Testing Methods to Minimise Range-shifting Time with Conservation Actions

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ABSTRACT

Climate change is a global threat to species, and their capability to invade and colonise new landscapes could be limited by the habitat fragmentation. Improving landscapes by adding additional resources to landscapes is an important initiative to restore habitats. Such improvements will be particularly important to promote species recovery in fragmented landscapes and to understand as well as facilitate range-shifting for species (also called an invasion). We use a recent method to approximate the time taken by species to invade landscapes and reach the new areas of suitable environment, which based on network flow theory. Based on this, we propose and test a new method that can help to compute the best locations in landscapes in order to restore habitat which leads to minimising the expected time taken by species to invade and reach targets. The new optimisation method has been compared with other two baseline methods. The evaluation conducted using real heterogeneous landscapes shows that the proposed method outperforms the competitive baseline methods in terms of proposing landscape modifications that minimise the expected time of the invasion process.

CCS CONCEPTS

• **Applied computing → Life and medical sciences**; *Computational biology*; • **Theory of Computation → Design and analysis of algorithms**; **Mathematical optimization**; **Continuous optimization**; Convex optimization; Stochastic control and optimization; Bio-inspired optimization; • **Networks** → Network algorithms.

KEYWORDS

Invasion process, Invasion time, Landscape, Simulations, Network flow, Convex Programming.

1 INTRODUCTION

Climate change is a growing threat to species throughout the world and interacts with the major threats to biodiversity, which are habitat loss and fragmentation [3, 14]. It has been observed that species can respond to these threats by shifting (invading) their geographic ranges [4, 16], however in order to do so, they need sufficient habitat in the range where they exist, in the range where they are going to be as well as any intermediate areas in between to enable species population survival and colonisation [5, 6, 9]. This means that the availability of suitable habitat is very important to protect and conserve species [11, 15]. One of the best ways to protect species against extinction is to prevent their deterioration by restoring habitat. To protect and restore habitat on landscapes, computational decision support tools are needed to find the best locations in landscapes for habitat restoration, given that land and funding for conservation are limited. In a changing climate, the best locations are arguably the places that are most likely to lead to a large decline in the expected time for species to invade landscapes and speed up reaching the target locations.

The field of 'systematic conservation planning' already uses some optimisation techniques, mostly based on integer or linear programming [12], however these have not been applied to the goal of minimising range-shifting time (called invasion time throughout this paper), partly because this is a more complex, likely non-linear problem. Hodgson et al. in [10] made some progress in developing heuristics to improve landscapes in a stepwise manner, by showing that some network properties (based on circuit theory) can predict the marginal change in invasion time upon adding or removing a network node.

Recently, Aloqalaa et al. in [1] proposed a method that approximates the invasion time in real heterogeneous landscapes. Their method is based on using graph theory to capture the characteristics of landscapes and species to explain the invasion process. They represented a given two dimensional rectangular grid landscape as

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a directed and weighted graph $G = (V, E)$, where each vertex represents a patch of habitat (henceforth patch) in the landscape and each edge weight represents the probability of invading the species in one step from the beginning to the end patch of the edge. They distinguished two sets of patches: the source patches represent initially populated patches in which species are located, and the target patches represent the target locations for the invasion process. Following this graph representation, they used network flow approach to approximate the invasion time. In particular, for a given landscape they constructed a family of sub-networks which represent a sequence of small and partly overlapping sub-landscapes and computed the maximum flow for each of the sub-networks. Then, the sum of the inverses of the computed maximum flows over all sub-networks is used to approximate the invasion time with constant factor.

1.1 Our results

In this paper, we aim to study how to improve the invasion process, in particular, how to increase the speed of invasion, by modifying the landscape. We consider the scenario where we are given a certain budget that we can use to modify the landscape, e.g., but not restricted to, to enlarge patches that are populated or add new patches to form stepping stones or corridors. We restrict our attention to increase quality of some selected patches within the given budget. This problem can be seen as an optimisation problem in which we want to determine the best locations to make modifications (i.e., to spend budget) on landscapes to minimising the duration of the invasion process.

Based on the developed method in [1] (mentioned above), *we propose and test a new method that determines the best locations in the landscape to spend a bounded given budget.* We model and solve this optimisation problem, called min-invasion-time problem, as a convex program. *We also compare our optimisation method with two baseline methods by implementing them on real landscapes to produce improved landscapes.* On these improved landscapes, we run simulations to find out how the duration of the invasion process is influenced by the landscapes' modifications.

2 MODEL, NOTATIONS AND METHODS

We are given a 2-dimensional rectangular grid landscape of height H (rows) and width W (columns) as an input. Each point of the grid is called a patch, and the set of patches is denoted by V. Let $q(v)$ denote the quality of patch v, where the quality is a number between zero and one given as input. Denote by Q the sum of quality over all vertices in the landscape graph and it is defined as $Q = \sum\limits_{v \in V} q(v)$. We distinguish two sets of patches, S and T, where S denotes the set of populated source patches and T denotes the set of unpopulated target patches.

The landscape is associated with a directed weighed graph $G = (V, E)$, called a *landscape graph*, comprising a set V of patches. In this work we assume that for each pair of patches $v, u \in V$ there is a directed edge $(v, u) \in E$ of weight $p(v, u) \in [0, 1]$, called a *transition probability* between vertex v and u (see the definition of *transition probability* later in Section 3.3). For a given landscape graph G, we consider $\frac{W}{10} - 2$ sub-landscapes covering the whole landscape such that each one of these sub-landscapes has width of $2R$ with added source and target patches, where R is a sparsification parameter corresponding to the landscape G (see [1] for more details about computing R for a given landscape). For each of these sub-landscapes, we define a network N constructed in the following paragraph; the family of all these sub-landscapes and their corresponding networks is denoted by $\mathcal{N}$.

Network N. The network N is the corresponding network for a sub-landscape that belongs to the family $\mathcal{N}$ of sub-landscapes. We construct the network N as follows. We denote the set of vertices of N by V_N and the set of edges by E_N. We put all vertices of the sub-landscape to set V_N and distinguish two sets of vertices (each of length 10 columns): the initial populated set S_N and the target set T_N. We add a virtual source vertex s and connect it to each vertex in the initial populated set S_N by a directed edge with a weight λ, where λ is the maximum, over all vertices, of the sum of the weight of adjacent edges, $\lambda = \max\{\lambda_v : v \in V\}$, where $\lambda_v = \sum_{u \in V} p(v, u)$. We also add a virtual target vertex t and connect each vertex in the target set T_N to the additional target vertex t by a directed edge with weight λ. Each intermediate vertex (except the source vertex s and the target vertex t) is connecting to all other vertices by directed edges and given weights that equal to the *transition probabilities* $p(v, u)$ between the patches. We compute the network flow of this constructed network N with the weight as the capacity (see [1] for more details).

2.1 The solutions to the min-invasion-time problem

In the min-invasion-time problem, the goal is to find the best locations (i.e., vertices or patches) to increase their qualities by bounded weights, where the overall of the added weights is restricted to a limited budget, such that the invasion time is minimised. We first introduce two baseline optimisation approaches, called *random allocation approach* and *heuristic approach*, that we use to evaluate the quality of the new optimisation approach, called *Convex Programming for the Inverse of Maximum Flow*, to the problem.

2.1.1 *Random allocation approach.*

The random allocation approach is a very simple and natural approach in which for a given landscape graph, distinguished source and target patches, we choose a patch v randomly that does not belong to the source and target patches and its quality value $q(v)$ is less than one. Then, we increase the quality value of the chosen patch v by a weight $w(v)$, which is a generated random number between zero and $1 - q(v)$. This scenario is repeated many times until there is no more budget to be spent.

We repeat the whole process four times to produce four different random solutions. For each random solution, we run simulations 100 times, independently, to estimate the expected invasion time in each of these four landscapes. Then we compute the average expected invasion time over the four expected invasion times computed in simulations.

2.1.2 *Heuristic approach.*

The heuristic approach is an optimisation method developed by Hodgson et al. in [10] to manipulate landscapes to improve the expected time of invasion. In their work, they used the electrical circuit theory to approximate the duration of the invasion process. In particular, they approximated the time for the species to reach the target by the overall resistance of a circuit with patches as vertices (equivalent to the vertices of our graph G), colonisation times as links (symmetric and equivalent to our edge *transition probabilities*), and fixed potentials at the source (1) and target (-1) nodes. Based on this, their optimisation method is to compute the electrical power of every link (graph edge) as current flow · potential difference, find the link with the highest power and add habitat to the cell located halfway along that link (see [10] for more details). In our implementation, we increase the quality $q(v)$ of the patch v, which is located halfway along the link with the highest power between two patches by a weight $w(v)$, which is equal to $1 - q(v)$. We repeat this scenario until we spend the whole budget. Both the heuristic approach and the random approach are applied to the entire graph G, rather than to the sub-networks N. Addition of habitat to the source and target sets S and T is not allowed.

2.1.3 Convex Programming for the Inverse of Maximum Flow (CP-IMF). This approach is the main contribution of this paper – a new optimisation method based on convex programming. Consider a directed network $N \in \mathcal{N}$ with a set of vertices V_N and set of edges E_N. Recall that each vertex $v \in V_N \setminus \{s, t\} \subseteq V$ is associated with a quality $q(v)$. In a min-invasion-time problem, each edge $e = (v, u) \in E_N$ has a nonnegative capacity $c(v, u)$, which represents the maximum flow that can pass through the edge and equal to the *transition probability* $p(v, u)$ between the vertices (see the definition of *transition probability* later in Section 3.3) plus an additional weight $w(v)$. Let B denote the budget to be distributed and added to the landscape graph, where the budget is a number given as input such that, $0 < B \leq n - Q$. There are three decision variables. The first decision variable is $w(v)$ per vertex $v \in V$. Each $w(v)$ represents a weight of vertex v to be added to the quality $q(v)$ of vertex v and satisfies the following allocation restrictions:

(1) Weight constraint:
$$0 \leq w(v) \leq 1 - q(v), \text{ for each vertex } v \in V.$$
(2) Budget and weight constraint:
$$\sum_{v \in V} w(v) \leq B.$$

The second decision variable is a function f_N assigning each edge $e = (v, u) \in E_N$ a value $f_N(e)$ in $[0, 1]$. Each $f_N(e)$ represents a flow from vertex v to vertex u in a network N. Function f_N satisfies the following constraints:

(1) Capacity constraints:
$$0 \leq f_N(e) \leq \lambda, \text{ for each edge } e \text{ from } s \text{ to } v \in S_N$$
$$0 \leq f_N(e) \leq \lambda, \text{ for each edge } e \text{ from } v \in T_N \text{ to } t$$
$$0 \leq f_N(e) \leq \left[q(v) + w(v)\right] \cdot \frac{\exp(-\alpha d(v, u))}{\left(\frac{2\pi}{\alpha^2}\right) - 1},$$
for each edge e from v to u, where $v, u \in V_N \setminus \{s, t\}$
(α is a parameter of the *transition probability* $p(v, u)$ between vertices v and u, which is defined later in Section 3.3; $d(v, u)$ is the Euclidean distance between vertices v and u).

(2) Flow conservation constraint:
$$\sum_{e \to v} f_N(e) = \sum_{e \leftarrow v} f_N(e), \text{ for each vertex } v \in V_N \setminus \{s, t\}.$$

The third decision variable is M_N per network $N \in \mathcal{N}$. Each M_N represents the value of a maximum flow in a network N and satisfies the following constraint:
$$\sum_{e \leftarrow s} f_N(e) \geq M_N, \text{ for each network } N \in \mathcal{N}.$$

For each network $N \in \mathcal{N}$, C_N denotes a constant, which is the average of the total number of vertices in network N that have non-zero quality and the total number of all vertices in network N.

The min-invasion-time problem is to find the best allocation of a given budget B in a given landscape graph that minimises the total cost (i.e., the expected time of invasion) subject to the budget allocation restrictions as well as the capacity and flow conservation constraints. It can be written as a convex program, c.f., Figure 1.

$$
\begin{aligned}
&\text{minimise} \quad \sum_{N \in \mathcal{N}} \frac{C_N}{M_N} \\
&\text{subject to:} \\
&0 \leq w(v) \leq 1 - q(v), \quad \forall v \in V \\
&\sum_{v \in V} w(v) \leq B \\
&0 \leq f_N(e) \leq \lambda, \quad \forall N \in \mathcal{N} \quad \forall e = (s, v) \in E_N \quad v \in S_N \\
&0 \leq f_N(e) \leq \lambda, \quad \forall N \in \mathcal{N} \quad \forall e = (v, t) \in E_N \quad v \in T_N \\
&0 \leq f_N(e) \leq \left[q(v) + w(v)\right] \cdot \frac{\exp(-\alpha d(v, u))}{\left(\frac{2\pi}{\alpha^2}\right) - 1}, \\
&\qquad \forall N \in \mathcal{N} \quad \forall e = (v, u) \in E_N \quad v, u \in V_N \setminus \{s, t\} \\
&\sum_{e \to v} f_N(e) = \sum_{e \leftarrow v} f_N(e), \quad \forall N \in \mathcal{N} \quad \forall v, u \in V_N \setminus \{s, t\} \\
&\sum_{e \leftarrow s} f_N(e) \geq M_N, \quad \forall N \in \mathcal{N}.
\end{aligned}
$$

Figure 1: The convex program for the min-invasion-time problem.

We formulate and solve this convex program using IPOPT (Interior Point OPTimizer) package in Python programming language, which is a software package designed to find (local) solutions of nonlinear optimisation problems.

3 EVALUATING THE QUALITY OF THE CP-IMF METHOD

In this section we describe how we evaluate the quality of our new optimisation method (CP-IMF), landscapes, simulations method that we used for evaluation, and present the results of evaluation.

3.1 Evaluation methodology

In order to evaluate the quality of the CP-IMF method, we first extract two real landscapes (see the landscapes later in Section 3.2). Then, we do the following for each extracted landscape:

(1) Implement the three optimisation methods (i.e., *random allocation method*, *heuristic method*, and *CP-IMF method*) on the selected landscapes within several values of the budget which are equal to 1-5%$(n - Q)$. The results from implementing each method are new improved/modified landscapes.
(2) For each modified landscape, enhanced by the budget and returned by each method/solver, we do the following. Assume that the source area is the first ten columns and the

target area is the last ten columns. Then, run the *full* simulations (see the *full* simulations method later in Section 3.3) 100 times independently to compute the average number of rounds for the invasion process (invasion time) over the 100 independent repetitions.

(3) Following that, we compare the computed invasion times in point (2) to evaluate the quality of the CP-IMF method with respect to the two baseline methods.

The above three steps are done for different values of the dispersal coefficient α: 0.25, 0.5, 1 and 2.

3.2 The landscapes

In this section, we give details of the landscapes used. The landscapes were of size 5 rows/height (pixels) and 49 columns/width (pixels) extracted from Great Britain Landcover Map 2007 (LCM2007) data [13] and gridded at 1km resolution (see Figure 2). Each patch (pixel) in each extracted landscape provides the percentage cover of semi-natural grassland aggregate class across GB [13]. The percentage cover at each patch is considered as the quality of the patch. For examination purposes, three groups of landscape qualities namely: low quality, medium quality, and high quality have been formulated to represent the quality of each extracted landscape. In such an extracted landscape, if the average of all patches' qualities is between 0% and 5%, 5% and 25%, 25% and 100%, then the landscape is of low, medium, and high quality, respectively.

In this paper, we aim to minimise the invasion time in low and medium quality landscapes only (in high quality landscapes there is no need for big improvement as the invasion time is already short).

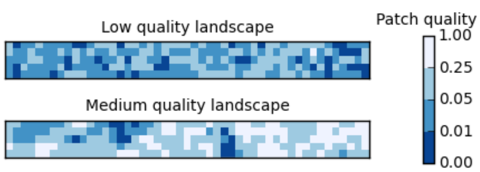

Figure 2: Two landscapes of size 5 × 49 of low and medium quality extracted from semi-natural grassland map (LCM2007 GB maps). The colour in each landscape gradations from dark blue to light blue corresponds to the gradations of the quality from the smallest to largest quality, zero, low (0.01-0.05), medium (0.05-0.25), and high quality (0.25-1).

It has been assumed that all patches at the first 10 columns of each landscape are occupied by species and the goal is to compute the average number of rounds (i.e., the expected time of invasion) for populating any of patches at the target area, which is the last 10 columns. Since our new optimisation method (CP-IMF) to minimise the invasion time is based on the developed method in [1], which defines the invasion time as the sum of estimates of the invasion times over a sequence of small and partly overlapping sub-landscapes, we do the following. We number columns starting from 0, therefore the area between column 0 and 9 is populated (source patches). We consider columns number 19, 29, and 39 as the first column of the target areas, which are of 10 columns length, for the occupied patches at the first 10 columns. Therefore, each landscape used in simulations has been extracted according to the following criteria. At least one of the patches at each target area (i.e., 19-28, 29-38, 39-48) has non-zero quality.

3.3 The *full* simulations method

In this section we describe the simulation method we use to compute the expected number of rounds for the invasion process (i.e., the expected time of invasion) in each modified landscape enhanced by the budget and returned by each optimisation method.

For a landscape graph G of size $H \times W$, we use the formula of colonisation probability proposed by Hodgson et al. [7] to define the *transition probability* between patches v and u as

$$p(v,u) = q(v) \cdot \frac{\exp(-\alpha d(v,u))}{\left(\frac{2\pi}{\alpha^2}\right) - 1},$$

where $\alpha > 0$ is the dispersal coefficient assumed to be the same for all patches and $d(v,u)$ is the Euclidean distance between patches v and u. We simulate the behaviour of the invasion process by building a simulator that uses the *full* method. In each round of the invasion process, for every pair of patch vertices v and u such that v is populated and u is not, we determine whether v populates u or not by the probability $p(v,u)$. In the *full* invasion method, each populated patch vertex in the landscape tries to populate every other unpopulated patch in the whole landscape.

More formal description of the structure of the *full* method is given in Algorithm 1. The generic structure of the *full* method contains input parameters, output variable (presented in Table 1), and Count rounds function.

Table 1: Input and output parameters for Algorithm 1.

Input parameters:	
1.	G: 2-dimensional array stores qualities of patches in a given real landscape
2.	S: vector containing indices of initial populated patches (source patches)
3.	T: vector containing indices of unpopulated target patches
4.	α: given number > 0
Output variable:	
1.	Number of rounds needed for successful invasion

The Count rounds function counts the number of rounds required for invasion. The function includes nested loops of three levels. The main loop (starts at line 6) counts the number of rounds to populate any of the target patches. The second level loop (starts at line 8) is for all populated patches that are trying to populate unpopulated patches. The inner level loop (starts at line 11) is for all unpopulated patches. Each unpopulated patch becomes populated if the *transition probability* between the populated and unpopulated patches is greater than a random generated number between zero and one (lines 14-17). We consider only populating a patch with non-zero quality because patch has zero value means "no habitat" and thus the species could not reproduce there. The Count rounds function terminates when any of the non-zero target patches become populated and returns the number of rounds needed for successful invasion.

Algorithm 1 Modelling invasion process using *full* simulations method (G, S, T, α)

```
function COUNT ROUNDS(G, S, T, α)
    Create 2-dimensional array B having size equal to G ← 0
    for each index of populated patch in vector S do
        B(index) ← 1
    Rounds ← 0
    while all target patch in T is unpopulated do
        Rounds ← Rounds+1
        for i ← 0 to number of rows in G do
            for j ← 0 to number of columns in G do
                if patch B(i, j) is populated then
                    for z ← 0 to number of rows in G do
                        for l ← 0 to number of columns in G do
                            if patch B(z, l) is unpopulated and q(B) ≠ 0 then
                                p ← Transition probability between B(i, j) and B(z, l)
                                w ← Generate a random number between 0 and 1
                                if w < p then
                                    Populate patch B(z, l)
    return Rounds
```

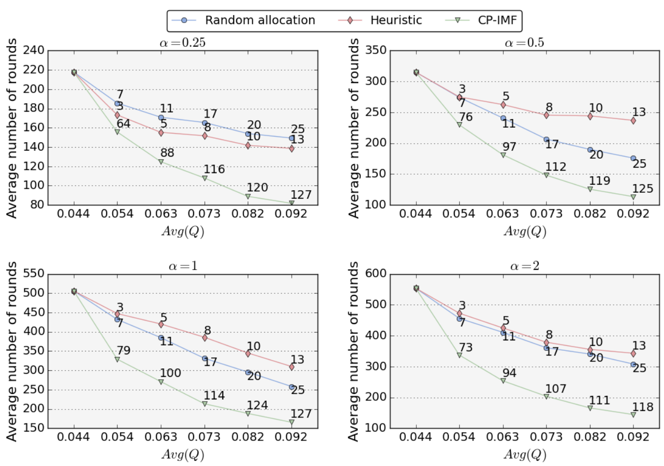

Figure 3: The average number of rounds computed by *full* simulations for 5×49 landscapes of *low* quality enhanced by the budget and returned by random allocation, heuristic, and CP-IMF optimisation methods for different values of the dispersal coefficient α: 0.25, 0.5, 1 and 2.

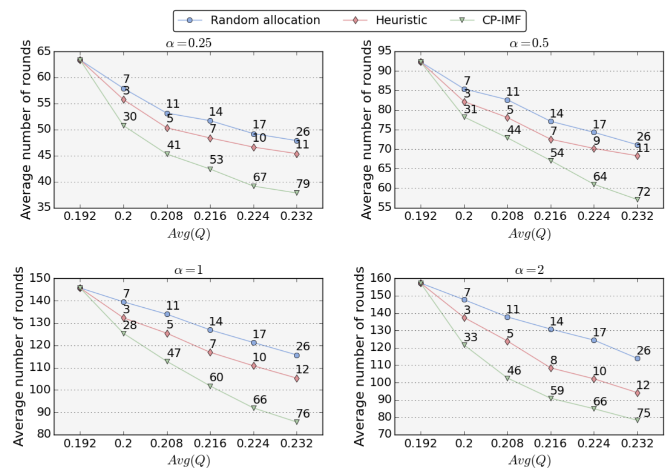

Figure 4: The average number of rounds computed by *full* simulations for 5×49 landscapes of *medium* quality enhanced by the budget and returned by random allocation, heuristic, and CP-IMF optimisation methods. for different values of the dispersal coefficient α: 0.25, 0.5, 1 and 2.

3.4 Evaluation results

3.4.1 Minimising invasion time using three methods. The average number of rounds over 100 independent repetitions (i.e., the estimated time of invasion) decreases as more budget (i.e., additional quality) is added to a landscape. This is illustrated in Figures 3 and 4, for for 5×49 landscapes of *low/medium* quality enhanced by the budget (additional quality) and returned by random allocation, heuristic, and CP-IMF optimisation methods. In the random case, several different random arrangements are used. The x-axis in both figures gives the exact value of the average qualities in the landscape after adding budget. The first mark in each figure represents the average number of round in the original landscape (without modifications). The total number of modified patches is associated with each point for each method. That is done for different values of the dispersal coefficient α: 0.25, 0.5, 1 and 2.

For different amounts of the budget, the CP-IMF method always chooses/finds the best locations (patches) to add budget. Therefore, the estimated time of the invasion in the improved landscapes and produced by the CP-IMF method is the minimum among the three methods. If the budget is added at random patches, the invasion time tends to be reduced gradually. If the budget is added to the patch that is located in the halfway across the highest power link between two patches, the invasion time tends to be reduced gradually as well. On the other hand, the invasion time tends to be reduced significantly to be the minimum over the three methods, if the budget is added by the CP-IMF method.

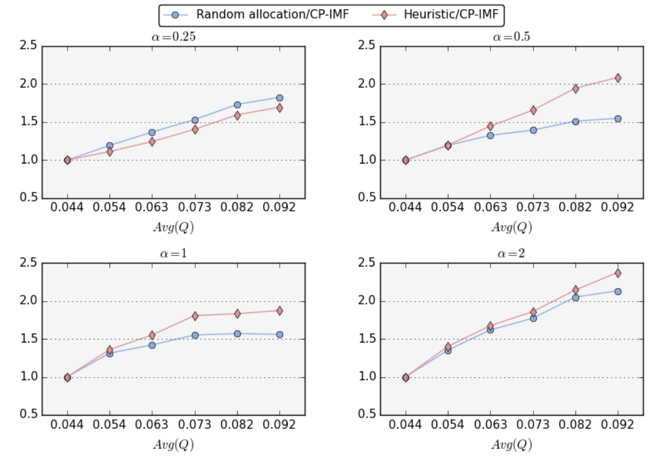

Figure 5: Ratio of the average number of rounds on *low* quality landscapes produced by *random allocation* and *heuristic* methods to the average number of rounds produced by the *CP-IMF* method, for α: 0.25, 0.5, 1 and 2.

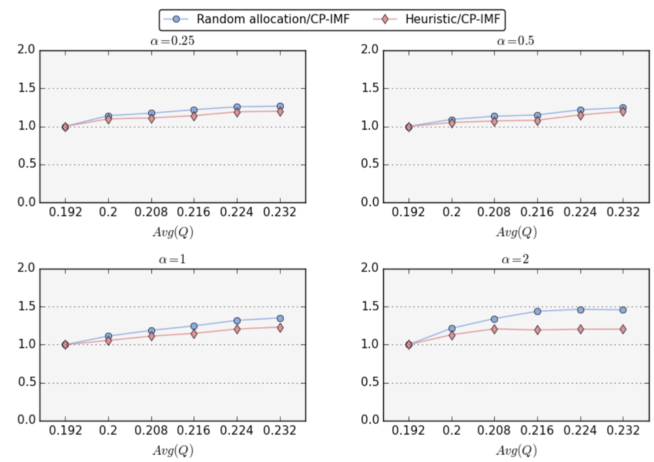

Figure 6: Ratio of the average number of rounds on *medium* quality landscapes produced by *random allocation* and *heuristic* methods to the average number of rounds produced by the *CP-IMF* method, for α: 0.25, 0.5, 1 and 2.

Figures 5 and 6 show the improvement in minimising the invasion time by the CP-IMF method, for α equal to 0.25, 0.5, 1, 2, and in 5×49 low and medium quality landscapes, respectively. The improvement is shown by computing the ratio of the average number of rounds on improved landscapes by the random allocation method to the average number of rounds on improved landscapes by the CP-IMF method. The same ratio is computed with respect to the heuristic and CP-IMF methods. The obtained improvement using the CP-IMF method is between 1-2.5 and 1-1.5 in low and medium landscapes, respectively. The CP-IMF method outperforms the others especially in the low quality landscape, and for less dispersive species, and these are the situations where conservation intervention is most needed (i.e. where species would be less likely to keep up with climate change under the status quo).

3.4.2 The spatial allocation of budgets. Allocating the budget for low quality landscape, using CP-IMF and heuristic methods for α = 0.25, 2, is shown in Figures 7-10 (the analogous figures for other values of α and for low/medium quality landscapes are in the Supplementary materials [2]). For small values of α (i.e., α = 0.25, 0.5), the heuristic method tends to allocate the budget close to the source and target patches. While for the large values of α (i.e., α = 1, 2), the heuristic method tends to allocate the budget in a way to form corridors or paths from the source patches (the first ten columns) to the target patches (the last ten columns). This could be because low α implies a species that can disperse a long distance and hence 'jump' over unsuitable areas. When α is high, the range expansion will be more dependent on many short-distance colonisation events, and these become more likely in a 'corridor' of uniform quality.

It is very striking that the CP-IMF always allocates its budget in small quotients over many of the landscapes' cells. By contrast, the heuristic method is restricted to improve each chosen cell to $q = 1$ before selecting another cell. We can speculate that the heuristic method might produce better results if this restriction were relaxed. The resultant landscapes produced by the CP-IMF method are often quite homogeneous in quality (Figures 8 and 10), especially for landscapes of low quality, yet one could still notice some 'islands' or (more or less regular) 'corridors' of higher quality created automatically by the CP-IMF despite of its general tendency of spreading the budget across the whole area. If uniform quality was generally a pattern to maximise invasion speed, this would be a very simple message for conservation in practice, however we suspect that this is not a general rule: for example, Hodgson et al. in [8] found that concentrated corridors of habitat led to faster invasion than the same amount of habitat spread evenly across a square landscape. Since the landscapes used here are relatively narrow strips, it is difficult to tell whether there is some optimal 'width' for a corridor to promote invasion. It will be valuable to test the CP-IMF method in larger landscapes, and because it works by analysing smaller sub-networks, we hope that this can be achieved without too much increase in computation time.

4 CONCLUSION

This paper proposed and tested a new method that chooses the best locations in real landscapes to spend a limited given budget, in order to minimise the invasion time and therefore to assist decision-making. Our new method is based on the developed method by Aloqalaa et al. in [1], which approximates the invasion time using the network flow approach. We show the capability of the new method to propose landscapes' modifications, which lead to reduce the invasion time to the minimum. We believe that it has great potential to be used in practical landscape restoration planning.

As for the future work, we suggest testing for larger landscapes and analysis how to *slow-down* the invasion process.

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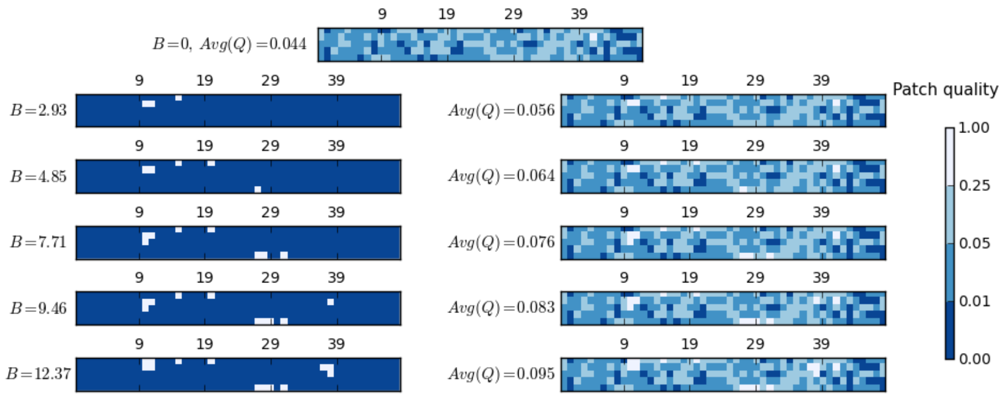

Figure 7: The results of improving 5×49 landscape of *low* quality for α equal to 2. The map at the top shows the landscape before improvement. The maps in the left column show only the allocation of the budget B using the *heuristic* method. The maps in the right column show the landscape after improvement.

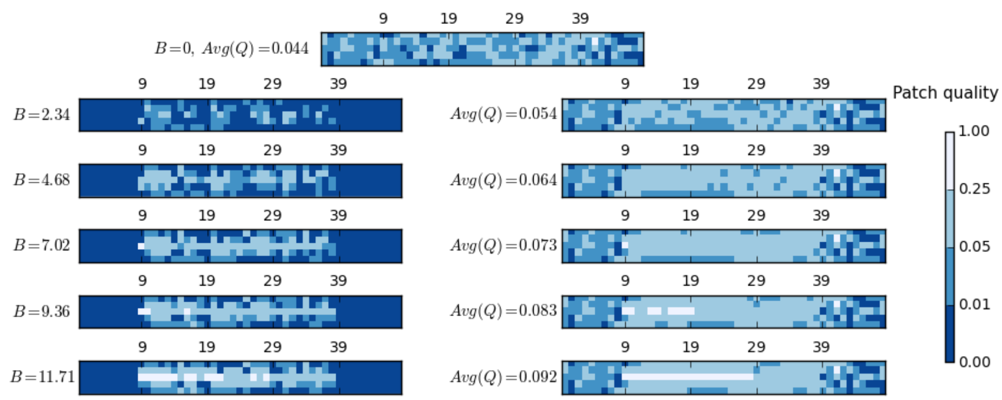

Figure 8: The results of improving 5×49 landscape of *low* quality for α equal to 2. The map at the top shows the landscape before improvement. The maps in the left column show only the allocation of the budget B using the *CP-IMF* method. The maps in the right column show the landscape after improvement.

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APPENDIX - ADDITIONAL FIGURES

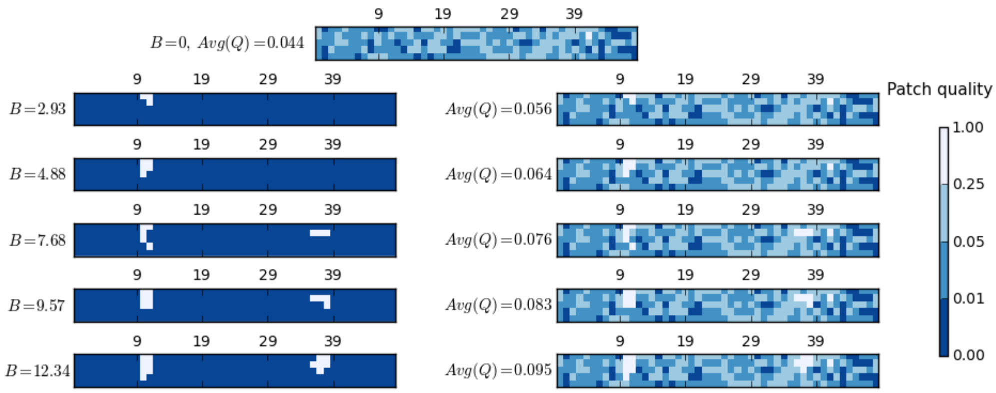

Figure 9: The results of improving 5×49 landscape of *low* quality for α equal to 0.25. The map at the top shows the landscape before improvement. The maps in the left column show only the allocation of the budget B using the *heuristic* method. The maps in the right column show the landscape after improvement.

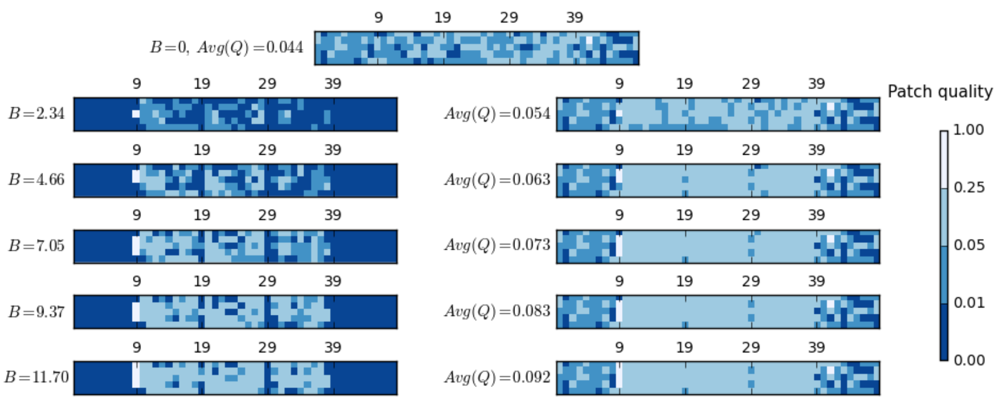

Figure 10: The results of improving 5×49 landscape of *low* quality for α equal to 0.25. The map at the top shows the landscape before improvement. The maps in the left column show only the allocation of the budget B using the *CP-IMF* method. The maps in the right column show the landscape after improvement.