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Constrained optimization of landscape indices in conservation planning to support ecological restoration in New Caledonia

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Abstract

1. Curbing habitat loss, reducing fragmentation, and restoring connectivity are frequent concerns of conservation planning. In this respect, the incorporation of spatial constraints, fragmentation, and connectivity indices into optimization procedures is an important challenge for improving decision support.

2. Here we present a novel optimization approach developed to accurately represent a broad range of conservation planning questions with spatial constraints and landscape indices. Relying on constraint programming, a technique from artificial intelligence based on automatic reasoning, this approach provides both constraint satisfaction and optimality guarantees.

3. We applied this approach in a real case study to support managers of the "Côte Oubliée – 'Woen Vùù – Pwa Pereeù" provincial park project, in the biodiversity hotspot of New Caledonia. Under budget, accessibility, and equitable allocation constraints, we identified restorable areas optimal for reducing forest fragmentation and improving inter-patch structural connectivity, respectively measured with the effective mesh size and the integral index of connectivity.

4. *Synthesis and applications.* Our work contributes to more effective and policy-relevant conservation planning by providing a spatially-explicit and problem-focused optimization approach. By allowing an exact representation of spatial constraints and landscape indices, it can address new questions and ensure whether the solutions will be socio-economically feasible, through optimality and satisfiability guarantees. Our approach is generic and flexible, thus applicable to a wide range of conservation planning problems such as ecological restoration planning, reserve or corridor design.

Keywords: Conservation planning, ecological restoration, connectivity, fragmentation, landscape indices, constraint programming, artificial intelligence, New Caledonia.

1 Introduction

As the Earth has entered the Anthropocene, human impacts on the environment have led to the current global biodiversity crisis. Habitat loss and degradation due to land-use change are the leading causes of ecosystem collapse and biodiversity decline (Haddad et al., 2015). Landscape configuration can also have profound impacts on ecological processes such as dispersal, gene flow, or fire resistance (Taylor et al., 1993; Fahrig, 2003). These impacts are often assessed through habitat fragmentation metrics and inter-patch connectivity measures (Uuemaa et al., 2013). Fragmentation refers to the spatial patterns of habitat distribution (Fahrig, 2003) and inter-patch connectivity to the potential ability of species to migrate or disperse between habitat patches (Taylor et al., 1993).

Restoration and conservation planning can help to curb habitat loss and promote suitable landscape configurations, as well as helping to identify trade-offs between conservation targets and managers' objectives (Rodrigues et al., 2000; Knight et al., 2008). Efficient decision support processes must rely on spatially-explicit, systematic, and reproducible approaches (Pressey et al., 1993). Over the last few decades, many such approaches have been devised, from geometric principles derived from biogeography theory (Diamond, 1975) to the principle of complementarity in the representation of biodiversity features (Vane-Wright et al., 1991). Systematic conservation planning (SCP) is now an active field of conservation biology. There is also a consensus on the mutual importance of spatial configuration and the representation of biodiversity features in the planning of conservation actions, to express managers' constraints as much as ecological requirements (Margules and Pressey, 2000; Williams et al., 2005).

Many optimization methods for SCP have been proposed, mostly relying on *ad hoc* heuristics, metaheuristics, or mixed-integer linear programs (MILP). *Ad hoc* heuristics are problem-specific local search algorithms either based on a forward (greedy) (e.g. Kirkpatrick, 1983; Nicholls and Margules, 1993) or backward (stingy) procedure (e.g. Zonation software, Moilanen et al., 2014). In constructive heuristics (resp. destructive), solutions are obtained by iteratively adding (resp. removing) the planning unit which offers the highest gain (resp. loss) according to an objective function to maximize (resp. minimize). Metaheuristics are high-level and problem-independent stochastic search heuristics, such as simulated annealing (e.g. Marxan software, Ball et al., 2009) or tabu search (e.g. ConsNet software, Ciarleglio et al., 2010). The main advantage of heuristics is that they are often straightforward to understand and implement, but produce solutions of unknown quality relative to optimality. Finally, MILP is a constrained mathematical optimization approach where the objective function and the constraints are stated as linear equations, with some or all the variables being integers (Billionnet 2013; Dilkina et al. 2017; oppr R package, Hanson et al. 2019). Exact approaches such as MILP can require more time to generate solutions than heuristics, however, they offer guarantees relative to optimality and constraint satisfaction. Indeed, even though heuristics can reach constraint satisfaction for loosely constrained problems (e.g. species set covering problem, ReVelle et al. 2002), they can fail to provide this guarantee for highly constrained problems (e.g. Billionnet, 2013). Constraint satisfaction problems on a finite domain are indeed in general NP-Complete (Dechter et al., 2003). Although less widely used, dynamic programming approaches (e.g. Meir et al., 2004) and Markov decision processes (e.g. Schapaugh and Tyre, 2012) have also brought substantial advances in SCP but are limited to smaller problem sizes than the approaches described above.

Recent work has introduced several perspectives towards the integration of landscape spatial configuration in SCP optimization procedures. For instance, Marxan software uses a boundary length penalty in its objective function to influence the spatial configuration of the solutions. Additionally, Marxan Connect (Daigle et al., 2020) provides many options to include structural or functional connectivity data in Marxan's input. Similarly, Zonation provides eight different methods to integrate connectivity in its prioritization process (Moilanen et al., 2014). In MILP approaches, several options are available to ensure spatial requirements, such as strictly guaranteeing the connectivity and compactness of delineated areas, or designing buffer zones (Billionnet, 2013; Wang and Önal, 2016). Other approaches such as LQGraph (Fuller and Sarkar, 2006) or Linkage Mapper (McRae et al., 2012) specifically aim to identify optimal corridors between core areas or existing protected areas. On the other hand, landscape ecologists have devised many indices to evaluate the level of fragmentation (McGarigal, 2014) and connectivity (Pascual-Hortal and Saura, 2006; Saura and Pascual-Hortal, 2007) within a landscape. Except Xue et al. (2017) and to the best of our knowledge, such connectivity and fragmentation indices were mainly used in scenario analysis contexts (e.g. Bodin and Saura, 2010). Integrating such indices into constrained optimization approaches is difficult due to their non-linearity and the curse of dimensionality. Nonetheless, it would improve the value of decision support by taking into account more powerful and ecologically relevant metrics in SCP.

Recently, we introduced a novel and generic SCP framework based on constraint programming (Justeau-Allaire et al., 2019), an exact constrained optimization technique based on automated reasoning. In this article, we have extended this framework with landscape indices and applied it in a current reforestation project in the "Côte Oubliée – 'Woen Vùù – Pwa Pereeù" provincial park in the New Caledonia biodiversity hotspot. We worked in close collaboration with New Caledonian environmental managers to provide spatially-explicit decision support focused on reducing forest fragmentation and isolation, which are known to have adverse effects on tree communities in this region (Ibanez et al., 2017). Under budget, land accessibility and equitable allocation constraints, we computed optimal solutions for two landscape indices: the effective mesh size (MESH; Jaeger, 2000) and the integral index of connectivity (IIC; Pascual-Hortal and Saura, 2006) applied to structural connectivity. MESH is a measure of landscape fragmentation which is based on the probability that two randomly chosen points are located in the same patch. Maximizing it in the context of reforestation favours fewer and larger forest patches. On the other hand, IIC is a graph-based inter-patch connectivity index based on a binary connection model. Its maximization in the context of reforestation favours restoring structural connectivity between large patches. Our results demonstrated the flexibility of this approach and how its expressiveness (i.e. the breadth and variety of problems that it can represent and solve) facilitates the representation of the inherent diversity of real-world conservation problems, offering new perspectives for designing decision support tools in ecological restoration and more broadly in conservation planning (e.g. for reserve or corridor design).

2 Material and Methods

2.1 Case study: reforestation planning in the "Côte Oubliée – 'Woen Vùù – Pwa Pereeù" provincial park, New Caledonia

New Caledonia is a tropical archipelago located in the South Pacific (see Figure 1.a). As the smallest biodiversity hotspot in the world, it hosts megadiverse marine and terrestrial ecosystems. Notably, New Caledonian flora is distinguished by one of the highest rates of endemism in the world – approximately 76% (Myers et al., 2000; Morat et al., 2012), a high beta-diversity (Ibanez et al., 2014), and the presence of relict taxa (Grandcolas et al., 2008; Pillon, 2012). However, New Caledonian forests are under threat and the remaining forest is highly fragmented, as the result of anthropic activities such as bushfires, logging, urbanization, and nickel mining. New Caledonia is an overseas French collectivity which was first populated by the Kanak people. In this territory, the French Common Civil Code coexists with the Customary Civil Code, and institutions such as the Customary Senate provide a political framework to the Kanak people for promoting their culture, traditions, and environment. In this respect, customary authorities of the "Côte Oubliée 'Woen Vùù – Pwa Pereeù", a large area in the Southeast of the main island of New Caledonia, "Grande Terre" (see Figure 1.b), established a moratorium on nickel mining activity between 2014 and 2016. They called for cessation on any road, mining or infrastructure project, in response to the erosion of many areas, due to bushfires and mining activity. This moratorium was renewed for ten years (from 2018 to 2028) and led to the creation in April 2019 of the "Côte Oubliée 'Woen Vùù – Pwa Pereeù" Provincial Park by the South Province of New Caledonia. With 93000 ha of terrestrial and 27000 ha of marine protected area, the provincial park blocked 102 mining concessions, includes three existing natural reserves and is adjacent to four existing natural reserves (see Figure 1.c). It now remains for the managers of the South Province's Sustainable Development Department for the Territories (SDDT) to establish the management plan of the park, with a strong emphasis on reducing forest fragmentation.

In this study, we focus on a reforestation project that must be planned by the SDDT. One of its objectives is expected to be the zoning of two suitable areas for reforestation, one in each of the two customary districts of the Côte Oubliée, respectively Borendy and Unia, to involve both communities in the project. Since the Côte Oubliée is a low urbanized and mountainous area, most locations are difficult to access. Accordingly, to be accessible reforestation areas must be compact (within an enclosing circle whose maximum diameter is 1500 m) and close to existing tracks (at a maximal distance of 1000 m). In this study, we considered a realistic cost corresponding to 200 ha to reforest, equitably divided between Borendy and Unia (100 ha $\pm$ 10% in each district). Under these constraints, the aim was to optimize the potential contribution of the reforested areas to reduce forest fragmentation and improve forest structural connectivity in the provincial park.

2.2 Data

The Côte Oubliée is a poorly studied area, and we still have little knowledge about the dispersal of New Caledonian animal and plant forest species (see the last biological knowledge

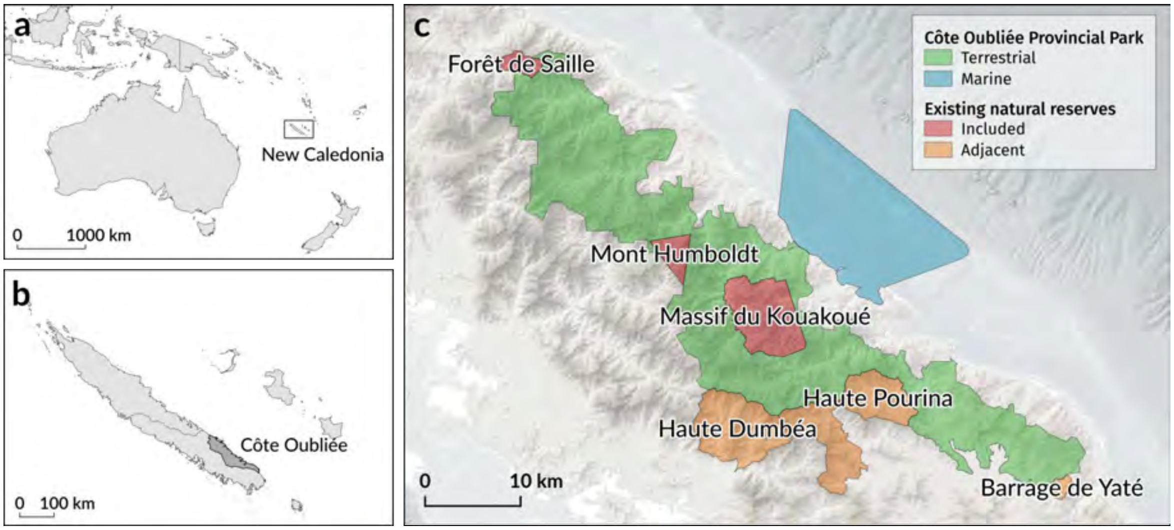

Figure 1: (**a**) Location of New Caledonia. (**b**) Location of the "Côte Oubliée" area. (**c**) Map of the "Côte Oubliée – Woen Vùù – Pwa Pereeù" provincial park, with included and adjacent existing natural reserves.

synthesis on the Côte Oubliée: Guillemot et al., 2016). Although species occurrences are useful to guide planning, the region is insufficiently sampled to ensure an unbiased selection. Species distribution models (SDMs) of tree species could also help to identify adequate reforestation areas. However, it would be necessary to have more occurrences in this region to obtain reliable predictions, due to the heterogeneity of tree community compositions which is still not well understood (Pouteau et al., 2019). In this respect, we adopted a forest-cover approach using remote sensing data (the dominant forest type in this area is dense rainforest). In this respect, we relied on a 2019 30 m binary forest-cover raster (cf. Figure 2.a), based on the historical analysis of temporal series from Landsat data (1982 to 2018) (Vancutsem et al., 2020). We focused on the extent of the Côte Oubliée Provincial Park (55.68 km height and 81.6 km width) and resampled the forest-cover raster to a resolution of 480 m (16×16 30 m cells) as a compromise between conservation planning and computational solving (480 m $\times$ 480 m $\approx$ 23 ha). We obtained a 116×170 raster map where each 480 m cell is characterized by a forest-cover proportion, according to the number of covered 30 m forest pixels. A 480 m cell was considered as degraded if its forest-cover proportion was smaller than 70% (Fahrig, 2013; Vieilledent et al., 2018). As reforestation must occur in the provincial park, we retained the cells within the boundaries of the provincial park to which we included parts of forest patches extending outside the park to avoid the boundary problem (Moser et al., 2007). The resulting raster map contained 3629 forest cells and 2715 non-forest cells, as illustrated in Figure 2.b. Consequently, we quantified the area to be reforested in each 480 m cell as the area needed to reach a forest-cover proportion of 70% (cf. Figure 2.d). Finally, we identified accessible areas for reforestation as a 1000 m buffer around tracks using the tracks vector data provided by the SDDT, classified according to the two customary districts covered by the provincial park, Borendy and Unia (see Figure 2.c).

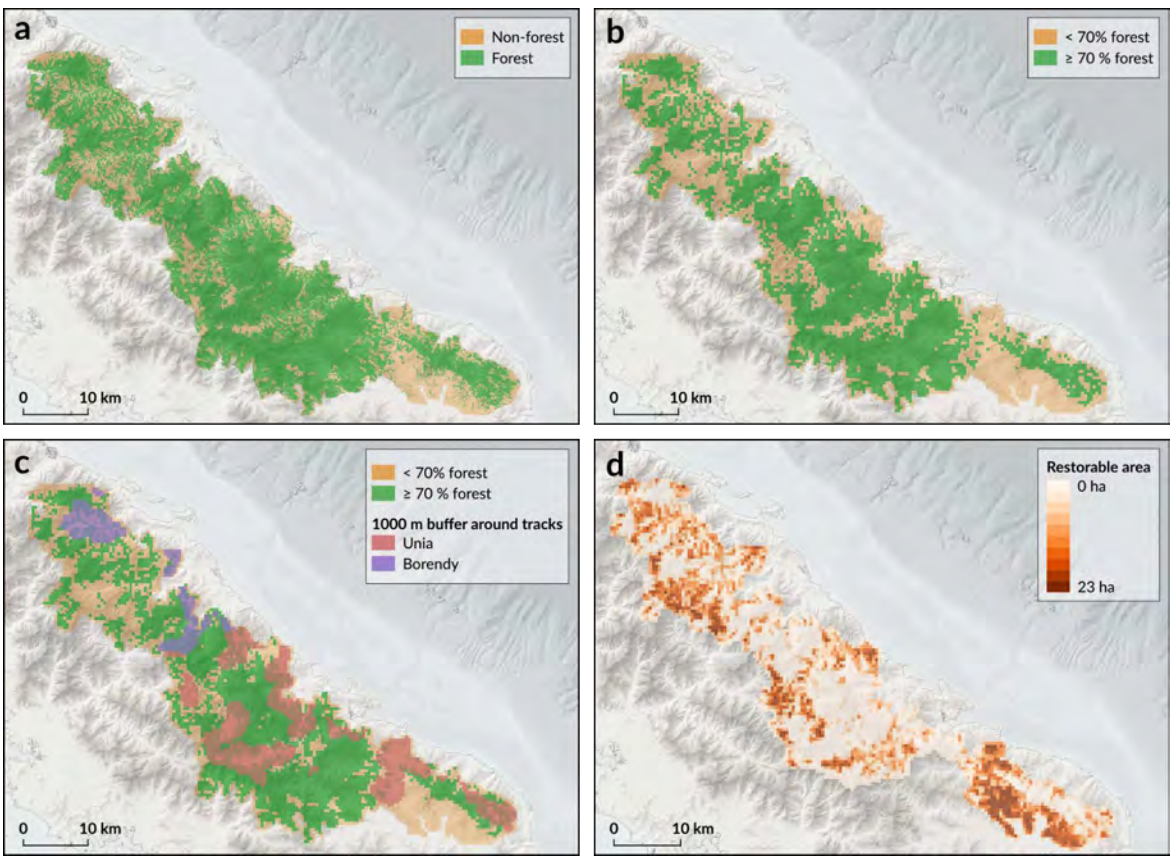

Figure 2: Input data maps. (**a**) 2019 30 m binary forest map produced from Landsat historical data analysis. (**b**) Upscaled 480 m binary forest map. A 480 m cell was considered as forest if its forest-cover proportion at 30 m was at least 70%. (**c**) 480 m accessible areas (1000 m buffer around tracks) map, classified by customary districts. (**d**) 480 m restorable area map, that is the non-forest area for each cell.

2.3 Mathematical formulation

2.3.1 Base problem: variables and managers' constraints

To each cell of the input raster grid we associate a planning unit (PU) that can be selected for reforestation, these are the decision variables of our base model. Let $\mathcal{S}$ be the set of PUs in the study area, we define the following subsets of $\mathcal{S}$ according to the data:

$$\begin{aligned}
&\mathcal{U}, \text{the set of accessible PUs located in the Unia district;}\\
&\mathcal{B}, \text{the set of accessible PUs located in the Borendy district;}\\
&\mathcal{F}_{\geq 70\%}, \text{the set of PUs with forest-cover proportion} \geq 70\%;\\
&\mathcal{F}_{<70\%}, \text{the set of PUs with forest-cover proportion} < 70\%.
\end{aligned} \tag{1}$$

Let $R_u \subseteq \mathcal{F}_{<70\%}$ and $R_b \subseteq \mathcal{F}_{<70\%}$ be the sets of PUs to reforest respectively in Unia and Borendy, that is sets of PUs available for restoration. The sets $R_u, R_b, \mathcal{F}_{\geq 70\%}$, and $\mathcal{F}_{<70\%} \setminus (R_u \cup R_b)$ must form a partition of $\mathcal{S}$, and $R_u \cup R_b \cup \mathcal{F}_{\geq 70\%}$ corresponds to the potential forest-cover resulting from reforestation. To each of these sets is associated a grid graph. For a given set, each PU in the set is a node and two nodes are connected if and only if the corresponding PUs are adjacent according to the four-connected neighbourhood definition in the regular square grid. We now introduce the following constraints:

Constraint 1 (CONNECTED)**.** Let $R \subseteq \mathcal{S}$ be a region, CONNECTED(R) holds if and only if the region R is connected according to its associated graph.

Constraint 2 (RESTORABLE)**.** Let $R \subseteq \mathcal{S}$ be a region, a an integer variable, and $p \in [0, 1]$. RESTORABLE(R, a, p) holds if and only if each PU in R can be restored to a forest-cover proportion of p by reforesting at least a ha. In any solution satisfying this constraint, the value of a thus corresponds to the minimum area to restore to reach a forest-cover proportion of p. Formally, let v_x^p be the minimum area to reforest to restore the PU x to p, then:

$\textsc{Restorable}(R, a, p) \Leftrightarrow a = \sum_{x \in R} v_x^p.$

Constraint 3 ($\textsc{Radius}$)**.** Let $R \subseteq \mathcal{S}$ be a region and ρ a real variable. $\textsc{Radius}(R, \rho)$ holds if and only if the radius of the smallest enclosing circle containing R equals ρ (in meters).

Given two regions $R_u \subseteq \mathcal{S}$ and $R_b \subseteq \mathcal{S}$, the budget, accessibility, and equitable allocation requirements are satisfied if and only if all the following constraints are satisfied:

$$R_u \subseteq \mathcal{U} \cap \mathcal{F}_{<70\%} \wedge R_b \subseteq \mathcal{B} \cap \mathcal{F}_{<70\%}; \tag{2}$$

$$\textsc{Connected}(R_u) \wedge \textsc{Connected}(R_b); \tag{3}$$

$$a_u \in 0.5 \cdot A_{\text{max}} \pm 10\% \wedge \textsc{Restorable}(R_u, a_u, 70\%); \tag{4}$$

$$a_b \in 0.5 \cdot A_{\text{max}} \pm 10\% \wedge \textsc{Restorable}(R_b, a_b, 70\%); \tag{5}$$

$$a_u + a_b \leq A_{\text{max}}; \tag{6}$$

$$a_{\text{max}} \in [0, +\infty] \wedge \textsc{Restorable}(R_u \cup R_b, a_{\text{max}}, 100\%); \tag{7}$$

$$a_{\text{max}} \geq A_{\text{max}}; \tag{8}$$

$$\rho_u \in [0, P_{\text{max}}] \wedge \textsc{Radius}(R_u, \rho_u); \tag{9}$$

$$\rho_b \in [0, P_{\text{max}}] \wedge \textsc{Radius}(R_b, \rho_b). \tag{10}$$

With A_{max} the total area to reforest (200 ha) and P_{max} the maximum radius of the smallest circle enclosing reforested areas (1500 m). Constraint (2) ensures that the reforested regions are located in accessible and degraded areas respectively in Unia and Borendy. Constraint (3) ensures that each reforested region is connected. Constraints (4) and (5) ensure that the budget is equitably allocated between Unia and Borendy, with a_u and a_b two integer variables representing the minimum areas to restore respectively in Unia and Borendy. Constraint (6) ensures that the minimum area to restore in Unia and Borendy together does not exceed A_{max}. Constraint (7) ensures that the integer variable a_{max} equals the total area that can be reforested in Unia and Borendy together. Constraint (8) ensures that the totality of the budget can be invested in the selected areas. Finally, Constraints (9) and (10) ensure that each selected region is compact.

2.3.2 Constrained optimization of fragmentation indices

From the base problem described in the previous section, we defined two optimization problems, respectively associated with the maximization of MESH and IIC. We computed the value of each index in the current landscape, then we found every optimal solution and retained the index optimal value, the improvement brought by the optimal value compared to the current one, the number of optimal solutions, and the solving times for reaching the optimal value and then enumerate all optimal solutions. In the following, we denote the set of patches of a region R by $P(R)$. These patches are directly derived from the raster representation of the landscape by extracting the connected components of the grid graph associated with the raster grid, as illustrated in Figure 3.

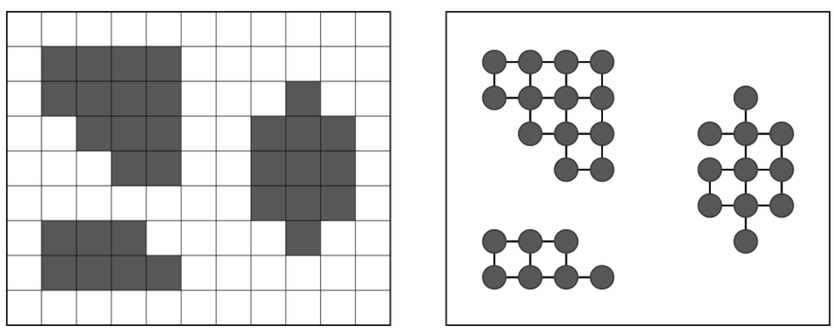

Figure 3: Raster representation of the landscape (left) and the associated grid graph (right). In this example, there are three connected components, thus three patches.

Maximization of MESH. MESH is a fragmentation index based on habitat patch sizes distribution within the landscape. It expresses an area unit and corresponds to the area of patches when the investigated region is divided into equally sized patches such that the probability that two randomly chosen points are in the same patch remains the same (Jaeger, 2000). For a region R, it is given by:

$$\text{MESH}(R) = \frac{1}{A_L} \sum_{k \in P(R)} A_k^2. \tag{11}$$

With A_k the area of patch k, and A_L the total landscape area. The constrained optimization of MESH associated with our case study is given by:

$$\begin{aligned} &\underset{(R_u, R_b) \subseteq \mathcal{S}^2}{\text{maximize}} \quad \text{MESH}(R_u \cup R_b \cup \mathcal{F}_{\geq 70\%}); \\ &\text{subject to:} \quad (2) \wedge (3) \wedge (4) \wedge (5) \wedge (6) \wedge (7) \wedge (8) \wedge (9) \wedge (10). \end{aligned} \tag{12}$$

Maximization of IIC. IIC is a graph-based inter-patch connectivity index introduced by Pascual-Hortal and Saura (2006). It focuses on groups of patches (components) that are structurally or functionally connected and evaluates their sizes distribution along with the topological complexity of these components (i.e. the potential ability to move from one patch to another within a component). It ranges from 0 (no habitat in the landscape) to 1 (all the landscape is occupied by habitat). For a region R, it is given by:

$$\text{IIC}(R) = \frac{1}{A_L^2} \sum_{k \in P(R)} \sum_{l \in P(R)} \frac{A_k \cdot A_l}{1 + d_{kl}}. \tag{13}$$

Where A_k is the area of the patch k, A_L the total landscape area and d_{kl} the topological distance (i.e. shortest path length) between k and l in the landscape graph. Due to the lack of knowledge on species dispersal in the Côte Oubliée area, we used IIC as a structural connectivity index. To determine whether two forest patches are structurally connected, which is required to calculate IIC (see Pascual-Hortal and Saura, 2006), we used the smallest possible edge-to-edge distance threshold of at most one non-forest cell. This distance threshold can be represented by the two-wide-four-connected neighbourhood (Justeau-Allaire et al., 2019). Two examples illustrating the construction of the landscape graph from a raster representation are provided in Figure 4 and Figure 5. The constrained optimization of IIC associated with our case study is given by:

$$\begin{aligned} \underset{(R_u, R_b) \subseteq \mathcal{S}^2}{\text{maximize}} \quad & \text{IIC}(R_u \cup R_b \cup \mathcal{F}_{\geq 70\%}); \\ \text{subject to:} \quad & (2) \wedge (3) \wedge (4) \wedge (5) \wedge (6) \wedge (7) \wedge (8) \wedge (9) \wedge (10). \end{aligned} \tag{14}$$

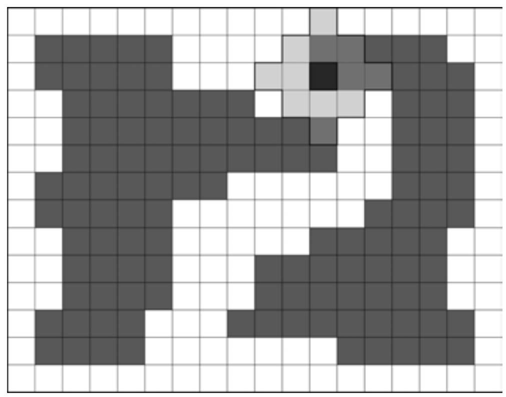

Figure 4: Illustration of the two-wide-four-connected neighbourhood distance threshold used to construct the landscape graph needed to compute IIC. The left patch intersects with the two-wide-four-connected neighbourhood of the black pixel located in the right patch. The patches are thus considered structurally connected.

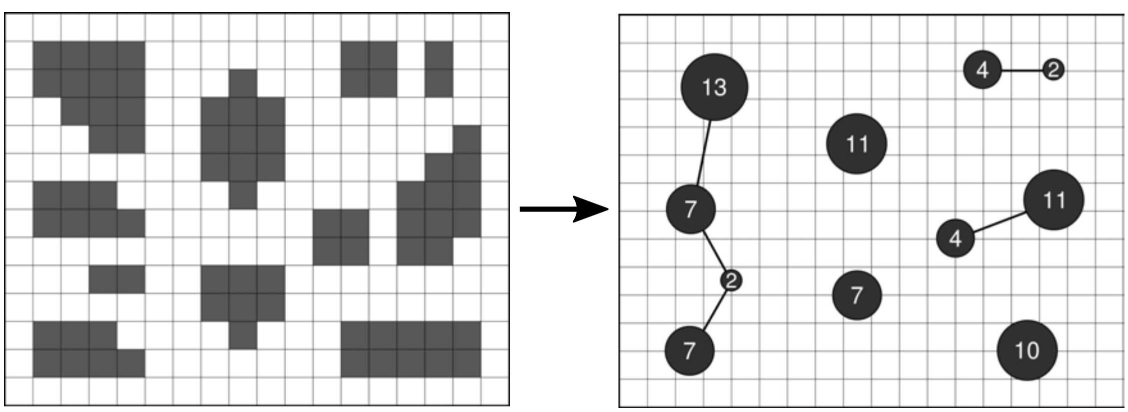

Figure 5: Construction of the forest landscape graph from a raster-based representation, using the two-wide-four-connected neighbourhood distance threshold.

2.4 Solving method: The constraint-based systematic conservation planning framework

To solve this problem, we used the constraint-based systematic conservation planning (SCP) framework briefly presented in the introduction (Justeau-Allaire et al., 2019). As this framework relies on constraint programming (CP), we have provided a quick description of this technique's fundamental principles in Box 1. In this constraint-based SCP framework, any problem states as follows: given a tessellated geographical space $\mathcal{S}$, find a partitioning of $\mathcal{S}$ into n regions $\{R_0, ..., R_{n-1}\}$ satisfying a set of constraints C, available from a constraint catalogue. The CP model associated with this formulation relies on three representations of the space: integer variables (one for each PU), set variables (one for each region), and graph variables (one for each region), and each user constraint applies to the most relevant space representation. This formulation allows the modelling of regions' expected properties through constraints. This framework was implemented upon the java open-source CP solver Choco (Prud'homme et al., 2017), and its source code is available on GitHub[1]. Most of the constraints needed by the case study were already available in the framework. We, however, extended it with the RADIUS constraint, implemented with a linear-time filtering algorithm based on the best-known algorithm for the smallest enclosing circle problem (Welzl, 1991), the MESH constraint, and the IIC constraint, implemented with a two-stage algorithm which first constructs the landscape graph from the raster representation and then computes all-pairs shortest paths by performing a breadth-first search from each node of the landscape graph. We ran all optimization problems described in the previous section on a Linux server (Intel Xeon E5-2620 CPU 2.40GHz $\times$ 12, 64GB RAM). The case study source code is available on GitHub[2] and we packaged an executable command-line jar to reproduce the single-region version of the problem (installation and usage instruction are available on the GitHub page).

[1]https://github.com/dimitri-justeau/choco-reserve
[2]https://github.com/dimitri-justeau/cote-oubliee-choco-reserve-code

Box 1: Constraint programming in a nutshell

Constraint programming (CP) is a declarative paradigm for modelling and solving constraint satisfaction and constrained optimization problems. In this context, declarative means that the modelling of a problem is decoupled from its solving process, which allows the primary focus to be on *what* must be solved rather than describing *how* to solve it. CP is a subfield of artificial intelligence which relies on automated reasoning, constraint propagation and search heuristics. As an exact approach, CP can provide constraint satisfaction and optimality guarantees, as well as enumerating every solution of a problem. In CP, the modeller represents a problem by declaring *variables* whose possible values belong to a specified finite *domain*, by stating *constraints* (mainly logical relations between variables), and eventually by defining an objective function to minimize or maximize. A solution to the problem is an instantiation of every variable such that every constraint is satisfied. As opposed to mixed-integer linear programming, constraints can be non-linear and variables of several types (e.g. integer, real, set, graph). A CP solver then handles the solving process relying on an automated reasoning method alternating a constraint propagation algorithm (deduction process on values within domains that does not lead to any solution) and a backtracking search algorithm. In a nutshell, more than satisfiability, each constraint embeds a filtering algorithm able to detect inconsistent values in variables domains. At each step of the backtracking search algorithm, the solver calls the constraint propagation algorithm that repeatedly applies these algorithms until a fixpoint is reached. When it is proven that a part of the search tree contains no solution, the solver rolls back to a previous state and explores another part of the search tree: this is backtracking. Note that most CP solvers are also able to handle Pareto multi-objective optimization. Interested readers can go further by reading the Handbook of Constraint Programming (Rossi et al., 2006).

3 Results

We summarized the results of the constrained optimization of MESH and IIC in Table 1 and mapped optimal solutions in Figures 6 and 7. First, the solver found the optimal value for MESH in about 30 minutes and quickly enumerated all optimal solutions. Conversely, the solver took several hours to reach the optimal solution for IIC and about 20 minutes to enumerate all optimal solutions. Moreover, although several optimal solutions were found, for a given index they were all located in the same zone and reconnected the same patches.

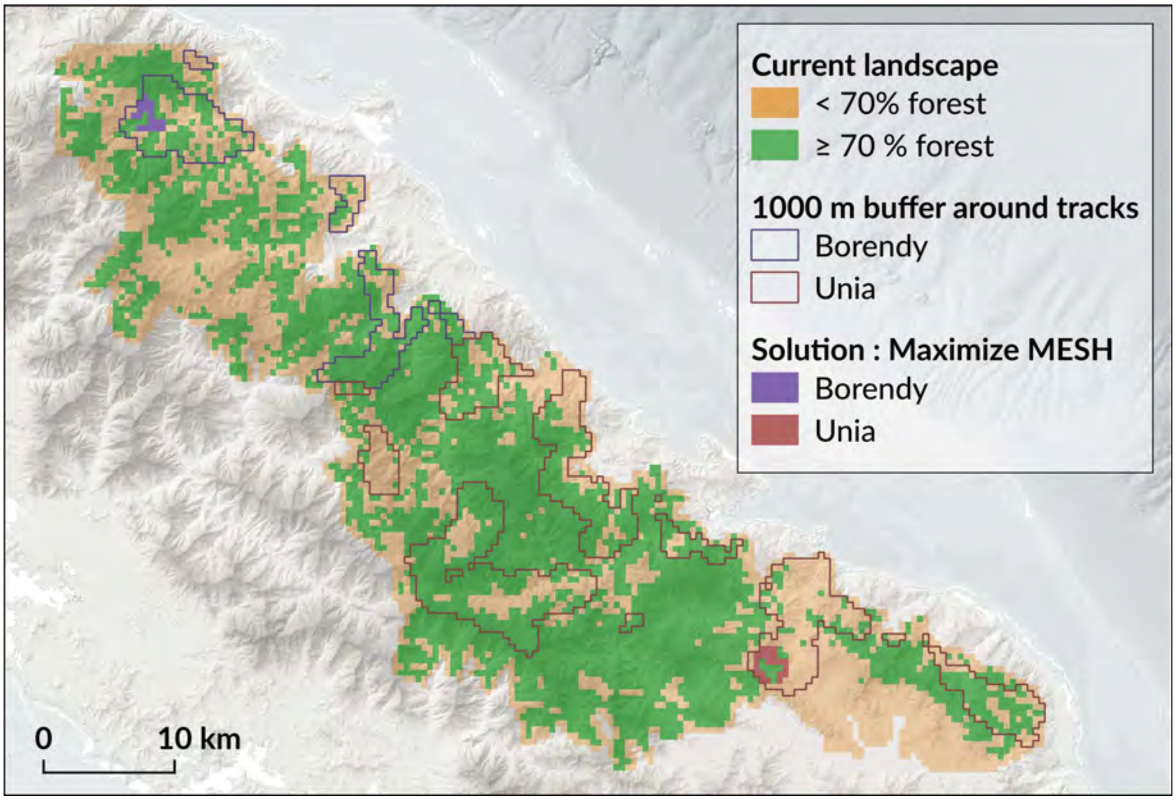

Figure 6: Mapping of a solution maximizing the effective mesh size (MESH).

Objective	maximize MESH	maximize IIC
Current value	24 542 ha	0.20691
Optimal value	25 502 ha	0.22986
Improvement	3.91%	11.09%
No. optimal solutions	7	3
Solving time (optimize)	14.7 min	5.8 h
Solving time (enumerate)	18 s	19.7 min

Table 1: Results characteristics: for each index, its value in the current landscape, its optimal value, the improvement after optimization, the number of optimal solutions and solving times. MESH: effective mesh size, IIC: integral index of connectivity.

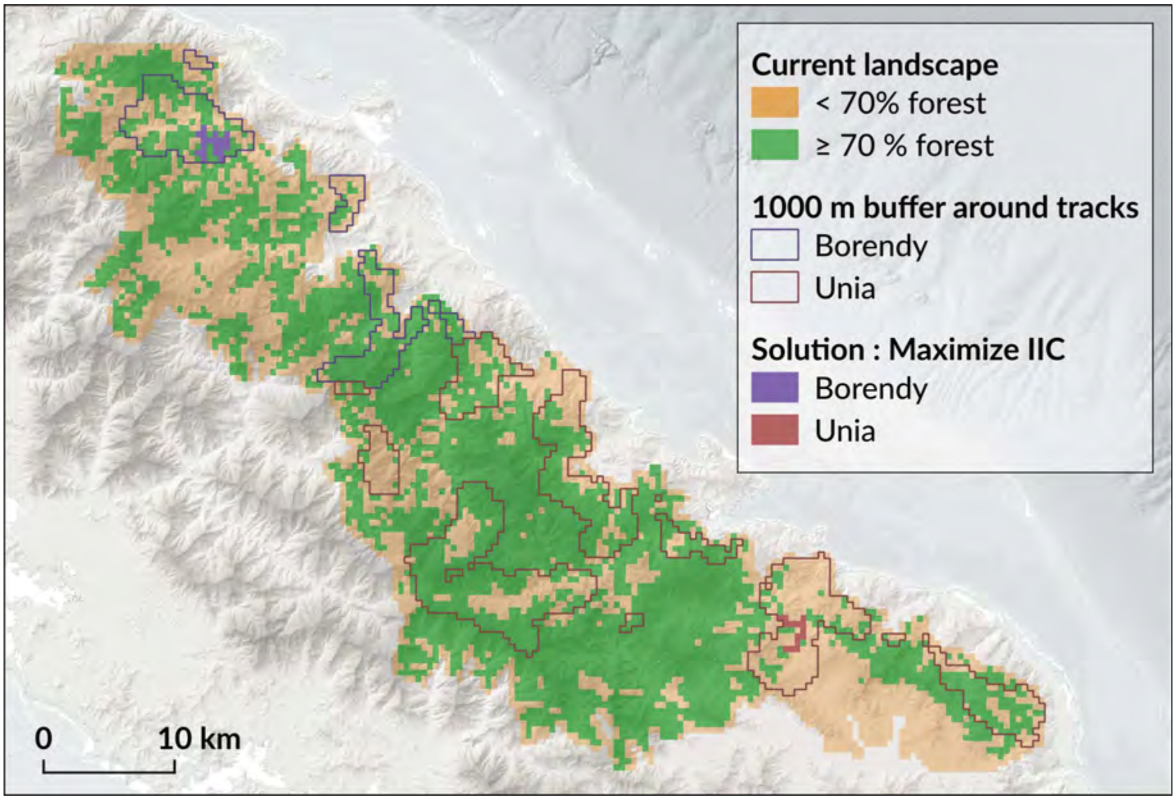

Figure 7: Mapping of a solution maximizing the integral index of connectivity (IIC).

4 Discussion

4.1 Contribution to decision support in the "Côte Oubliée – 'Woen Vùù – Pwa Pereeù" reforestation project

Under budget, accessibility and equitable allocation constraints, we computed all optimal solutions for a fragmentation index (MESH) and an inter-patch connectivity index (IIC) within relatively short amounts of time. There was a considerable computing time difference between MESH and IIC, due to the combinatorial complexity involved by the construction of the patch-based landscape graph from a raster landscape representation. Optimal areas for MESH and IIC were not overlapping and offered two reforestation scenarios for managers. MESH did not assume any possible link between physically disconnected forest patches, thus highlighted areas favouring the physical connection of large patches together. In Borendy, it connected medium-sized patches into a large patch. In Unia, it merged two small patches with a large patch. On the other hand, IIC assumed possible links between physically disconnected but close patches, thus did not consider the medium-sized patch in Borendy as disconnected and favoured merging several small patches to reduce the topological complexity of the forest component. In Unia, it reconnected the southernmost forest component with the main forest component of the provincial park.

These results contributed to decision support by providing two scenarios that are optimal according to their respective index. In this regard, they provided a spatially-explicit and problem-focused baseline for discussions between stakeholders of the project, as well as specific areas presenting particular landscape-scale properties, thus potential candidates to prospection for local-scale assessments. Such results, along with the proposed methods, were well received and considered useful by the stakeholders of the "Côte Oubliée – 'Woen Vùù – Pwa Pereeù". Most importantly, they were enthusiastic to see that the solver guarantees that every constraint will be satisfied by the solutions and that it will inform the user when no solution exists that satisfies all the constraints.

4.2 On the use of landscape indices in systematic conservation planning

These results illustrated the potential for integrating more complex and ecologically meaningful landscape indices into conservation planning to reduce fragmentation and improve connectivity. Fragmentation is known to have adverse effects on forest tree communities in New Caledonia (Ibanez et al., 2017) and there is strong evidence on the importance of structural connectivity for facilitating species dispersal, persistence, and gene flow between communities (Taylor et al., 1993). Optimizing such indices in systematic conservation planning (SCP) is thus useful to inform on the potential benefits of conservation actions on landscape fragmentation and connectivity. Being able to take into account the benefits of conservation projects over several indices is also an important step for providing holistic management recommendations. The main advantage of constrained optimization over prioritization and scenario analysis approaches is that the solutions are produced considering every possible combination of planning units satisfying user-defined constraints. This characteristic assures decisions makers that no feasible or better (according to an optimization objective) opportunity has been missed.

4.3 Advantages of the constraint-based approach for systematic conservation planning

Our constraint-based SCP framework demonstrated its ability to address and solve real-world SCP problems with satisfiability and optimality guarantees. By emphasizing a spatially-explicit and problem-focused approach, it presents several strengths. First, its expressiveness (i.e. the breadth and variety of problems that it can represent and solve) allows an accurate representation of the various constraints that stakeholders need to take into account for implementing conservation actions. Combined with a satisfiability guarantee, we can ensure that the proposed solutions will satisfy every managers' constraint and thus be socio-economically feasible, which is a requirement for policy-relevant conservation science (Game et al., 2015; Williams et al., 2020). Moreover, the flexibility of our approach makes it relevant to a wide range of conservation planning questions, as constraints and objectives can be seamlessly modified, added, or removed from the model without affecting the solving process. For instance, it can help to design optimal corridors, protected areas, fire-protected zones, or even provide insight for maintaining and restoring connectivity for migratory species. Note that although our use case was focused on forest cover, our constraint-based approach is also suited to include several biodiversity features and can handle multiple management zones. We believe that, besides being a useful methodological tool, such an approach can contribute to narrowing the "research-implementation gap" (Knight et al., 2008). With a modelling tool expressive enough to represent accurately conservation scientists' aims along with managers' constraints, it becomes possible to design conservation actions that are realistic for managers, as well as offering an integrative and evidence-based tool for scientists.

4.4 Current limitations and perspectives for systematic conservation planning

A lot of effort is still required to invest in development to provide a wide-audience software package, as our framework in its current state still requires knowledge of constraint programming (CP) to be used correctly. Moreover, as CP is an exact optimization approach, computation of optimal solutions can take time for large problems, and it is difficult to predict this time as it depends on the problem's structure (e.g. problem size, number and nature of the constraints). In its current implementation, we can, however, assert that exercises involving 50000 planning units (which is Marxan's limit in most cases; Ardron et al., 2008) would likely exceed the memory capacity of a standard desktop computer or not complete within a feasible amount of time. Another limitation directly relates to the regular square grid representation, which involves a trade-off between the spatial resolution and the sophistication of the model. In our case study, this spatial resolution limited the distance threshold needed to compute IIC to at least 480 m, which can be too large for some species. A promising perspective to overcome this limitation would consist of using an irregular grid representation to locally increase the spatial resolution without increasing the number of planning units.

Nevertheless, we have shown that there is good potential for formulating and solving SCP problems using CP. There is a continued debate on the importance of optimality in SCP methods, which mainly contrasts local search approaches with MILP (Underhill, 1994; Pressey et al., 1996; Rodrigues and Gaston, 2002; Hanson et al., 2019). However, optimality should not be the only consideration. We even argue that expressiveness is a prerequisite to optimality (Rodrigues et al., 2000; Moilanen, 2008). To conclude, recent years have seen substantial advances in artificial intelligence. We believe that, as illustrated by this study, such advances are providing new opportunities for formulating and solving conservation planning problems.

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Authors' contributions

G.V., N.R., and D.J. collected and prepared the data. P.B., N.R., G.V., and D.J. conceived the ideas and the methodology. X.L., P.V., and D.J. modelled the problem, designed the algorithms, and produced the source code. P.B., G.V., X.L., and D.J. analysed the results. D.J. led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

Data availability statement

Data available via the Dryad Digital Repository https://doi.org/10.5061/dryad.p8cz8w9nw (Justeau-Allaire et al., 2020b). Source code available via the Zenodo Digital Repository https://doi.org/10.5281/zenodo.4202715 (Justeau-Allaire et al., 2020a) or via the GitHub Digital Repository https://github.com/dimitri-justeau/cote-oubliee-choco-reserve-code.

References

Ardron, J.A., Possingham, H.P. and Klein, C.J. Marxan good practices handbook. Pacific Marine Analysis and Research Association, Vancouver, page 149, 2008.

Ball, I.R., Possingham, H.P. and Watts, M.E. Marxan and Relatives: Software for Spatial Conservation Prioritization. page 12, 2009.

Billionnet, A. Mathematical optimization ideas for biodiversity conservation. European Journal of Operational Research, 231(3):514–534, Dec. 2013. ISSN 03772217. doi: 10.1016/j.ejor.2013.03.025.

Bodin, Ö. and Saura, S. Ranking individual habitat patches as connectivity providers: Integrating network analysis and patch removal experiments. Ecological Modelling, 221(19):2393–2405, Sept. 2010. ISSN 0304-3800. doi: 10.1016/j.ecolmodel.2010.06.017.

Ciarleglio, M., Barnes, J.W. and Sarkar, S. ConsNet—A tabu search approach to the spatially coherent conservation area network design problem. Journal of Heuristics, 16(4):537–557, Aug. 2010. ISSN 1381-1231, 1572-9397. doi: 10.1007/s10732-008-9098-7.

Daigle, R.M., Metaxas, A., Balbar, A.C. et al. Operationalizing ecological connectivity in spatial conservation planning with Marxan Connect. Methods in Ecology and Evolution, 11(4):570–579, 2020. ISSN 2041-210X. doi: 10.1111/2041-210X.13349.

Dechter, R. et al. Constraint Processing. Morgan Kaufmann, 2003.

Diamond, J.M. The island dilemma: Lessons of modern biogeographic studies for the design of natural reserves. Biological Conservation, 7(2):129–146, Feb. 1975. ISSN 0006-3207. doi: 10.1016/0006-3207(75)90052-X.

Dilkina, B., Houtman, R., Gomes, C.P. et al. Trade-offs and efficiencies in optimal budget-constrained multispecies corridor networks. Conservation Biology, 31(1):192–202, Feb. 2017. ISSN 1523-1739. doi: 10.1111/cobi.12814.

Fahrig, L. Effects of Habitat Fragmentation on Biodiversity. Annual Review of Ecology, Evolution, and Systematics, 34(1):487–515, 2003. doi: 10.1146/annurev.ecolsys.34.011802.132419.

Fahrig, L. Rethinking patch size and isolation effects: The habitat amount hypothesis. Journal of Biogeography, 40(9):1649–1663, 2013. ISSN 1365-2699. doi: 10.1111/jbi.12130.

Fuller, T. and Sarkar, S. LQGraph: A software package for optimizing connectivity in conservation planning. Environmental Modelling & Software, 21(5):750–755, May 2006. ISSN 1364-8152. doi: 10.1016/j.envsoft.2006.01.005.

Game, E.T., Schwartz, M.W. and Knight, A.T. Policy Relevant Conservation Science. Conservation Letters, 8(5):309–311, 2015. ISSN 1755-263X. doi: 10.1111/conl.12207.

Grandcolas, P., Murienne, J., Robillard, T. et al. New Caledonia: A very old Darwinian island? Philosophical Transactions of the Royal Society B: Biological Sciences, 363(1508):3309–3317, Oct. 2008. ISSN 0962-8436. doi: 10.1098/rstb.2008.0122.

Guillemot, N., Gaillard, T. and Lagrange, A. Biodiversité et environnement dans la région de la Côte Oubliée « Woen Vùù » : état des connaissances et identification des intérêts écologiques | Oeil Nouvelle-Calédonie. Technical report, OEIL, 2016.

Haddad, N.M., Brudvig, L.A., Clobert, J. et al. Habitat fragmentation and its lasting impact on Earths ecosystems. Science Advances, 1(2):e1500052, Mar. 2015. ISSN 2375-2548. doi: 10.1126/sciadv.1500052.

Hanson, J.O., Schuster, R., Strimas-Mackey, M. and Bennett, J.R. Optimality in prioritizing conservation projects. Methods in Ecology and Evolution, 10(10):1655–1663, 2019. ISSN 2041-210X. doi: 10.1111/2041-210X.13264.

Ibanez, T., Munzinger, J., Dagostini, G. et al. Structural and floristic diversity of mixed tropical rain forest in New Caledonia: New data from the New Caledonian Plant Inventory and Permanent Plot Network (NC-PIPPN). Applied Vegetation Science, 17(3):386–397, 2014. ISSN 1654-109X. doi: 10.1111/avsc.12070.

Ibanez, T., Hequet, V., Chambrey, C. et al. How does forest fragmentation affect tree communities? A critical case study in the biodiversity hotspot of New Caledonia. Landscape Ecology, 32(8): 1671–1687, Aug. 2017. ISSN 0921-2973, 1572-9761. doi: 10.1007/s10980-017-0534-7.

Jaeger, J.A. Landscape division, splitting index, and effective mesh size: New measures of landscape fragmentation. Landscape Ecology, 15(2):115–130, Feb. 2000. ISSN 1572-9761. doi: 10.1023/A:1008129329289.

Justeau-Allaire, D., Vismara, P., Birnbaum, P. and Lorca, X. Systematic Conservation Planning for Sustainable Land-use Policies: A Constrained Partitioning Approach to Reserve Selection and Design. In Proceedings of the Twenty-Eighth International Joint Conference on Artificial Intelligence, pages 5902–5908, Macao, China, 2019. International Joint Conferences on Artificial Intelligence Organization. ISBN 978-0-9992411-4-1. doi: 10.24963/ijcai.2019/818.

Justeau-Allaire, D., Vieilledent, G., Rinck, N. et al. Source code from: Constrained optimization of landscape indices in conservation planning to support ecological restoration in New Caledonia. Zenodo, Nov. 2020a.

Justeau-Allaire, D., Vieilledent, G., Rinck, N. et al. Data from: Constrained optimization of landscape indices in conservation planning to support ecological restoration in New Caledonia, 2020b.

Kirkpatrick, J.B. An iterative method for establishing priorities for the selection of nature reserves:

An example from Tasmania. Biological Conservation, 25(2):127–134, Feb. 1983. ISSN 0006-3207. doi: 10.1016/0006-3207(83)90056-3.

Knight, A.T., Cowling, R.M., Rouget, M. et al. Knowing But Not Doing: Selecting Priority Conservation Areas and the Research–Implementation Gap. Conservation Biology, 22(3):610–617, 2008. ISSN 1523-1739. doi: 10.1111/j.1523-1739.2008.00914.x.

Margules, C.R. and Pressey, R.L. Systematic conservation planning. Nature, 405(6783):243–253, May 2000. ISSN 0028-0836. doi: 10.1038/35012251.

McGarigal, K. Landscape Pattern Metrics. In Wiley StatsRef: Statistics Reference Online. American Cancer Society, 2014. ISBN 978-1-118-44511-2. doi: 10.1002/9781118445112.stat07723.

McRae, B.H., Hall, S.A., Beier, P. and Theobald, D.M. Where to Restore Ecological Connectivity? Detecting Barriers and Quantifying Restoration Benefits. PLOS ONE, 7(12):e52604, Dec. 2012. ISSN 1932-6203. doi: 10.1371/journal.pone.0052604.

Meir, E., Andelman, S. and Possingham, H.P. Does conservation planning matter in a dynamic and uncertain world? Ecology Letters, 7(8):615–622, Aug. 2004. ISSN 1461-023X, 1461-0248. doi: 10.1111/j.1461-0248.2004.00624.x.

Moilanen, A. Two paths to a suboptimal solution – once more about optimality in reserve selection. Biological Conservation, 141(7):1919–1923, July 2008. ISSN 0006-3207. doi: 10.1016/j.biocon.2008.04.018.

Moilanen, A., Pouzols, F., Meller, L. et al. Zonation–Spatial conservation planning methods and software. version 4. user manual. University of Helsinki: Finland, 2014.

Morat, P., Jaffré, T., Tronchet, F. et al. The taxonomic reference base Florical and characteristics of the native vascular flora of New Caledonia. Adansonia, 34(2):179–221, 2012. ISSN 1280-8571.

Moser, B., Jaeger, J.A.G., Tappeiner, U. et al. Modification of the effective mesh size for measuring landscape fragmentation to solve the boundary problem. Landscape Ecology, 22(3):447–459, Mar. 2007. ISSN 1572-9761. doi: 10.1007/s10980-006-9023-0.

Myers, N., Mittermeier, R.A., Mittermeier, C.G. et al. Biodiversity hotspots for conservation priorities. Nature, 403(6772):853–858, Feb. 2000. ISSN 0028-0836, 1476-4687. doi: 10.1038/35002501.

Nicholls, A.O. and Margules, C.R. An upgraded reserve selection algorithm. Biological Conservation, 64(2):165–169, Jan. 1993. ISSN 0006-3207. doi: 10.1016/0006-3207(93)90654-J.

Pascual-Hortal, L. and Saura, S. Comparison and development of new graph-based landscape connectivity indices: Towards the priorization of habitat patches and corridors for conservation. Landscape Ecology, 21(7):959–967, Oct. 2006. ISSN 1572-9761. doi: 10.1007/s10980-006-0013-z.

Pillon, Y. Time and tempo of diversification in the flora of New Caledonia. Botanical Journal of the Linnean Society, 170(3):288–298, 2012. ISSN 1095-8339. doi: 10.1111/j.1095-8339.2012.01274.x.

Pouteau, R., Munoz, F. and Birnbaum, P. Disentangling the processes driving tree community assembly in a tropical biodiversity hotspot (New Caledonia). Journal of Biogeography, 46(4):796–806, Apr. 2019. ISSN 0305-0270, 1365-2699. doi: 10.1111/jbi.13535.

Pressey, R.L., Humphries, C.J., Margules, C.R. et al. Beyond opportunism: Key principles for systematic reserve selection. Trends in Ecology & Evolution, 8(4):124–128, Apr. 1993. ISSN 0169-5347. doi: 10.1016/0169-5347(93)90023-I.

Pressey, R.L., Possingham, H.P. and Margules, C.R. Optimality in reserve selection algorithms: When does it matter and how much? Biological Conservation, 76(3):259–267, Jan. 1996. ISSN 0006-3207. doi: 10.1016/0006-3207(95)00120-4.

Prud'homme, C., Fages, J.G. and Lorca, X. Choco Documentation. 2017.

ReVelle, C.S., Williams, J.C. and Boland, J.J. Counterpart Models in Facility Location Science and Reserve Selection Science. Environmental Modeling & Assessment, 7(2):71–80, June 2002. ISSN 1420-2026, 1573-2967. doi: 10.1023/A:1015641514293.

Rodrigues, A.S., Cerdeira, J.O. and Gaston, K.J. Flexibility, efficiency, and accountability: Adapting reserve selection algorithms to more complex conservation problems. Ecography, 23(5):565–574, Oct. 2000. ISSN 1600-0587. doi: 10.1111/j.1600-0587.2000.tb00175.x.

Rodrigues, A.S.L. and Gaston, K.J. Optimisation in reserve selection procedures—why not? Biological Conservation, 107(1):123–129, Sept. 2002. ISSN 0006-3207. doi: 10.1016/S0006-3207(02)00042-3.

Rossi, E.F., van Beek, P. and Walsh, T. Handbook of Constraint Programming. page 969, 2006.

Saura, S. and Pascual-Hortal, L. A new habitat availability index to integrate connectivity in landscape conservation planning: Comparison with existing indices and application to a case study. Landscape and Urban Planning, 83(2):91–103, Nov. 2007. ISSN 0169-2046. doi: 10.1016/j.landurbplan.2007.03.005.

Schapaugh, A.W. and Tyre, A.J. A simple method for dealing with large state spaces. Methods in Ecology and Evolution, 3(6):949–957, 2012. ISSN 2041-210X. doi: 10.1111/j.2041-210X.2012.00242.x.

Taylor, P.D., Fahrig, L., Henein, K. and Merriam, G. Connectivity Is a Vital Element of Landscape Structure. Oikos, 68(3):571, Dec. 1993. ISSN 00301299. doi: 10.2307/3544927.

Underhill, L.G. Optimal and suboptimal reserve selection algorithms. Biological Conservation, 70(1):85–87, Jan. 1994. ISSN 0006-3207. doi: 10.1016/0006-3207(94)90302-6.

Uuemaa, E., Mander, Ü. and Marja, R. Trends in the use of landscape spatial metrics as landscape indicators: A review. Ecological Indicators, 28:100–106, May 2013. ISSN 1470-160X. doi: 10.1016/j.ecolind.2012.07.018.

Vancutsem, C., Achard, F., Pekel, J.F. et al. Long-term (1990-2019) monitoring of tropical moist forests dynamics. bioRxiv, page 2020.09.17.295774, Jan. 2020. doi: 10.1101/2020.09.17.295774.

Vane-Wright, R.I., Humphries, C.J. and Williams, P.H. What to protect?—Systematics and the agony of choice. Biological Conservation, 55(3):235–254, Jan. 1991. ISSN 0006-3207. doi: 10.1016/0006-3207(91)90030-D.

Vieilledent, G., Grinand, C., Rakotomalala, F.A. et al. Combining global tree cover loss data with historical national forest cover maps to look at six decades of deforestation and forest fragmentation in Madagascar. Biological Conservation, 222:189–197, June 2018. ISSN 0006-3207. doi: 10.1016/j.biocon.2018.04.008.

Wang, Y. and Önal, H. Optimal design of compact and connected nature reserves for multiple species: Reserve Networks for Multiple Species. Conservation Biology, 30(2):413–424, Apr. 2016. ISSN 08888892. doi: 10.1111/cobi.12629.

Welzl, E. Smallest enclosing disks (balls and ellipsoids). In Maurer, H., editor, New Results and New Trends in Computer Science, Lecture Notes in Computer Science, pages 359–370, Berlin, Heidelberg, 1991. Springer. ISBN 978-3-540-46457-0. doi: 10.1007/BFb0038202.

Williams, D.R., Balmford, A. and Wilcove, D.S. The past and future role of conservation science in saving biodiversity. Conservation Letters, n/a(n/a):e12720, 2020. ISSN 1755-263X. doi: 10.1111/conl.12720.

Williams, J.C., ReVelle, C.S. and Levin, S.A. Spatial attributes and reserve design models: A review. Environmental Modeling & Assessment, 10(3):163–181, Sept. 2005. ISSN 1420-2026, 1573-2967. doi: 10.1007/s10666-005-9007-5.

Xue, Y., Wu, X., Morin, D. et al. Dynamic Optimization of Landscape Connectivity Embedding Spatial-Capture-Recapture Information. page 7, 2017.