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Multi-objective optimization to evaluate tradeoffs among forest ecosystem services following fire hazard reduction in the Deschutes National Forest, USA

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ABSTRACT

Forest owners worldwide are increasingly interested in managing forests to provide a broad suite of ecosystem services, balancing multiple objectives and evaluating management activities in terms of potential tradeoffs. We describe a multi-objective mathematical programming model to quantify tradeoffs in expected sediment delivery and the preservation of Northern spotted owl (NSO) habitat following fuel treatments to reduce fire hazard in the Deschutes National forest in Central Oregon, USA. Our model integrates the management objective of fire hazard reduction and the provision of ecosystem services (water quality and NSO habitat protection) and helps evaluate tradeoffs among them. Our results suggest significant reductions in fire hazard can be achieved without compromising any NSO habitat by strategically placing the treatments; however, the treatments will lead to a short term increase in sediment delivery. An analysis of environmental risks showed that over the longer term, the increase in sediment delivery and NSO habitat loss caused by wildfires would be 30–50% greater in areas without fuel treatments. The use of the multi-objective optimization model described in this study can help managers quantify and assess potential tradeoffs among ecosystem services and provide data for more informed decision making.

1. Introduction

An important goal of forest management is to ensure the sustainable provision of ecosystem services such as timber, clean water, recreation, wildlife habitat, and carbon sequestration (MEA, 2005). Wildfires can threaten these services; therefore, fuel treatments that remove woody material via thinning or prescribed burning to reduce fire hazard are often used in forest regions with high risk of catastrophic fire (Noss et al., 2006). The management goal is not to exclude fire from the ecosystem, but reduce its intensity and create conditions that would allow managers to use low-risk fire-fighting strategies in case wildfire extends to sensitive areas, such as watershed or wildlife habitat. Fuel treatments, however, can, in the short term, compromise ecosystem services such as wildlife habitat and/or clean water provision. We show how multi-objective optimization can be used for integrative ecosystem services assessment and quantitative analysis of these tradeoffs in a watershed in the Deschutes National Forest, USA, where the protection of water quality and northern spotted owl habitat (Strix occidentalis caurina; NSO) are both critical objectives. In the following, we summarize what we know about the positive and negative effects of fuel treatments on ecosystem services and discuss how optimization has been used in the past for tradeoff analysis in an attempt to find balanced compromises in forest and fire management.

Strategically allocated fuel treatments not only modify fuel conditions to reduce fire severity and intensity to avoid significant loss of forest ecosystem services (Kalabokidis and Omi, 1998) such as wildlife habitat (Courtney et al., 2007), they can also have indirect effects on water quality. High-severity wildfires in mountainous watersheds can destabilize soils, leading to increased sedimentation (Meyer et al., 2001; Rieman and Clayton, 1997; Wondzella and King, 2003), and potentially erode stream channels, fish habitat and drinking water in the long term; thus, fire management's goal is to minimize these consequences. Fuel treatments can also have negative effects on forest ecosystem services. Prescribed burning removes ground cover, causing erosion and changes in soil carbon and nitrogen concentration (Neary et al., 2003), and increased sedimentation following fuel

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treatments are well documented (Elliot, 2005; Cram et al., 2007; Reid, 2010; Rhodes, 2007; USDA Forest Service, 2005 and Wright et al., 1976). The effects of fuel treatments, however, are not as adverse and long-lasting as the effects of severe wildfires (USDA Forest Service, 2005). A number of programs emphasize the importance of protecting watersheds, the source of much of the drinking water in the Western US, in fire prone forests because fuel treatments there help avoid costs associated with restoring water supply and quality post-fire (Carpe Diem West, 2015). Therefore, forest managers face the dilemma of how much area should be treated, and how, when and where treatments should occur to strike a balance between short-term costs and long-term benefits.

As far as wildlife habitat is concerned, we know that fuel treatments reduce canopy closure, stem density and ground cover – by design. This, at least for the short term, may disrupt the habitat of sensitive species such as NSO that lives in old-growth forests in the Pacific Northwest, USA. Forests on the east side of the Cascade Range, where our study is located, provide habitat for NSO and its prey species (Hummel and Calkin, 2005; Buchanan et al., 1995; Everett et al., 1997); these forests, however, are prone to severe wildfires. For this reason, some researchers have suggested that habitat protection could be a limiting factor for fuel treatments (Gaines et al., 2010; Calkin et al., 2005). Others argue that modest treatments are unlikely to affect NSO habitat (Lee and Irwin, 2005). While there is uncertainty regarding the exact nature of these short term effects (Bond et al., 2002; Lee and Irwin, 2005), the long term benefits of fuel treatments are indisputable. High severity wildfires often destroy NSO habitat, which takes a long time to recover (Courtney et al., 2007), and fuel treatments, although their efficacy may vary, can significantly reduce the severity of wildfire effects (Murphy et al., 2010; Omi et al., 2010; Fernandes and Botelho, 2003; Pollet and Omi, 2002). Using forest vegetation and wildfire spread simulations, Ager et al. (2007) has previously shown that the expected loss of NSO habitat in late seral stage forests can be reduced substantially by strategically placing treatments outside the habitat areas because the treatments retarded the fire spread onto the habitat area. One of the benefits of the multi-objective optimization model proposed in this paper is that it can help us quantify the maximum reduction in fire hazard, defined as wildfire's resistance to control, both with and without treatments in NSO habitat (resistance to control is “the relative difficulty of constructing and holding a control line as affected by resistance to line construction and by fire behavior” (National Wildfire Coordinating Group, 2014)). The model not only finds the complete set of tradeoffs for fire hazard vs. NSO habitat but it also does so for water quality (as defined here by the expected amount of sediment delivery).

Multi-objective mathematical programs comprise a set of functions that represent management objectives such as minimizing fire hazard or expected sediment delivery, and a set of inequalities that capture the constraints on management; e.g., budgetary, logistical or environmental restrictions. Both the objective functions and the inequalities are formulated as functions of the management decisions that are available on the ground. Thus, once solved, the model identifies the set of decisions that would need to be made to best achieve the objectives. Since forest management objectives are often in conflict, unique solutions that simultaneously optimize all objectives might not be attainable; hence the need for tradeoff analysis. Multi-objective mathematical programs quantify these tradeoffs by finding the set of solutions that are Pareto-optimal with respect to the objectives. A solution to the program (i.e., a management plan) is Pareto-optimal, i.e., none of the objectives can be further improved without compromising another objective. Such integration of ecosystem services and objectives is important in practice because land managers want to achieve as much reduction in fire hazard as possible with as little short-term impact on water quality and wildlife habitat as possible.

While this paper is the first attempt to map out the tradeoffs of fire hazard reduction and multiple ecosystem services for a real management problem, there are plenty of examples of other uses of multi-objective optimization in natural resources. Bare and Mendoza (1988) reported one of the first applications in forest management but instead of quantifying the entire set of tradeoffs, found solutions for competing timber and wildlife objectives via interactions with the decision makers who modified their preferences as new information became available. A significant advantage of our model is that it does not rely on interactions with the decision makers during optimization and identifies the entire set of Pareto-efficient solutions up front to let them make choices based on complete tradeoff information about chosen ecosystem services. In addition, our model's solutions, unlike Bare and Mendoza's (1988), are spatially explicit, due to the fact that integer, as opposed to linear, programming is used. Landscape-level fire management, along with its ecological consequences, has spatial implications that are best assessed with a spatial model, as presented in this study. Other studies have previously tested existing and proposed algorithms only on illustrative examples in the areas of harvest scheduling and optimal reserve selection (Tóth et al., 2006; Tóth and McDill, 2009; Burns et al., 2013; Tóth et al., 2010, 2013). The present paper is one of the first real applications.

FuelSolve provided an important step in the development and application of multi-objective optimization techniques for wildfire management (Lehmkuhl et al., 2007; Kennedy et al., 2008). FuelSolve used an evolutionary algorithm to iteratively approximate the Pareto set of fuel treatment choices in the presence of wildlife objectives including NSO habitat, understory vegetation and the habitat of the NSO prey species. All of the wildlife objectives were formulated to support NSO, thus, the tradeoffs acquired in the authors' analyses were limited to the interaction between treatment costs (area treated was used as a proxy) and treatment effects on NSO habitat. Our model incorporates an additional ecosystem service (water quality), to assist analysis of the impacts of fuel treatments, and both short and long term tradeoffs of the treatments. This is possible because our treatment allocation model is both spatially and temporally explicit. Our model, unlike FuelSolve, counts NSO habitat only if it occurs in large enough contiguous patches (c.f., Rebain and McDill, 2003). The contribution of patches of habitat that are smaller than a threshold size are discounted in the objective function, recognizing that contiguous interior habitat is more important for NSO than fragmented habitat. In addition, our approach allows capturing habitat connectivity using binary constraints (Rebain and McDill, 2003; Önal and Briers, 2006; Tóth et al., 2009; Conrad et al., 2012), which cannot be addressed with evolutionary programming (as in FuelSolve).

Lastly, it is important to point out that there have been two fundamentally different ways to model fire behavior in optimization models. One focused on the projected effects of wildfires on particular values of interest such as ecosystem services or property values. For example, Ager et al. (2013) used the expected post-fire area of old-growth ponderosa pines as a proxy for the general health of a fire-adapted ecosystem. The authors then analyzed the tradeoffs using this metric as a function of the area treated – a proxy for cost. Another example is Chung et al. (2013) who simply deferred to the user to assign a value index for each treatment unit. They minimized the expected post-fire loss of the total of these indices as a function of the treated area using simulated annealing. An added benefit of their model was the capability to create treatment clusters for cost-efficiency. The second approach