Fuel treatment planning maintaining habitat availability and connectivity for endangered species conservation

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Abstract

Fuel treatment activities are primarily driven by the need to reduce fuel accumulation in fire-prone landscapes to reduce the risk of catastrophic wildfires, with occasional fuel treatments designed to address ecological objectives. Reducing fuel in the landscape while maintaining habitat for fauna, fragmenting areas of high fuel loads while ensuring connectivity of habitat, 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. Importantly, our approach also ensures that at the time an area is treated a suitable neighbouring habitat is available to allow fauna to relocate. Furthermore, the model sets a minimum acceptable target for contiguous habitat at any time to conserve fauna especially endangered species. 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 a hypothetical landscape represented in grid cells with a single vegetation type and a single faunal species. Our experiments show that it is possible to reduce the risk of wildfires while ensuring sufficient contiguous areas of habitat over both space and time. This is critical for the conservation of fauna and of special concern for endangered species.

Keywords: Forest management, Habitat conservation, Wildfire, Optimisation, Fuel treatment, Endangered species

1 Introduction

Fire plays an important role in maintaining ecological integrity in many natural ecosystems (Keane and Karau, 2010). However, large wildfires can cause loss of habitat, both temporary and permanent, as well as loss of human life and economic assets (King et al., 2008). Fire management agencies in Australia (McCaw, 2013; Boer et al., 2009) and the USA (Ager et al., 2010; Collins et al., 2010) have initiated extensive fuel management programs to lessen the possibility of large wildfires in fire-prone areas. Fuel management is the process of altering the structure and amount of forest fuel accumulation through the application of treatments, such as prescribed burning or mechanical clearing.

Each year parts of the landscape are treated to reduce the overall fuel in order to diminish the risk and impact of wildfires for subsequent fire seasons. Fuel management is a cyclic activity, varying in treatment frequency, partially dictated by the vegetation community. Fuel load or biomass accumulation is a continuous ecosystem process. As such, it is infeasible to prevent all wildfires from occurring through fuel treatment. However, this activity is acknowledged as reducing the suppression efforts required with wildfires being easier to contain in areas having received fuel reduction treatments.
Martell (2015). Treating the landscape in this way breaks the connectivity of high fuel loads, helping to prevent or minimise the spread and intensity of wildfire.

Previous studies have observed the importance of landscape-level fuel treatment (Chung 2015). The spatial arrangement of fuel treatment planning plays a substantial role in providing better protection in the landscape (Rytwinski and Crowe 2010). Fuel arrangement can modify fire behaviour and when fragmented, can lessen the chance of large wildfires (Kim et al. 2009). The main factor that affects wildfire extent is the connectivity of ‘old’ untreated patches (Boer et al. 2009). Wei and Long (2014) proposed a single-period model to break the connectivity of high fuel load patches by taking into account the duration and speeds of a future fire. Taking into account the vegetation dynamics over time is fundamental to accurate fuel treatment planning (Krivtsov et al. 2009). Minas et al. (2014) achieved a multi-period model for fuel treatment planning. This model breaks the connectivity of ‘old’ patches in the landscape to minimise fire spread and takes into account the vegetation dynamics for treated and untreated areas at each time increment. This model tracks changes in fuel for a single vegetation type, yet does not take into consideration habitat connectivity or any other ecological requirements. Habitat connectivity is vital to support the ecology and genetics of local populations and endangered species (Rayfield et al. 2015). To date, no approach has been developed for the fuel treatment and habitat conservation problem.

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 the habitat connectivity to be modelled and solved using exact optimisation. In this proposed approach, the minimum and maximum Tolerable Fire Intervals (TFIs) are used to describe the ecological fire requirements of the ecosystem. TFIs are the minimum and maximum recommended times between fire events for a particular vegetation type (Cheal 2010). We assume that fuel treatment can support the ecosystem’s health if it is conducted when the vegetation age is between these two intervals. The vegetation types whose age are over the maximum TFI are also treated to help maintain vegetation condition and renewal.

The efficacy of the applications of fuel treatment remains debated among experts according to different perspectives (Penman et al. 2011). Fuel treatments reduce the overall fuel load in landscapes (Martell 2015) that at the same time may result in significant habitat modification for species populations living within the treated area. If 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 (Brown et al. 2009) for survival. This vegetation recovers very slowly after fuel treatments, and the Mallee emu-wren is unable to survive in vegetation aged less than 15 years. Similarly, frequent fires in California can destroy the mature coastal sage scrub habitat required for the coastal cactus wren and the California gnatcatcher on which these species rely (Conlisk et al. 2015). If we want to conserve these species, it is important to maintain the availability and connectivity of their habitats. The question that then arises is: Can fuel treatments be scheduled to break the connectivity of high fuel load areas while limiting its negative impacts on the ecosystem?

Similarities exist between the fuel treatment problem described here and the forest harvesting problem and its impact on the environment. 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 adverse side effects to natural ecosystems, such as habitat loss. Previous studies in the forest harvesting problem have taken into account some ecological requirements. Öhman and Wikström (2008) 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, the compactness of the habitat for species can be achieved. The model was run in a five-yearly planning horizon across a landscape that comprised 924 stands within a reasonable computational time. However, their model
did not consider habitat connectivity across time. Addressing this shortcoming, Könnyű et al. (2014)
proposed a model that ensures mature forest patches are temporarily connected between time-steps
while scheduling forest harvesting. The model works well and does not substantially reduce timber
revenues. However, like the previous fuel treatment models, 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.

Therefore, this paper brings together ideas from previous research in forest harvesting operations
by incorporating habitat connectivity across time as well as maintaining habitat connectivity within
each time period, to formulate an approach to the fuel treatment and habitat planning problem. Furthermore, the fuel treatment problem requires the landscape to be fragmented, whereas in contrast, the
forest management problem seeks to maintain clusters in the landscape.

A Mixed Integer Programming (MIP) approach is presented here for fuel treatment planning to
fragment the high fuel load areas as much as possible while still considering the TFIs to support
biodiversity and maintaining two forms of habitat connectivity in the landscape with a single vegetation
type and a single species. We assume that the animal species can relocate to a neighbouring area that
has similar habitat characteristics (for example, the same vegetation age stage). In the first form
of habitat connectivity, each treated region forming a habitat has to be connected to an alternative
habitat for the species to relocate (that is, neighbouring mature areas). Second, at any period, a
minimum acceptable target is set for habitat connectivity to conserve species. The model is then
demonstrated on a series of hypothetical landscapes comprising rectangular grid cells.

2 Model formulation

In this paper, cells represent the candidate locations for fuel treatment in a landscape. For each cell,
time since treatment or fuel age (years) is tracked. Fuel treatment determines the cell’s fuel age at each
period. The cell’s fuel age is reset to zero if the cell is treated or incremented by one if untreated. Each
cell has its minimum and maximum tolerable fire intervals (TFIs). Each cell also has its mature age
threshold which determines the suitability of the cell as a habitat and high fuel load age threshold which
determines whether the cell poses a high level of risk for fire. We assume that these two thresholds are
between the minimum and the maximum TFIs. The mature age threshold is less than the high fuel
load age threshold. The relationship between these thresholds are represented in Figure 1. If ignition
occurs , the fire will potentially spread through connected high fuel load cells. Therefore, if these
high fuel load cells are disconnected (using fuel treatment), the chance of disastrous wildfires should
be reduced. At the same time, this fuel treatment activity destroys the habitat for species. For the
purposes of illustration, we assume that the animal species of our concern live in mature or older cells.
To conserve this species, for each habitat cell to be treated, we have to provide an alternative habitat
(i.e. neighbouring mature cells) for the species to occupy during the next period.

The following mixed integer programming model is formulated to optimally decide which cells
should be treated each year to break the connectivity of high fuel load cells in the landscape while
providing continuing of habitat for the species of concern.

Sets:
Indices:

\(i = \text{cell}\)
\(t = \text{period}, \ t = 0, 1, 2, \ldots T\)

Parameters:

\(a_i = \text{initial fuel age of cell } i\)
\(\rho = \text{treatment level (in percentage), i.e. the maximum proportion of the total area in a landscape selected for treatment}\)
\(R = \text{the total area of cells in the landscape}\)
\(c_i = \text{area of cell } i\)
\(d_i = \text{high fuel load age threshold for cell } i\)
\(m_i = \text{mature age threshold for cell } i\)
\(G_t = \text{desired target of mature cell connectivity in time } t\)
\(MaxTFI_i = \text{maximum tolerable fire interval (TFI) of cell } i\)
\(MinTFI_i = \text{minimum TFI of cell } i\)

Decision variables:

\(A_{i,t} = \text{fuel age of cell } i \text{ in time } t\)
\(x_{i,t} = \begin{cases} 1 & \text{if cell } i \text{ is treated in time } t \\ 0 & \text{otherwise} \end{cases}\)
\(Mature_{i,t} = \begin{cases} 1 & \text{if cell } i \text{ is classified as ‘mature cell’ in time } t \\ 0 & \text{otherwise} \end{cases}\)
\(HabitatConn_{i,j,t} = \begin{cases} 1 & \text{if connected cell } i \text{ and } j \text{ are both mature cells in time } t \\ 0 & \text{otherwise} \end{cases}\)
\(High_{i,t} = \begin{cases} 1 & \text{if cell } i \text{ is classified as high fuel load cell in time } t \\ 0 & \text{otherwise} \end{cases}\)
\(HighConn_{i,j,t} = \begin{cases} 1 & \text{if connected cell } i \text{ and } j \text{ are both high fuel load cells in time } t \\ 0 & \text{otherwise} \end{cases}\)
\(Old_{i,t} = \begin{cases} 1 & \text{cell in time } t \\ 0 & \text{otherwise} \end{cases}\)

minimise the connectivity of high fuel load cells

\[ z = \sum_{t=1}^{T} \sum_{i \in C} \sum_{j \in \Phi_i, i < j} HighConn_{i,j,t} \]  

subject to

\[ \sum_{i} c_i x_{i,t} \leq \rho R, \ t = 1 \ldots T, \forall i \in C \]
\[ A_{i,0} = a_i, \forall i \in C \] (3)

\[ A_{i,t} \geq A_{i,t-1} + 1 - M_1 x_{i,t}, t = 1 \ldots T, \forall i \in C \] (4)

\[ A_{i,t} \leq M_2 (1 - x_{i,t}), t = 1 \ldots T, \forall i \in C \] (5)

\[ A_{i,t} \leq A_{i,t-1} + 1, t = 1 \ldots T, \forall i \in C \] (6)

\[ A_{i,t} - d_i \leq M_3 \text{High}_{i,t} - 1, t = 1 \ldots T, \forall i \in C \] (7)

\[ A_{i,t} \geq d_i \text{High}_{i,t}, t = 1 \ldots T, \forall i \in C \] (8)

\[ \text{High}_{i,t} + \text{High}_{j,t} - \text{HighConn}_{i,j,t} \leq 1, t = 1 \ldots T, \forall j \in \Phi_i, i < j, \forall i \in C \] (9)

\[ A_{i,t} - m_i \leq M_4 \text{Mature}_{i,t} - 1, t = 1 \ldots T, \forall i \in C \] (10)

\[ A_{i,t} \geq m_i \text{Mature}_{i,t}, t = 1 \ldots T, \forall i \in C \] (11)

\[ \sum_{j \in \Phi_i} \text{Mature}_{j,t} \geq x_{i,t}, t = 1 \ldots T, \forall i \in C \] (12)

\[ \text{Mature}_{i,t} + \text{Mature}_{j,t} - \text{HabitatConn}_{i,j,t} \leq 1, t = 1 \ldots T, \forall j \in \Phi_i, i < j, \forall i \in C \] (13)

\[ \text{Mature}_{i,t} + \text{Mature}_{j,t} \geq 2 \text{HabitatConn}_{i,j,t}, t = 1 \ldots T, \forall j \in \Phi_i, i < j, \forall i \in C \] (14)

\[ \sum_{i \in C} \sum_{j \in \Phi_i, i < j} \text{HabitatConn}_{i,j,t} \geq G_t, t = 1 \ldots T, \forall i \in C \] (15)

\[ A_{i,t} - \text{MaxTFI}_i \leq M_5 \text{Old}_{i,t} - 1, t = 0 \ldots T - 1, \forall i \in C \] (16)

\[ A_{i,t} \geq \text{MaxTFI}_i \text{Old}_{i,t}, t = 0 \ldots T - 1, \forall i \in C \] (17)

\[ \text{Old}_{i,t-1} + \frac{1}{|\Phi_i|} \sum_{j \in \Phi_i} \text{Mature}_{j,t} \leq 1 + x_{i,t}, t = 1 \ldots T, \forall i \in C \] (18)

\[ A_{i,t-1} \geq \text{MinTFI}_i x_{i,t}, t = 1 \ldots T, \forall i \in C \] (19)

\[ x_{i,t}, \text{High}_{i,t}, \text{HighConn}_{i,j,t}, \text{Mature}_{i,t}, \text{Old}_{i,t} \in \{0, 1\} \] (20)

The objective function (1) minimises the connectivity of high fuel load cells in a landscape across planning horizon. Constraint (2) specifies that the total area selected for fuel treatment should not exceed the total area allocated for fuel treatment in each period.

Constraint (3) sets the initial fuel age in a cell. Constraints (4) to (6) track the fuel age of each cell. Constraints (4) and (5) indicate that if a cell is not treated, then the cell’s fuel age will be incremented by one in the following period. Whereas if a cell is treated, the fuel age will reset to zero. Constraints (4) and (6) increment fuel age by exactly one year if the cell is not treated.
Fig. 2: Proportion of initial cell’s fuel age in the landscape for the computational experiments

Constraints (7) and (8) use binary variable $High_{i,t}$ to classify a cell to be 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 time $t$.

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 this period unless there is at least one neighbouring mature cell in the following period.

In this model, we also consider maintaining habitat (mature-cell) connectivity in the landscape for each period. Constraints (13) and Constraint (14) ensure that $HabitatConn_{i,j,t}$ takes exactly value one if and only if connected cells $i$ and $j$ are both classified as mature cells at time $t$. Constraint (15) makes sure that the number of habitat connections each year is greater than the desired target, $G_t$.

Constraints (16) to (17) classify a cell to be an ‘over- the-maximum-TFI’ cell (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 maximum TFI, and there is at least one neighbouring mature cell in the following period. 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.

3 Model illustration

In this section, we demonstrate the approach discussed in Section 2 using hypothetical random landscapes comprising 100 grid cells, generated using the NLMpy package (Etherington et al., 2015). We assume that there is a single fuel type in the landscape, with the thresholds of mature 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, respectively. 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 2 represents the assumed distribution of the initial cell fuel age. A cell is assumed to be connected to its immediate neighbouring cells that have shared boundaries (Figure 3). 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.

Initially, the landscape has 13 high fuel load cell connections and 39 habitat connections that we want to maintain over the planning horizon, as illustrated in Figure 4. In this model illustration, we compare four different settings (Table 1). In the first and second settings, we maintain the initial number of 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 we do not have that requirement enforced. In the third setting, 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 any species conservation consideration. All settings are different in terms of the first and second form of habitat connectivity. However, they are the same in terms of the requirement for conducting the fuel treatment planning between the minimum and the maximum TFIs.

The solutions to settings 1 to 4 are illustrated in Figure 5, Figure 6, Figure 7 and Figure 8, respectively. Under settings 1, 2 and 3, in some years, the number of treated cells is less than the treatment level (ten percent of the total landscape) due to the habitat conservation requirements. In settings 3 and 4, the high fuel load cells in the landscape are fully fragmented more quickly than settings 1 and 2 within the planning horizon, because under settings 1 and 2, there are 39 connections of the habitat that need to be maintained each year. All settings show that while this landscape is homogeneous in terms of fuel type, there is no particular pattern in treating the cells each year. This irregular pattern is due partially to factors such as the varied initial ages and minimum and maximum TFI requirements. Although the cells treated in the first year would grow over the high fuel load threshold by year 13, the figures show that the cells selected for fuel treatment in year one may or may not be re-selected in year 13. Results of settings 1 and 3 show that in the absence of adjacent mature habitat cells, the cells exceeding the maximum TFI cannot be treated. The number of habitat connectivity and the high fuel load area connectivity resulting from the four settings of the model illustration are represented in Figure 9.

From the solutions of this model illustration, we also track the existence of animals in mature cells in the landscape over the planning horizon for the four settings, as represented in figures 5 to 8. We assume that initially, all mature/high fuel load cells are populated by an endangered species. The species can only move from one habitat to another habitat, and they will not populate a new habitat unless there is a direct connection. Here, we use the same definition of connection as illustrated in Figure 3, meaning that in a single period, the species can only move one cell away to four neighbouring cells (right, left, up, or down). The proportion of mature cells with species in the landscape for the model illustration is represented in Figure 11.
Fig. 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
- Non-mature cell
- Mature and high fuel load age cell

2 Cell's fuel age
Fig. 5: Fuel treatment schedule with ten percent treatment level and thirteen-year planning horizon for the first setting, $G_t= initial$
Fig. 6: Fuel treatment schedule with ten percent treatment level and thirteen-year planning horizon for the second setting, $G_t = \text{initial, without applying Constraint (12)}$.
Fig. 7: Fuel treatment schedule with ten percent treatment level and thirteen-year planning horizon for the third setting, $G_t = 0$. 

![Fuel treatment schedule diagram](image-url)

- **t = 0**: Initial state of the fuel treatment.
- **t = 1**: First year of treatment.
- **t = 2**: Second year of treatment.
- **t = 3**: Third year of treatment.
- **t = 4**: Fourth year of treatment.
- **t = 5**: Fifth year of treatment.
- **t = 11**: Eleventh year of treatment.
- **t = 12**: Twelfth year of treatment.
- **t = 13**: Thirteenth year of treatment.

Legend:
- [ ] Treated cell
- [ ] Cell's fuel age
- [ ] Under minimum TFI cell
- [ ] Non-mature cell
- [ ] Mature fuel age cell
- [ ] Mature and high fuel load age cell
- [ ] Mature fuel age cell with species
- [ ] Mature and high fuel load age cell with species
Fig. 8: Fuel treatment schedule with ten percent treatment level and thirteen-year planning horizon for the fourth setting, $G_t = 0$, and without applying Constraint (12)
Fig. 9: The number of habitat connectivity and high fuel load connectivity of the model illustration (10 × 10 grid cells, ten-percent treatment level)

Fig. 10: The proportions of high fuel load cells and mature cells in the landscape for the model illustration (10 × 10 grid cells, ten-percent treatment level)
4 Computational experiments

A series of computational experiments were conducted by 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 64 GB of RAM is used for the computational experiments. The landscape sizes are $10 \times 10$ and $15 \times 15$ grid cells.

The computational experiments are conducted with these following steps. Firstly, for each landscape size, 30 hypothetical landscapes are generated using NLMpy package. Figure 2 represents the assumed percentages of the initial cell’s fuel age in each landscape. Then, we ran four different settings based on Table 1. In the first two settings, we evaluated the initial number of connected habitat (connected mature cells) for each landscape. Based on this result, we maintain this number over the planning horizon.

For each setting, we ran computational experiments for 30 landscapes for each landscape size ($10 \times 10$ and $15 \times 15$ grid cells), with ten-percent treatment level and a ten-year planning horizon. In the first and second settings, we found that for some landscapes, it is impossible to maintain the initial number of habitat over the planning horizon. To deal with this infeasibility, we ran the model by assigning a lower value of $G_t$ for the first years in a planning horizon, and setting the higher value (the initial number of habitat connectivity) of $G_t$ for the rest of the year within the planning horizon only once it is feasible.

The 95% confidence intervals of the number of high fuel load cell connectivity and habitat connectivity for the four settings are summarised in Figure 12. This figure shows that for the first two settings the number of high fuel load cells connectivity decreases over time, and the number of habitat connectivity is relatively stable and can be maintained at their initial level. For the third and fourth settings, the number of high fuel load cells connectivity reaches zero since year two, but the number of habitat connectivity decreases significantly over time. Figure 13 summarises the 95% confidence intervals of the proportions of the high fuel load cells and mature cells for the four settings. The third and fourth settings provide less mature cells than the first and second settings, and the first setting outperforms the others.

The proportion of mature cells with species in the landscape for these computational experiments is summarised in Figure 14. The difference between settings 3 and 4 clearly shows that requirement of having a neighbouring mature cell for treatment itself is important in the absence of maintaining the overall habitat connectivity. The difference between the first two settings and the last two settings shows that the overall limit on connectivity works well for this measure.
Fig. 12: 95% confidence interval of high fuel load cell connectivity and habitat connectivity for the computational experiments.
Fig. 13: 95% confidence interval of proportions of high fuel load cells and mature cells in the landscape for the computational experiments

Fig. 14: Proportion of mature cells with species in the landscape for the computational experiments
5 Conclusion

In this paper, we proposed a mixed integer programming approach to schedule fuel treatments. This approach tracks the age of vegetation in each cell in each year and optimally decides when and where to conduct fuel treatment to fragment high fuel load cells in the landscape while meeting ecological requirements. Three types of ecological constraints were considered comprising the following; the minimum and maximum Tolerable Fire Intervals (TFIs); the availability of suitable habitat adjacent to areas being treated at any time; maintain the initial level of habitat connectivity in the landscape throughout the planning horizon. The application of the model to hypothetical landscapes demonstrated that the objective could be achieved while meeting the ecological constraints discussed above.

The problem dealt with in this paper has similarities to the problem of scheduling forest harvests. An important difference in our work is that after treatment (such as controlled burning) we require high fuel load areas to be as dispersed as possible to reduce the risk of wildfires spreading over large areas. This is not a consideration in the forest harvesting problem. Our problem is further complicated by the two separate requirements of ensuring sufficient contiguity of habitat at any particular time and the need for appropriate habitat to neighbour any area that is to be treated. These two requirements together also need to ensure that fauna do not become trapped in an area that needs treatment.

We anticipate that for practical implementations, our approach can assist fire and land management agencies in making their decisions about timing and locations of future fuel treatments while considering critical ecological requirements.

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