

Meeting species persistence targets under climate change: A spatially explicit conservation planning model

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Abstract

Aim: Climate change threatens the effectiveness of existing protected areas, pivotal, yet static, instruments to promote the persistence of biodiversity. The identification of the areas more likely to be used by multiple species to track their most suitable changing climates is therefore an important step in conservation planning. Species persistence targets and budget limitation are two critical ingredients constraining target-based conservation area selection. However, defining adequate persistence targets under budget constraints is far from intuitive.

Location: Unspecific.

Methods: We propose a two-staged mixed-integer linear programming model to determine optimized persistence targets for several species, for a given time horizon and climate change scenarios, under budgetary limitation. The first stage tunes pre-established targets for each species with a bound on the size of the area to select. The second stage identifies a set of areas of minimum cost that allows the persistence levels optimized in the first stage to be achieved. We apply a heuristic to test whether small deviations from optimal persistence settings (i.e., targets for multiple species) do influence cost-effectiveness of final solutions. Analyses were undertaken using a synthetic data set replicating changes of environmental suitability for several simulated species using several experimental designs.

Results: Our results showed that minor differences to the optimal persistence scores can result in large contraction of cost-effectiveness in final solutions.

Main conclusions: Persistence targets should be carefully assessed case by case, and alternative species persistence settings should be considered, as they potentially result in important reductions of cost-effectiveness. Our model along with the respective heuristic can be used as a tool to efficiently promote species persistence under climate change.

KEYWORDS

biogeography conservation, decision support tools, mixed-integer programming, reserve design, risk analysis, spatial optimization

1 | INTRODUCTION

The ultimate goal of conservation planning is the persistence of biodiversity (Margules & Pressey, 2000; Williams & Araujo, 2000). Recently, through the Convention on Biological Diversity 2010, world leaders

have committed, to achieve by 2020 a significant reduction of the current rate of biodiversity loss (Perrings et al., 2010). These intents are expressed in five strategic goals (UNEP, 2010) encompassing various types of conservation responses (e.g., protected area designation, restoration of habitats, commercial laws, species protection, etc.).

Under Goal C, target 11 claims the expansion of the current protected areas into a functional network of areas encompassing 17% of land surface and 10% of sea surface. It has been settled as a landmark in the conduction of spatial conservation plans (Barnes, 2015). In order to identify such areas and to objectively quantify the progress in the accomplishment of such intents, explicit and accountable targets need to be established for the biodiversity at risk of extinction (Tittensor et al., 2014). These targets typically call for the protection of a given distributional area of a particular feature, assuming that the amount of area protected and feature persistence are positively related (Justus, Fuller, & Sarkar, 2008; Possingham, Ball, & Andelman, 2000; Rondinini & Chioza, 2010). However, this direct relationship is simplistic and potentially inaccurate, as a range of factors control the persistence of biodiversity at the long term (Araújo & Williams, 2000; Cabeza & Moilanen, 2001; Graham, VanDerWal, Phillips, Moritz, & Williams, 2010; Pressey, Cabeza, Watts, Cowling, & Wilson, 2007). Assessments on demographic, environmental and genetic processes are fundamental to determine persistence accurately. Furthermore, connectivity and extinction/colonization mechanisms should be interpreted in order to capture biodiversity persistence spatially (Di Marco et al., 2016). Given the complexities, particularities and data demands related with persistence assessments, systematic persistence evaluations are seldom available for most of the species. Simplified approaches, employing persistence proxies (Collingham, Wadsworth, Huntley, & Hulme, 2000; Pearson & Dawson, 2003) are therefore central to make conservation plans operational (Araújo & Williams, 2000; Di Fonzo et al., 2016; Di Marco et al., 2016).

Climate change is predicted to have major implications for species and ecosystems. It acts as a driver of biodiversity loss, amplifying the effects of existing threats (Araújo & Rahbek, 2006; Graham & Grimm, 1990; Walther et al., 2002). Unlike some other threats to biodiversity loss (e.g., over-exploitation, habitat loss and fragmentation), climate change is global in extent and pervasive in nature; therefore, it challenges the way conservation planning is undertaken (Hannah et al., 2002, 2007). Climate change-concerned conservation plans need to embrace change, shifting their perspectives from preserving current ecosystem and habitats to managing and supporting the dynamic responses of species and ecosystems (Crossman, Bryan, & Summers, 2012; Meir, Andelman, & Possingham, 2004; Strange, Thorsen, & Bladt, 2006). Under climate change, the relationship between representation targets and species persistence is much more uncertain. For example, in highly dynamic contexts species are seldom in equilibrium with the environment and, consequently, their distributional areas do not reflect their persistence prospects (Araújo & Pearson, 2005). In many locations (e.g., rear edges), populations exhibit fitness deficits (i.e., decreasing population trends, genetic homogenization) that undermine their persistence in short-to-medium terms (Hampe & Petit, 2005). Although local conservation interventions are prescriptive for species protection (Hodgson, Moilanen, Wintle, & Thomas, 2011), the facilitation of connectivity between current suitable areas through the areas that are expected to be (highly) favourable for the species in the future is a fundamental step for effective conservation planning (Heller & Zavaleta, 2009).

In recent years, interest in the integration of adaptive responses of species to climate change in spatial conservation prioritization has grown. General purpose conservation planning software has been used for area prioritization (see Alagador, Cerdeira, & Araújo, 2016 for a review), and novel models have been specifically developed to address climate change concerns (Alagador et al., 2016; Jones, Watson, Possingham, & Klein, 2016). However, to our best knowledge only Alagador et al. (2016) have explicitly integrated persistence targets in climate change-concerned conservation plans (see Di Fonzo et al., 2016 and Di Marco et al., 2016, for similar approaches in other contexts). Because persistence targets are not trivial to interpret as representational targets are, their definition is challenging. For example, it might happen that an excessive demand for the persistence of a species jeopardizes the feasibility of a plan built for multiple species. A possibility would be to control feasible persistence scores for each species independently, but these values would not guarantee feasibility when used in multiple-species designs with large cost limitations.

This study covers the complexities associated with species persistence targets, by showing that small deviations on the established targets might generate significant losses of cost-effectiveness. We present a spatial prioritization model to tune persistence targets for a set of species in conservation contexts characterized by climate change and budget limitation. The model is formulated with two sequential mixed-integer programming (MIP) problems. In the first problem, the objective is to minimize the summed species-specific persistence gaps (i.e., differences) to their initially demanded persistence targets, not exceeding a bound on the size of areas to be selected. The second problem minimizes the cost of the areas that satisfy the tuned persistence targets, but now with the guarantee that these targets are achievable in areas with size below the size-bound. We use a recently proposed heuristic algorithm for the problem (Alagador & Cerdeira, 2015) to work on the sensitivity of multiple-species persistence-based conservation plans for minimal deviances from persistence optimality. We test these effects using different synthetic data sets to illustrate plausible spatio-temporal dynamics of environmental suitability for several simulated species. Analyses are performed assuming various problem designs in respect to persistence demand, the number of corridors put available for selection (i.e., corridor pool), the area of final solutions and the number of species in analysis. Results show that minor differences in the persistence targets can generate large variability in solution costs. Our model and the proposed heuristic have potential for providing guidelines and decision support for scheduling investments in climate change-concerned conservation planning as long as the effects of establishing persistence targets for several species are acknowledged and carefully evaluated case by case.

2 | METHODS

2.1 | Climate change corridor

The model here presented is based on the concept of climate change corridor (sensu Williams et al., 2005; Phillips, Williams, Midgley, & Aaron, 2008). A climate change corridor, $cor = (v_1, v_2, \dots, v_m)$, is a

sequence of areas, v_t (one area per time period, t) defining a pathway of a given species population from a baseline period, 1, to an ending period, m (Figure 1). The persistence of a species s in the corridor $cor = (v_1, v_2, \dots, v_m)$ is:

$$p_s^{cor} = po_s^{v_1} \times pd_s^{v_1, v_2} \times po_s^{v_2} \times pd_s^{v_2, v_3} \times \dots \times pd_s^{v_{(m-1)}, v_m} \times po_s^{v_m}, \quad (1)$$

where $po_s^{v_t}$ is the estimated occurrence probability of species s on area v_t on time period t (dependent on local climatic factors) and $pd_s^{v_t, v_{(t+1)}}$ denotes the probability of species s to move from v_t to $v_{(t+1)}$ from time period t to $(t+1)$.

Two corridors $cor = (v_1, v_2, \dots, v_m)$ and $cor' = (v'_1, v'_2, \dots, v'_m)$ are independent (sensu Williams et al., 2005) if they do not intersect in the same time period, that is $v_t \neq v'_t$, for $t = 1, \dots, m$ (see Figure 1). To compute the persistence of a species within the selected corridors, only the independent ones are considered. Accounting only for independent corridors provides robustness to the conservation area sets, as it mitigates the expansion of negative unforeseen events through a network of interconnected corridors that share a given area in a given time period (Heller & Zavaleta, 2009). Independent sets of corridors thus enforce functional redundancy in conservation plans. Hence, given a set of corridors C and a species s , the persistence of s among C is defined as the maximum sum of the persistence scores of s among the independent corridors in C .

2.2 | Problem formulation

We now introduce sets, parameters and variables that will be used in our model. For each species s , cor_s defines a set of corridors with nonzero persistence; $cor_s^{v_t}$ represents the subset of corridors of cor_s , which covers area v at time period t , and P_s defines the desirable persistence for species s , taken as the sum of persistence scores for s along independent corridors in cor_s . We use S to denote the set of the concerning species, V the set of all areas (i.e., grid cells in a map), and N^t the maximum number of areas that can be selected in each time period t . Variables z_s^l indicate whether corridor $l \in cor_s$ is selected ($z_s^l = 1$) or not ($z_s^l = 0$), and variables x_v^t indicate if area v is selected in period

t ($x_v^t = 1$) or not ($x_v^t = 0$). The first stage of our model (MIP1) retrieves non-negative values for variables y_s that define the persistence gap of species s (i.e., the difference between the desirable persistence, P_s , and the maximum persistence that can be achieved among independent corridors, given the limited number of areas to select).

$$\min \sum_{s \in S} y_s, \quad (2)$$

Subject to:

$$y_s \geq P_s - \sum_{l \in cor_s} p_s^l z_s^l, \quad \forall s \in S, \quad (3)$$

$$\sum_{l \in cor_s^t} z_s^l \leq 1, \quad \forall s \in S, \forall v \in V, t = 1, \dots, m, \quad (4)$$

$$x_v^t \geq z_s^l, \quad \forall s \in S, \forall v \in V, t = 1, \dots, m, \forall l \in cor_s^{v_t}, \quad (5)$$

$$\sum_{v \in V} x_v^t \leq N^t, \quad t = 1, \dots, m, \quad (6)$$

$$x_v^t \in [0, 1], \quad \forall v \in V, t = 1, \dots, m, \quad (7)$$

$$z_s^l \in \{0, 1\}, \quad \forall s \in S, \forall l \in cor_s, \quad (8)$$

$$y_s \geq 0, \quad \forall s \in S. \quad (9)$$

Inequalities (4) state that no more than one corridor from $cor_s^{v_t}$ (i.e., having the same area at the same time period) is used to evaluate the persistence of species s . Thus, to compute the persistence of each species among the selected corridors (i.e., the sum in the right hand side of inequalities 3) only independent corridors are considered. Inequalities (5) establish that $x_v^t = 1$, indicating that area v is used in time period t , whenever some corridor, l , with area v in time period t , is selected, that is $z_s^l = 1$ and $l \in cor_s^{v_t}$. Constraints (6) guarantee that, in every time period t , the sum of variables x_v^t , which is the number of areas used in time period t , does not exceed the maximum number of areas to be selected for that time period. The sum in the right hand side of inequalities (3) defines the persistence of species s along the independent corridors assigned to the species. Thus, in (3) y_s is at

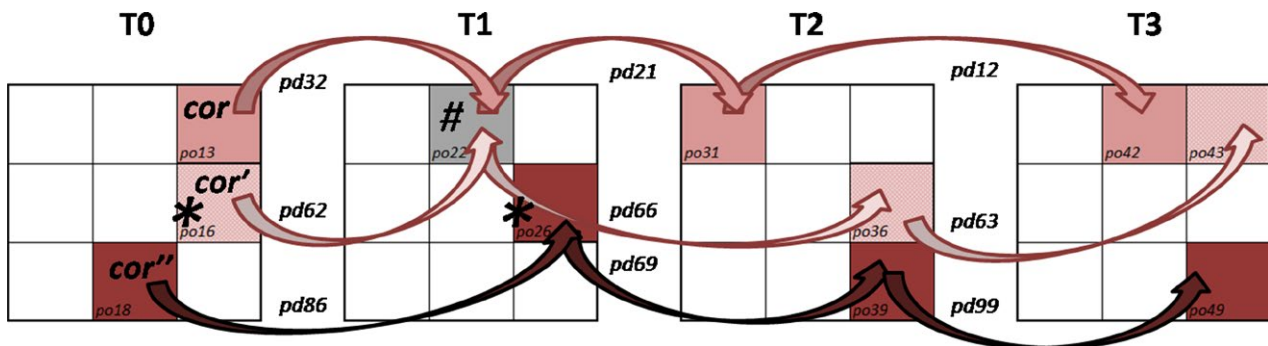


FIGURE 1 Conceptual model of three climate change corridors defined for a species. Each corridor (cor , cor' and cor'') is composed by a grid cell in each time period (T0, T1, T2 and T3). Corridors cor' and cor'' are independent albeit using the same grid cell 6 (*), but in distinct time periods. Corridors cor and cor' intersect in grid cell 2 (#) at time T1 making them non-independent. The persistence of a species in a corridor is given by the product of the local occurrence probabilities (po) by the probabilities of successful dispersal events (pd) (grid cells and dispersal events are coloured in order to differentiate the corridors). Numerical indices in po refer to grid cells' ids in a given time period. Numerical indices in pd refer to the ids of the source and the colonizing grid cells, respectively. [Colour figure can be viewed at wileyonlinelibrary.com]

least the difference between the persistence initially established for species s and the persistence obtained from the selected independent corridors, that is the minimum gap for species s . If $y_s = 0$, the corridors satisfy the required persistence for species s . The objective function (2) seeks to minimize the sum of the persistence gaps y_s . Finally, constraints (7–9) define domains for the variables.

Given the relations between y_s , x_v^t and z_s^l , assuming the variables x_v^t are continuous in interval $[0,1]$ (expression 7) suffices to make x_v^t binary in optimal solutions, with $x_v^t = 1$ indicating that area v is selected in time period t .

The second model's stage (MIP2) uses the tuned persistence values, $\hat{P}_s = P_s - \hat{y}_s$, where \hat{y}_s are the values of y_s in an optimal solution from MIP1, as targets, such that the total cost of the solution is minimized. Thus, MIP2 consists of

$$\min \sum_{t=1, \dots, m} \sum_{v \in V} c_v^t x_v^t, \quad (10)$$

Subject to:

$$\sum_{l \in \text{cor}_s} p_s^l z_s^l \geq \hat{P}_s, \forall s \in S, \quad (11)$$

and constraints (4–9).

Constraints (11) assure that the persistence target for every species (within independent corridors) will be at least the persistence value retrieved by MIP1. The objective function (10) looks for a solution that minimizes the cost of conserving all the areas in their assigned time periods.

Both MIP1 and MIP2 use variables z_s^l associated with every corridor, $l \in \text{cor}_s$, the set of all corridors for which species s has positive persistence. Given that the number of potential nonzero persistence corridors for a species might be excessively large, we propose to replace the sets cor_s by subsets c\`or_s consisting on the k_s corridors with the largest persistence for species s (i.e., a pool of good-quality corridors). Defining c\`or_s can be quickly achieved for moderately large values of k_s , using for instance the algorithm presented by Martins, Pascoal, and Santos (1999).

2.3 | The heuristic

Given that the more informative conservation plans handle extensive and high resolute data sets, MIP problems of this size might be computationally hard to solve. We therefore developed a Generalized Random Search Procedure (GRASP-heuristic) (Feo & Resende, 1995) to overcome that limitation (Alagador & Cerdeira, 2015).

Like MIP1 and MIP2, the heuristic is structured in two stages. The first (a feeding stage) starts with an empty set C of corridors. In each iteration, a species, s , for which the desired persistence target, P_s , is still not fulfilled with independent corridors in C , is randomly selected and the highest ranked corridor in cor_s , not yet included in C , adds up to C . To check whether corridors in C enable P_s to be accomplished, evaluations have to be made in order to control corridor independence. As such, a graph G is built, where nodes represent corridors and edges

link nodes if their respecting corridors intersect in the same area at the same time period (i.e., non-independent corridors). For each species, persistence within a corridor is defined in G as a node weight. An algorithm then identifies a set of independent corridors whose summed persistence is maximized. Once again we implemented a GRASP procedure to obtain the maximum weighted stable set in a graph (i.e., a set of nodes, no two of which are linked, with maximum sum of node weights). Given the randomized nature of the approach, distinct (maximal) stable sets are expected from different runs.

Corridors are added to C as described above, until persistence targets, P_s , are satisfied for all species, or until area limit, N^t , is reached in some time period. At the end of the feeding stage, persistence of each species s in set C is recorded, P_s^C . For the species whose persistence targets are accomplished (i.e., $P_s^C \geq P_s$) P_s^C is set to be equal to the originally settled target, P_s . For the species whose targets were not attained, P_s^C saves the maximum persistence in a stable set from graph G .

In the second heuristic stage (pruning stage), redundant corridors are removed from C . In each iteration, a time period, t , is selected randomly and among the areas included in the corridors of C in time period t , an area, v , is selected with probability proportional to its cost (i.e., higher-cost areas are more likely to be selected). Next, the corridors that include area v in time period t are deleted from C and the persistence values P_s^C are updated for each species using the maximum-persistence stable set algorithm. If the updated P_s^C is lower than the original P_s^C for at least one species, then the area v in time period t is considered mandatory in final solution and those corridors are not removed from C . Otherwise all those corridors are permanently removed from C , thus reducing from the current solution the cost associated with area v in time period t . This stage stops when all the areas represented in all the m time periods have been evaluated for removal.

It is worth mention that the heuristic was intentionally designed to be of random nature, thus permitting the identification of a set of different solutions from different runs. This feature provides planners several good-quality solutions to examine and compare when negotiating with decision-makers (Cowling et al., 2003).

2.4 | Computational experiments

We tested at what levels suboptimal settings of species persistence targets (provided by the feeding stage heuristic) influence cost-effectiveness of final solutions (MIP2). For that we produced synthetic data controlling for several characteristics that could potentially impact the heuristic performance (Figure 2). We generated data with distinct: (1) number of species ($|S| = 10$; $|S| = 50$); (2) map sizes ($|V| = 10 \times 10$; $|V| = 25 \times 20$; $|V| = 25 \times 40$ grid cells); (3) corridor pool sizes ($k_s = 50$; $k_s = 200$ corridors); and (4) area limit per time period ($N^t = 0.1|V|$; $N^t = 0.5|V|$). We ran the model using an optimal approach and the above-defined heuristic for instances combining all these features using two persistence target requisites: (1) an ambitious-target setting ($P_s^t = X$), and a (2) relaxed-target setting ($P_s^t = X/10$), where X was randomly defined from a Gaussian distribution, $N(1,1)$.

We generated suitability maps for $m = 4$ time periods using the *gstat* function, from The Comprehensive R Archive Network (R

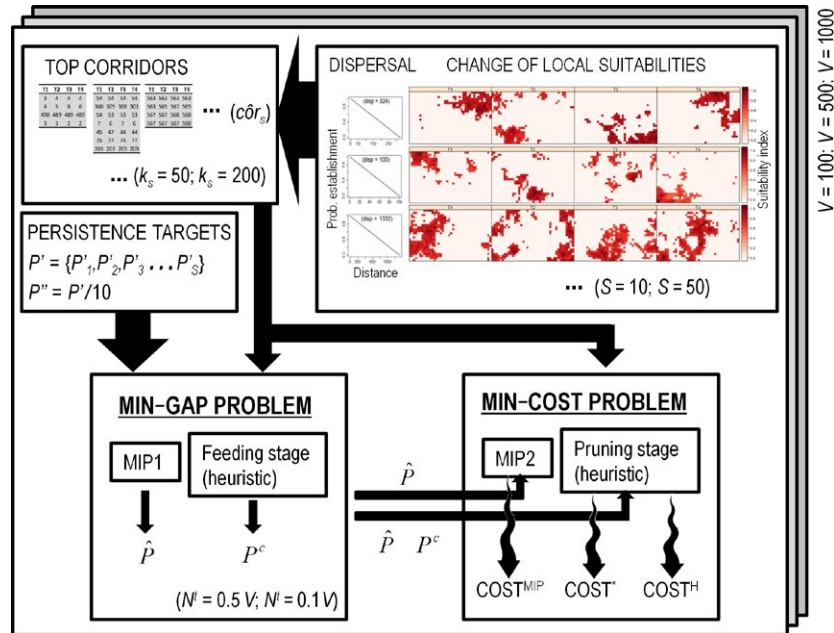


FIGURE 2 Schematic representation of the analytical steps followed in the study. From a set of S simulated species distributions, changing with time, and their respective dispersal kernels, the top- k_s persistence corridors ($c\hat{o}r_s$) are identified for each species. A set of randomly generated species persistence targets, P , is randomly defined to serve as constraints to the first problem. This problem looks for the corridors which minimize the summed gaps to the targets, P , in a limiting covering area (N^l). These values are obtained both optimally (\hat{P}) and heuristically (P^c) and are used next in the second problem, which identifies the corridors that assure those tuned persistence targets (\hat{P} , P^c) with a minimum cost, using the same areal restrictions of the first problem. The optimal approach is fed with the optimal persistence values (full optimal) and the heuristic approach is run twice: one time using the optimal persistence values; the other time using with the heuristic persistence values (full heuristic). The costs of these final runs are recorded ($COST^{MIP}$, $COST^*$ and $COST^H$, respectively). These analyses are replicated for species generated in maps with distinct number of grid cells (V). [Colour figure can be viewed at wileyonlinelibrary.com]

Development Core Team, 2015), that stochastically defines a spatial autocorrelation structure using a semi-variogram function (Appendix S1). We used an exponential model to represent the variance response in space with the sill and range parameters varying randomly for each map. Sills were selected from a uniform distribution $U[0.5;1.0]$ and ranges were obtained from $U[0.05.diam;0.33.diam]$, where $diam$ corresponds to the maximum distance in the map (upper-left diagonal to lower-right diagonal). The prevalence of each species, $prev_s$, in the baseline time period map (i.e., number of grid cells with non-null suitability) was defined randomly, $U(0.1|V;0.3|V)$, by keeping the top $prev_s$ suitability scores while reverting the remaining to zero. The $thr_s = (1 - prev_s/|V|)$ quantile for suitability scores in the baseline period was used as a threshold to turn to zero the suitability scores in the remaining periods in the areas showing a persistence value lower than thr_s (see Duan, Kong, Huang, Wu, & Wang, 2015, for a similar approach) (see a sample of maps in Figure S1). For each of the ($3 \times 2^3 = 24$) parameter combinations, the 10-species data sets ($|S| = 10$) corresponded to the subset that retained the first 10 species in the respective 50-species data sets ($|S| = 50$).

For all the data sets, we randomly defined a dispersal range for each species (number of consecutive grid cells that a species is able to disperse in-between time periods, $disp_s$) from an integer interval $[1;15]$. We also defined for each species a dispersal kernel informing on the probability of successful dispersal in-between grid cells depending on their geographical distance. We assumed a linear decaying

function with $pd_s^{vt,v(t+1)} = 1$ if distance from vt and $v(t+1)$ is zero and $pd_s^{vt,v(t+1)} = 0$ if distance between source and terminal areas is larger than $disp_s$ (see a sample of kernel plots in Figure S2). Given that the maps for the $m = 4$ time periods were generated independently, they miss the temporal autocorrelation patterns that characterize environmental processes and, consequently, species distributions. This limitation is not especially problematic. Indeed, neglecting temporal autocorrelation implies that the suitability areas for a species will likely be located at larger distances along the timeline, than what would be expected to occur in the real world: this pattern, therefore, might be interpreted as representing potential distributions of species exposed to habitat fragmentation, and thus of conservation concern.

We assigned a unitary cost to every grid cell in the maps for all the time periods. As such, the cost of a solution equals the number of grid cells selected among all the time periods.

We used CPLEX 12.5.1 (URL: <http://www-01.ibm.com/software/integration/optimisation/cplex-optimiser>), to solve MIP1 (with default suboptimality tolerance: 10^{-4}) and obtain persistence gaps, \hat{y}_s . We also launched the heuristic feeding stage (10 runs saving the best one, using Equation 2) to obtain the approximated persistence gaps, $P_s - P_s^c$. We also recorded the number of covered species, that is species whose persistence targets were fulfilled, in the optimal and heuristic solutions, as this can have important conservation interest.

We then ran the second stage of the problem under two forms. Firstly, we ran CPLEX to obtain optimal solutions for MIP2 using the

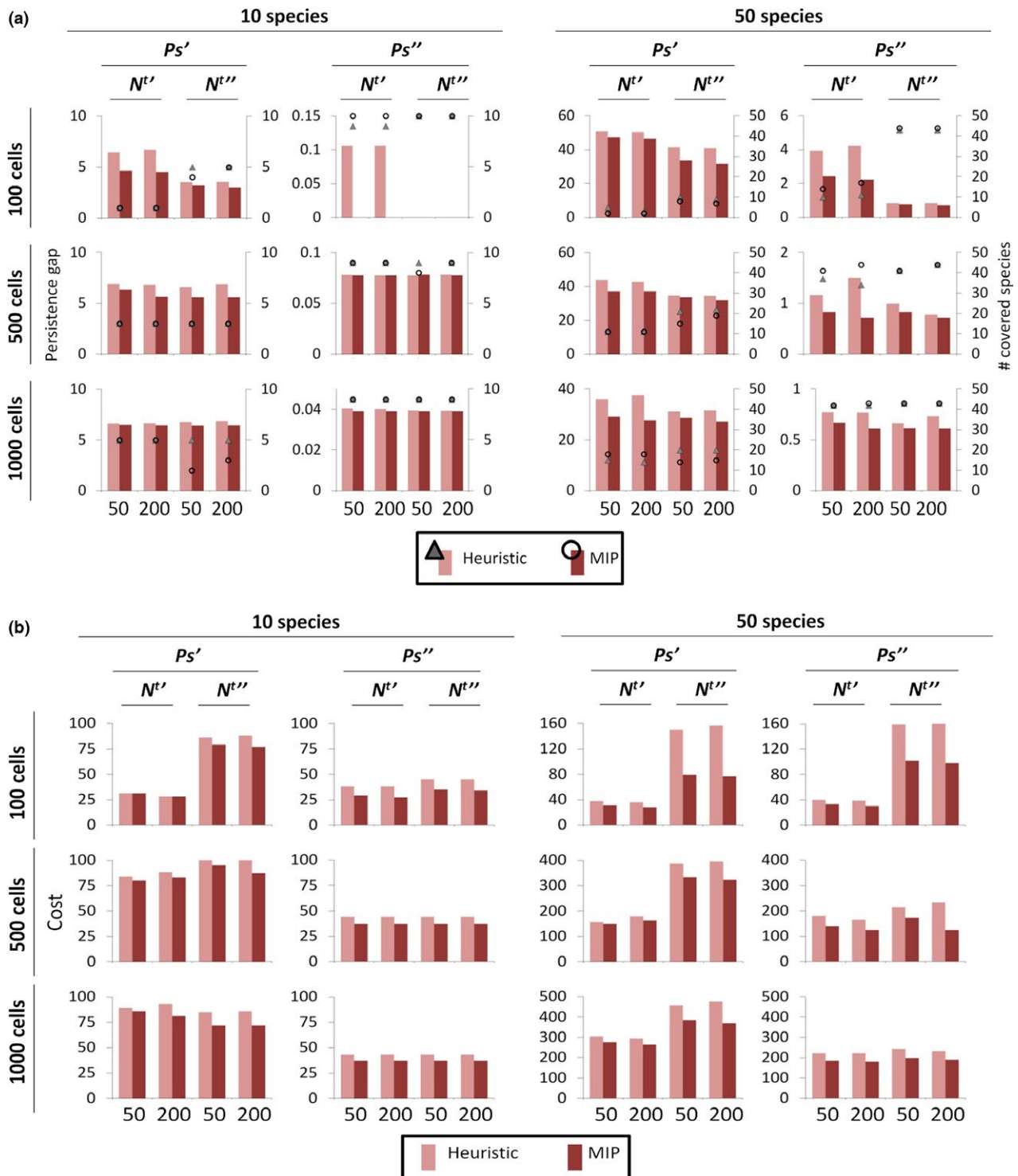


FIGURE 3 The results generated by the optimal and the heuristic approaches for the two stages of the persistence-tuning model. (a) Bars refer to total persistence gaps, symbols represent the number of species with persistence targets totally covered after MIP1 and the feeding stage of the heuristic were implemented (the first model stage). (b) Bars refer to total solution costs obtained under MIP2 and the heuristic pruning stage, both departing from persistence targets adjusted by the heuristic feeding stage (the second model stage). Analyses refer to several simulated case studies characterized by 10 and 50 species; two initial species persistence target settings (P_s' and $P_s'' = P_s'/10$); two distinct maximum area constraints ($N_t' = 0.1|V|$ and $N_t'' = 0.5|V|$) and corridor pools per species of 50 and 200 size, in maps of 100, 500 and 1,000 grid cells. [Colour figure can be viewed at wileyonlinelibrary.com]

tuned species persistence targets from MIP1 \hat{P}_s (the full-optimal approach). We also ran the pruning stage of the heuristic algorithm with the persistence targets, P_s^C , obtained in the heuristic's feeding stage

(10 runs saving the min-cost solution) (the full-heuristic approach). Secondly, we compared the performance of the heuristic pruning stage (i.e., total solution cost), with MIP2, by starting both procedures

with the same persistence targets (Figure 2). We have prescribed sub-optimal persistence targets from the heuristic framework (i.e., feeding stage), but any other target settling scheme could be implemented and tested.

3 | RESULTS

3.1 | The persistence targets

By comparing the persistence gaps of the MIP1 solutions ($\hat{y}_s > 0$) with the persistence gaps obtained using the heuristic method ($P_s - P_s^C > 0$), we found that they were not significantly distinct (on average, heuristic gaps were 19% higher than the optimal gaps, Figure 3a; Table S1). When we standardize these values by the number of species, $|S|$, we found that for $|S| = 10$ each species accrued, on average, 10%–15% of the optimal gap to the heuristic solutions. For the experiments using $|S| = 50$, those per-species values decreased significantly to 2%–4%, on average.

Interestingly, we observed that, in a few cases, some species were favoured in the heuristic solutions (see Figure 4: the symbols below the dotted line) when compared with their persistence achievements

in the optimal solutions. This result was especially evident for the smallest maps in analysis (Figure 4a). In the largest maps, the values from the heuristic and the optimal solutions were more homogeneous within each species, given that the experiments combining N^t and k_s parameters performed equivalently (Figure 4c). We also found that the number of covered species for some heuristic solutions was larger than for the corresponding solutions obtained with the optimal method (e.g., five against two species for the heuristic and optimal solutions, respectively, obtained with $|S| = 10$; $|V| = 1,000$ grid cells; $N^t = 0.5|V|$ and P_s^t). It should be clear that, as the objective function (2) minimizes the sum of persistence gaps among species and does not maximize the number of covered species, optimal solutions might cover less species or even result in larger persistence gaps for some species than heuristic solutions. That is, for some species, $P_s^C > \hat{P}_s$, that is the persistence obtained heuristically being larger than the persistence obtained in MIP1, although $\sum_{s \in S} P_s^C \leq \sum_{s \in S} \hat{P}_s$ is certainly verified.

Additionally, our results showed that the reduction of pool size, k_s , from 200 to 50 corridors only slightly decreased the persistence results. Total persistence gaps obtained with $k_s = 50$ were 0%–15% (average 5%) lower than those of the corresponding solutions with $k_s = 200$ (Figure 3a).

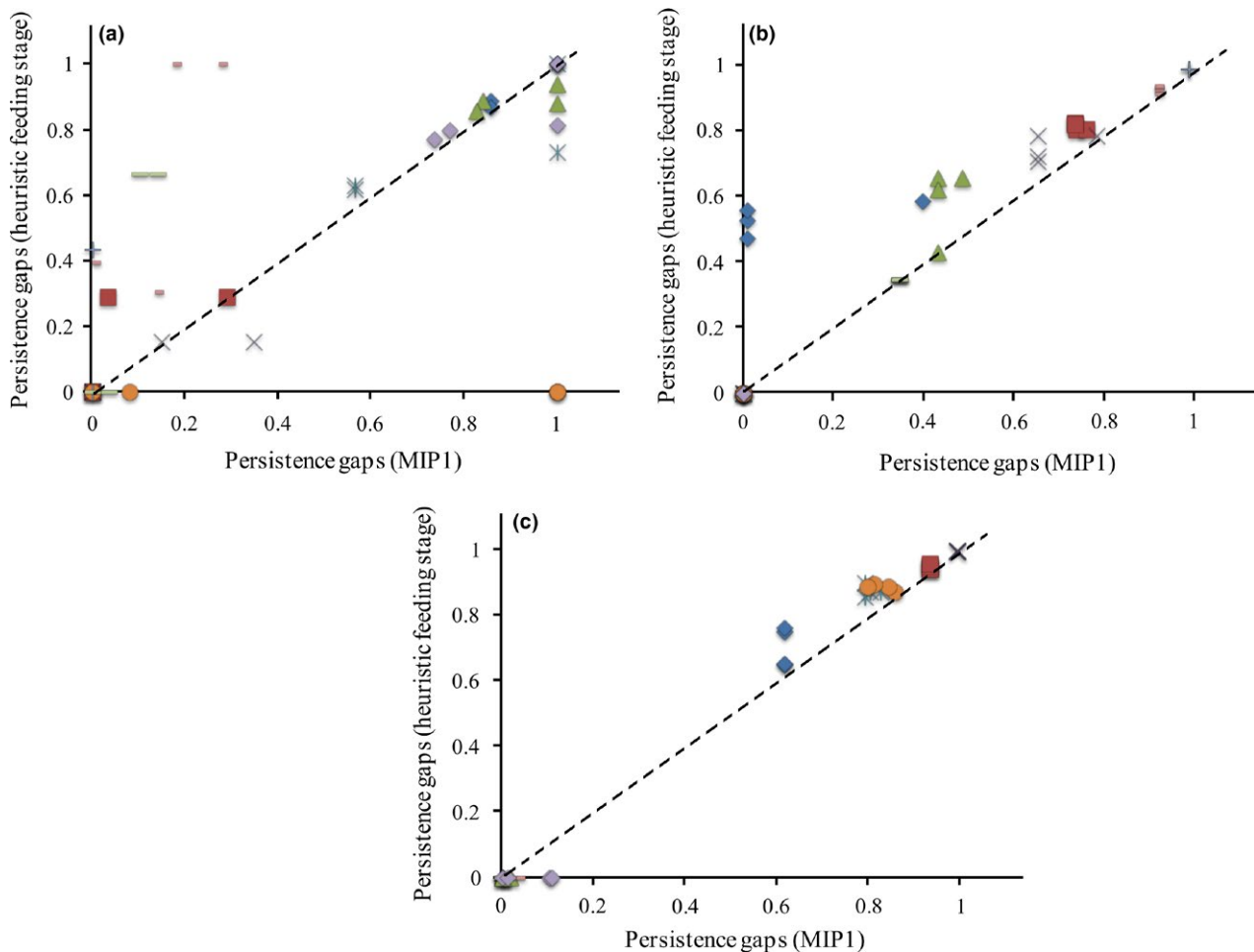


FIGURE 4 The optimal (MIP1) and heuristic (feeding stage) gaps to the persistence targets established in advance for 10 species (distinct symbols) under different simulation experiments in maps made of: (a) 100 grid cells; (b) 500 grid cells; and (c) 1,000 grid cells. In the distinct maps, there is no correspondence between species coded with the same symbols. [Colour figure can be viewed at wileyonlinelibrary.com]

3.2 | Matching heuristic and optimal species persistence with solution costs

Given that in the pruning stage the heuristic approach runs with lower persistence targets than the targets obtained optimally, (i.e., for some species s , $P_s^C < \hat{P}_s$), solution costs from the full-heuristic approach might be lower than the total costs of the corresponding full-optimal solutions (Figure 5). But this was not always the case as, for some runs, a small difference in the achieved persistence for all the analysed species led to significant cost discrepancies, with some solutions presenting higher costs (lower cost-effectiveness) and others presenting smaller costs (higher cost-effectiveness) (e.g., the vertical vectors in Figure 5). For other runs, a large difference of persistence scores obtained heuristically to their related optimal solutions would be resolved optimally with minor increases in solution cost (i.e., the horizontal vectors in Figure 5), thus demonstrating the good analytical performance of the heuristic.

We also found that, for most of the settings, solution costs obtained in the pruning stage of the heuristic did not diverge significantly from the costs obtained with MIP2 when starting with the same set of persistence targets (average difference of 20%, Figure 3b).

4 | DISCUSSION

We introduced a model to address an important and non-trivial issue in target-based conservation prioritization that might be especially

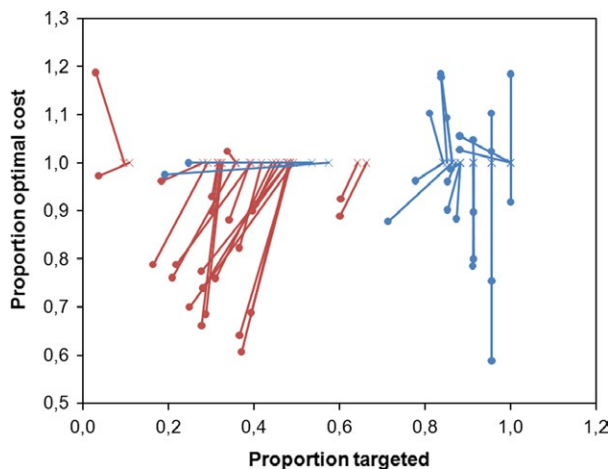


FIGURE 5 Comparisons total persistence and total cost in solutions obtained under a full-optimal and a full-heuristic approach. Analyses focus on the amount of the predefined persistence targets that are met using MIP1 (optimal) and after the heuristic feeding stage (x-axis) and their respective solution costs (referenced to optimal solutions costs) (y-axis). Each simulated case study is represented by a vector linking circle-like nodes (representing the heuristic solutions) to cross-like nodes (representing the corresponding optimal solutions). Blue vectors indicate solutions departing with the least demanding persistence targets ($P'' = P_s/10$), and the red vectors represent solutions departing from the most demanding persistence targets (P_s). [Colour figure can be viewed at wileyonlinelibrary.com]

prevalent in scenarios of climate change: how to adjust desirable, but often infeasible, species persistence targets while accounting for budgets constraints. The model integrates three properties that ideally should be part of functional conservation plans (Wilson, Cabeza, & Klein, 2009). Effectiveness and adequacy are integrated in a first stage in which the available resources are distributed among species, such that the total persistence gap to the persistence targets (defined in advance) is minimized within the selected areas. The second stage of the model promotes efficiency, given that the costs related with the corridors in which the previously optimized persistence targets are attained are minimized. In this hierarchical framework, the costs of final solutions are reliant on the adjusted persistence targets such that the more ambitious are the targets, the higher the costs required to meet them. However, the magnitude of such differences varies nonlinearly. As illustrated in our results (Figure 5), for some of the experiments a full-optimal approach (MIP1 and MIP2) defined areas encompassing insignificant extra costs when compared with the costs obtained using a full-heuristic approach (feeding and pruning stage) even if in the latter the adjusted persistence targets (in the feeding stage) were much lower than the persistence targets obtained exactly (in MIP1). For several of the experiments, this trend was even accentuated, with optimal solutions that presented higher species persistence scores than heuristic ones resulted in lower cost solutions.

The findings obtained herein go directly into the heart of the 'heuristic vs. optimal solutions' debate in conservation planning (Rodrigues & Gaston, 2002; Vanderkam, Wiersma, & King, 2007). Our results evidence that, in general, the heuristic performs well, with persistence scores achieved in the feeding stage close to the ones obtained optimally (MIP1). Costs are also close to the optimal costs obtained using MIP2 when run with the same persistence targets. Moreover, the small persistence differences obtained in the first stage of the model translate in a range of solution costs that are hard to elucidate and control. These idiosyncrasies should be taken into account when deciding whether a heuristic, an optimal or a mixed approach is to be implemented. The combination of optimal and heuristic procedures might be highly informative to support decision-making in biodiversity conservation. For example, the persistence obtained optimally and their respective minimum cost solutions might be used as a reference to which several heuristic runs are compared. Provided with a series of optimal and approximated solutions, decision-makers can account for the deficits on the cost and effectiveness of each solution and chose according their own assessment (i.e., accounting personal or socio-ecological factors that were not incorporated in the area prioritization modelling) (Addison et al., 2013). Case by case, researchers, planners and decision-makers should decide if they are willing to soften the effectiveness, adequacy and/or efficiency of a solution in order to get operational savings in time and computational resources (Rodrigues, Cerdeira, & Gaston, 2000) (see Table S2 for computation times of optimal and heuristic methods herein). But, since the analytic performance of a heuristic is contingent on data particularities, their time and computational savings are also likely to vary. These contingencies make useful that optimal and heuristic methods are available in order for comparisons be made between their outcomes, as advocated herein. Importantly, we note that there is still potential to strengthen

the performance of the heuristic here used and that other approaches are also able to be implemented (e.g., meta-heuristics, column generation, distributed computing) to improve both the analytical results (i.e., suboptimality) and the computational efficiency (i.e., solving time and RAM).

Our results also highlight that the distribution of resources among species varies idiosyncratically (see Figure 4 and Table S1). This finding goes in line with the arguments presented elsewhere (Di Minin & Moilanen, 2012; Moilanen & Arponen, 2011) for the effects of representational target setting in static-based conservation assessments. Transposing such arguments into a time-based scenario (as the ones addressed in climate change-concerned plans), several factors might incite deficits in the achievement of the established conservation targets. Firstly, if the geographical distribution of a species changes through time, and if the range size reduces significantly, then an ambitious target might get impossible to reach. Equally, if climate change leads to a contraction of the climates tolerated by a species, the species range is likely to be reduced making the species exposed to climate debts and extinction in short-to-medium time (Urban, 2015). Secondly, the velocities of climate change might be such that the dispersal capabilities of some species leave them without the capacity to follow their tolerable spatial-changing climates (García, Cabeza, Altwegg, & Araújo, 2016). In these scenarios, species are not able to colonize the existing tolerable climatic regions and therefore no functional area might be available for the conservation targets to be met, unless controversial and costly management actions, as assisted colonization, are carried out (Lawler & Olden, 2011). Lastly, given that spatial conservation programmes commonly need to minimize the amount of area required for protection, or, equivalently, do operate under limited budgets, there might not be sufficient areal or financial resources to assist the protection of a species at a given level, especially when several species with distinct requirements are assessed in conjunction. In these cases, triage assessments are typically undertaken, on which the species are ranked according to a series of conservation features (Bottrill et al., 2009) and the conservation plan is only implemented for the species of highest rank, for which the available budget suffices.

Based on synthetic data, our results were largely consistent with the ones observed in the real world. The persistence targets that we have defined stochastically for each species were seldom met (either by area limitation or deprecated environmental suitability) (see Hannah et al., 2007; for similar findings) and, as expected, the largest gaps were obtained for the most demanding persistence targets (P_s^*) and the largest species sets ($|S| = 50$) (Di Minin & Moilanen, 2012). The dynamism intrinsic to the assessments made through time makes persistence targets more complex to predict than static-based representation targets. In our experiments, the persistence targets required for each species were settled randomly, but a precautionary principle would be easily integrated in the choice of persistence targets. For example, managers might consider adequate to define targets based on the expected persistence of each species assuming that present-time environmental conditions are maintained, and therefore rejecting decline of species persistence expectancies from their present values. In a framework like the one here considered (i.e., using distribution maps of suitable

areas), these assessments would be carried out by fixing present-time species distribution maps for the future time periods, followed by the implementation of an adapted version of MIP1 for each species, s , a time. In this single-species problem, the inequalities (3) would be omitted and the objective function (2) would be modified in order to maximize persistence of species s (i.e., $\max \sum_{l \in \text{cor}_s} p_s^l z_s^l$) for a given area limit. These values would then be used as persistence targets entering MIP1. Furthermore, in the light of probability theory persistence targets may also reflect the expected number of independent populations of a species persisting until the end of the planned horizon of time (Camm, Norman, Polasky, & Solow, 2002). Given that probability is the natural form to express uncertain events, planners may control out the robustness of solutions by, for example, defining as viable corridors only the ones that guarantee more than a given level of persistence for a species.

Instead of guiding area selection into the minimization of total persistence gaps, planners may consider a related (but distinct) problem in which the number of species whose persistence targets are adequately achieved within a constrained area is maximized. This new problem is made up of expressions (4–8), a new set of variables that identifies whether species s is covered ($y_s^* = 1$) or not ($y_s^* = 0$), constraints $y_s^* \leq \sum_{l \in \text{cor}_s} p_s^l z_s^l / P_s$, $\forall s \in S$, that replace the inequalities (3), and the objective function $\max \sum_{s \in S} y_s^*$. In this model, conservation success is measured by the number of species whose targets are met even if that implies that the persistence achieved for other species is largely distant to their initial targets. This modelling framework entangles stricter decisions, such that a species is only considered adequately protected if its persistence is larger than its targeted score, thus resulting in larger biases of protection adequacies among species, than the model here implemented. In both our original proposal and in this modified version, weights might be assigned to species in order to establish a species prioritization scheme (e.g., giving more importance to endangered species). However, planners need to be cautious in implementing this mixed weight-target protocol given that targets should already differentiate species based on species conservation value (Carwardine, Klein, Wilson, Pressey, & Possingham, 2009).

As mentioned earlier (see Introduction), target-based conservation planning presents conceptual weaknesses that are seldom recognized (Di Minin & Moilanen, 2012): (1) targets commonly rely on high-uncertain data and are too prescriptive; (2) targets, that ideally have an ecological basis, are highly affected by the way biodiversity features and costs are distributed in space; and (3) although defined independently for each species, when integrated in multiple-species assessments, they are largely impacted by the way species distributions overlap.

With an explicit call for optimized distributions of financial resources among species given the advanced persistence targets, our model adequately overcomes point 3). However, it does not escape criticisms 1) and 2) which are inherent to target-based methods. Rather than minimizing solution costs for the achievement of several targets, approaches may be shaped for maximizing high-level benefits obtained from aggregated single-species representations (Laitila & Moilanen, 2012). If the main purpose of a conservation plan is good performance in terms of aggregate measures (e.g., average species representation, span of conservation areas), then such maximum-utility methods are

best suited, especially under high budget/area constraints (Di Minin & Moilanen, 2012). We foresee the possibility of our model to be adapted to handle conservation problems not grounded on targets. In the spirit of maximum-utility approaches, climate change corridors may be ranked according to the amount of species persistence therein (e.g., persistence averages among species), and the costs associated with their compounding areas. A greedy procedure may be employed in order to rank sets of corridors, by either removing from (or adding to) the incumbent solution the corridor that best improves the objective function (e.g., formula in [2]). Given the requirement of corridor independency, the maximum weight stable set in the graphs defined for each species needs to be evaluated in each iteration (see the GRASP procedure implemented in the heuristic's feeding phase). In the final solutions, the climate change corridors available in a region are ranked according to their persistence, cost and within-species spatial independency.

5 | CONCLUDING REMARKS

We propose a model that captures and combines three fundamental concerns of biodiversity conservation: climate-dependent species distributions, species dispersal rates (taken against climate change velocity) and areal/budgetary restrictions. The model consists of a sequence of two MIP models that (1) determines adequate levels of persistence for species over time; and (2) finds the areas where the determined levels of persistence are achieved, minimizing total cost. We present an approximation method which we used, together with the exact approach, to solve the problem for several synthetic data sets. Results permitted to draw some conclusions on achieving species persistence targets and the resulting trade-offs among species persistence and solution costs. We found, which seems quite realistic, that there are species for which even modest levels of persistence might be not attainable, even when there are large budgets available. We also found that costs and species persistence vary quite nonlinearly and that area prioritization and persistence achievement are very sensitive to the advanced target settings.

This study makes two main recommendations for target-based conservation planning: (1) the need to carefully establish persistence targets for species, an issue which is extremely important and certainly non-trivial; and (2) the need to consider different persistence target scenarios, as slight changes might result in high differences on costs.

We hope that the proposed model contributes to widen the spectrum of tools available for planners and decision-makers to make rational decisions under complex and dynamic scenarios, and thus to improve biodiversity persistence, the ultimate goal of conservation science and policy.

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D.A. and J.O.C. conceived the ideas; D.A. produced and analysed the data; and D.A. and J.O.C. wrote the manuscript.

SUPPORTING INFORMATION

Additional Supporting Information may be found online in the supporting information tab for this article.

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