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Fuel treatment planning: fragmenting high fuel load areas while maintaining availability and connectivity of faunal habitat

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Abstract

Reducing the fuel load in fire-prone landscapes is aimed at mitigating the risk of catastrophic wildfires but there are ecological consequences. Maintaining habitat for fauna of both sufficient extent and connectivity while fragmenting areas of high fuel loads presents land managers with seemingly contrasting objectives. Faced with this dichotomy, we propose a Mixed Integer Programming (MIP) model that can optimally schedule fuel treatments to reduce fuel hazards by fragmenting high fuel load regions while considering critical ecological requirements over time and space. The model takes into account both the frequency of fire that vegetation can tolerate and the frequency of fire necessary for fire-dependent species. Our approach also ensures that suitable alternate habitat is available and accessible to fauna affected by a treated area. More importantly, to conserve fauna the model sets a minimum acceptable target for the connectivity of habitat at any time. These factors are all included in the formulation of a model that yields a multi-period spatially-explicit schedule for treatment planning. Our approach is then demonstrated in a series of computational experiments with hypothetical landscapes, a single vegetation type and a group of faunal species with the same habitat requirements. Our experiments show that it is possible to fragment areas of high fuel loads while ensuring sufficient connectivity of habitat over both space and time. Furthermore, it is demonstrated that the habitat connectivity constraint is more effective than neighbourhood habitat constraints. This is critical for the conservation of fauna and of special concern for vulnerable or endangered species.

Keywords: Environmental modelling, Wildfire, Landscape management, Habitat conservation, Optimisation

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1. Introduction

Fire plays an important role in maintaining ecological integrity in many natural ecosystems [1] but wildfires also pose a risk to human life and economic assets [2]. Climate change is expected to aggravate these risks [3] but they can be reduced through fuel management [4, 5, 6]. This is the process of altering the structure and amount of fuel accumulation in a landscape. It is achieved through the application of treatments, such as prescribed burning or mechanical clearing. To reduce the risk of large wildfires, fire management agencies in Australia [7, 8] and the USA [9, 10] have initiated extensive fuel management programs in fire-prone areas. Fuel load or biomass accumulation is a continuous ecosystem process. Each year parts of the landscape are treated to reduce the overall fuel load for subsequent fire seasons. Treatment frequency is partially dictated by the vegetation community. Reducing the fuel load in the landscape in this way helps to prevent or minimise the spread and intensity of wildfire.

Similarities exist between the fuel treatment problem described here and the planning problem for forest harvesting. Both of these problems consider vegetation dynamics and can be seen as a 'timing problem', meaning that the risk and values change over time as the vegetation grows. In the fuel treatment problem, an area is treated to reduce fuel load; in the forest harvesting problem, an area is harvested using mechanical clearing for timber production. Both activities have consequences for the habitat. Previous studies in the forest harvesting problem have taken into account some ecological requirements. For example, in [11] a Tabu search algorithm is used to schedule timber harvest subject to spatial wildlife goals. Specifically, they maintained sufficient habitat of a certain maturity within a specified distance of a hiding or thermal place. Öhman and Wikström [12] proposed an exact method for long-term forest planning to maintain the biodiversity of the forest. They believe that biodiversity in the forest ecosystem can be maintained by minimising the total perimeter of old forest patches so that the fragmentation of old forest is reduced. Hence, compactness of the habitat for species can be achieved. However, their model did not consider habitat connectivity across time. Addressing this shortcoming, a model was proposed [13] that ensures mature forest patches are temporarily connected between time-steps while scheduling forest harvesting. The model achieves this without substantial reduction in timber revenues. However, this model does not take into account the overall habitat connectivity of each period, nor does it track the habitat connectivity across the entire planning horizon, both of which are important for the persistence of species.

Various methods have been proposed for incorporating the effect of wildfires into harvest planning models. A comprehensive review is provided in [14]. More recently it was shown that including

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wildfire risks into a harvesting planning model with adjacency constraints can yield improved outcomes [15]. The spatial arrangement of fuel treatment planning plays a substantial role in providing better protection in the landscape [16]. Fuel arrangement can modify fire behaviour and when fragmented, can lessen the chance of large wildfires [17]. The connectivity of 'old' untreated patches is an important factor affecting the extent of a wildfire [8].

Wei and Long [18] proposed a model to break the connectivity of high fuel load patches by considering the duration and speed of a future fire. Their model was for a single period. Fundamental to accurate fuel treatment planning requires consideration of the vegetation dynamics over time [19]. With the objective of minimising the 'value at risk' [20] used simulated annealing to determine a long-term schedule for the location and timing of prescribed burns on a landscape. A multi-period model for fuel treatment planning that included the dynamics of a single vegetation type was formulated in [21]. The objective in this model was to break the connectivity of 'old' patches in the landscape over the entire solution period of a few decades. This model was extended by [22] to multiple vegetation types and applied to a real landscape.

The efficacy of the application of fuel treatment remains debated among experts according to different perspectives [23]. Fuel treatments reduce the overall fuel load in landscapes but at the same time may result in significant habitat modification for fauna living within the treated area. If the right mix of habitat availability in the landscape is not maintained, populations may be adversely affected, leading to local extinctions where minimum viable population thresholds are no longer met. For example, the Mallee emu-wren, a native bird of Australia, depends on 15-year-old mallee-Triodia vegetation for survival [24] . This vegetation recovers very slowly after fuel treatments, and the Mallee emu-wren is unable to survive in vegetation aged less than 15 years. Another Australian example is the Southern Brown Bandicoot. The species requires 5-15 year old heathland [25]. Similarly, in California, frequent fires can destroy the mature coastal sage scrub habitat required for the coastal cactus wren and the California gnatcatcher on which these species rely [26]. For a given vegetation type, the age of the vegetation is the most significant factor determining its suitability as habitat for the species discussed above. Thus henceforth we refer to areas of vegetation of the appropriate age for a species simply as habitat. If we want to conserve these species, it is important to maintain the availability and connectivity of their habitats. In fact, more generally, habitat connectivity is vital to support the ecology and genetics of local populations [27, 28]. The question then arises: Can fuel treatments be scheduled to break the connectivity of high fuel load areas while maintaining the availability and

connectivity of habitats?

Here we significantly extend current models by tracking and maintaining defined levels of habitat connectivity over time, in addition to reducing and fragmenting high fuel loads across the landscape. The model we present is the first multi-period fuel treatment model that takes into account habitat connectivity and solved using exact optimisation. The proposed model is designed for fire-dependent landscapes so additional ecological constraints are imposed based on the concept of Tolerable Fire Intervals (TFI's) [29]. It is harmful for vegetation in an area to be subjected to another fire before a certain time (the minimum TFI) has elapsed since the last fire in that area. It is also desirable that a burn *does* take place before a certain time (the maximum TFI) has elapsed since the last fire. Thus fuel treatment in each area is constrained to occur in a time-window between the minimum and maximum TFI since the last burn in that area. The TFI's are vegetation-dependent.

Mixed Integer Programming (MIP) models have been employed in a great diversity of problems. Applications include waste disposal [30], facility layout problems [31], oil-refinery scheduling [32] and a forest management problem [33] to list just a few. Further examples can be found in [34]. Of closer relevance to the problem considered here are the MIP papers listed in an overview of wildfire considerations in forest planning [14].

Here we present a MIP for fuel treatment planning. Subject to the time-windows imposed by the TFI's, the objective is to fragment high fuel load areas as much as possible while maintaining habitat connectivity in the landscape. The model is illustrated with a single vegetation type and a single animal species. We assume that the animals can relocate to a neighbouring area that has similar habitat characteristics. The model is demonstrated on a series of hypothetical landscapes.

2. Model formulation

In this formulation, cells represent the candidate locations for fuel treatment in a landscape. The 'fuel age' (years) in each cell is defined as the time elapsed since the last treatment of that cell. The cell's fuel age is reset to zero if the cell is treated or incremented by one if untreated in any year. Each cell has its minimum and maximum tolerable fire intervals (TFIs) which depend on the vegetation type in that cell. Within the time-window defined by the minimum and maximum TFI, there is a time at which the vegetation is regarded as high risk from then on until the cell is treated. This time will be referred to as the 'high fuel load' threshold. Without being specific, for this formulation we shall consider a vertebrate that requires habitat offering 'mature' vegetation. The vegetation age (time since last burnt) at which vegetation is considered 'mature' will be referred to as the 'mature' threshold.

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In our example the mature threshold is less than the high fuel load threshold but the formulation is more general. The relationship between these thresholds is represented in Figure 1. Reducing the

Figure 1: The relationship between the minimum TFI, mature, high fuel load, and the maximum TFI threshold values
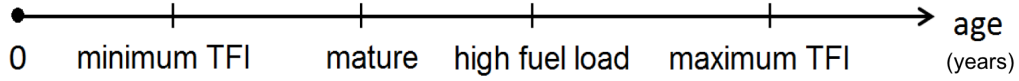
connectedness of high fuel load cells through fuel treatment should reduce the risk of fire spreading over a large area. Fuel treatment, however, modifies habitat. For each cell treated in a given year, suitable neighbouring habitat should be available in the following year. Moreover, for metapopulation persistence, to the extent possible we require the neighbouring habitat to be connected to other cells of mature habitat.

The following mixed integer programming model is formulated to determine a multi-period optimal schedule for treatment of cells. The objective is to break the connectivity of high fuel load cells in the landscape each year while providing continuity of habitat for the species of concern.

Sets:

C is the set of all cells in the landscape

Φ_i is the set of cells connected to cell i

T is the planning horizon

Indices:

$i = $ cell

$t = $ year, $t = 0, 1, 2, \ldots T$

Parameters:

$a_i = $ initial fuel age of cell i

R = the total area of cells in the landscape

ρ = treatment level (percentage), i.e. the maximum fraction of R that can be selected for treatment in any one year

c_i = area of cell i

d_i = high fuel load threshold for cell i

m_i = mature threshold for cell i

G_t = desired target of mature cell connectivity in year t

$MaxTFI_i$ = maximum tolerable fire interval (TFI) of cell i

$MinTFI_i$ = minimum TFI of cell i

M is a "big M" parameter (It must be greater than the maximum fuel age. For example, in the illustration that follows $M = 20$)

Decision variables:

$A_{i,t}$ = fuel age of cell i in year t

$$x_{i,t} = \begin{cases} 1 & \text{if cell } i \text{ is treated in year } t \\ 0 & \text{otherwise} \end{cases}$$

$$Mature_{i,t} = \begin{cases} 1 & \text{if cell } i \text{ is classified as 'mature ' in year } t \\ 0 & \text{otherwise} \end{cases}$$

$$HabitatConn_{i,j,t} = \begin{cases} 1 & \text{if connected cells } i \text{ and } j \text{ are both 'mature' cells in year } t \\ 0 & \text{otherwise} \end{cases}$$

$$High_{i,t} = \begin{cases} 1 & \text{if cell } i \text{ is classified as high fuel load cell in year } t \\ 0 & \text{otherwise} \end{cases}$$

$$HighConn_{i,j,t} = \begin{cases} 1 & \text{if connected cells } i \text{ and } j \text{ are both high fuel load cells in year } t \\ 0 & \text{otherwise} \end{cases}$$

$$Old_{i,t} = \begin{cases} 1 & \text{if the fuel age in cell } i \text{ is classified as over the maximum TFI in year } t \\ 0 & \text{otherwise} \end{cases}$$

The model

The objective is to minimise z, the connectivity of high fuel load cells

$$\min z = \sum_{t=1}^{T} \sum_{i \in C} \sum_{j \in \Phi_i, i < j} HighConn_{i,j,t} \tag{1}$$

subject to

$$\sum_{i \in C} c_i x_{i,t} \leq \rho R, \; t = 1 \ldots T \tag{2}$$

$$A_{i,0} = a_i, \; \forall i \in C \tag{3}$$

$$A_{i,t} \geq A_{i,t-1} + 1 - M x_{i,t}, \; t = 1 \ldots T, \forall i \in C \tag{4}$$

$$A_{i,t} \leq M(1 - x_{i,t}), \; t = 1 \ldots T, \forall i \in C \tag{5}$$

$$A_{i,t} \leq A_{i,t-1} + 1, \; t = 1 \ldots T, \forall i \in C \tag{6}$$

$$A_{i,t} - d_i \leq M \, High_{i,t} - 1, \; t = 1 \ldots T, \forall i \in C \tag{7}$$

$$A_{i,t} \geq d_i \, High_{i,t}, \; t = 1 \ldots T, \forall i \in C \tag{8}$$

$$High_{i,t} + High_{j,t} - HighConn_{i,j,t} \leq 1, \; t = 1 \ldots T, \forall j \in \Phi_i, i < j, \forall i \in C \tag{9}$$

$$A_{i,t} - m_i \leq M \, Mature_{i,t} - 1, \; t = 1 \ldots T, \forall i \in C \tag{10}$$

$$A_{i,t} \geq m_i \, Mature_{i,t}, \; t = 1 \ldots T, \forall i \in C \tag{11}$$

$$\sum_{j \in \Phi_i} Mature_{j,t+1} \geq x_{i,t}, \; t = 1 \ldots T, \forall i \in C \tag{12}$$

$$Mature_{i,t} + Mature_{j,t} - HabitatConn_{i,j,t} \leq 1, \; t = 1 \ldots T, \forall j \in \Phi_i, i < j, \forall i \in C \tag{13}$$

$$Mature_{i,t} + Mature_{j,t} \geq 2HabitatConn_{i,j,t}, \; t = 1 \ldots T, \forall j \in \Phi_i, i < j, \forall i \in C \tag{14}$$

$$\sum_{i \in C} \sum_{j \in \Phi_i, i < j} HabitatConn_{i,j,t} \geq G_t, \; t = 1 \ldots T \tag{15}$$

$$A_{i,t} - MaxTFI_i \leq M \, Old_{i,t} - 1, \; t = 0 \ldots T - 1, \forall i \in C \tag{16}$$

$$A_{i,t} \geq MaxTFI_i \, Old_{i,t}, \; t = 0 \ldots T - 1, \forall i \in C \tag{17}$$

$$Old_{i,t-1} + \frac{1}{\mid \Phi_i \mid} \sum_{j \in \Phi_i} Mature_{j,t} \leq 1 + x_{i,t}, \ t = 1 \dots T, \forall i \in C \qquad (18)$$

$$A_{i,t-1} \geq MinTFI_i \, x_{i,t}, \ t = 1 \dots T, \forall i \in C \qquad (19)$$

$$x_{i,t}, \ High_{i,t}, \ HighConn_{i,j,t}, \ HabitatConn_{i,j,t}, \ Mature_{i,t}, \ Old_{i,t} \in \{0,1\} \qquad (20)$$

The objective function (1) minimises the connectivity of high fuel load cells in a landscape across the planning horizon. Note that connectedness is a two-way relationship in this context and we could have defined two separate decision variables for each direction but knowing that they will always take the same value defining only one of them removes a large number of binary decision variables. This choice does not have any impact on the value of the optimal solution but helps with the modelling and solution efficiency. Constraint (2) specifies that the total area selected for fuel treatment each year should not exceed a fixed proportion of the total area of the landscape. Constraint (3) sets the initial fuel age in a cell. Constraints (4) to (6) track the fuel age of each cell. Constraints (4) and (6) increment fuel age by exactly one year if the cell is not treated. Constraint (5) forces the fuel age to be reset to zero if the cell is treated. Note that the $A_{i,t}$ are continuous variables although only integer values are assigned to them.

Constraints (7) and (8) use binary variable $High_{i,t}$ to classify a cell as a high fuel load cell if and only if the fuel age exceeds a threshold value. In Constraint (9), $HighConn_{i,j,t}$ takes the value one if connected cells i and j are both classified as high fuel load cells in year t.

Constraints (10) to (11) classify a cell to be a 'mature' cell, if and only if the fuel age is over the mature age threshold. Constraint (12) states that we cannot treat a cell in this period unless there is at least one neighbouring mature cell in the following year.

In this model, we also ensure that sufficient habitat (mature-cell) connectivity in the landscape as a whole is available each year. Constraints (13) and (14) ensure that $HabitatConn_{i,j,t}$ takes the value one if and only if connected cells i and j are both classified as mature cells in year t. Constraint (15) ensures that the number of habitat connections each year is greater than the desired target, G_t.

Constraints (16) to (17) classify a cell as 'Old' if and only if the fuel age is over the maximum TFI. Constraint (18) ensures that a cell must be treated if the cell's fuel age is over the maximum TFI, and there is at least one neighbouring mature cell in the following period. It is necessary to include the cardinality of the neighbourhood set ϕ_i in the denominator of the second term. Without this, two mature cells in ϕ_i could force $x_{i,t} = 1$ even with $Old_{i,t-1} = 0$. This constraint avoids a deadlock that

may occur when the cell's fuel age is over the maximum TFI and there are no neighbouring mature cells for the next period. In this study, we break the deadlock in favour of mature cell availability. Constraint (19) ensures that the cell with fuel age less than the minimum TFI cannot be treated. Constraint (20) ensures that the decision variables take binary values.

Connectivity

Connectivity is an important concept in this work. The objective function aims to minimise the connectivity of high fuel load cells while an important constraint is imposed to ensure habitat connectivity. The concept as used in our model is perhaps more easily understood when described in terms of Graph Theory. The landscape can be represent by a graph $G(V, E)$ where the set of vertices, V, represent the cells and the edges, E, the connections between the vertices. In any given year, there will be two sub-graphs of G, one representing cells of suitable habitat, G_H , and another cells of high fuel load, G_F. An edge connects two cells of the same property and in the same neighbourhood. With this representation the objective is equivalent to minimising the *total degree* of the sub-graph, G_H [35]. To illustrate the effect of this measure at the landscape level see Figure 2. In this illustration a cell j is only considered to be in the neighbourhood of another cell i if cells i and j share a common boundary but the model formulation is valid for other (wider) definitions of neighbourhood. It is clear that the *total degree* of a graph will increase with increased connectedness of the vertices even with edges only connecting adjacent vertices. The measure of connectivity in our model is exactly equal to half the *total degree* of a graph.

Method of solution

Great progress has been made in solving large Mixed Integer Programming problems over the last few decades [36] and there is strong competition amongst Solvers. The computational results below were all achieved using ILOG CPLEX 12.6.2 with the Python 2.7.2 programming language using PuLP modeller. The experiments were ran on Trifid, a computer cluster of V3 Alliance. A single node with 16 cores of Intel Xeon E5-2670 and 64 GB of RAM was used.

3. Model illustration

In this section, we demonstrate the model formulated in Section 2 using hypothetical random landscapes comprising 100 grid cells, generated using the NLMpy package [37]. (Note that the model

Figure 2: Connectivity. The edges of the 4 vertices in the first row sum to 2 whereas the edges of the 4 vertices in row 2 sum to 3. Similarly, note that the bottom figure has 8 vertices which is the same as the two top figures combined yet the bottom figure has 10 edges compared with only 2+3=5 edges for the top two figures.
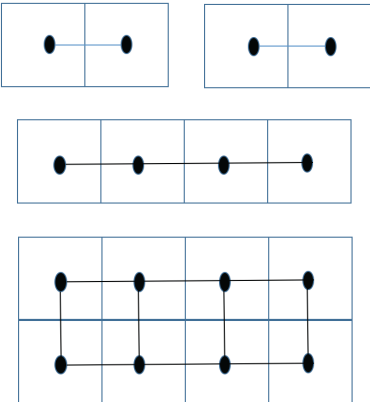
does not require a regular grid. Cells can be any shape and all that is needed is that the neighbours of each cell are specified.) For this illustration we assume that there is a single fuel type in the landscape, with the thresholds of mature (suitable habitat) and high fuel load ages set as 8 and 12 years old, respectively. The minimum and the maximum TFIs are chosen as 2 and 16 years. The initial fuel ages in the landscape are between 0 and 16 years, this means that not all the cells are categorised as high fuel load. Figure 3 represents the assumed distribution of the initial cell fuel age. Suppose that there are at most ten cells to be treated each year (ten percent of the total area in the landscape), and the length of planning horizon is 13 years.

As shown in Figure 4, initially the landscape has 13 high fuel load cell connections that we want to reduce with time. It also has 39 habitat connections that we want to maintain over the planning

Figure 3: Initial proportion of cells in the landscape of each fuel age group for the computational experiments
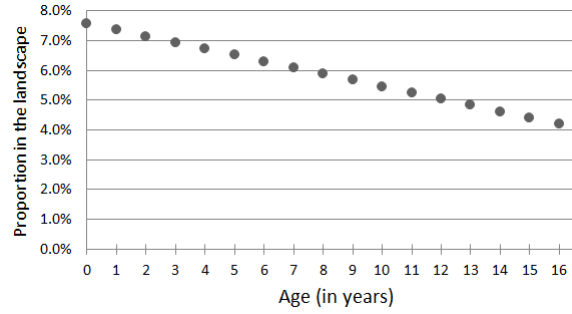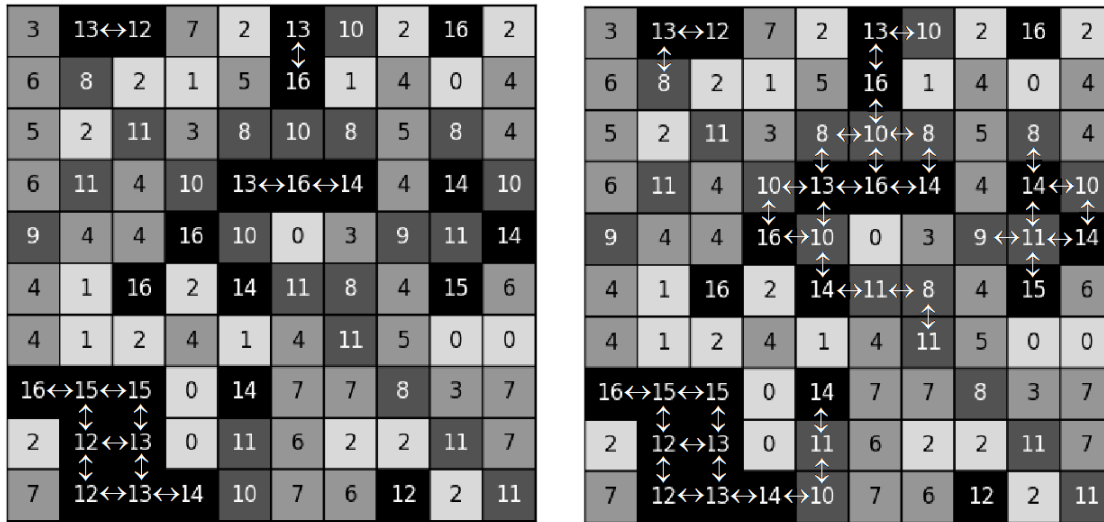

Figure 4: Illustration of initial high fuel load cell and habitat connectivity in the landscape, the arrow (↔) represents one connection

(a) 13 high fuel load cell connectivity   (b) 39 habitat connectivity

☐ Under minimum TFI cell   ■ Mature fuel age cell   2 Cell's fuel age
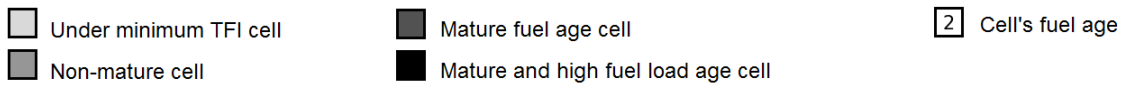■ Non-mature cell   ■ Mature and high fuel load age cell

Table 1: Four settings for the model illustration and the computational experiments

	Limit on overall habitat connectivity	Neighbouring habitat cell requirement for treatment
Setting 1	G_t is set to the initial number of habitat connectivity of the landscape	yes
Setting 2	G_t is set to the initial number of habitat connectivity of the landscape	no
Setting 3	G_t is set to zero	yes
Setting 4	G_t is set to zero	no

horizon. In this model illustration, we compare four different settings (Table 1).

In the first and second settings, we maintain the initial habitat connectivity, at a minimum level of 39 connections. In the first setting we enforce the requirement that a cell can only be treated if there is a neighbouring cell forming a suitable habitat, but in the second setting that requirement is relaxed. In the third setting, only the neighbouring habitat cell requirement is enforced without maintaining the overall habitat connectivity. Setting 4 represents the base case with the only aim of fragmenting high fuel load cells without habitat considerations.

4. Illustration Results

A sequence of landscape mosaics for the solution to setting 1 is given in Figure 5. At $t = 0$ note that the fuel age of cell $(1, 9)$ has reached its maximum TFI. It is not selected for treatment as there is no neighbouring cell with suitable habitat i.e. no neighbouring mature cell (age ≥ 8). Recall that, for this illustration, only cells that share a common boundary are regarded as neighbours. Thus even at $t = 5$ this cell is not considered for treatment. At this stage, however, the two row neighbours both have a fuel age of 7 and so at $t = 6$ will provide suitable 'mature' habitat and the cell is in fact treated at this time (not shown but can be deduced from the fuel age shown at $t = 11$).

It is also worth noting the four cells in the bottom right hand corner. Initially two of these cells are occupied. At $t = 5$ the animals have moved to suitable neighbouring habitat and the cells remain unoccupied until $t = 13$ when recolonisation has begun. It appears that the model is achieving the conservation goals. It is easy to see that the fragmentation of high fuel cells has also been achieved. None of the high fuel load cells (in red) have a high fuel load neighbour.

A comparison of the results for all four settings is shown in Figure 6. The high fuel load cells in the landscape are fully fragmented more quickly for settings 3 and 4 than settings 1 and 2. This is to be expected as the habitat constraints are relaxed for settings 3 and 4 and habitat connectivity drops rapidly as a consequence. Nevertheless, from $t = 4$ on settings 1 and 2 do achieve similar

Figure 5: Fuel treatment schedule with ten percent treatment level and thirteen-year planning horizon for the first setting, $G_t=$ initial
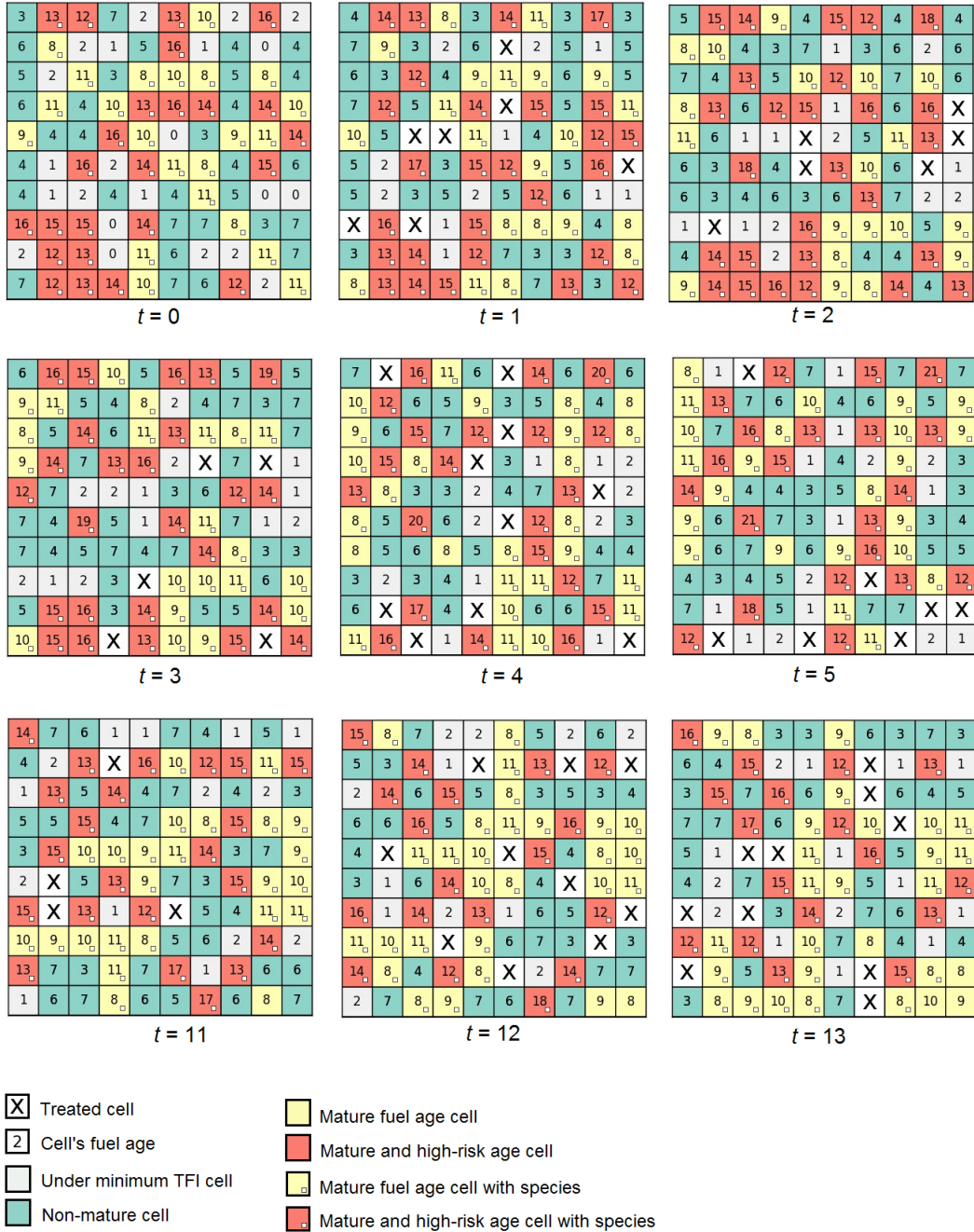
Figure 6: Habitat connectivity and high fuel load connectivity for the illustrative example
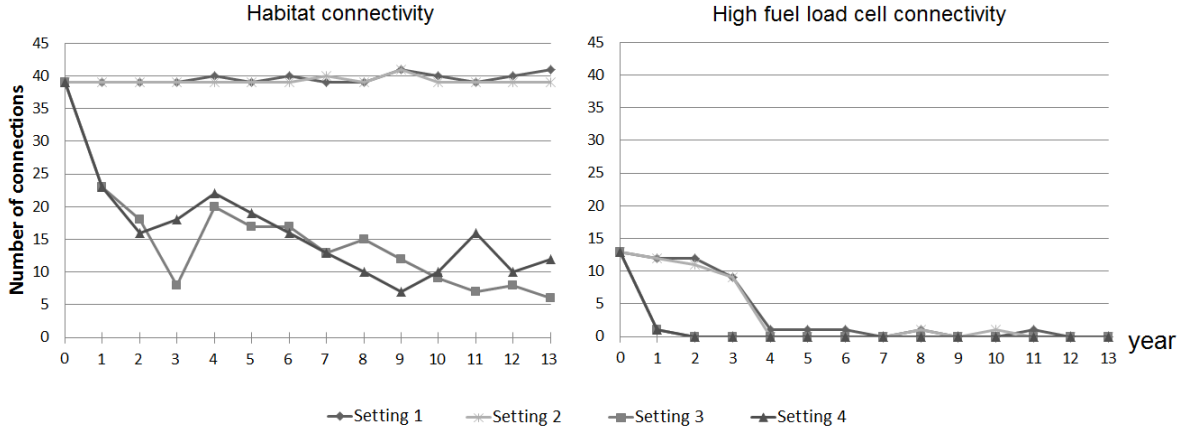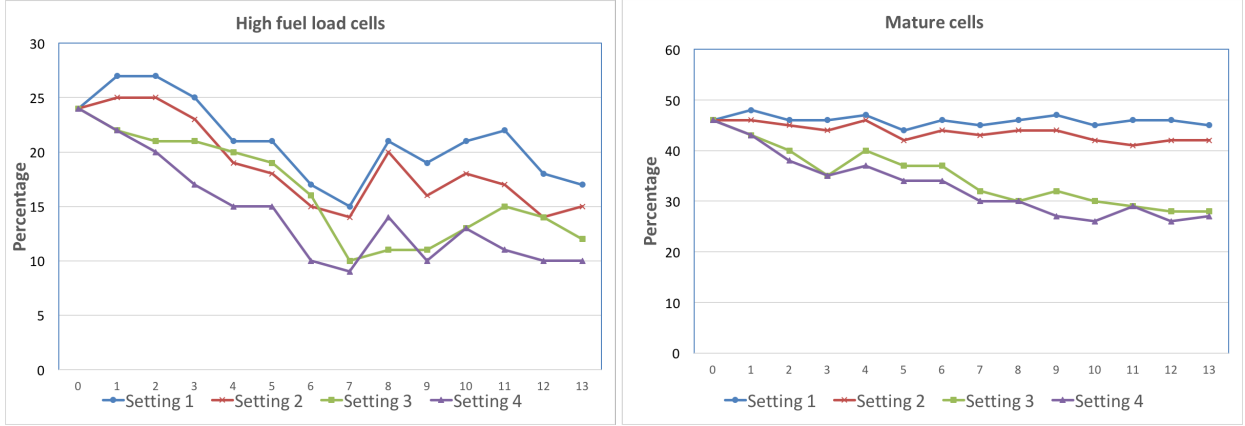

Figure 7: The percentages of high fuel load cells and mature cells in the landscape for the model illustration

fuel fragmentation while maintaining habitat connectivity throughout. In this case, however, Figure 7 shows that the landscapes comprise a greater number of high fuel load cells. On the other hand settings 3 and 4 not only perform poorly with regard to habitat *connectivity* but habitat availability (mature cells) also declines as seen in Figure 7.

To gain further understanding from our results of the efficacy of our method we consider an animal population that requires 'mature' habitat. It is assumed that initially all mature cells (includes high fuel load cells) are populated. We then track the location of animals in mature cells in the landscape over the planning horizon for the four settings. We assume that the mobility of this species is such that, in any given year, individuals are only able to move to a neighbouring cell. We assume that any animals in a cell to be treated will survive or perish depending on whether or not there is a mature

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Figure 8: The percentage of mature cells in the landscape with animals present.
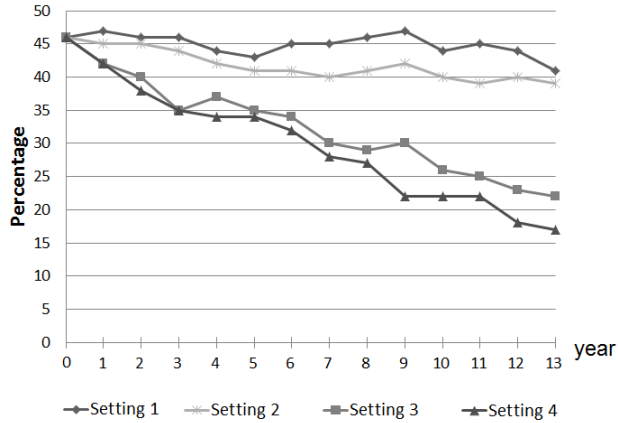

neighbouring cell. We further assume that an unoccupied mature cell can be (re)colonised from an occupied neighbour. An analysis for the four settings can be undertaken using Figure 5 for setting 1 and similar graphs (not shown) for the other three settings. The results are shown in Figure 8. The value of the connectivity constraints is now even more apparent. By the end of the planning horizon only 17% of the landscape is occupied in setting 4 as opposed to 41% for setting 1. Furthermore, setting 2 which includes the connectivity constraint but not the neighbourhood constraint ends up with 39% of the landscape occupied compared with only 22% for setting 3. Recall that setting 3 imposes neighbourhood but not connectivity constraints.

5. Computational experiments

The illustration in the previous section was for a particular configuration of initial fuel age of cells in a 10x10 landscape. Were the previous findings simply a consequence of the initial configuration? In this section we explore landscapes with randomly generated initial configurations but with the same proportions of initial fuel age cells as given in Figure 3.

We consider landscape sizes of 10x10 and 15x15 cells. In each case 30 landscapes were generated using the NLMpy package. The model was solved for each of the four settings given in Table 1. A ten percent treatment level was applied with a planning horizon of 10 years. For the first two settings, we evaluated the initial number of connected mature cells for each landscape. This value of habitat connectivity, G_t, was then maintained over the planning horizon by constraint (15). We found, however, that for some landscapes it is impossible to maintain the initial extent of habitat over the planning horizon. To deal with this infeasibility, we ran the model by assigning a lower value of

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Figure 9: High fuel load connectivity and habitat connectivity with 95% confidence intervals for the computational experiments
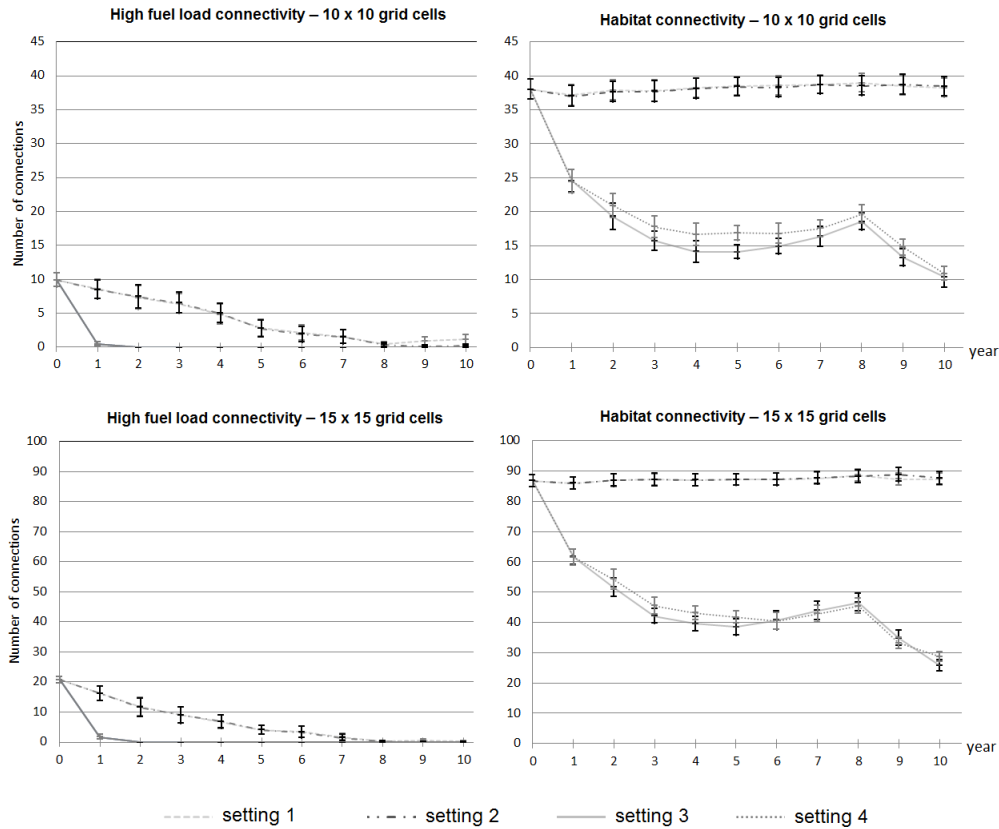
G_t for the first years of a planning horizon, and setting the higher value (the initial level of habitat connectivity) of G_t for the remainder of the planning horizon only once it was feasible.

6. Results of computational experiments

Overall this more comprehensive analysis does not reveal any surprising differences from that observed in the model illustration. Figure 9 shows that, on average, settings 1 and 2 do reduce the high fuel load connectivity but more slowly than in the case of the model illustration. On the other hand settings 3 and 4 achieve a rapid reduction in high fuel load connectivity but to the detriment of habitat connectivity. Figure 10 shows, not unexpectedly, that settings 1, 2 and 3 all leave a greater proportion of high fuel load cells in the landscape compared with setting 4. Given that the difference betweeen setting 2 and setting 3 is that the former is concerned only with habitat connectivity and the latter with only with suitable neighbouring sites Figure 11 reveals a remarkable difference between their performance in maintaining sites with a faunal presence.

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Figure 10: Proportions of high fuel load cells and mature cells in the landscape with 95% confidence intervals for the computational experiments
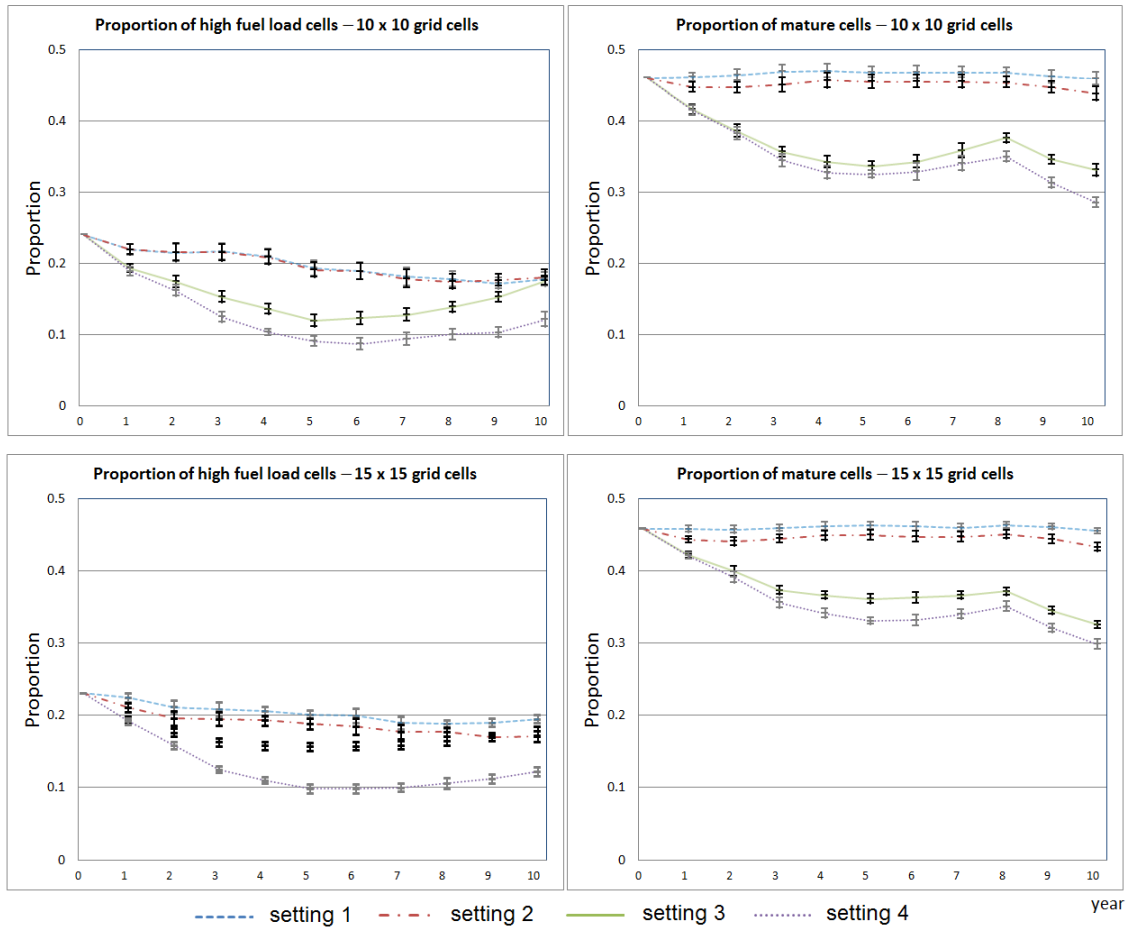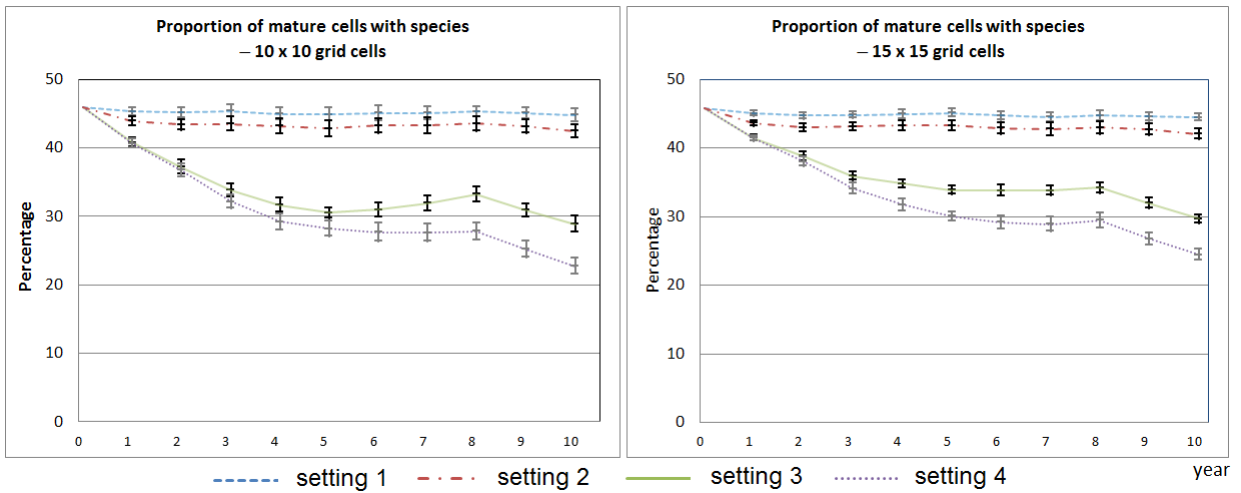

Figure 11: Proportion of mature cells in the landscape with a faunal presence for the computational experiments

7. Discussion

The model results show that it is possible to achieve reductions in the number and connectivity of high fuel load cells in the landscape while simultaneously ensuring habitat indices are maintained at their initial levels. While the reduction in the number of high fuel load cells is not as good when habitat connectivity constraints are imposed, even in this case there is still a significant reduction in the overall *connectivity* of high fuel load cells. The work of Wei and Long [18] indicates that this fragmentation of high fuel load areas is likely to reduce the risk of large wildfires. On the other hand others [17] concluded from their simulations that management activities that are arranged in spatial patterns only marginally reduced risk during severe wildfire weather. The "Black Saturday" fires in Victoria, Australia, in 2009, was an extreme high-temperature and high-wind day where medium- and long-range spotting overran all areas. This included areas that had undergone prescribed burning although the intensity in these areas was reduced.

Two strategies were considered to meet conservation goals. One strategy was to maintain habitat connectivity and the other was to ensure that no cell was treated unless there was suitable habitat in its neighbourhood. The results clearly suggest, however, that the habitat connectivity constraints we used for setting 1 and 2 produced a significantly better outcome than the neighbourhood constraints in terms of the fraction of the landscape occupied by our representative faunal species.

In our model we defined the neighbourhood set to be the same for both high fuel load as well as habitat. In practice, the set of habitat cells and the set of high fuel load cells forming the neighbourhood of a given cell will differ. In the case of a high fuel load cell the neighbouring cells could be weighted to take fire spread dynamics into account. In the case of habitat, neighbouring cells would need to be defined in terms of the particular requirements and mobility of denizens living in a cell selected for treatment. In both cases of high fuel load and habitat, 'neighbourhoods' might comprise more than just adjacent cells. Mathematically, this is easy to accommodate. The sets Φ_i used in constraints (13), (14) and (18) would simply be replaced by another set Ψ_i, say, specifying the sites that form the neighbourhood of site i.

The model presented in this paper comprises hypothetical landscapes with a single vegetation type and a single faunal species. The model was developed particularly for a fire-dependent vegetation type in a fire-prone landscape. An extension of the model to multiple vegetation types without the habitat connectivity has already been demonstrated on a real landscape [22]. In principle, extensions to include multiple groups of faunal species can be achieved with the inclusion of additional constraints

of the type (13), (14) and (18). In practice habitat connectivity would need to be limited to a few groups of species. The needs of keystone species and vulnerable or endangered species would require particular attention. To some extent the problem is a dynamic version of the Reserve Design Problem [38, 39, 40]. In this case the landscape from which areas for the reserve are to be selected change each year. Moreover decisions made in one period affect the subsequent landscape and hence the actions to be taken in future periods.

8. Conclusion

In this paper, we proposed and tested a mixed integer programming model that aimed to simultaneously fragment areas of high fuel load while maintaining the initial level of habitat connectivity. The model was tested on a hypothetical landscape with a single vegetation type and a single faunal species with the same habitat needs. Some reduction in high fuel load areas could still be achieved after imposing a habitat connectivity constraint. Perhaps more importantly it was possible to achieve significant overall reductions in high fuel load connectivity while maintaining habitat connectivity. The model, designed for fire-dependent landscapes achieves these outcomes whilst also ensuring that the vegetation is subject to fire of a necessary and sufficient frequency within tolerable limits.

The approach was based on a theoretical perspective and has not yet been applied to real landscapes. Nevertheless, a model based on a similar concept with multiple vegetation types but without the habitat connectivity considerations has been successfully applied to a real landscape [22] and closely related problems have successfully applied heuristics such as simulated annealing [20] and Tabu search [11].

The development of optimised solutions for conflicting objectives has the potential to improve planning and operational decision making of prescribed burning strategies. It is hoped that our approach can assist fire and land management agencies in making their decisions about the timing and locations of future fuel treatments while considering critical ecological requirements. For this purpose we plan to extend the model to include multiple types of habitat and species in the landscape.

Spatial optimisation models addressing 'connectivity' have been developed before for various purposes. Such models are useful, for example, when parcels of land need to be acquired for a particular purpose such as an airport or golf course. In the problem addressed here not only is 'connectivity' in the landscape required for one attribute but also required in the same landscape is disconnectedness or fragmentation for another attribute. This new class of problem could prove useful for other purposes

such as designing a connected reserve for an endangered species while fragmenting the habitat needs for an invasive species.

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