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A review of operations research (OR) methods applicable to wildfire management

Suggested running head: A review of OR methods for wildfire management

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Abstract

Across the globe wildfire-related destruction appears to be worsening despite increased fire suppression expenditure. At the same time, wildfire management is becoming increasingly complicated due to factors such as an expanding wildland-urban interface, inter-agency resource sharing and the recognition of the beneficial effects of fire on ecosystems. OR is the use of analytical techniques such as mathematical modelling to analyse interactions between people, resources and the environment to aid decision-making in complex systems. Fire managers operate in a highly challenging decision environment characterised by complexity, multiple conflicting objectives and uncertainty. We assert that some of these difficulties can be resolved with the use of OR methods. We present a range of OR methods and discuss their applicability to wildfire management with illustrative examples drawn from the wildfire and disaster OR literature.

Additional keywords: bushfire, forest fire, wildland fire, operational research, decision-making, management science

Summary for Table of Contents

Wildfire managers operate in a highly challenging decision environment characterised by complexity, multiple conflicting objectives and uncertainty. Operations research (OR) is a discipline that uses analytical techniques to aid

- 28 decision making in complex systems. This paper discusses a range of OR methods available to assist wildfire
- 29 managers with illustrative examples drawn from the wildfire and disaster OR literature.

30 **Introduction**

31

32 The February 2009 bushfires in Victoria, Australia provided a stark reminder of the destructive potential of wildfire.
 33 The fires resulted in 173 fatalities and damage to property, infrastructure and the natural environment with an
 34 estimated total cost of over A\$4 billion (Teague et al. 2010). Globally, wildfire-related destruction is a problem that
 35 appears to be worsening. In the Mediterranean basin a sharp increase in wildfire events has been observed over the
 36 past several decades despite increased investment in prevention and suppression (Carmel et al. 2009; Pappis and
 37 Rachaniotis 2010). Increased wildfire activity has also been observed in the United States (Westerling et al. 2006) and
 38 Canada (Podur et al. 2002). This upward trend appears set to continue due to rising temperatures and changed weather
 39 conditions associated with climate change (Wotton et al. 2003; Westerling et al. 2006). As suppression expenditures
 40 continue to rise, governments seek wildfire management approaches that are economically efficient and that take into
 41 account both market and non-market benefits (Venn and Calkin 2011).

42

43 Wildfire managers operate in a difficult decision environment. They are faced with limited time, constrained
 44 resources, extreme uncertainty and multiple objectives that may conflict (Martell et al. 1998). In recent years, wildfire
 45 management has become increasingly complex with the advent of inter-agency resource sharing arrangements and the
 46 recognition of the beneficial effects of fire on ecosystems (Martell 2011). Operations Research (OR) is a discipline
 47 that is uniquely placed to assist managers operating in this challenging environment. OR is the use of analytical
 48 techniques such as mathematical modelling to analyse complex interactions between people, resources and the
 49 environment to aid decision-making and the design and operation of systems (Altay and Green 2006). Wildfire
 50 managers have access to a proliferation of data from a variety of sources including geospatial databases and fire
 51 behaviour and climatology models. OR methods can provide a framework to help wildfire managers make sense of
 52 this information and use it to guide decision-making.

53

54 There is a large body of disaster management OR work relating to non-routine emergency events such as:
 55 earthquakes, floods and hurricanes (Altay and Green 2006). There is also a substantive literature on the application of
 56 OR to wildfire-specific management problems. Martell (1982) conducted a comprehensive review of wildfire OR

57 work from 1961 to 1981 with elements of this review updated in 1998 (Martell et al. 1998), as such this paper will
58 focus on post-1998 wildfire OR work. The remainder of the paper is structured as follows. A range of OR methods
59 will be discussed in terms of their ability to address some of the defining challenges of wildfire management, namely:
60 complexity, multiple conflicting objectives and uncertainty. Illustrative examples and case studies drawn from the
61 wildfire and disaster OR literature will be presented for each of the OR methods discussed.

62 **Methods for handling complexity**

63

64 *Mathematical programming*

65

66 Wildfire managers are often faced with complex problems consisting of a large number of inter-related decisions
 67 together with resourcing and other operational constraints. Mathematical programming (MP) is a field of OR that can
 68 assist with such problems. MP methods are concerned with the optimization, that is maximization or minimization, of
 69 some explicit and quantifiable objective (Williams 1990). In an MP model this objective is defined as a mathematical
 70 function of the decision variables in the form of an ‘objective function’ and is optimized subject to a series of related
 71 constraints (Hillier and Lieberman 2005). Several categories of MP: linear programming (LP), integer programming
 72 (IP), nonlinear programming (NLP) and dynamic programming (DP) are described in further detail below together
 73 with examples from the wildfire and disaster OR literature.

74

75 Linear programming (LP) can be used when a problem’s objective function and constraints can be formulated as a
 76 linear combination of the decision variables (Ragsdale 2008). Hof et al. (2000) developed a timing-oriented LP model
 77 for the spatial allocation of suppression effort for an existing fire. Their model’s objective was to delay the ignition of
 78 “protection areas” such as population centres. In an extension of this work Hof and Omi (2003) described the
 79 application of a similar timing-oriented LP model to a fuel management scheduling problem. In their model, spatial
 80 application of fuel-reduction treatments were determined so as to mitigate the effects of a particular “target fire” with
 81 a known origin and spread behaviour. When a LP model is solved a “shadow price” is generated for each constraint as
 82 a standard model output. Shadow prices can be interpreted as the marginal effect that tightening or relaxing a
 83 constraint has on the objective value obtained (Williams 1990). Armstrong and Cumming (2003) used shadow prices
 84 obtained from a timber-harvesting LP model to estimate the potential cost of land based changes due to wildfire.
 85 Spatially explicit values-at-risk information like this can be useful for fuel treatment and suppression preparedness
 86 planning.

87

Integer programming (IP) models feature inputs or outputs that are required to take on discrete whole number values. IP can be useful for modelling problems that feature: indivisible resources, “yes or no” decisions or logical connections such as “if” and “then” (Wolsey 1998). IP methods have been applied to a range of wildfire management problems. The maximal covering location model (MCLM) is a classic IP model that has been used extensively in emergency service deployment (Church and ReVelle 1974). Dimopoulou and Giannikos (2001; 2004) described the use of an MCLM model for suppression resource deployment as part of a decision support system that also included a simulation module and a GIS interface. Kirsch and Rideout (2005) presented an IP 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 (WAP) for a given level of budget funding, with weights assigned based on protection priorities. Donovan (2006) presented a model for determining the optimal mix of agency and contract fire crews to minimise costs and satisfy demand across a fire season. A multi-period transportation formulation was used with the fire season modelled as a series of discrete time periods with differing levels of demand. This approach resulted in reduced computational complexity for this type of problem as compared to a standard IP formulation. Donovan and Rideout (2003) described an IP model to determine the optimal mix of fire-fighting resources to dispatch to a given fire to achieve containment with minimal resultant costs and damages. Wei et al. (2008) formulated an IP 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. Higgins et al. (2011) used an IP approach to develop a seasonal resource allocation model for planning fuel reduction burning on public lands in Victoria, Australia.

Nonlinear programming (NLP) methods are used when a problem features a nonlinear objective function or nonlinear constraints. The probability of containing a wildfire and the suppression time required to do so are nonlinear functions of fire size at the start of initial attack. This means small delays in dispatch of initial attack resources can result in dramatic fire loss increases (MacLellan and Martell 1996). Rachaniotis and Pappis sought to incorporate this element of fire behaviour in an NLP model via the use of the “deteriorating jobs” concept. Their model tackled the problem of scheduling a single fire-fighting resource when there are several existing fires to be controlled (Rachaniotis and Pappis 2006; Pappis and Rachaniotis 2010; Rachaniotis and Pappis 2011). The model was subsequently extended to allow scheduling of multiple fire-fighting resources (Pappis and Rachaniotis 2009). Minciardi et al. (2009) formulated

116 two related NLP models, one for deployment of wildfire suppression resources in the pre-operational phase and the
117 other for dispatch of resources to fires in the operational phase.

118

119 Dynamic programming (DP) is an optimisation method that is particularly useful when sequences of interrelated
120 decisions need to be made. In deterministic DP the state of the system at the next stage is completely determined by
121 the current system state and the policy decision made (Hillier and Lieberman 2005). Wiitala (1999) used a DP model
122 to determine the most efficient mix of available initial attack resources to dispatch to a fire.

123 ***Problem structuring methods***

124

125 Traditional 'OR' methods such as mathematical programming are suited to well-structured problems that can be
 126 clearly formulated in terms of performance measures, constraints and relations between action and consequence.
 127 However, many wildfire and disaster management problems lack structure and are typified by multiple perspectives,
 128 disagreement amongst experts and the presence of intangibles and uncertainties. Problem structuring methods (PSM)
 129 are a suite of techniques that can assist in resolving some of these difficulties. Compared to traditional 'hard' OR
 130 methods PSM typically employ rudimentary mathematical or statistical techniques (Mingers and Rosenhead 2004).
 131 Two PSM methods, decision conferencing and expert judgement elicitation, are discussed in further detail below.

132

133 Decision conferencing can be an effective method for assisting with longer-term collaborative decision making. A
 134 decision conference is typically a two-day event that brings together decision makers from various organisations to
 135 discuss issues and work out a way forward. A facilitator is present to keep the discussion focused. An analyst is also
 136 present to build a series of analytical decision models with a view to developing a shared understanding of the
 137 problem (French 1996). A series of decision conferences were held in the USSR following the 1986 Chernobyl
 138 nuclear accident. The aim was to identify the major factors influencing decision-making on relocation and other long
 139 term protective measures. The decision conferences helped develop a common understanding amongst participants
 140 including government ministers, policy-makers and scientists and successfully identified a number of key medical,
 141 socio-economic and political factors influencing protective measures undertaken (French et al. 1992). Decision
 142 conferencing could be similarly used following major wildfires to facilitate dialogue between stakeholders and aid
 143 recovery-phase planning.

144

145 Expert judgement elicitation (EJE) is the use of structured methods to elicit expert opinions in a planned, formal
 146 manner that attempts to minimize bias. EJE typically involves interviewing or surveying "subject experts" and then
 147 analysing their answers together with information about their background and experience. EJE methods can provide
 148 an understanding of the degree of and reasons for consensus or disagreement amongst experts and can be useful in
 149 facilitating learning and dialogue (Gregory et al. 2006). Furthermore, EJE studies are often a cost-effective and
 150 practical means of obtaining valuable information. In the wildfire context, EJE methods have been used to estimate

151 fire containment probabilities and fire-line construction rates. In these instances, alternate methods such as
152 observation of actual or experimental fires are often deemed to be too expensive, time-consuming and dangerous
153 (Hirsch et al. 1998). In one of the earliest applications of EJE methods to wildfire management subjective probability
154 assessments of daily forest fire occurrence were derived using information elicited from experienced fire managers in
155 Ontario (Cunningham and Martell 1976). Hirsch et al. (1998) used an EJE approach to model the relationship between
156 fire size, fire intensity and probability-of-containment by a 5-7 person initial attack crew. In their study they
157 interviewed crew leaders from four Canadian forest fire agencies and elicited probability-of-containment estimates for
158 various fire scenarios (Hirsch et al. 1998). Gilless and Fried (2000) surveyed California fire-fighters and used their
159 responses to estimate probability distributions for fire-line construction rates for different fire-fighting resources under
160 a range of conditions. These fire-line construction rate distributions were subsequently incorporated into the CFES2
161 simulation model used for initial attack planning in California. Similarly, Hirsch et al. (2004) interviewed crew
162 leaders in Ontario and developed probability distributions for production rates of three and four person initial attack
163 crews for a range of fuel types and fire intensities. Rideout et al. (2008) used EJE methods in their Marginal Attribute
164 Rate of Substitution (MARS) approach to assessing values-at-risk for initial attack planning.

165 *System dynamics*

166

167 In complex systems, components can interact with one another via a web of feedback loops meaning a small change
168 to input parameters can produce a drastic change to the whole system (Anderson 1999). These feedback effects can be
169 modelled using system dynamics (SD). Unlike many traditional 'hard' OR approaches that are static and linear in
170 character, SD can accept the nonlinearity and feedback loop structures of real world social and physical systems.
171 Whilst SD uses a 'soft' PSM-like approach for information elicitation and problem structuring, it includes two
172 additional 'hard' steps: model definition using rate and level equations and the running of model simulations. An SD
173 model initially serves to demonstrate how the problem under consideration is being generated in the real world, it is
174 subsequently used to test alternative policies and structures (Forrester 1994). Hoard et al. (2005) discussed the
175 application of SD methods to disaster preparedness planning in rural areas with a focus on hospital surge capacity for
176 a variety of disaster types. A similar SD approach could be used in wildfire preparedness planning to explore surge
177 capacity considerations in suppression resource deployment and rostering of fire-fighting personnel.

178 *Hyper-projects*

179

180 Wildfire incident controllers are dealing with a problem that is emergent in nature. They are faced with a 'moving
181 target' or a dynamic set of changing circumstances. The incident trajectory is influenced by actions taken such as fire
182 suppression and external forces such as weather (Faraj and Xiao 2006). Simpson (2006) defined a class of project, the
183 'hyper-project', that captures these emergent characteristics. Hyper-projects are characterised by the presence of a
184 dynamic, external 'pacing function' and a set of defined tasks and resource requirements that interact with this pacing
185 function. Time pressure is an inherent feature of hyper-projects, with tasks measured in minutes or hours. Simpson
186 (2006) used the hyper-project construct to model response to a residential structure fire, a similar approach could be
187 used to model real-time wildfire suppression decision-making. In such a model various suppression resources would
188 be dispatched and tactical fire-fighting decisions made relative to an external pacing function, which in this case
189 would be the growth and lifecycle of the uncontained wildfire. The hyper-project approach can capture threshold
190 effects, a key feature of complex biophysical systems. Thresholds are breakpoints that occur in systems with multiple
191 stable states where crossing a threshold results in a shift from one state to another (Berkes 2007). An example being
192 when a wildfire crosses the 4000 kW/m threshold it can be said to have changed state from a controllable fire to a spot
193 generating fire (Gill 2005) thus requiring a different suppression response. The hyper-project provides a framework
194 for responding to state changes via the execution of a flexible set of tasks that vary in a pre-defined manner relative to
195 the pacing function.

196 **Methods for handling multiple conflicting objectives**

197

198 *Multi-objective optimization*

199

200 Wildfire management involves various agencies and groups with different priorities and objectives including:
 201 reduction of impacts on public safety, private property and ecosystem processes as well as cost minimisation (Martell
 202 2007). Instances will often arise where multiple objectives conflict with one another, for example frequent planned
 203 burning can provide additional protection to built assets but may have a negative impact on biodiversity in some
 204 ecosystems (Driscoll et al. 2010). Where multiple objectives can be expressed in terms of market values they can be
 205 aggregated into a single cost minimization objective. However wildfire managers are required to consider potential
 206 impacts on non-market values such as: ecosystem health, conservation of flora and fauna, air quality, water quality,
 207 recreational opportunities and cultural heritage (Venn and Calkin 2011). In many cases ascribing a monetary value to
 208 these items would be an expensive, time-consuming and uncertain exercise. This lack of a common currency makes it
 209 difficult to evaluate and compare the outcomes of decisions or strategies. Multi-objective optimization (MO) is a
 210 technique that is suited to these types of problems. MO models are formulated with more than one objective function
 211 to find a set of Pareto optimal solutions. A solution is Pareto optimal if none of the objectives can be improved
 212 without making another objective worse. Decision-makers can assess alternatives from this set of Pareto optimal
 213 solutions by examining trade-offs amongst the various objective values. This explicit identification and structured
 214 exploration of trade-offs provides a level of transparency in the decision process (Gregory et al. 2006). Lehmkuhl et
 215 al. (2007) described FUELSOLVE a prototype decision support system that incorporates MO modelling into fuel
 216 management decision-making to consider both ecological and cost objectives. Kennedy et al. (2008) demonstrated the
 217 use of the FUELSOLVE MO model with a fuel treatment case study with trade-offs assessed between protection of
 218 endangered species habitat, preservation of old growth forest reserves and minimization of area treated.

219

220 Goal Programming (GP) is a branch of multi-objective optimization in which each of the multiple objectives takes the
 221 form of a goal. Goals are formulated as 'soft constraints' each with a target value it is desirable to satisfy. A penalty
 222 function is then specified that seeks to minimise deviations from this set of target values. Adjustments to the penalty

223 function parameters allows the exploration of trade-offs between objectives (Ragsdale 2008). Calkin et al. (2005) used
224 a GP approach to analyse trade-offs between fire threat reduction and habitat preservation in silvicultural treatment
225 scheduling. A goal programming module is currently under development as part of the United States Fire Program
226 Analysis (FPA) project (Kumar et al. 2010). The FPA project has been undertaken by the US Forest Service and other
227 federal land management agencies in an attempt to develop a wildfire management planning and budgeting decision-
228 support tool that will incorporate a full range of both market and non-market objectives (Venn and Calkin 2011).

229 **Methods for handling uncertainty**

230

231 ***Simulation***

232

233 Wildfire managers are required to make difficult decisions in conditions of uncertainty. Simulation is arguably the
 234 most robust and easily applied method for consideration of uncertainty in decision support systems (Mowrer 2000).
 235 Simulation is an approach used to model real-life stochastic systems that evolve probabilistically over time. The real-
 236 life system's performance is imitated by using probability distributions to generate various events that occur in the
 237 system (Hillier and Lieberman 2005). Prior to implementation, simulation models require validation to ensure they
 238 realistically represent the system being analysed and that the results they provide are reliable (Winston 1994).
 239 Simulation models feature in a number of decision support systems used by wildfire agencies for strategic planning
 240 purposes. The California Fire Economics Simulator version 2 (CFES2) is a stochastic simulation model that simulates
 241 fire occurrence and suppression on a daily basis. Simulation of many years of "data" makes it possible to undertake
 242 "what if" analysis for changes to organisational components such as: resource stationing, dispatch rules and staff
 243 schedules (Fried et al. 2006). The Level of Protection Analysis System (LEOPARDS) is underpinned by a simulation
 244 model that is spatially conscious and incorporates temporal queuing conflicts. LEOPARDS can model daily fire
 245 suppression activities and is used in Ontario to assess initial attack performance under a range of policy and budget
 246 conditions (McAlpine and Hirsch 1999). LEOPARDS has evolved from an initial attack simulation model that was
 247 developed in the early 1980s by Martell et al. (1984). The USDA Forest Service's National Fire Management
 248 Analysis System (NFMAS) Interagency Initial Attack Assessment (IIAA) is a simulation model that has been used in
 249 the past to test alternative initial attack organisations and strategies at various budget levels with a view to
 250 determining the Most Efficient Level (MEL) of funding (Lundgren 1999). Manipulation of simulation models can
 251 provide valuable insights into a problem, however the primary shortcoming of this approach is that it is only possible
 252 to find "the best" management alternative from those investigated. For large problems with many management
 253 alternatives it is unlikely that a near-optimal solution can be found in this manner. For this reason, mathematical
 254 programming (MP) methods that systemically explore the solution-space can add significant value to complex
 255 wildfire management problems (Hof and Haight 2007).

256 *Stochastic programming*

257

258 Stochastic programming (SP) is a method that combines mathematical programming methods with probability
 259 techniques to provide a constructive approach to tackling optimization problems that feature uncertain data. SP can be
 260 used when there are uncertain model parameters with probability distributions that are known or can be estimated
 261 (Kall and Wallace 1994). These parameter distributions can be either continuous or described by discrete scenarios
 262 and in some cases are generated using simulation techniques. The most common SP objective is optimization of the
 263 mean outcome or expected value of the system. An alternate formulation incorporating decision maker risk
 264 preferences is the optimization of a weighted sum of expected value and variance (Snyder 2006). SP models generate
 265 solutions that are less sensitive to data uncertainty than deterministic MP models, however large SP models can prove
 266 difficult to solve.

267

268 One of the earliest uses of SP methods in forest fire management was Boychuk and Martell's (1996) multi-stage
 269 model for forest-level timber management that considered uncertain losses that could result from fires. A common SP
 270 formulation is the two-stage model with recourse. In such models, a first-stage decision is made after which a random
 271 event occurs, a recourse decision can then be made in the second-stage that compensates for any undesirable effects.
 272 Hu and Ntaimo (2009) modelled the wildfire initial attack dispatch problem as a two-stage SP model with recourse. In
 273 their model the first stage decisions related to dispatch of suppression resources to reported wildfires, with recourse
 274 decisions made on fire-fighting tactics in the second stage. Stochastic parameters in the model included: fire growth
 275 scenarios, fire-line production rates, arrival times to fires and suppression resource operating costs. Ntaimo (2010)
 276 described an alternate application of a two-stage SP approach with deployment of suppression resources to bases in
 277 the first-stage and dispatch of resources to wildfires in the second stage. Two-stage SP models have been applied to a
 278 range of disaster management problems including: transportation of first-aid commodities on a disaster effected road
 279 network (Barbarosoglu and Arda 2004), pre-positioning of emergency supplies in a hurricane-threatened region
 280 (Rawls and Turnquist 2010) and locating storehouses and developing transportation plans for flood-relief logistics
 281 (Chang et al. 2007).

282

283 Probabilistic SP approaches, such as chance-constrained programming, require the probability of a constraint holding
284 to be above a specified threshold (Snyder 2006). Bevers (2007) demonstrated the use of chance-constrained
285 programming for a fire organisation budgeting problem. In his model formulation the probability of total fire costs
286 exceeding the budget was required to be less than a specified risk level.

287

288 Stochastic dynamic programming (SDP) is a method used for problems with sequential decisions that are subject to
289 uncertainty. SDP differs from deterministic DP in that state-to-state system transitions are governed by probability
290 distributions (Hillier and Lieberman 2005). Konoshima et al. (2008; 2010) demonstrated the use of an SDP approach
291 for determining optimal spatial patterns of fuel treatment and timber harvesting in a theoretical landscape subject to
292 fire risk. Spring and Kennedy (2005) developed an SDP model with decisions made at the beginning of each stage as
293 to which stands of trees are harvested and what level of fire protection is applied.

294 ***Robust optimization***

295

296 Like stochastic programming (SP), robust optimization (RO) provides a constructive approach to solving optimization
 297 problems that feature uncertain data (Vladimirou and Zenios 1997). However RO differs from SP in that probability
 298 distributions of uncertain parameters are not required. All that needs to be known about the uncertain parameters is
 299 that they belong to some ‘uncertainty set’ which may be described as either a continuous interval or as set of discrete
 300 scenarios (Ben-Tal and Nemirovski 2002). RO models are a great deal less sensitive to data perturbations than
 301 deterministic MP methods but substantially more difficult to solve. RO models can be formulated in a number of
 302 ways. The Minimax formulation seeks to minimise the maximum cost or damage across all possible scenarios. This is
 303 a highly conservative approach that provides costly solutions that cater for worst-case outcomes (Snyder 2006).
 304 Unless a model has significant built-in redundancies a solution is unlikely to remain both feasible and optimal across
 305 all scenarios (Vladimirou and Zenios 1997). Model and solution robustness approaches seek to balance optimality and
 306 feasibility based on the decision maker’s degree of risk aversion. Restricted scenario approaches minimise the
 307 maximum cost or damage across a restricted ‘reliability set’ of scenarios. This reliability set is specified by the
 308 decision maker based on risk preferences (Snyder 2006). Haight and Fried (2007) presented a scenario-optimization
 309 IP model for suppression resource deployment based on the classical maximal covering model (MCLM). Their
 310 formulation included a binary “standard response” variable that served as a proxy for fire-line construction. The
 311 model’s objective was to minimize the number of fires not receiving a “standard response” across a defined set of
 312 scenarios. Mercer et al.(2008) modified Haight and Fried’s standard-response model to incorporate the effects of fuel
 313 treatment. Other problems with relevance to wildfire and disaster management that RO methods have been applied to
 314 include evacuation transportation planning (Yao et al. 2009) and facility location under uncertainty (Snyder 2006).

315 ***Fuzzy models***

316

317 Stochastic programming and robust optimization methods are appropriate for problems where uncertainty is mostly
318 due to randomness, however uncertainty is sometimes due to other factors such as imprecision and ambiguity
319 (Verderame et al. 2010). Fuzzy set theory is an approach that can tackle problems that feature fuzzy predicates such as
320 'small' or 'safe', fuzzy quantifiers such as 'most' or 'often', and fuzzy probabilities such as 'likely' or 'unlikely'
321 (Smithson 1991). In classical set theory membership of a set is assessed in binary terms, that is an element either
322 belongs to a set or it doesn't. In fuzzy set theory 'degrees of membership' ranging from 0 to 1 are permitted based on
323 a fuzzy membership function (Dubois and Prade 1988). Models based on fuzzy set theory have been used to classify
324 areas into risk-zones for both fire prevention planning (Iliadis et al. 2002), (Iliadis et al. 2002b), (Iliadis 2005), (Iliadis
325 and Spartalis 2005), (Kaloudis et al. 2005), (Kaloudis et al. 2008), (Tsataltzinos et al. 2009), (Iliadis et al. 2010) and
326 disaster relief purposes (Sheu 2007), (Tan et al. 2009), (Sheu 2010).

327 **Conclusion**

328

329 In this paper we have presented a range of OR methods and discussed their ability to address some of the major
 330 challenges of wildfire management including: complexity, multiple conflicting objectives and uncertainty. Many of
 331 these OR methods are complimentary and can be used in conjunction with one another. Problem structuring methods
 332 (PSM) can be used to elicit objectives and opinions and to help develop a common understanding. Simulation and
 333 system dynamics (SD) methods can be used to model the dynamics of complex systems to gain insights into the
 334 problem structure and possible management prescriptions through the use of “what-if” analysis. Whilst optimization
 335 methods such as mathematical programming (MP) can be used to explore the decision space and seek good solutions
 336 from the many alternatives.

337

338 As more frequent and destructive wildfire events threaten lives and homes in an expanding wildland-urban interface,
 339 now more than ever we need to apply best practice analytical methods to assist wildfire managers in assessing
 340 alternatives and making decisions. However, there appears to be a large and growing gap between the decision
 341 support needs of fire managers and the decision support tools currently available (Martell 2011). We have
 342 demonstrated with the use of examples from the literature the role OR techniques can play in bridging this gap. The
 343 Victorian Bushfires Royal Commission investigated the catastrophic 2009 bushfires and made a series of
 344 recommendations aimed at reducing the risk and impacts of fire and minimising fire-related loss of life (Teague et al.
 345 2010). Of the 67 recommendations made, fifteen could be addressed with the use OR methods, including:
 346 consideration of multiple objectives in fuel treatment planning and pre-emptive risk-based deployment of aerial
 347 resources.

348

349 The many wildfire OR examples discussed in this paper range from those that are largely theoretical in nature to those
 350 that have been successfully implemented, such as the LEOPARDS model (McAlpine and Hirsch 1999). As OR
 351 formulation methods and algorithms continue to improve and greater computing power become available, it will be
 352 possible to tackle increasingly complex wildfire problems using OR methods. However in closing, it is apt to recall
 353 Martell’s (1982) reminder that OR specialists can develop decision-making aids that will enhance but not replace the

354 experience and intuition of wildfire managers, and that the successful application of OR methods will require the OR
355 analyst to work closely with wildfire agency personnel.

356

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358

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