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Welcome from Editor

It is my pleasure to bring to you the compiled papers from the Science Day of the AFAC and Bushfire CRC Annual Conference, held in the Sydney Convention Centre on the 1st of September 2011.

These papers were anonymously referred. I would like to express my gratitude to all the referees who agreed to take on this task diligently. I would also like to extend my gratitude to all those involved in the organising, and conducting of the Science Day.

The range of papers spans many different disciplines, and really reflects the breadth of the work being undertaken, The Science Day ran four steams covering Fire behaviour and weather; Operations; Land Management and Social Science. Not all papers presented are included in these proceedings as some authors opted to not supply full papers.

The full presentations from the Science Day and the posters from the Bushfire CRC are available on the Bushfire CRC website www.bushfirecrc.com.

Richard Thornton

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Integrated decision support model for fuel management and suppression preparedness planning

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Abstract

Bushfire management involves a complex mix of interrelated components including fuel management, fire prevention, fire detection and suppression preparedness planning. Previous wildfire optimisation models have tended to consider these components in isolation from one another. Such models fail to capture the interdependency of system elements and can lead to myopic decision making. We propose an approach that considers both fuel management and suppression preparedness planning within a single optimisation model. The model's effectiveness is tested using a series of hypothetical landscapes, with results indicating that an integrated approach to fuel management and suppression preparedness planning can lead to improved coverage outcomes. Model benefits, potential applications, future testing and possible model extensions are also discussed.

Introduction

Bushfire management involves a complex mix of interrelated components and processes including: fuel management, fire detection, fire weather forecasting, identification of vulnerable areas, inter-agency coordination, fire suppression and knowledge of fire behaviour (Bonazountas et al. 2007). Operations Research (OR) is a discipline that can assist managers operating in this challenging environment. OR is the use of analytical techniques such as mathematical modelling to analyse complex interactions between people, resources and the environment to aid decision-making and the design and operation of systems (Altay and Green 2006).

Fire managers are faced with complex problems consisting of a large number of inter-related decisions together with resourcing and other operational constraints. Optimisation is a field of OR that is suited to such problems. Optimisation is concerned with optimising the use of limited resources to achieve an objective. In an optimisation model this objective is defined as a mathematical function of the decision variables in the form of an 'objective function' and is optimised subject to a series of related constraints. Optimisation models have been applied to a range of wildfire management problems including: fuel management, fire prevention, fire detection, deployment of suppression resources to bases and dispatch of suppression resources to fires. Details of the use of optimisation methods in wildfire management from 1961-1981 can be found in Martell's (1982) comprehensive review of wildfire OR work, elements of this review were subsequently updated in 1998 (Martell et al. 1998). Minas et al. (paper in press) provide a detailed account of post-1998 wildfire optimisation work.

Fuel reduction burning is a bushfire management mechanism aimed at minimising risk to human assets and life. Fire agencies undertake fuel reduction burning with a view to reducing fuel loads in strategic areas and thus reducing the intensity and rate of spread of future bushfires (Penman et al. 2011). A number of optimisation models have been developed for spatial allocation of fuel treatment across a landscape. Hof and Omi (2003) developed a model to determine optimal spatial application of fuel reduction treatments so as to mitigate the effects of a particular "target fire" with a known origin and spread behaviour. Wei et al. (2008) formulated a model for optimal allocation of fuel treatment across a landscape based on spatially explicit ignition risk, fire spread probability, fire intensity levels and values-at-risk. Konoshima et al. (2008; 2010) used optimisation methods to explore optimal fuel treatment spatial patterns across a hypothetical landscape subject to fire risk.

Bushfire agencies establish fire suppression systems that seek to control and extinguish destructive fires. Limits to suppression system capacity are reached when: there are too many fires to attend at once, the fire perimeter grows more quickly than it can be put out, parts of the fire perimeter are too intense to control, or there are too many point assets such as houses to protect (Gill 2005). Fire managers make strategic preparedness decisions about where to base suppression resources in an attempt to maximise fire suppression system effectiveness. Optimisation methods have been applied to the problem of home-basing and deployment of suppression resources. The maximal covering location model (MCLM) (Church and ReVelle 1974) is a classic optimisation model that has been used extensively in emergency service deployment. Dimopoulou and Giannikos (2001; 2004)

used a variant of the MCLM model for suppression resource deployment as part of a larger wildfire decision support system. Kirsch and Rideout (2005) developed an optimisation model for initial attack preparedness planning. Their model deployed initial attack resources across a user-defined set of fires with the objective being to maximise the weighted area protected for a given level of budget funding, with weights assigned based on protection priorities. Haight and Fried (2007) formulated a scenario-optimisation model for suppression resource deployment that included a binary “standard response” variable as a proxy for fire-line construction. Their model’s objective was to minimise the number of fires not receiving a “standard response” across a defined set of scenarios.

The optimisation models discussed above consider the fuel treatment and suppression preparedness components of bushfire management in isolation from one another. However, these components are interrelated in that fuel treatment positively affects suppression efforts by reducing fire spread rates and fire intensity (Rideout et al. 2008). This altered fire behaviour has implications for suppression resource requirements and in turn suppression preparedness planning. This interrelation suggests a need for integrated approaches to fuel treatment and suppression preparedness planning. In this paper we present an optimisation model that incorporates both fuel management and suppression preparedness decisions. The model is presented in a general form and demonstrates how these interrelated fire management elements can be integrated into a single optimisation model. As such the model represents an important first step in the development of operational optimisation models that capture dependencies amongst fuel management and suppression preparedness actions. The remainder of the paper is structured as follows. The mathematical formulation of our model is presented and explained. The effectiveness of the model is then tested using a series of hypothetical landscapes with test results discussed. We then conclude by discussing future testing and possible model extensions and enhancements.

Model Formulation

We present an optimisation model that considers fuel management and suppression preparedness planning within an integrated framework. The model has been designed for seasonal (year-ahead) planning at either the state-wide or district scale. The mathematical formulation of the model is as follows.

Sets	
I:	Set of cells (candidate locations for fuel treatment and demand points), indexed i.
J:	Set of bases where suppression resources can be deployed, indexed j.
$NOTREAT$:	Set of cells where no fuel treatment is permitted, indexed i.
Variables	
$COVER_{ij}$:	$=1$, if cell i is covered by resources deployed at base j $=0$, otherwise
$TREAT_i$:	$=1$, if cell i is treated $=0$, otherwise
$PROX_{ij}$:	$=1$, if $TTIME_{ij}$ is less than the time taken for a fire in cell i to spread to 5Ha in size $=0$, otherwise
$SUFF_{ij}$:	$=1$, if resources deployed at base j are sufficient to cover a fire in cell i $=0$, otherwise
$DEPLOY_j$:	Number of suppression resources (e.g. crews) deployed to base j.
Parameters	
$VALUES_i$:	Values threatened by an uncontained fire originating in cell i.
ROS_i:	Time taken (mins) for an uncontained fire in cell i to grows to a size of 5Ha.
$PTROS_i$:	Time taken (mins) for an uncontained fire in cell i to spread to a size of 5Ha, if cell i is treated .
$TTIME_{ij}$:	Time taken (mins) for suppression resources to travel from base j to cell i.
HFI_i:	Head fire intensity (kW/m) of a fire in cell i.
$PTHFI_i$:	Head fire intensity (kW/m) of a fire in cell I, if cell i is treated .
f :	Conversion factor for relating suppression resource requirements in terms of HFI.
$MAXDEPLOY_j$:	Maximum number of suppression resources that can be deployed to base j.
$TBUDGET$:	Fuel treatment budget ($).
$TCOST_i$:	Cost ($) of treating cell i.
$DBUDGET$:	Suppression resource deployment budget ($).
$DCOST_j$:	Cost ($) of deploying a suppression resource to base j.

$$\text{MAX} \quad \sum_{i \in I} \sum_{j \in J} COVER_{ij} * \sum_{i \in I} VALUES_i \tag{1}$$

Subject to:

$$\forall i \in I \;\; \forall j \in J \qquad PROX_{ij} + SUFF_{ij} \geq 2 * COVER_{ij} \tag{2}$$

$$\forall i \in I \;\; \forall j \in J \qquad (1 - TREAT_i) * ROS_i + TREAT_i * PTROS_i \geq TTIME_{ij} * PROX_{ij} \tag{3}$$

$$\forall i \in I \;\; \forall j \in J \qquad SUFF_{ij} * [(1 - TREAT_i) * HFI_i + TREAT_i * PTHFI_i] \leq DEPLOY_j * f \tag{4}$$

$$\forall i \in I \qquad \sum_{j \in J} COVER_{ij} \leq 1 \tag{5}$$

$$\forall i \in NOTREAT \qquad TREAT_i = 0 \tag{6}$$

$$\forall j \in J \qquad DEPLOY_j \leq MAXDEPLOY_j \tag{7}$$

$$\sum_{i \in I} TREAT_i * TCOST_i \leq TBUDGET \tag{8}$$

$$\sum_{j \in J} DEPLOY_j * DCOST_j \leq DBUDGET \tag{9}$$

$$\forall i \in I \;\; \forall j \in J \qquad COVER_{ij} \text{ is binary} \tag{10}$$

$$\forall i \in I \;\; \forall j \in J \qquad PROX_{ij} \text{ is binary} \tag{11}$$

$$\forall i \in I \;\; \forall j \in J \qquad SUFF_{ij} \text{ is binary} \tag{12}$$

$$\forall i \in I \qquad TREAT_i \text{ is binary} \tag{13}$$

$$\forall j \in J \qquad DEPLOY_j \text{ is integer} \tag{14}$$

The objective function (1) maximises the weighted number of cells covered, with each cell's weighting based on the values threatened if a fire originating in that cell is not contained. Constraint (2) defines coverage, such that cell *i* is covered if there is a base *j* within close enough proximity with sufficient resources deployed there. Constraint (3) defines base *j* as within close enough proximity to cover cell *i* if the travel time between them is less than the anticipated time for a fire in cell *i* to spread to 5Ha in size. Constraint (4) defines whether or not there are sufficient resources at base *j* to cover cell *i* given the anticipated head fire intensity (HFI) in cell *i.* Constraint (5) ensures that each cell can only be covered once. Such a constraint is required in instances when there are insufficient resources available to cover all cells in the landscape. Constraint (6) identifies cells where treatment is not permitted. In practice treatment restrictions may apply for a number of reasons such biodiversity considerations or smoke hazard. Constraint (7) defines location specific deployment restrictions. In practice such restrictions would relate to a bases size or capacity. Constraint (8) imposes a budget on fuel treatment expenditure that cannot be exceeded. Constraint (9) imposes a budget on suppression resource deployment expenditure that cannot be exceeded. Constraints (10-13) restrict several variables to binary (zero or one) values. This

means a cell is either covered or it is not, a cell is treated or it is not and so forth. Constraints (14) restricts the number of resources deployed to a base to integer (whole number) values.

These binary and integer constraints lead to a more computationally complex model, making it is more difficult to solve. However they capture key of elements of the problem at hand such as the indivisibility of resource types such as tankers, and the requirement to select a certain number of cells for treatment rather than allowing “partial” treatment of the entire landscape.

A key and novel feature of the formulation is the inclusion of both fuel treatment and suppression deployment decision variables within a single model. Constraints (3 and 4) capture the interrelation between these variables, in that fuel treatment changes a cell’s fire behaviour properties which in turn effects the proximity and number of suppression resources required to cover the cell in question. In Constraint (3) application of fuel treatment reduces a cell’s rate of spread meaning suppression resources based further away can now cover the cell. In Constraint (4) fuel treatment lowers a fire’s head fire intensity meaning less suppression resources are required to cover the cell.

The model structure allows for the use of spatially-explicit data such as: fuel type, fuel load, likely fire behaviour, fuel treatment costs and restrictions, suppression resource deployment costs and restrictions, fuel treatment effectiveness, travel times and values-at-risk. Fire behaviour dependent model parameters such as pre and post treatment rate-of-spread (ROS) and head fire intensity (HFI) can be either estimated or obtained using fire behaviour models. Since these parameters will be fire-weather dependent, in practice it would be prudent to run the model for a range of fire-weather scenarios. Climatology models could potentially be used to help in the selection of these scenarios.

Application of the model requires the landscape to be divided into a number of cells that need not be uniform in shape or size. Rather this partitioning would be done based on what for practical purposes constitutes the fuel treatment units specific to the given landscape that is being modelled.

The values threatened by an uncontained fire in a given cell are used in the model’s objective function to weight or prioritise the coverage of cells. Estimation of this parameter requires an understanding of fire behaviour and the use of spatially explicit values-at-risk data. The model in its present form could consider a single value, such as the number of households threatened, or a number of different values provided they can be aggregated using a common currency such as monetary value. Consideration of multiple values that are not readily expressed in a common currency would require the model to be reformulated in multi-objective form. If spatially explicit values-at-risk data is not readily available the value term can be removed from the model, this is equivalent to giving all cells an equal weighting.

The model is presented here in a fairly general form, there are a number of simple extensions that could be added to the model without significantly changing the model’s structure or the solution approach. Such extensions could include the consideration of several different suppression resource and fuel treatment types with varying costs and levels of effectiveness. Another straightforward extension would be the addition of a discretionary

budget component that could be spent on either fuel treatment or suppression resource deployment, this could be used to assist with strategic budget allocation decisions.

Model Testing and Results

The model was tested using 50 hypothetical sixteen-cell landscapes with parameter values defined in Table 1 below. A landscape size of sixteen cells was chosen so as to generate sufficiently complex non-trivial test cases that are small enough that for demonstration purposes one can intuitively see how the model is working.

Parameters	
$VALUES_i$:	random value 0-9
ROS_i:	random value 0-200
$PTROS_i$:	200
$TTIME_{ij}$:	Within cell =20 One cell away = 150 Two cells away = 200 Three cells away = 300
HFI_i:	random value 0-8000
$PTHFI_i$:	800
f:	1000
$MAXDEPLOY_j$:	12
$TBUDGET$:	3
$TCOST_i$:	1
$DBUDGET$:	12
$DCOST_j$:	1

Table 1: Parameter values for model testing

The 50 hypothetical landscapes are composed of a mixture of randomly generated and arbitrarily chosen constant parameter values. Three parameters values were randomly generated: rate-of-spread (ROS_i), head fire intensity (HFI_i) and values threatened ($VALUES_i$). For simplicity post-treatment rate-of-spread ($PTROS_i$) and post-treatment head fire intensity ($PTHFI_i$) were set as constants for all cells, meaning all treated cells exhibited the same post-treatment fire behaviour irrespective of their pre-treatment states. Bases for suppression resource deployment were able to be established in each of the sixteen cells, with no restrictions on the number of resources permitted at each base. Similarly there was no fuel treatment restrictions, with treatment permitted in all 16 cells. A matrix of travel times was constructed based on relative position of cells in the landscape. The conversion factor *f* was set at 1000 meaning one suppression resource was required to contain fire of HFI 1000 kW/m, two resources for a fire of 2000 kW/m and so forth. For simplicity, deployment and treatment costs for all cells were set at a constant value of one. With a deployment budget of twelve and a treatment budget of three, the problem became selecting which three cells to

treat and deciding how to deploy the twelve available suppression resources. The integrated model was solved on a regular PC (Intel 2Duo 2.10 GHz processor and 2.00 GB RAM) using the CPLEX 12.2 off-the shelf solver with standard settings. Solution time for each instance varied between 6 seconds and 14 minutes.

In order to assess the integrated model's performance we compared it with two alternate optimisation approaches. In the first "no treatment" approach, suppression resource deployment was optimised with no fuel treatment permitted. In the second "sequential" approach, fuel treatment was optimised first, with cells selected for treatment based on a function of values threatened and fire behaviour parameters. Treatments were then applied to selected cells, with suppression deployment then optimised based on this post-treatment landscape. The three approaches were applied to each of the 50 test landscapes. A summary of results is presented in Table 2 below, with results presented in terms of both percentage of landscape values covered and number of cells covered.

	No Treatment Approach	Sequential approach	Integrated Approach
Average % of values covered	51.2%	74.2%	79.5%
Average number of cells covered	6.1	8.9	9.4

Table 2: Summary of model testing results (50 test landscapes)

The "no treatment" approach provides a baseline measure of the level of coverage suppression resources are able to provide in the absence of fuel treatment. When we allow fuel treatment to three of the sixteen cells (i.e. 18.8% of the landscape) in the "sequential" approach it is not surprising that we see a marked improvement in the level of coverage that suppression resources are now able to provide.

The integrated model outperforms the "sequential" approach by 7.8% on average, despite the fact that in both approaches we have the same number of fuel treatment and deployment resources at our disposal. Table 3 below provides a summary of the distribution of difference in coverage achieved across the 50 test landscapes for the two approaches.

Values covered % difference between integrated and sequential approaches	Number of test landscapes
0 %	11
1-5 %	9
5 – 10%	12
10-15 %	11
15-20%	5
>20%	2

Table 3: Distribution of difference in coverage (integrated and sequential approaches)

The results in Table 3 show that whilst in eleven instances the two approaches performed equally, the results obtained using the integrated model were never bettered by the sequential approach. In many cases the integrated model performed substantially better, with greater than a 10% difference seen in eighteen of the 50 test instances. To replicate conditions where resources are more highly constrained, the 50 test instances were re-run with the deployment budget reset to five, with all other parameter values remaining unchanged. In this more constrained setting the integrated model did even better outperforming the sequential approach by 14.5%. Whilst further testing is required on larger and more realistic landscapes, the results of this initial testing seem to suggest that an integrated approach to fuel management and suppression preparedness planning can lead to improved coverage outcomes.

An illustrative example was selected from amongst the 50 test instances to demonstrate how the integrated model outperforms the “sequential” approach. In Figure 1 cells are colour-coded on an increasing scale from pale yellow up to red based on rate-of-spread and head fire intensity. Numerical values in each cell indicate values threatened if a fire originating in that cell is not contained. It can be seen in Figures 1 and 2 below that the combination of treatment and deployment decisions employed by the integrated model leads to a higher of coverage than the use of separate models in sequence.

Figure 1: Treatment selection and suppression resource deployment (example test instance)

Separate models

6 **D=5**	9 **D=1**	7 **D=3**	3
7 **D=1**	7	1	4 **T**
8 **T**	9	7 **T**	5
2	6	4 **D=2**	6

Proportion of values covered = 64.8%
Number of cells covered = 9

Integrated model

6	9 **D=1**	7 **T**	3
7 **D=1**	7	1	4
8 **D=8**	9	7 **T**	5
2	6 **T**	4 **D=2**	6

Proportion of values covered = 72.5%
Number of cells covered = 10

Figure 2: Coverage comparison (example test instance)

6	9	7	3
7	7	1	4
8	9	7	5
2	6	4	6

Both models

Separate model

Integrated model

Discussion

Fire managers are faced with large and complex problems featuring a variety of interrelated decisions and operational constraints. In this context optimisation modelling can be a useful tool for systemically exploring the decision space and seeking good solutions from the many alternatives. The optimisation model presented in this paper provides an integrated spatially-explicit framework for fuel management and suppression preparedness planning. The model has been designed to incorporate inputs from a range of sources including geospatial databases, as well as fire behaviour, fuel and climatology models. The model provides a framework to assist fire mangers in using this information to guide fuel management and suppression preparedness decision making. The model captures the interaction between these two fire management elements, so it is not surprising that it appears to outperform approaches that treat these elements separately. The integrated modelling approach supports transparent, defensible decision making and allows for comparative cost-effectiveness analysis for strategic budget allocation decisions. An integrated model such as this could be employed to assist with determining spatial locations and extents of fuel treatment whilst concurrently considering suppression resource deployment locations. In its present form the model could be applied to year-ahead planning at a district scale.

The next stage of the model's development will be the undertaking of rigorous testing using both real data and a series of larger hypothetical landscapes with a range spatial attributes. Testing using real data will provide insights into the operational time required for application of the model in real life scenarios. This would include the time needed to source and format the requisite input data, as well as optimisation model solution times. This further testing will also incorporate the simple model extensions discussed earlier including: consideration of different suppression resource and fuel treatment types, and the addition of a discretionary budget component available for either fuel treatment or suppression resource spending.

There are a number of possible extensions that could be made to the model to expand the scope of analysis a few of these extensions are discussed briefly here. A multi-objective (MO) formulation could be employed to allow for the explicit consideration of conflicting objectives including the protection of various market and non-market values threatened by fire. An MO model would allow decision-makers to examine trade-offs amongst the various objectives and support transparent and defensible decision making. Another possible extension is the use of a multi-period formulation in order to consider fuel treatment over a number of years rather than just one year ahead. Such a model could incorporate "diminishing returns" on fuel treatment effect over time due to vegetation regrowth. A multi-year model could also include ecological considerations relating to burn frequency and spatio-temporal landscape composition. The problem could also be formulated as a two-stage stochastic programming model with recourse, with fuel treatment decisions made in the first stage and suppression deployment decisions made in the second stage.

References

Altay N, Green WG (2006) OR/MS research in disaster operations management. *European Journal of Operational Research* **175**(1), 475-493

Bonazountas M, Kallidromitou D, Kassomenos P, Passas N (2007) A decision support system for managing forest fire casualties. *Journal of Environmental Management* **84**(4), 412-418.

Church R, ReVelle C (1974) The maximal covering location problem. *Papers in regional science* **32**(1), 101-118.

Dimopoulou M, Giannikos I (2001) Spatial optimization of resources deployment for forest-fire management. *International Transactions in Operational Research* **8**(5), 523-534.

Dimopoulou M, Giannikos I (2004) Towards an integrated framework for forest fire control. *European Journal of Operational Research* **152**(2), 476-486.

Konoshima M, Albers H, Montgomery C, Arthur J (2010) Optimal spatial patterns of fuel management and timber harvest with fire risk. *Canadian Journal of Forest Research* **40**(1), 95-108.

Konoshima M, Montgomery C, Albers H, Arthur J (2008) Spatial-Endogenous Fire Risk and Efficient Fuel Management and Timber Harvest. *Land Economics* **84**(3), 449.

Gill M (2005) Landscape fires as social disasters: An overview of the bushfire problem. *Environmental Hazards* **6**(2), 65-80.

Haight RG, Fried JS (2007) Deploying wildland fire suppression resources with a scenario-based standard response model. *INFOR* **45**(1), 31-39.

Hof J, Omi P (2003). Scheduling removals for fuels management. RMRS USDA Forest Service. Fire, fuel treatments, and ecological restoration: Conference proceedings RMRS-P 29, pp.367–378 (Fort Collins, CO).

Kirsch A, Rideout D (2005). Optimizing initial attack effectiveness by using performance measures. PNRS USDA Forest Service. System analysis in forest resources: Proceedings of the 2003 symposium. General Technical Report PNW-GTR-656, pp.183-188 (Portland, OR).

Martell DL (1982) A review of operational research studies in forest fire management. *Canadian Journal of Forest Research* **12**(2), 119-140.

Martell DL, Gunn EA, Weintraub A (1998) Forest management challenges for operational researchers. *European Journal of Operational Research* **104**(1), 1-17.

Minas J, Hearne J, Handmer J A review of operations research (OR) methods applicable to wildfire management. *International Journal of Wildland Fire* **Paper in press**.

Penman, T. D., Christie, F. J., Andersen, A. N., Bradstock, R. A., Cary, G. J., Henderson, M. K., et al. (2011). Prescribed burning: how can it work to conserve the things we value? *International Journal of Wildland Fire, 20*(6), 721-733.

Rideout D, Wei Y, Kirsch A, Botti S (2008) Toward a unified economic theory of fire program analysis with strategies for empirical modelling. In 'The economics of forest disturbances: Wildfires, storms and invasive species.' (Eds T Holmes, J Prestemon and K Abt) pp. 361-380. (Springer: New York).

Wei Y, Rideout D, Kirsch A (2008) An optimization model for locating fuel treatments across a landscape to reduce expected fire losses. *Canadian Journal of Forest Research* **38**(4), 868-877.