

1 Constrained optimization of landscape indices in con- 2 servation planning to support ecological restoration in 3 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 im-
portant 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 Ou-
bliée – ‘Woen Vùù – Pwa Pereeu” 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 ap-
proach 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, land-
scape indices, constraint programming, artificial intelligence, New Caledonia.

38 1 Introduction

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

48 Restoration and conservation planning can help to curb habitat loss and promote suit-
49 able landscape configurations, as well as helping to identify trade-offs between conserva-
50 tion targets and managers' objectives (Rodrigues et al., 2000; Knight et al., 2008). Efficient
51 decision support processes must rely on spatially-explicit, systematic, and reproducible ap-
52 proaches (Pressey et al., 1993). Over the last few decades, many such approaches have been
53 devised, from geometric principles derived from biogeography theory (Diamond, 1975) to
54 the principle of complementarity in the representation of biodiversity features (Vane-Wright
55 et al., 1991). Systematic conservation planning (SCP) is now an active field of conserva-
56 tion biology. There is also a consensus on the mutual importance of spatial configuration
57 and the representation of biodiversity features in the planning of conservation actions, to
58 express managers' constraints as much as ecological requirements (Margules and Pressey,
59 2000; Williams et al., 2005).

60 Many optimization methods for SCP have been proposed, mostly relying on *ad hoc*
61 heuristics, metaheuristics, or mixed-integer linear programs (MILP). *Ad hoc* heuristics are
62 problem-specific local search algorithms either based on a forward (greedy) (e.g. Kirkpatrick,

63 1983; Nicholls and Margules, 1993) or backward (stingy) procedure (e.g. Zonation software,
64 Moilanen et al., 2014). In constructive heuristics (resp. destructive), solutions are obtained
65 by iteratively adding (resp. removing) the planning unit which offers the highest gain (resp.
66 loss) according to an objective function to maximize (resp. minimize). Metaheuristics are
67 high-level and problem-independent stochastic search heuristics, such as simulated anneal-
68 ing (e.g. Marxan software, Ball et al., 2009) or tabu search (e.g. ConsNet software, Ciar-
69 leglio et al., 2010). The main advantage of heuristics is that they are often straightforward
70 to understand and implement, but produce solutions of unknown quality relative to optimal-
71 ity. Finally, MILP is a constrained mathematical optimization approach where the objective
72 function and the constraints are stated as linear equations, with some or all the variables being
73 integers (Billionnet 2013; Dilkina et al. 2017; oppr R package, Hanson et al. 2019). Exact ap-
74 proaches such as MILP can require more time to generate solutions than heuristics, however,
75 they offer guarantees relative to optimality and constraint satisfaction. Indeed, even though
76 heuristics can reach constraint satisfaction for loosely constrained problems (e.g. species set
77 covering problem, ReVelle et al. 2002), they can fail to provide this guarantee for highly con-
78 strained problems (e.g. Billionnet, 2013). Constraint satisfaction problems on a finite domain
79 are indeed in general NP-Complete (Dechter et al., 2003). Although less widely used, dy-
80 namic programming approaches (e.g. Meir et al., 2004) and Markov decision processes (e.g.
81 Schapaugh and Tyre, 2012) have also brought substantial advances in SCP but are limited to
82 smaller problem sizes than the approaches described above.

83 Recent work has introduced several perspectives towards the integration of landscape
84 spatial configuration in SCP optimization procedures. For instance, Marxan software uses
85 a boundary length penalty in its objective function to influence the spatial configuration of
86 the solutions. Additionally, Marxan Connect (Daigle et al., 2020) provides many options to
87 include structural or functional connectivity data in Marxan's input. Similarly, Zonation pro-
88 vides 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 Pereeu” 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 Pereèù” 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 Pereèù”,

138 a large area in the Southeast of the main island of New Caledonia, “Grande Terre” (see Fig-
139 ure 1.b), established a moratorium on nickel mining activity between 2014 and 2016. They
140 called for cessation on any road, mining or infrastructure project, in response to the erosion
141 of many areas, due to bushfires and mining activity. This moratorium was renewed for ten
142 years (from 2018 to 2028) and led to the creation in April 2019 of the “Côte Oubliée ‘Woen
143 Vùù – Pwa Pereèù” Provincial Park by the South Province of New Caledonia. With 93000 ha
144 of terrestrial and 27000 ha of marine protected area, the provincial park blocked 102 mining
145 concessions, includes three existing natural reserves and is adjacent to four existing natural
146 reserves (see Figure 1.c). It now remains for the managers of the South Province’s Sustain-
147 able Development Department for the Territories (SDDT) to establish the management plan
148 of the park, with a strong emphasis on reducing forest fragmentation.

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

160 2.2 Data

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

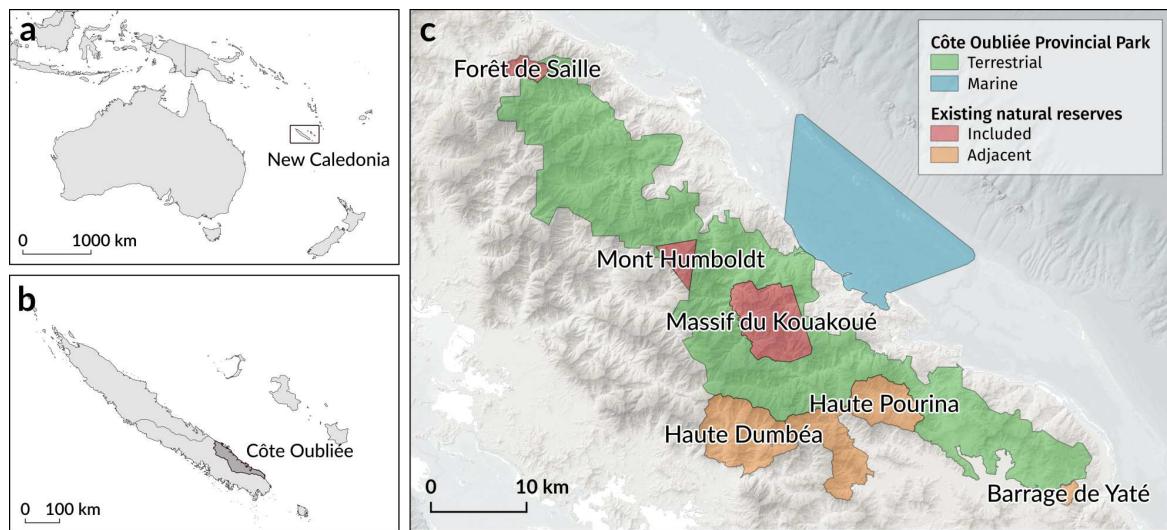


Figure 1: (a) Location of New Caledonia. (b) Location of the “Côte Oubliée” area. (c) Map of the “Côte Oubliée – Woen Vùù – Pwa Pereeù” provincial park, with included and adjacent existing natural reserves.

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 ($480 \text{ m} \times 480 \text{ m} \approx 23 \text{ ha}$). 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

178 than 70% (Fahrig, 2013; Vieilledent et al., 2018). As reforestation must occur in the provincial
179 park, we retained the cells within the boundaries of the provincial park to which we
180 included parts of forest patches extending outside the park to avoid the boundary problem
181 (Moser et al., 2007). The resulting raster map contained 3629 forest cells and 2715 non-
182 forest cells, as illustrated in Figure 2.b. Consequently, we quantified the area to be reforested
183 in each 480 m cell as the area needed to reach a forest-cover proportion of 70% (cf. Figure
184 2.d). Finally, we identified accessible areas for reforestation as a 1000 m buffer around tracks
185 using the tracks vector data provided by the SDDT, classified according to the two customary
186 districts covered by the provincial park, Borendy and Unia (see Figure 2.c).

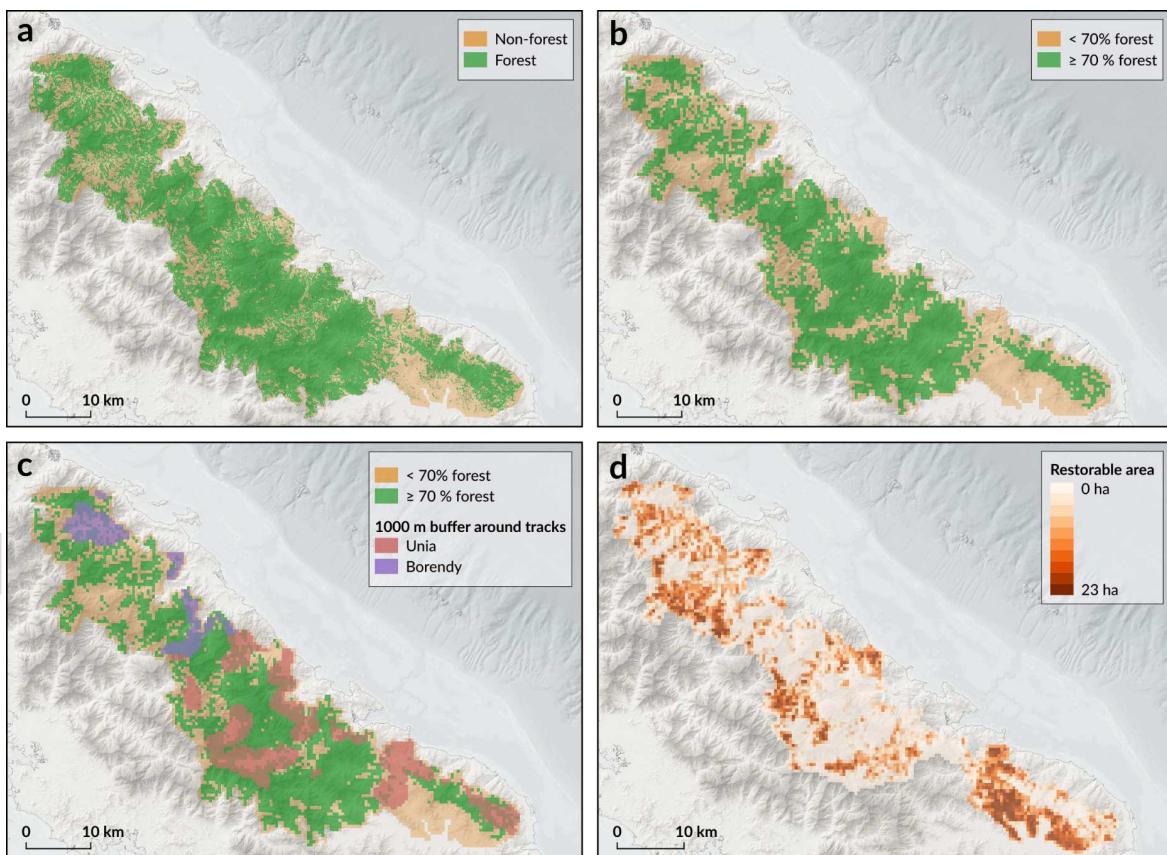


Figure 2: Input data maps. (a) 2019 30 m binary forest map produced from Landsat historical data analysis. (b) Upscaled 480 m binary forest map. A 480 m cell was considered as forest if its forest-cover proportion at 30 m was at least 70%. (c) 480 m accessible areas (1000 m buffer around tracks) map,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

187 2.3 Mathematical formulation

188 2.3.1 Base problem: variables and managers' constraints

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

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

192 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
193 Borendy, that is sets of PUs available for restoration. The sets R_u , R_b , $\mathcal{F}_{\geq 70\%}$, and $\mathcal{F}_{< 70\%} \setminus$
194 $(R_u \cup R_b)$ must form a partition of \mathcal{S} , and $R_u \cup R_b \cup \mathcal{F}_{\geq 70\%}$ corresponds to the potential
195 forest-cover resulting from reforestation. To each of these sets is associated a grid graph.
196 For a given set, each PU in the set is a node and two nodes are connected if and only if the
197 corresponding PUs are adjacent according to the four-connected neighbourhood definition in
198 the regular square grid. We now introduce the following constraints:

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

201 **Constraint 2 (RESTORABLE).** Let $R \subseteq \mathcal{S}$ be a region, a an integer variable, and $p \in [0, 1]$.
202 $\text{RESTORABLE}(R, a, p)$ holds if and only if each PU in R can be restored to a forest-cover
203 proportion of p by reforesting at least a ha. In any solution satisfying this constraint, the
204 value of a thus corresponds to the minimum area to restore to reach a forest-cover propor-
205 tion of p . Formally, let v_x^p be the minimum area to reforest to restore the PU x to p , then:

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

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

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

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

$$\text{CONNECTED}(R_u) \wedge \text{CONNECTED}(R_b); \quad (3)$$

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

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

$$a_u + a_b \leq A_{\max}; \quad (6)$$

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

$$a_{\max} \geq A_{\max}; \quad (8)$$

$$\rho_u \in [0, P_{\max}] \wedge \text{RADIUS}(R_u, \rho_u); \quad (9)$$

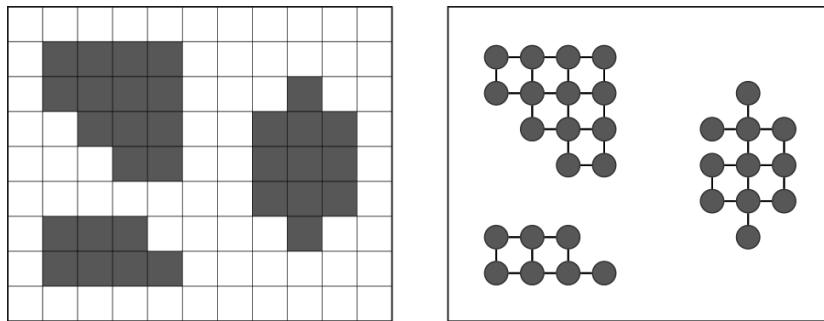
$$\rho_b \in [0, P_{\max}] \wedge \text{RADIUS}(R_b, \rho_b). \quad (10)$$

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

220 invested in the selected areas. Finally, Constraints (9) and (10) ensure that each selected
221 region is compact.

222 2.3.2 Constrained optimization of fragmentation indices

223 From the base problem described in the previous section, we defined two optimization prob-
224 lems, respectively associated with the maximization of MESH and IIC. We computed the
225 value of each index in the current landscape, then we found every optimal solution and re-
226 tained the index optimal value, the improvement brought by the optimal value compared to
227 the current one, the number of optimal solutions, and the solving times for reaching the op-
228 timal value and then enumerate all optimal solutions. In the following, we denote the set of
229 patches of a region R by $P(R)$. These patches are directly derived from the raster represen-
230 tation of the landscape by extracting the connected components of the grid graph associated
231 with the raster grid, as illustrated in Figure 3.



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

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

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

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

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

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

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

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

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

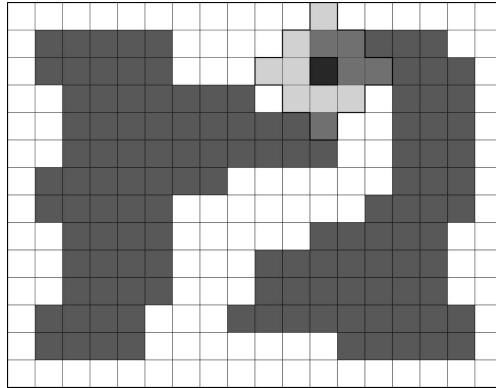


Figure 4: Illustration of the two-wide-four-connected neighbourhood distance threshold used to construct the landscape graph needed to compute IIC. The left patch intersects with the two-wide-four-connected neighbourhood of the black pixel located in the right patch. The patches are thus considered structurally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

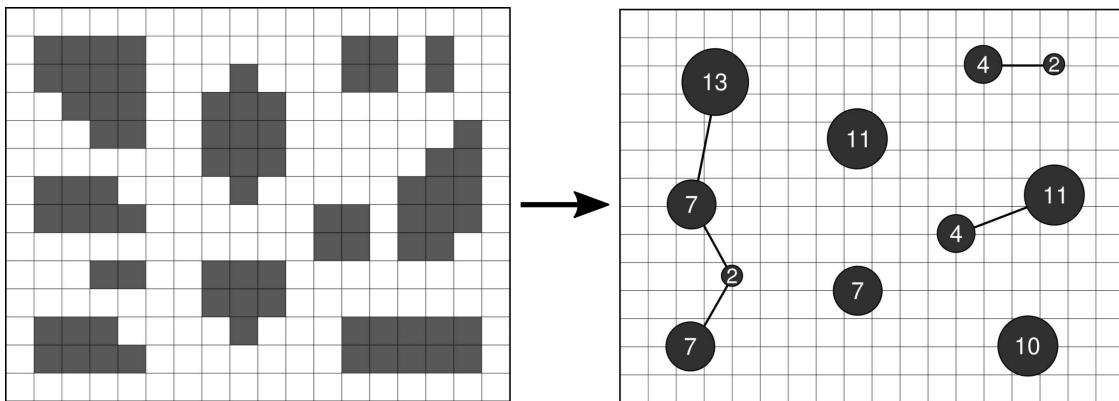


Figure 5: Construction of the forest landscape graph from a raster-based representation, using the two-wide-four-connected neighbourhood distance threshold.

255 2.4 Solving method: The constraint-based systematic conser- 256 vation planning framework

257 To solve this problem, we used the constraint-based systematic conservation planning (SCP)
258 framework briefly presented in the introduction (Justeau-Allaire et al., 2019). As this frame-
259 work relies on constraint programming (CP), we have provided a quick description of this
260 technique's fundamental principles in Box 1. In this constraint-based SCP framework, any
261 problem states as follows: given a tessellated geographical space \mathcal{S} , find a partitioning of \mathcal{S}
262 into n regions $\{R_0, \dots, R_{n-1}\}$ satisfying a set of constraints C , available from a constraint
263 catalogue. The CP model associated with this formulation relies on three representations
264 of the space: integer variables (one for each PU), set variables (one for each region), and
265 graph variables (one for each region), and each user constraint applies to the most relevant
266 space representation. This formulation allows the modelling of regions' expected properties
267 through constraints. This framework was implemented upon the java open-source CP solver
268 Choco (Prud'homme et al., 2017), and its source code is available on GitHub¹. Most of the
269 constraints needed by the case study were already available in the framework. We, however,
270 extended it with the RADIUS constraint, implemented with a linear-time filtering algorithm
271 based on the best-known algorithm for the smallest enclosing circle problem (Welzl, 1991),
272 the MESH constraint, and the IIC constraint, implemented with a two-stage algorithm which
273 first constructs the landscape graph from the raster representation and then computes all-pairs
274 shortest paths by performing a breadth-first search from each node of the landscape graph.
275 We ran all optimization problems described in the previous section on a Linux server (Intel
276 Xeon E5-2620 CPU 2.40GHz × 12, 64GB RAM). The case study source code is available
277 on GitHub² and we packaged an executable command-line jar to reproduce the single-region
278 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).

279 3 Results

280 We summarized the results of the constrained optimization of MESH and IIC in Table 1
281 and mapped optimal solutions in Figures 6 and 7. First, the solver found the optimal value
282 for MESH in about 30 minutes and quickly enumerated all optimal solutions. Conversely,

283 the solver took several hours to reach the optimal solution for IIC and about 20 minutes to
 284 enumerate all optimal solutions. Moreover, although several optimal solutions were found,
 285 for a given index they were all located in the same zone and reconnected the same patches.

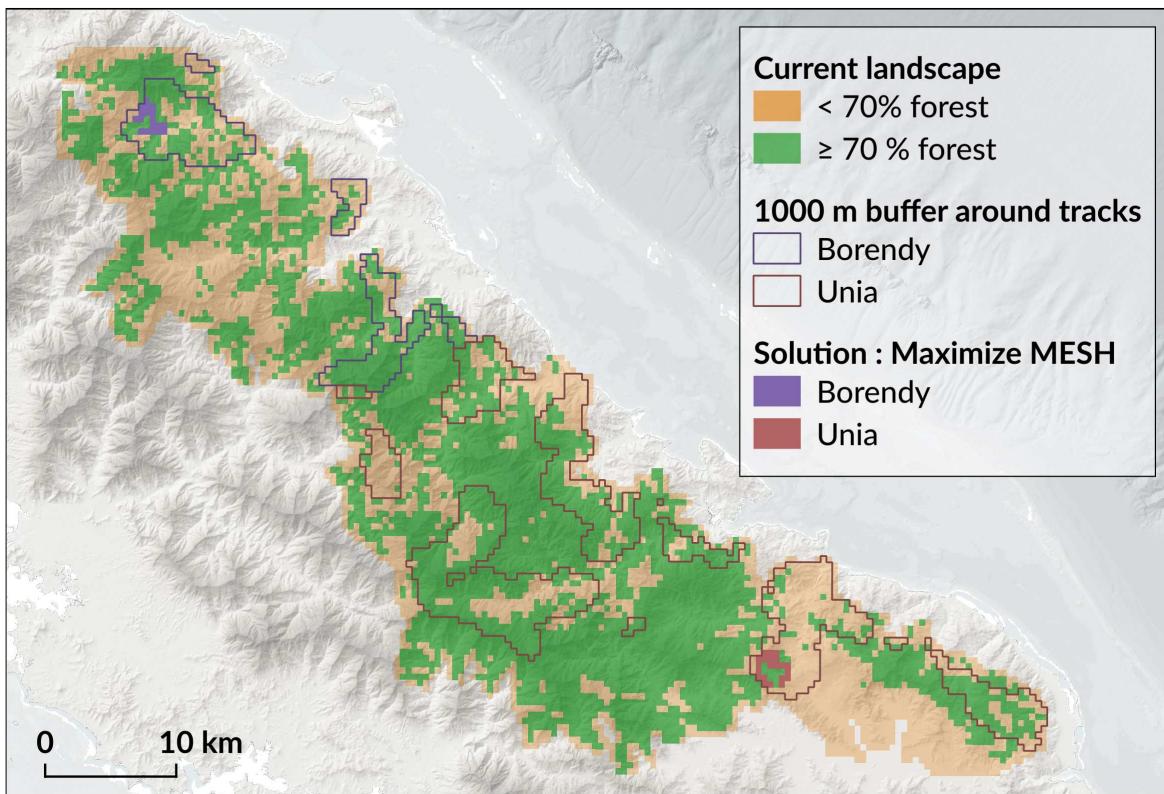


Figure 6: Mapping of a solution maximizing the effective mesh size (MESH).

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.

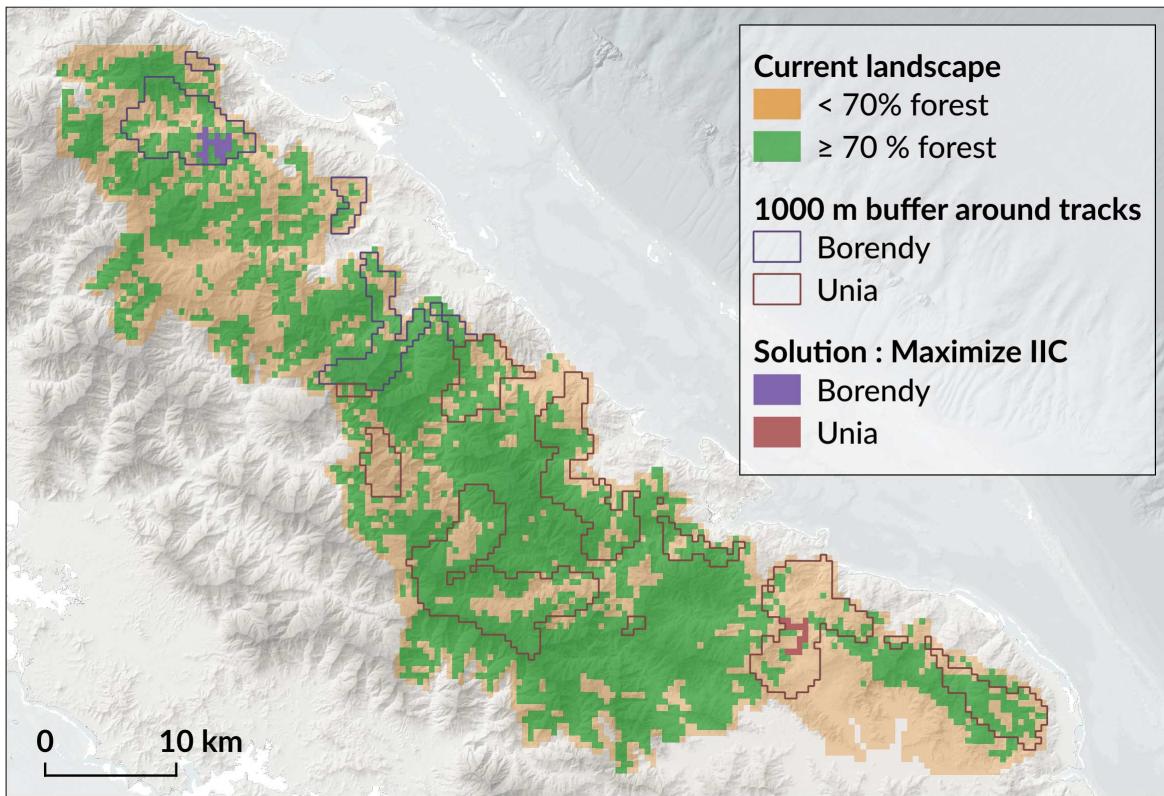


Figure 7: Mapping of a solution maximizing the integral index of connectivity (IIC).

286 4 Discussion

287 4.1 Contribution to decision support in the “Côte Oubliée – ‘Woen 288 Vuù – Pwa Pereeu” reforestation project

289 Under budget, accessibility and equitable allocation constraints, we computed all optimal so-
290 lutions for a fragmentation index (MESH) and an inter-patch connectivity index (IIC) within
291 relatively short amounts of time. There was a considerable computing time difference be-
292 tween MESH and IIC, due to the combinatorial complexity involved by the construction of
293 the patch-based landscape graph from a raster landscape representation. Optimal areas for
294 MESH and IIC were not overlapping and offered two reforestation scenarios for managers.
295 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 Vuù – Pwa Pereeu”. 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

346 to narrowing the “research-implementation gap” (Knight et al., 2008). With a modelling tool
347 expressive enough to represent accurately conservation scientists’ aims along with managers’
348 constraints, it becomes possible to design conservation actions that are realistic for managers,
349 as well as offering an integrative and evidence-based tool for scientists.

350 **4.4 Current limitations and perspectives for systematic conser- 351 vation planning**

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

366 Nevertheless, we have shown that there is good potential for formulating and solving
367 SCP problems using CP. There is a continued debate on the importance of optimality in
368 SCP methods, which mainly contrasts local search approaches with MILP (Underhill, 1994;
369 Pressey et al., 1996; Rodrigues and Gaston, 2002; Hanson et al., 2019). However, optimality
370 should not be the only consideration. We even argue that expressiveness is a prerequisite

371 to optimality (Rodrigues et al., 2000; Moilanen, 2008). To conclude, recent years have seen
372 substantial advances in artificial intelligence. We believe that, as illustrated by this study, such
373 advances are providing new opportunities for formulating and solving conservation planning
374 problems.

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385 **Authors' contributions**

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

391 Data availability statement

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

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