{z}) \qquad \text{(CB-MAP.1)}$$

$$\text{s.t.} \quad C(\mathbf{w}, \mathbf{x}, \mathbf{z}) \leq C_\rho \qquad \text{(CB-MAP.2)}$$

$$B(\mathbf{w}, \mathbf{x}, \mathbf{z}) \geq B^*_\rho \qquad \text{(CB-MAP.3)}$$

$$\text{(BMACP.3)-(BMACP.5)}; \qquad \text{(CB-MAP.4)}$$

let F^{**}_ρ be the attained objective value. Since F^{**}_ρ ensures a benefit that is *at least* B^*_ρ, and a total cost that is *at most* C_ρ, it holds that $(\mathbf{w}^{**}_\rho, \mathbf{x}^{**}_\rho, \mathbf{z}^{**}_\rho)$ is such that it is not possible to find a solution with an ecological performance better than $B^*\rho$ and a fragmentation smaller than F^{**}_ρ, at a total cost less or equal than C_ρ.

Our method relies on iteratively solving problems (C-MAP.1)-(C-MAP.3) and (CB-MAP.1)-(CB-MAP.3), consecutively, for different values of ρ. The chosen lexicographic order (first (C-MAP.1)-(C-MAP.3) and then (CB-MAP.1)-(CB-MAP.3)) responds to the decision setting in which it is inscribed.

By proceeding in this way, although we cannot ensure Pareto optimality of the obtained solution (as underlying MIP problems are not necessarily solved to optimality), we can approach the Pareto frontier induced by the objectives $B(\cdot,\cdot,\cdot)$ and $F(\cdot,\cdot,\cdot)$, as we seek for an trade-off among them (for a sequence of values of budget levels). As we will show in the following section, the application of this simple strategy allows to highlight the trade-offs among ecological, functional and economical objectives, and enables decision-makers to perform a more accurate characterization of what a cost-effective management plan is expected to be. This managerial functionality of the proposed framework, shows the potential of mathematical programming as a modeling and algorithmic framework for addressing complex conservation planning problems.

Algorithm 1 Strategy for solving BMACP

procedure APPROXIMATEPARETOFRONTIER
  Calculate $(\mathbf{w}', \mathbf{x}', \mathbf{z}') = \arg\max \{B(\mathbf{w}, \mathbf{x}, \mathbf{z}) \mid \text{(BMACP.3)-(BMACP.5)}\}$
  Set $B^* = B(\mathbf{w}', \mathbf{x}', \mathbf{z}')$ ▷ Definition of B^*
  Set $F^* = F(\mathbf{w}', \mathbf{x}', \mathbf{z}')$ ▷ Definition of F^*
  Calculate $(\mathbf{w}^*, \mathbf{x}^*, \mathbf{z}^*) = \arg\min \{C(\mathbf{w}, \mathbf{x}, \mathbf{z}) \mid B(\mathbf{w}, \mathbf{x}, \mathbf{z}) \geq B^* \wedge \text{(BMACP.3)} - \text{(BMACP.5)}\}$
  Set $C^* = C(\mathbf{w}^*, \mathbf{x}^*, \mathbf{z}^*)$ ▷ Definition of C^*
  Set $\rho \in [0, 1]$ ▷ Definition of ρ as a set of *fractions* of C^*
  for `each element in` ρ **do**
    Calculate $(\mathbf{w}^*_\rho, \mathbf{x}^*_\rho, \mathbf{z}^*_\rho) = \arg\max \{B(\mathbf{w}, \mathbf{x}, \mathbf{z}) \mid C(\mathbf{w}, \mathbf{x}, \mathbf{z}) \leq \rho C^* \wedge \text{(BMACP.3)-(BMACP.5)}\}$
    Set $B^*_\rho = B(\mathbf{w}^*_\rho, \mathbf{x}^*_\rho, \mathbf{z}^*_\rho)$ ▷ Definition of B^*_ρ
    Set $F^*_\rho = F(\mathbf{w}^*_\rho, \mathbf{x}^*_\rho, \mathbf{z}^*_\rho)$ ▷ Definition of F^*_ρ
    Calculate $(\mathbf{w}^{**}_\rho, \mathbf{x}^{**}_\rho, \mathbf{z}^{**}_\rho) = \arg\min \{F(\mathbf{w}, \mathbf{x}, \mathbf{z}) \mid C(\mathbf{w}, \mathbf{x}, \mathbf{z}) \leq \rho C^* \wedge B(\mathbf{w}, \mathbf{x}, \mathbf{z}) \geq B^*_\rho \wedge$ (BMACP.3)-(BMACP.5)$\}$
    Set $F^{**}_\rho = F(\mathbf{w}^{**}_\rho, \mathbf{x}^{**}_\rho, \mathbf{z}^{**}_\rho)$ ▷ Definition of F^{**}_ρ
  end for
end procedure

We shall point out that the strategy outlined by Algorithm 1 does not need nor assume a pre-defined preference of the decision-maker with respect to the performance of the sought solutions in the considered criteria. Instead, the exploration of the search space is performed by iteratively solving constrained optimization problems (lines 2, 5 and loop in lines 8-14 of Algorithm 1). However, there are other approaches for multicriteria optimization where the decision-maker can provide target or reference values for the different criteria and, therefore, enable the design of guided strategies. An example of such techniques corresponds to Goal Programming (see, e.g., Romero, 2004), where the user defines target values for each criterion and the aim is to find the solution that approximates, simultaneously, to those target values as much as possible. Complementary, an extension of Goal Programming is presented in (Skulimowski, 1997), where the concept of target values are extended by the so-called reference sets, which not only represent desirable values for the criteria (as target values do in the case of Goal Programming), but they can also represent avoidable values so the sought solutions should induce criteria values as distance as possible to those avoidable reference values. Further recent developments of this approach are presented (Skulimowski, 2018), where the author proposed a sensitivity analysis method based on investigating the properties of attainable criteria values minimizing the distance to perturbed reference sets.

The solution scheme presented above, as well as the underlying model, assumes that both threats and actions are of a static nature. Such assumption is considered in most of systematic conservation planning approaches (Wiersma and Sleep, 2016) and biodiversity reserves design models (Billionnet, 2013); and decision-makers are expected to update solutions (i.e., run the static models) during the execution stage in order to adjust the conservation plans to dynamic nature of the input data. This is crucial for ensuring the effectiveness of the attained conservation policies as their validity is likely to degrade as they might not respond properly to the different phenomena embodied by the species that we aim to protect, the threats that we aim to tackle and the effects of the actions that we aim to carry out. Likewise, static models can be exploited to tackle a dynamic setting within ad-hoc frameworks (see, e.g., Snyder et al., 2005). Despite of this, it has been recognized that threats and actions actually have a dynamic nature (see, e.g., Ikin et al., 2016; Bonneau et al., 2018, for recent references on this issue in single objective settings) and, therefore, future research on multicriteria approaches for multi-species multi-action shall incorporate this feature.

2.3 Further exploration of the BMACP solutions

Preliminary results obtained when applying Algorithm 1 suggested that in most cases, we can find conservation management plans that verify an efficient trade-off between ecological benefit and fragmentation, for different levels of budget. Furthermore, due to the functional importance of having a reduced spatial fragmentation (which is normally very hard to measure), one could try to exploit this interaction between ecological benefit and fragmentation, in order to find conservation management plans having a much more reduced fragmentation at the expenses of *sacrificing* only a fraction of the originally attained ecological benefit. In other words, for a given Pareto (near) optimal solution encoded by pair (B^*_ρ, F^{**}_ρ), and for a given *benefit-fraction* factor $\alpha \in [0,1]$, we would like to find the solution obtained when solving

$$(\mathbf{w}^{**}_{\alpha,\rho}, \mathbf{x}^{**}_{\alpha,\rho}, \mathbf{z}^{**}_{\alpha,\rho}) = \arg\min \; F(\mathbf{w},\mathbf{x},\mathbf{z}) \qquad (\alpha\text{-CB-MAP.1})$$
$$\text{s.t.} \quad C(\mathbf{w},\mathbf{x},\mathbf{z}) \leq C_\rho \qquad (\alpha\text{-CB-MAP.2})$$
$$B(\mathbf{w},\mathbf{x},\mathbf{z}) \geq \alpha B^*_\rho \qquad (\alpha\text{-CB-MAP.3})$$
$$\text{(BMACP.3)-(BMACP.5);} \qquad (\alpha\text{-CB-MAP.4})$$

where αB^*_ρ is the *minimum* ecological benefit ($\alpha B^*_\rho \leq B^*_\rho$) that we require to the new solution $(\mathbf{w}^{**}_{\alpha,\rho}, \mathbf{x}^{**}_{\alpha,\rho}, \mathbf{z}^{**}_{\alpha,\rho})$, whose corresponding optimal function value $F^{**}_{\alpha,\rho}$ is expected to be such that $F^{**}_{\alpha,\rho} \leq F^{**}_\rho$. Such a solution, also corresponds to a solution of the BMACP, and, as it will be shown later in §3.3, its analysis allows a broader understanding of the spatial and functional aspects of the proposed models.

3. Computational results

In this section we describe the case study and corresponding attained computational results.

3.1 Case study

The Northern Australia Water Futures Assessment program Department of Agriculture & Water Resources (2012), is a conservation plan aiming at protecting northern Australia's water resources. Within this program, we find the Northern Australia Aquatic Ecological Assets initiative Griffith University (2012) (NAAE), which focuses on conducting fine-scale assessments of particular catchments in northern Australia. One of the catchment areas considered by the NAAE initiative is the Mitchell River catchment, located in Queensland, northern Australia (see Figure 1).

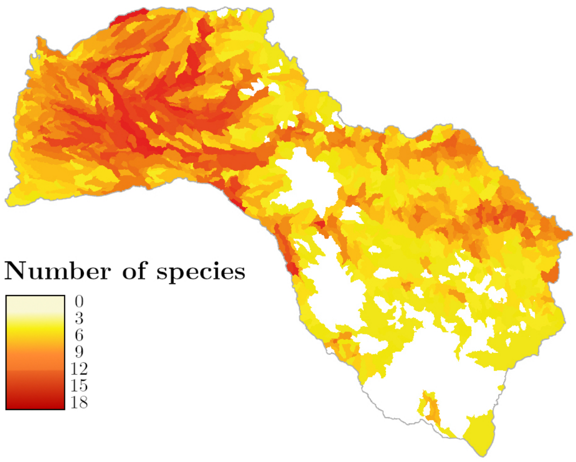
The studied area (71,630 km^2) was divided into 2,316 land parcels (i.e., sub-cachments) (for further details, see Cattarino et al., 2015). In the considered region, 31 species (all of them were freshwater fishes) were classified as threatened. Figure 2(a) shows the spatial distribution of these species. In this catchment, the considered species are menaced by four major threats: water buffalo (*Bubalus bubalis*), cane toad (*Bufo marinus*), river flow alterations (caused by impoundments, channels for water extractions and levee banks), and grazing land use. In Figure 2(b) we show these threats are spatially distributed in the considered area. As can be seen from these figures, species and threats co-occur, with different concentration, across the whole studied area, which emphasizes the need of a sophisticated decision-making tool for designing a functional and economically effective multi-action management plan.

Experimental settings We run our experiments in a Intel® Core™ i7-4770MQ 2.20GHz machine with 12GB RAM, and Ubuntu 16.04 LTS. The underlying MIP instances were solved using ILOG® CPLEX® 12.6.3; we used default settings except for the time limit which was set to 1800 seconds. As said in §2, the non-linearity associated to the definition of the ecological benefit b_{si} (for arbitrary elements $s \in S$ and $i \in I$) are handled by the `IloPiecewiseLinear` function of IBM ILOG CPLEX® 12.6.3. Preliminary results showed that 5 breakpoints offered the best trade-off between solution accuracy and computational tractability.

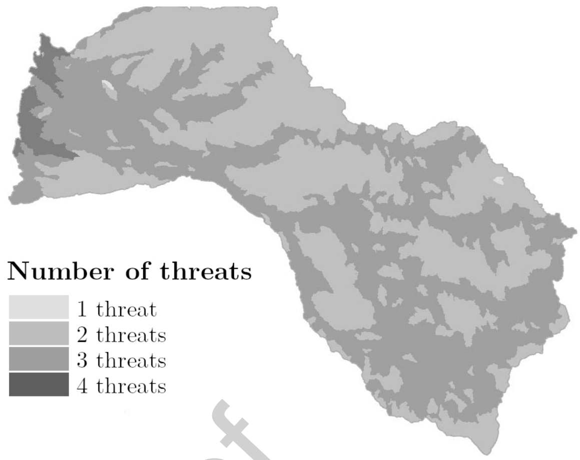
3.2 Trade-off analysis: Exploring the (approximated) Pareto frontier

As described in §2.2, if no explicit information is known regarding the available budget for the conservation management plan, the first step for finding solutions that approximate the Pareto front of the BMACP is to solve model (MAP.1)-(MAP.2) and then (MAP.3)-(MAP.5), in order to obtain the so-called *ideal* budget C^*; i.e., the (minimum) cost of the solution that allows the best possible ecological benefit. In our case study, the optimal solution to these models yields an optimal ecological benefit $B^* = 10,954$, which associates a total cost $C^* = 6,317$ kUSD along with a spatial fragmentation $F^* = 481.2$. The obtained solution, from solving (MAP.3)-(MAP.5), is shown in Figure 2(c). As can be seen, the obtained conservation plan is comprised by a diverse combination of actions across a large portion of the territory. The large territorial extension, and the corresponding high cost of the conservation management plan shown in Figure 2(c), turns this solution impractical.

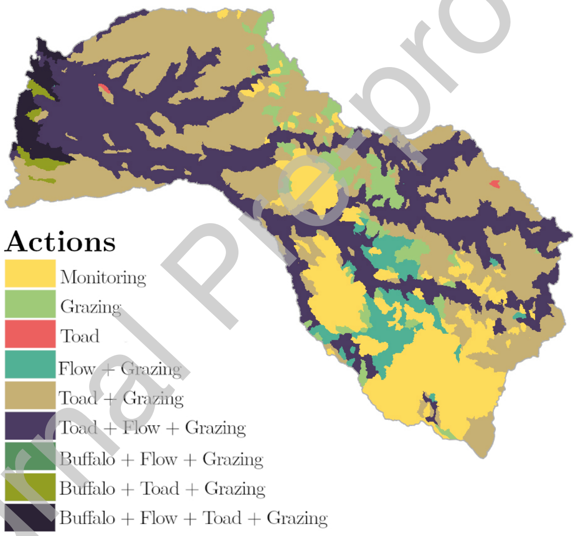
Following the algorithmic scheme outlined in §2.2, we are interested in exploring alternative solutions that, while ensuring a maximal ecological benefit, they respect a budget constraint given as a portion of C^*. Such solutions are found by solving model (C-MAP.1)-(C-MAP.3), for different right-hand-side values C_ρ of the



(a) Species distribution



(b) Threats distribution

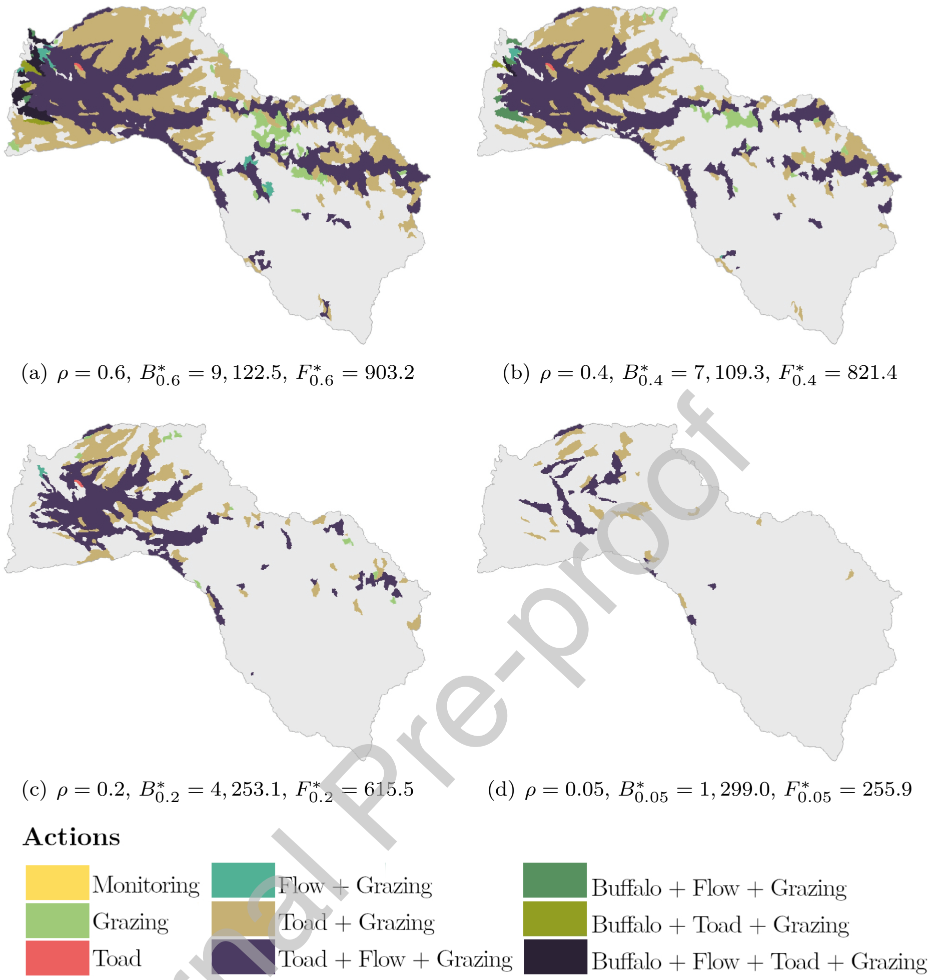


(c) MAP solution

Figure 2: Mitchell River catchment case study data (2(a) and 2(b)), and MAP solution (2(c)).

budget constraint (C-MAP.2), given as $C_\rho = \rho 6,317$, with ρ taking values in $[0, 1]$; in our experiments, we considered $\rho \in \{0.05, 0.1, 0.15, 0.2, \ldots, 1\}$. In Figure 3, we show how the characteristics (measured by B^*_ρ and F^*_ρ), as well as the territorial and functional structure of some solutions, change when having different levels of budget (induced by $\rho \in \{0.05, 0.2, 0.4, 0.6\}$). As can be seen from these figures, there is a clear, and rather obvious, trade-off between these; the more budget we have, the more ecologically effective management plan we can design.

In Table 1, we report more detailed results associated to the resolution of instances of model (C-MAP.1)-(C-MAP.3), for different values of ρ. In column 'ρ' we show the different budget-fraction values, while in column 'C_ρ' we report the resulting budget values (in thousands of US dollars, kUSD). In column 'B^*_ρ' we report the ecological benefit level attained when solving (C-MAP.1)-(C-MAP.3), for the corresponding values of ρ; likewise,



(a) $\rho = 0.6$, $B^*_{0.6} = 9,122.5$, $F^*_{0.6} = 903.2$

(b) $\rho = 0.4$, $B^*_{0.4} = 7,109.3$, $F^*_{0.4} = 821.4$

(c) $\rho = 0.2$, $B^*_{0.2} = 4,253.1$, $F^*_{0.2} = 615.5$

(d) $\rho = 0.05$, $B^*_{0.05} = 1,299.0$, $F^*_{0.05} = 255.9$

Figure 3: Solutions of model (C-MAP.1)-(C-MAP.3), for different values of ρ.

the fragmentation associated to these solutions is reported in column 'F^*_ρ'. The quality of the attained solutions is shown in column 'gap (%)', whose entries correspond to the primal/dual gap attained, within the time limit, when solving the corresponding instances of the C-MAP model using CPLEX. From this later column, we can conclude that the proposed approach is quite effective for computing good quality solutions in short computing times (at most 1800 seconds); the average gap is 2.01% and, with two exceptions, the attained gaps are always below 5%. The deterioration of the attained gaps, as the value of ρ decreases, is explained by the fact that smaller budgets induce a smaller space of feasible solutions, making the optimization process more difficult (specially due to the combinatorial nature of the solutions). Although the obtained solutions are not optimal, this does not affect any of the conclusions drawn in this paper.

From the values reported in Table 1, we can clearly see the relation between C_ρ and B^*_ρ: the more budget we have, the more ecological benefit we can attain. However, the relation of C_ρ and B^*_ρ with F^*_ρ, requires further insights, which are inferred from the plots shown in Figure 4. The plot in Figure 4(a) shows the trade-off between budget C_ρ and the attained ecological benefit B^*_ρ. In this plot, each point is associated with a value of ρ (which is explicitly shown in the corresponding labels), and it is possible to see that the ecological benefit

ρ	C_ρ (kUSD)	B^*_ρ	F^*_ρ	gap (%)	F^{**}_ρ
1	6,317.0	10,954.0	481.2	0.0	214.8
0.95	6,001.2	10,887.0	528.3	0.0	360.8
0.9	5,685.3	10,780.1	506.5	0.0	473.4
0.85	5,369.5	10,605.7	626.4	0.3	557.9
0.8	5,053.6	10,394.9	662.1	0.5	618.2
0.75	4,737.8	10,147.8	724.9	0.6	678.4
0.7	4,421.9	9,840.6	821.7	0.7	648.9
0.65	4,106.1	9,518.4	867.5	0.8	805.7
0.6	3,790.2	9,122.5	903.2	1.2	815.0
0.55	3,474.4	8,699.5	925.7	1.3	881.2
0.5	3,158.5	8,218.1	905.6	1.5	849.8
0.45	2,842.7	7,685.4	918.6	2.0	864.0
0.4	2,526.8	7,109.3	922.3	2.3	821.4
0.35	2,211.0	6,478.3	844.7	2.6	749.4
0.3	1,895.1	5,790.9	801.8	3.0	679.2
0.25	1,579.3	5,057.1	716.6	3.2	644.2
0.2	1,263.4	4,253.0	615.5	3.5	533.1
0.15	947.6	3,375.8	479.5	3.7	398.9
0.1	631.7	2,391.8	393.6	5.4	341.4
0.05	315.9	1,299.0	255.9	7.5	218.0

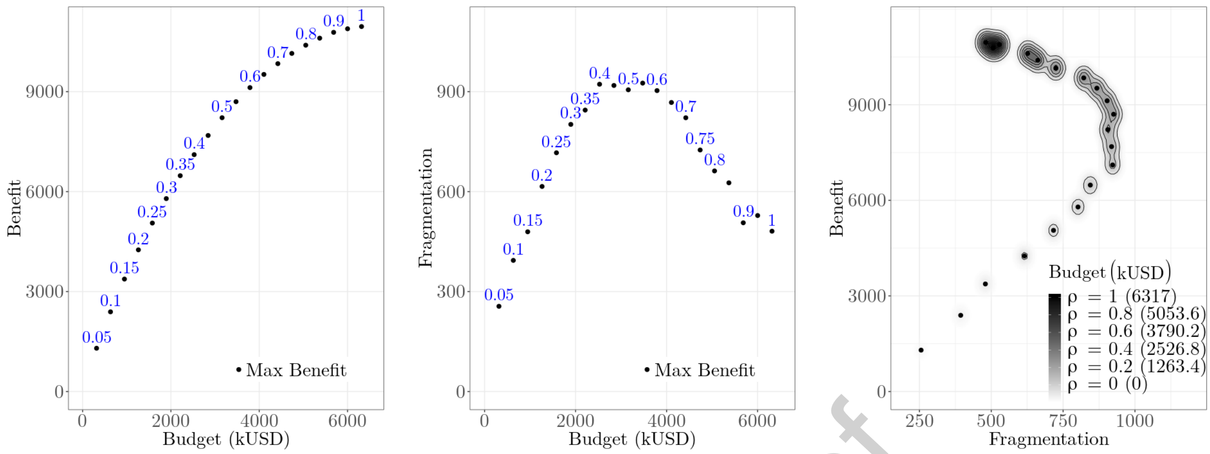
Table 1: Relationship between C_ρ, B^*_ρ,F^*_ρ and F^{**}_ρ to different budget fraction-values (ρ)

asymptomatically increases to reach the maximum value $10,954$ when $C_1 = C^* = 6,317$.

In the plot in Figure 4(b), we show the relation between the fragmentation F^*_ρ of the solution and budget C_ρ. The *low-high-low* behavior of the relation between these two characteristics can be explained be the following three observations. First, when having a very limited budget ($\rho \to 0$), the fragmentation tends to be *numerically* small since, in practice, few units can be selected as part of the management plan and, therefore, they are easy to aggregate. Second, when having a high budget ($\rho \to 1$), the fragmentation tends to be *spatially* small since it is possible to monitor and intervene larger portions of the territory. And third, maximizing the ecological benefit implies to select attractive units (i.e., where many species co-occur and few threats are present) for monitoring, and eventually intervene them; however, intermediary values of the budget (specially those around $C_{0.5}$), only allow to select the most beneficial ones in which it is induces a very high fragmentation.

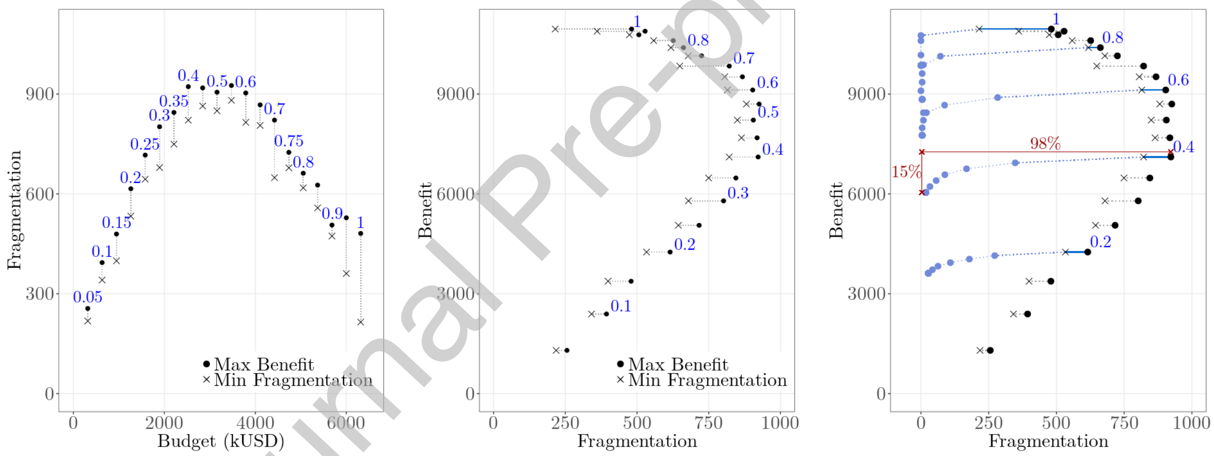
The relation between F^*_ρ and B^*_ρ, obtained when solving (C-MAP.1)-(C-MAP.3) is shown in the level-curve plot shown in Figure 4(c). The shape of the plot indicates that there is no direct correlation between the mathematical measures of fragmentation and ecological benefit, when having different levels of budget (lower budgets are associated to curves in lower levels, while larger budgets are associated to curves in higher levels). As a matter of fact, when comparing the solutions obtained when setting $\rho = 0.15$ and $\rho = 0.95$, respectively, we can clearly see that the first has a low benefit and the second has a very high benefit; however, both associate more or less the same fragmentation. This relation is directly explained by the impact of the budget. A low budget (e.g, induced by $\rho = 0.15$) means that few units can be managed and few actions can be performed, which ultimately leads to a poor ecological performance. On the contrary, a large budget (e.g, induced by $\rho = 0.95$), means that many units, along with many actions, can be incorporated as part of the conservation plan, which results in attaining a high ecological benefit and a reduced fragmentation.

Following the methodology described in §2.2, after solving instances of the C-MAP for different values of ρ



(a) B^*_ρ v/s C_ρ (b) F^*_ρ v/s C_ρ (c) B^*_ρ v/s F^*_ρ

Figure 4: Trade-offs among ecological benefit B^*_ρ, fragmentation F^*_ρ and budget C_ρ, obtained by solving (C-MAP.1)-(C-MAP.3)



(a) F^*_ρ,F^{**}_ρ v/s C_ρ (b) B^*_ρ v/s F^*_ρ, F^{**}_ρ (c) $B^*_{\rho,\alpha}$ v/s F^*_ρ, $F^{**}_{\rho,\alpha}$

Figure 5: Pareto (nearly) optimal solutions obtained when solving (CB-MAP.1)-(CB-MAP.4)

(whose results were just analyzed above), it is necessary to seek for non-dominated solutions, in terms of the attained fragmentation, by solving instances of the CB-MAP given my model (CB-MAP.1)-(CB-MAP.4). In column 'F^{**}_ρ' of Table 1, we report the values of spatial fragmentation obtained when solving the corresponding instances of model (CB-MAP.1)-(CB-MAP.4). When comparing the values reported in column 'F^*_ρ' with those reported in 'F^{**}_ρ', it is clear that there are in most cases in which is possible to obtain solutions with the same cost and same benefit, but a much lower fragmentation (e.g., when $\rho = 0.7$). These results are complemented by the plots shown in Figures 5(a) and 5(b), where we graphically show how, for a given pair (F^*_ρ, C_ρ) and (B^*_ρ, F^*_ρ), the spatial fragmentation significantly improves to F^{**}_ρ without worsening the corresponding values of C_ρ nor of B^*_ρ, respectively.

So far, we have presented the trade-offs among the ecological benefit and the fragmentation, when seeking (nearly) optimal levels of them, for a given implementation budget. In the following, we will extend our analysis by further exploring how the benefit-fragmentation trade-offs behave when a accepting solution yielding a sub-optimal ecological benefit for fixed levels of budget.

3.3 Further exploration: solving (α-CB-MAP.1)-α-*CB-MAP.4*

The results displayed in Figures 5(a) and 5(b) can be further explored by solving (α-CB-MAP.1)-α-CB-MAP.4 for different values of α.

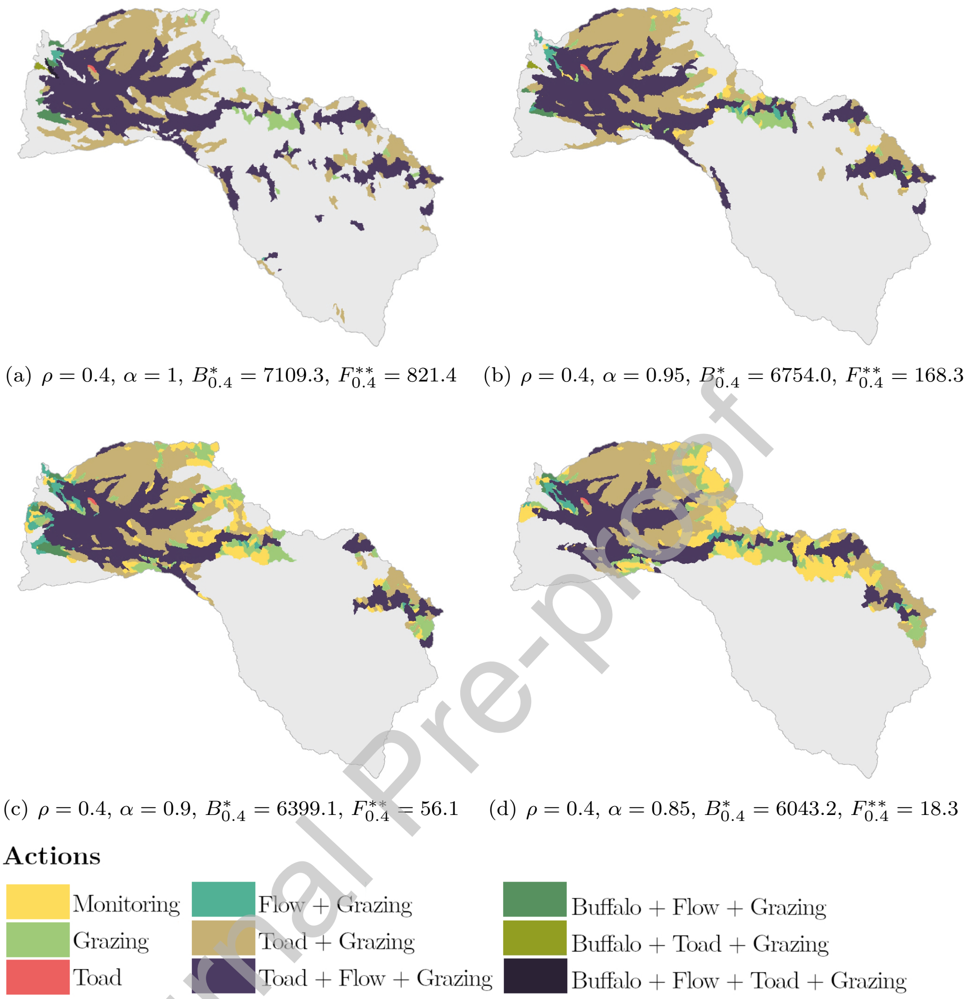
In Figure 5(c), we show for five values of ρ (1, 0.8, 0.6, 0.4 and 0.2), how the trade-offs between fragmentation and benefit can be further explored by solving (α-CB-MAP.1)-(α-CB-MAP.4), for α taking values in $\{0.975, 0.95, 0.925, 0.90, 0.875, 0.85\}$. For the five curves highlighted in the plot, we can see that a quite small reduction in the attained ecological benefit (e.g., a 2.5% reduction, which is induced by $\alpha = 0.975$), leads to a significant reduction of the spatial fragmentation. Moreover, as can be seen in the curve associated to $\rho = 0.4$, we can reduce the fragmentation in almost a 98% (which means to have a barely fragmented solution), if we are willing to accept a management conservation that is only a 15% worse compared to the original one.

Further insights on how this later model behaves are provided in the maps in Figure 6. These maps correspond to the spatial deployment of solutions obtained when solving model (α-CB-MAP.1)-(α-CB-MAP.4) for $\rho = 0.4$ and different values of α. The map in Figure 6(a) correspond to the solution associated to the Pareto (optimal) solution encoded by $(B^*_{0.4}, F^{**}_{0.4})$; while the solutions in Figures 6(b), 6(c) and 6(d), correspond to those obtained when setting α to 0.95, 0.9 and 0.85, respectively. It turns out clear that the solution shown in Figure 6(a) is much more fragmented than the one shown in Figure 6(d); as a matter of fact, the later one is almost one large component (and that it is why its spatial fragmentation is as low as 18.3). More interesting, the corresponding mix of conservation actions is similar for both solutions, which is reasonable since both induce a similar ecological benefit.

4. Discussion

The results presented in the previous section show that our MIP-based methodology features three main attributes. First, it is capable of effectively providing a wide range of solutions with different trade-offs among the decision criteria. Second, the quality of the attained solutions (in terms of their maximal distance to the optimal solution) is always known. And third, it exposes that effective conservation plans do not necessarily require excessively high budgets, as long as the type of actions and their spatial deployment are conveniently chosen. In the following, we will provide further ecological insights on the obtained results.

As pointed out in the analyses of the Pareto fronts shown in Figures 4 and 5, when maintaining the budget fixed, there is a strong trade-off between the ecological benefits and the reduction of fragmentation. Both objectives *compete* for the (eventually limited) budget, so reducing fragmentation could only be achieved at the expenses of compromising ecological benefit. However, waving some ecological benefit, derived from the intervention at local scale, could be worth in overall terms as there are additional benefits related to enhancing spatial aggregation. For example, reducing the fragmentation also reduces the probability of recolonization of areas (where threats have been addressed already) from other surrounding areas that have not been intervened (see, e.g., Januchowski-Hartley et al., 2011). This translates into an indirect global ecological benefit, as the reduced probability of reappearance of threats is likely to increase the probability of persistence of species, and therefore the probability of success of intervention. Moreover, although not directly addressed in this study for the sake of simplicity, the spatial aggregation of management actions could also derive in economic benefits. From a tactical and operative point of view, the implementation of management actions in aggregated patches



(a) $\rho = 0.4$, $\alpha = 1$, $B^*_{0.4} = 7109.3$, $F^{**}_{0.4} = 821.4$ (b) $\rho = 0.4$, $\alpha = 0.95$, $B^*_{0.4} = 6754.0$, $F^{**}_{0.4} = 168.3$

(c) $\rho = 0.4$, $\alpha = 0.9$, $B^*_{0.4} = 6399.1$, $F^{**}_{0.4} = 56.1$ (d) $\rho = 0.4$, $\alpha = 0.85$, $B^*_{0.4} = 6043.2$, $F^{**}_{0.4} = 18.3$

Figure 6: Solutions of model (α-CB-MAP.1)-(α-CB-MAP.4) for $\rho = 0.4$ and different values of α

is cheaper than distributing the same effort scattered across the whole study region (see, e.g., Breaux et al., 2005; Frazee et al., 2003, for simular discussions).

When analyzing different budget levels, the relation between benefit and fragmentation presents a more interesting behavior, as depicted in Figures 4(c), 5(b) and 5(c). On the one hand, there is a constant increase of the ecological benefit for raising budgets, with the larger increases at lower budgets and tending to plateau at large ones (see Figure 4(a)). On the other hand, fragmentation reached a maximum at intermediate budgets ($\rho \approx 0.5$) and is higher for large or small ones. High connectivity values at low budgets could be related to the fact that the number of units selected for treatment was small and then easy to aggregate. At large budgets, the number of units that could be prescribed for treatment of threats extended over large regions of the study area including whole tributaries completely connected in the solutions. The difference in behavior of both objectives under increasing budgets translated into two different strategies: i) investment in increasing ecological benefits until intermediate budgets were available, but at the expenses of increasing fragmentation values; and ii) improving both objectives at the same time when enough budget was available after an inflexion point located in about $\rho = 0.5$. The fact that fragmentation behaves in a low-high-low pattern with respect to the available budget, reaching an inflexion point for $\rho \approx 0.5$, means that, from a practical point of view, interesting trade-offs occur for budgets levels below this point. This means that the trade-off between the objectives described above would only be true for budgets below the inflexion point. As a matter of fact, despite that securing budgets large enough to be over the inflexion point would be clearly beneficial as trade-offs would no longer matter, in practical terms these budgets could be too large to be attainable. Further examples would be needed to explore the relationship between these two objectives, confirm the existence of the inflexion point and evaluate the factors that determine when this occurs. Evidently, the larger the budget, the better the ecological benefit, but securing such budgets is unlikely, especially if we consider that beyond this inflexion point, low fragmentations levels are reached only when $\rho \to 1$.

The obtained results uncovered two alternative strategies for reducing fragmentation (or, equivalently, improving aggregation), and the corresponding additional ecological and economic benefits mentioned above. The first one is straightforward, and it follows from the analysis presented in the previous paragraph, i.e., ensuring (if possible) budget levels as close as possible to the ideal budget C^*. The second approach is associated to the capabilities of model (CB-MAP.1)-(CB-MAP.4) that enables us to find significant improvements to the spatial aggregation (e.g., reductions of the spatial fragmentation of up to 98%) for small declines in ecological benefit. From the ecological point of view, what this model does is to reduce the budget allocated to the treatment of threats and allocate it to increase the number of units that are only monitored; this, ultimately, leads to a marginal reduction of the ecological benefit from an aggregated point of view (as shown in Figure 5(c)), although significant from a local-based point of view. In this way, treatment of threats and monitoring efforts focus on larger extensions of the catchment, which translates into a higher probability of success of the management plan in the long term as propagation or re-infestation of threats is better strained, as represented in the solutions reported in Figure 6. This means that management plans as the one shown in Figure 6(d), which considers larger monitored areas, are more likely to survey the potential propagation of threats into treated areas *downstream*, while their almost full connectivity lead to a quite practical operative stage. On the contrary, plans such as the one shown in Figure 6(a), are likely to fail in preserving their performance in the long-term, as the lack of monitoring actions surrounding small threated areas and the operation difficulty of managing such fragmented deployment, will relentlessly leads to a re-infestation (specially in areas located *upstream*).

The previous discussion demonstrates that we have developed a powerful decision-aid tool for designing and implementing conservation management plans. Furthermore, due to the modeling and algorithmic elements that comprise it, this tool can be used not only to tackle the same spatial deployment decision setting on another dataset, but rather to a different context. For instance, it could be adapted for incorporating conservation decisions into forest management models, for designing biodiversity restoration plans in damaged catchment areas, or for more general territorial design settings involving, simultaneously, industrial, urban and conservation decisions and conflicting objectives.

Along with the practical benefits of the proposed tool, there are some drawbacks that shall be taken into account when incorporating it as part of a decision-making setting. Among these drawbacks, the most important is the fact that the computational performance of the tool (i.e., the running times and the quality of the attained solutions) strongly relies on the solver used to solve the underlying MIP instances. In our case, we used the academic version of CPLEX (which is one of the most powerful solvers available Jünger et al., 2009), but it might occur that a different solver requires longer computing times to achieve solutions of similar quality.

5. Conclusions and future work

The discussion presented above reveals the strategical importance of using multicriteria optimization frameworks, which are known to be effective in many decision-making settings, when designing complex management plans in ecology and environmental sciences. As shown by the results obtained from the Australian case study, our optimization strategy enables decision-makers to explore and analyze a broad range of conservation plans, and select the one exhibiting the best quantitative and qualitative strategical and operational outcomes. As an example, when comparing the results associated to two fractions of C^*, those obtained by $\rho = 0.85$ and $\rho = 0.8$, we can observe the capabilities of the proposed tool. While for $\rho = 0.85$ we can obtain an ecological a benefit of 10605.7, for $\rho = 0.8$ the benefit corresponds to 10394.9. This means that by reducing the budget in 5%, the ecological benefit reduces less than 2%.

This paper is another example of the synergies featured by interdisciplinary collaborations among ecologists, forest scientists, and operations researchers, when elaborating solutions to environmental and ecology challenges. This shall motivate us to extend our methodology in two directions; first, to incorporate further spatial synergy and functionality among intervened units and implemented actions, and second, to tackle other conservation problems, such as a landscape recovery, threat propagation control, or when planning conservation-aware exploitation of natural resources. These examples appear as attractive paths of future research.

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