THESIS

INTERNALIZING THE SOCIAL COST OF SMOKE EMISSIONS INTO STRATEGIC FUELS PLANNING MODELS

Submitted by

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ABSTRACT

INTERNALIZING THE SOCIAL COST OF SMOKE EMISSIONS INTO STRATEGIC FUELS PLANNING MODELS

Emissions of fine particulate matter from prescribed burns are a growing concern for wildland fire managers. Stringent air quality regulations and community discern over the emissions from prescribed fire smoke often severely restrict the ability to implement restorative and precautionary fuels treatments. While some extent of emissions are unavoidable, strategic planning can help reduce their impacts. Estimating the cost of smoke and incorporating it into landscape level fire planning may reduce the burden on wildland fire officials confronted with a complex set of choices and constraints. Currently, no decision-support systems are available for strategically incorporating the cost of smoke in fire planning at the landscape level. A decision model is developed to address this void by estimating the value of fire and fuels management at the landscape level by including the cost of smoke in cellular level estimates social returns. By working with locally defined emission standards and translating them into a cost per unit of smoke impact, I was able to internalize the external impact of smoke emissions into a strategic fuels planning model by reprioritizing the optimal selection of landscape grid cells to target for prescribed fire investments. This has the potential to aid the fire planner in analyzing trade-offs for prescribed fire management. In a case study at King’s Canyon National Park, emissions standards are used to estimate a relative unit cost of impact (per unit of emissions). The unit cost is subtracted from cellular estimates of marginal social returns to re-prioritize the spatial design of landscape scale fuel treatments.

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1. Introduction

Emissions from controlled burning of forest fuels often restrict the fire manager's ability to generate ecosystem services. These services are produced from the restoration of fire-deprived landscapes to facilitate resilient wildlife habitat and protect nearby human communities from wildfire damages through the reduction of hazardous fuels (Arbaugh et al., 2009; Hesseln, 2000). However, prescribed burning practices that are utilized to promote and protect the flows of such services inevitably generate smoke emissions in the short run (Hall, 1972). Due to the simultaneous generation of smoke emissions, the risk of escape, and associated impacts on local communities (Brunson and Evans, 2005), these practices have been subject to increasingly stringent air quality regulations (Quinn-Davidson and Varner, 2011), and complaints from local populations of the impacts of smoke emissions represent obstacles to the implementation of prescribed fire (Winter et al., 2002; Daniel, 1988). These conditions restrict the fire manager's ability to take advantage of a full suite of strategic fuels management strategies by increasing the costs of preparing controlled burn plans and often canceling them altogether (Barrett et al., 2000; Gonzalez-Caban, 1997).

Decision tools are desired to help fire managers employ an optimal level of prescribed fire effort while instantaneously avoiding exceedance of federal or regional air quality standards (Riebau and Fox, 2001). A decision model is proposed here to help the fire manager construct an optimal design of prescribed fire efforts which considers such difficult tradeoffs. The decision model is applied to a case study landscape at King's Canyon National Park in California to demonstrate the process of altering the spatial design of prescribed fire treatments in light of available data describing the landscape's emissions potential.

1.1 Challenges to the employment of prescribed fire efforts due to smoke emissions

Under the U.S. Clean Air Act, state governments and regional pollution control boards are granted the responsibility of enforcing the National Ambient Air Quality Standards (NAAQS) (set forth by the Environmental Protection Agency (EPA) most recently in 1990). The EPA identifies counties across the U.S. which consistently exceed NAAQS as 'non-attainment' regions. In these regions, concentrations of damaging air pollutants frequently exceed the national standards and require further management tactics or control strategies to return air quality to a more desirable state. Federal lands (which include national forests, wilderness areas, and national parks) are further identified by the EPA as 'Class I non-attainment' areas. This additional classification subjects federal lands to the tightest standards for marginal pollution contributions and re-classification is not permitted (Peterson, 2001). Many of these federal lands also fall within 'non-attainment' regions which already experience tight constraints for marginal pollution contributions.

Federal lands commonly conduct prescribed burns to carry out the objectives outlined by the Healthy Forests Restoration Act of 2003 (16 U.S.C. § 402 and § 604). However, the EPA has identified wildland fires and prescribed fires from federal lands as additional threats to the exceedance of national and regional air quality standards (U.S. Environmental Protection Agency, 1990). NAAQS include the allowable atmospheric concentrations of, among other air pollutants, fine particulate matter. This complicates fire management as the primary pollutant emitted from the burning of wildland fuel is fine particulate matter (both $PM_{2.5}$ and PM_{10}; Ward and Hardy, 1991). Social impacts of fine particulate matter from prescribed fire have been well documented. Particulate matter emissions from prescribed fires threatens nearby public health (Core and Peterson, 2001) and regional visibility (Fox and Riebau, 2009; Core, 2001). This may subject the prescribed burning programs in Class I areas to additional restrictions if the program benefits are not adequately justified in a Smoke Management Program (SMP), (Sandberg et al., 2002). These programs are prepared for state pollution control boards so that any exceedances of NAAQS can be justified to the EPA in a State Implementation Plan.

Under these regulatory constraints, fire managers seek to balance the desirable returns from prescribed fire investments against these social impacts in order to select the most cost-effective prescribed fire strategy. Such a strategy would need to reduce the social impacts of harmful smoke emissions associated with prescribed fire programs yet also achieve the ecological benefits from prescribed fire as envisioned by the EPA Interim Air Quality Policy on Wildland and Prescribed Fires (U.S. Environmental Protection Agency, 1998). The strategy would need to be prepared and outlined in a SMP to achieve these objectives.

1.2 Review of current smoke management models

Some contemporary fire models are currently able to capture the impacts of prescribed fire smoke into SMPs (Reinhardt et al., 2001). This is accomplished by utilizing smoke dispersion assessments to detect the level of a nearby community's exposure to wildfire emissions (as covered by Wain et al., 2009 or Lavdas, 1996). Measurements of smoke impact from these models are typically conducted the day of a prescribed burn using the prevailing wind conditions and thus provide information on the management of 'second-order' fire effects. Second-order effects are comprised of post-burn impacts of wildland fire behavior (Reinhardt et al., 2001). These models are useful for informing tactical management decisions, such as *when* to place prescribed fire efforts on the landscape under favorable weather conditions to avoid the risk of escape or the dispersion of smoke emissions towards down-wind populations. These decisions regarding *when* prescribed burn treatments will be made are commonly included in SMPs to demonstrate that adequate efforts to limit smoke impacts are carried out by the burning agency.

In contrast, 'first-order' effects are those occurring immediately as the fire burns biomass and relate to fire severity (Reinhardt and Dickinson, 2010). This information is better suited to support long-run fire management strategies and *where* to place landscape-scale prescribed fire efforts (Reinhardt and Dickinson, 2010). First-order fire effects (burn severity and smoke impact) are directly manipulated by altering the rate of fire spread as the density and connectivity of the fuel bed prior to an unplanned fire event. Such information can be useful for the construction of optimal spatial designs for prescribed fire efforts because it presents information regarding the expected return and the emissions potential of a prescribed burn across alternative locations. Allowing for a spatial analysis to inform the planning process described in SMPs may complement current analyses in such planning documents to evaluate both the optimal timing *and* location for prescribed fire treatment.

Currently, no comprehensive framework exists for comparing the relative returns from landscape-scale prescribed fire investments against the added costs of smoke pollution (Kline, 2004). A decision model is proposed here to weigh the costs of smoke impacts against the benefits of prescribed fire to improve spatial planning strategies for controlled burning efforts. The decision model can assist forest managers' ability to comply with NAAQS and reduce the negative impacts of prescribed burning programs on regional air quality. The model produces a 'smoke-informed' treatment alternative which generates less total smoke impacts than an alternative that is generated without considering relative smoke costs. The smoke-informed treatment alternative maybe used in a fire behavior simulator to determine if the new spatially explicit prescribed fire strategy improves the expected relative value from a series of wildfire simulations over time. This change to the optimal spatial planning strategy may enhance the fire manager's ability to generate desirable services from prescribed fire efforts while simultaneously limiting the costs of smoke emissions.

2. Methods

This development of a strategic decision model for prescribed burning effort seeks to spatially optimize prescribed fire fuel treatments across a landscape given its potential to generate harmful emissions. First, a simplified theory of a forest site value model is presented within the strategic smoke management framework. Next, the marginal cost of smoke at the location of the binding constraint is derived from a constrained decision problem. This calculation of the marginal cost is subsequently used to generate an alternative calculation of expected marginal return from prescribed fire investments across a landscape with spatial variation in cover type and emissions potential. Accounting for these additional costs adjusts the measure of social returns, and changes the optimal choice of cells targeted for treatment.

2.1 Review of the applied site value model

Social returns from prescribed fire programs are often difficult to quantify due to the non-use nature of many such returns of ecosystem services (like biodiversity and soil quality benefits) and the long run time horizon for which social returns accrue (in the form of avoided loss to human structures). Where the returns from prescribed burning practices are difficult to quantify in monetary terms, cost-effective analysis is utilized with non-monetized estimates of marginal value (Rideout et al., 1999). This requires an elicitation of the management unit's marginal values across various fire-affected resources as shown by Rideout et al. (2008). Given the fire manager's objective to maximize the value of the landscape, Rideout et al. (2014) derive the first-order conditions for selecting the optimal locations for fire management effort. Satisfaction of these conditions will generate the highest possible total social returns from a limited budget for a fuels management program.

2.2 Extending the applied site value model to consider smoke costs

Here, I will expand on Rideout et al.'s (2014) applied site value model to consider smoke costs. The total social returns from the fire manager's landscape-scale prescribed burning efforts are expressed by the function, $R(C)$, where C is the level of prescribed burning effort. As C increases, more grid cells on the landscape are selected for prescribed fire treatments to generate returns. Prescribed fire effort is expanded at the extensive margin by targeting additional cells across the landscape for treatment. Taking the first differential of this total value function gives the marginal return from the prescribed fire effort on each additional cell, $\frac{dR(C)}{dC}$. The set of cells with the highest marginal returns are selected for treatment until the manager's dollar budget is exhausted. $R(C)$ will display the typical properties of concavity in C and strong monotonicity that are common in production schedules (Varian, 1992).

Since the generation of smoke emissions is an unavoidable byproduct from controlled burning practices, a second ("joint") output of smoke impact (S) is also produced as cells across the landscape are selected for treatment with prescribed fire. Total impact of particulate matter emissions on local communities from prescribed burning across the landscape can be expressed by the general function $S(C)$. Smoke impacts from each cell burned $\left(\frac{dS(C)}{dC}\right)$ vary with the level of prescribed fire management effort, depending on the physical properties of fuel that characterize the land, their proximity to nearby developments, and elevation.

2.3 Deriving the marginal cost of smoke

The fire manager is often limited in the amount of value that they can add to the landscape through prescribed burning efforts due the imposition of smoke pollution on local communities from smoke emissions (Kline 2004; Yokelson et al., 2000). Where fire managers are constrained in this way, they can express the binding constraint as one where the total smoke impact associated with some level of prescribed fire effort must not exceed a specified threshold, S^o. This constraint on returns is expressed in terms of smoke impact.

We assume here that the smoke impact constraint is tighter than the manager's fuels budget constraint. This implies that the cap on emissions impact S^o implicitly contributes to both the optimized level of land scape grid cells targeted for treatment (C^o) and the associated total returns $\left(R^o(C^o)\right)$. Therefore, when the smoke emissions constraint is binding, the fire manager's decision problem can be expressed as a constrained composite function:

$$\max\{R(C) : C = C^o(S^o)\}$$

[2.1]

Formulating the manager's decision problem as one of constrained optimization enables us to identify the marginal cost of the smoke impact contraint where the optimal level of prescribed fire effort is limited by such a constraint. The smoke impact constraint is binding such that it precludes the fire manager's dollar budget from being binding. The decision problem in equation [2.1] suggests that the smoke emisions impact constraint is met with equality. Under this assumption, the level of effort is bound to the level associated with the defined cap on smoke impact, so the solution function is given by $C^* = C^*(S^o)$. The solution function can be plugged back into the objective function to obtain the "indirect" total return function $\left(R^*\left(C^*(S^o)\right)\right)$ and the comparative statics result, $\frac{dR^*}{dS^o}$ or "λ^*". This derives the shadow price by taking the change in optimized total return from an incremental tightening of the smoke impact contraint: $\frac{dR^*\left(C^*(S^o)\right)}{dC^*(S^o)}\left(\frac{dC^*(S^o)}{dS^o}\right) = \lambda^*$.

2.4 Illustration of the derivation of marginal smoke cost

In a discrete application, λ^* can be approximated by tightening the smoke impact by an additional unit from S^0 to S' to yield a difference in the optimized total returns: $R^o\big(C^o(S^o)\big) - R'\big(C'(S')\big) = \lambda^*$. This difference is illustrated in Figure 1, where under the smoke impact constraint, the level of effort (C) is given by the inverse of the smoke impact function, $S^{-1} = C(S)$. As the smoke impact constraint is relaxed (as S increases), more cells are brought into the prescribed fire program $\left(\frac{dC(S)}{dS} > 0\right)$. This also implies that as the emissions impact constraint is relaxed, the total return increases at all levels of effort less than C^{**}. In this general formulation, the unconstrained maximimum level of effort exists at C^{**}, or where $\frac{dR(C(S))}{dC(S)}\left(\frac{dC(S)}{dS}\right) = 0$.

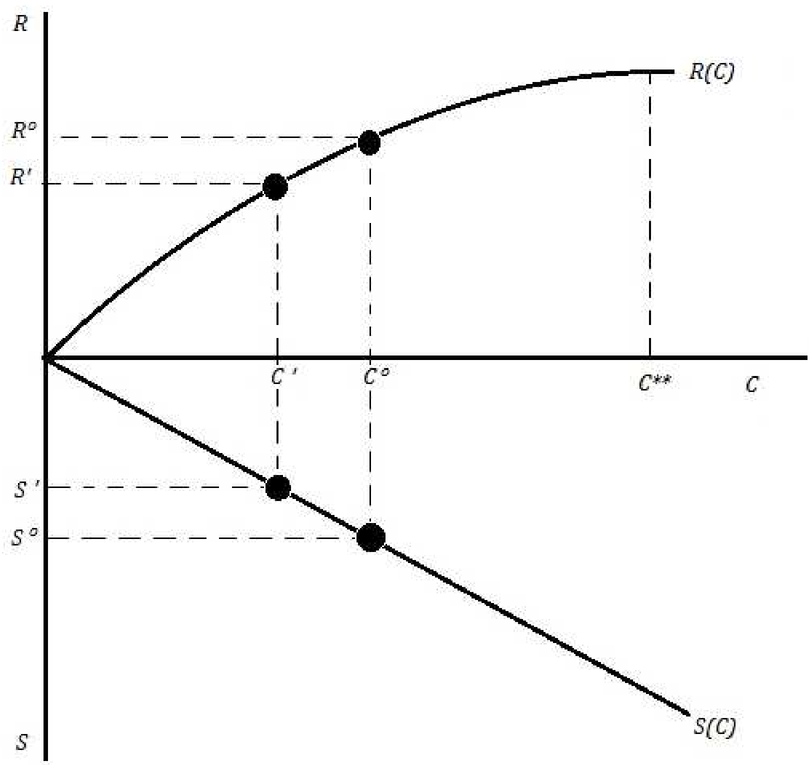

Figure 1 – Composition of R and S

In Figure 1, a general formulation of $R(C)$ and $S(C)$ is shown to illustrate how the optimized and attainable level of total returns can change in regards to a change in the smoke impact constraint. In formal appliations where discrete data is used to estimate the shapes of $R(C)$ and $S(C)$, it is not possible to optimize both schedules over C. This implies that a smooth function can only be obtained for either $R(C)$ or $S(C)$, but not for both $R(C)$ or $S(C)$. A common decision heuristic is to first sort the data over $R(C)$. Whichever schedule is chosen to be sorted second will appear non-smooth in C and its first derivative will not be continuous. Therefore, we cannot also expect $S(C)$ to be perfectly linear in a discrete application as is shown in the simplified Figure 1.

The term "λ^*" represents the marginal cost of the smoke impact constraint because it describes the forgone social returns from tightening the constraint by an additional unit. This defines the marginal cost of smoke impacts and will serve as a means for re-prioritizing landscape-level fuels treatments by adjusting the calculation of the marginal return from selecting each cell for treatment. The following application uses discrete data to demonstrate how this adjustment of the relative marginal return calculations changes the optimal solution and leads to an internalization of smoke impacts in the fire manager's decision process.

3. Test case

A test case is presented here to demonstrate the process of selecting an optimal spatial design of fuels treatments after internalizing the marginal cost of smoke impacts using the method decribed in Section 2. The test case uses a discrete application of the above method for calculating the social costs of smoke impacts on . A smoke-adjusted calculation of relative returns from prescribed fire efforts is calculated for a Class I landscape falling in a federally classified non-attainment region for $PM_{2.5}$. Changes in relative marginal return calculations at each location across the landscape alters the optimal spatial design of prescribed burning effort across the landscape. All spatial data used for this test case are mapped using ArcMap 10.3.1 while the derivation of the shadow price is calculated using the R statistical computing environment (version 3.2.1).

3.1 Study site

King's Canyon National Park (KICA) is located in the Southern Sierra Nevada range of California. It contains conifer and ponderosa pines that are characterized by thick bark and a short fire return interval. The San Joaquin Valley Air District oversees the region's air quality which has received a federal classification of severe nonattainment for fine particulate matter and ozone (Arbaugh et al. 2009). Due to KICA's frequent use of prescribed burning, it's Class I designation for additional smoke pollution and requirements for compliance of NAAQS, it serves as an excellent study site for this research. I focus the analysis on a management zone in the 'King's Basin'. Figure 2 shows the location of the case study landscape in relation to counties across California which exceed EPA standards for allowable concentrations of fine particulate matter.

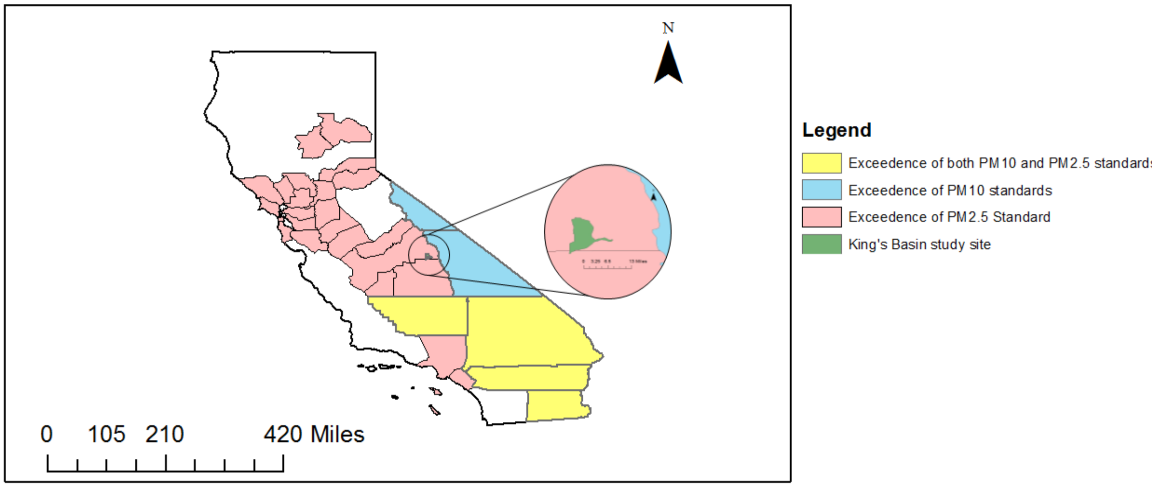

Figure 2 – Location of the King's Basin study site in relation to California counties classified as severe non-attainment for fine particulate matter. Source: EPA, Oct. 2015

The management zone lies in Fresno County, which consistently exceeds EPA standards for allowable $PM_{2.5}$ concentrations (EPA, Oct. 2015). The King's River runs from east to west through the bottom of the basin. This low elevation point with areas of high-valued human development (including Cedar Grove Village with campgrounds and a lodge) increases the management concern over the impacts of smoke emissions in the region. Highway 180 runs alongside the King's River and presents additional visibility concerns from prescribed fire emissions.

3.2 Spatial data obtained for the test case

A collection of spatial raster layers previously processed for the study site was supplied for this research at a 240 meter resolution. They include the following:

1. the location of fire-affected resources for $i = 1$ to 1789 grid cells at the study site (shown in Figure 3). Each cell is identified by fire managers to be positively or negatively affected by fire and are assigned a relative marginal value from burning, MV_i (Rideout et al., 2008),

2. a burn probability layer (P_i) that estimates the burn potential across the landscape (Rideout and Wei, 2013),
3. Scott and Burgan fuel models (Scott and Burgan, 2005) which describe the fuel density and moisture content across the study region, F_i,
4. An expected relative marginal value layer (V_i) that estimates the potential for fire management actions to add value to the landscape (Rideout et al., 2014)[1],
5. The relative treatment cost associated with selecting different vegetation types for fuels management effort across the study site (W_i).

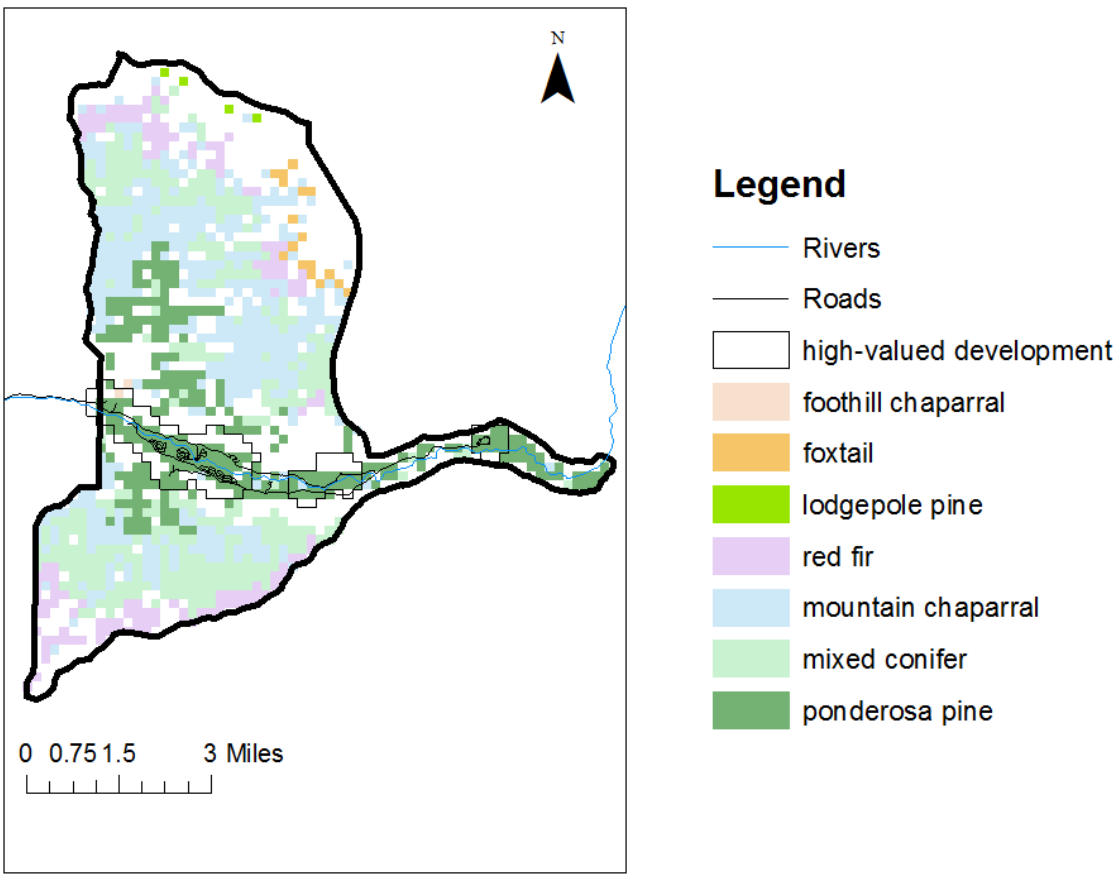

Figure 3 – Map of fire-affected resources at the King's Basin study site

[1] Expected marginal values are arrived at through the following formula to describe the expected deviation of each cell from a fully restored condition after a series of fire spread simulations: $V_i = MV_i^- \cdot P_i + MV_i^+ - MV_i^+ \cdot P_i$

3.3 Prioritizing areas on the landscape for prescribed burning investments

In cost-effectiveness analysis, the efficiency criterion can be obtained by an ordering of alternatives based on their benefit-cost ratio (Ferraro, 2003; Boardman et al.,1996). When non-monetized estimates of expected returns are divided by the cost of the investment, a relative benefit-cost ratio calculation is produced and can be used as a way to evaluate program efficiency (U.S. Department of the Interior, 2012). Optimal spatial fuels planning has used the relative benefit to treatment cost ratio to determine which set of landscape cells provide the highest return per unit cost (Scott, 2006). A comparison of burning alternatives at the study site is represented by evaluating the relative return on prescribed fire investments across all cells i at the study site:

$$R_i = \frac{V_i}{W_i} \tag{3.1}$$

In equation [3.1], V_i represents the expected marginal values (the expected marginal benefits) from prescribing fire on cell i and W_i are the relative marginal costs of making a prescribed burn investment. Landscape cells are targeted for prescribed fire management efforts by selecting the cells with the highest relative marginal return until the available funds are spent. Figure 4 shows the spatial arrangement of grid cells characterized by equation [3.1]. If the fire manager were unconstrained by an annual fuels budget or by air quality regulations, all areas with a positive marginal return would be selected for treatment. Altering the calculation of relative marginal return at each cell in light of smoke costs will generate an alternative measure of returns to that shown by equation [3.1] and serve as a new criterion for ordering prescribed burning alternatives across the study site. A description of data used to achieve this alternative calculation of marginal returns is summarized in section *3.4*.

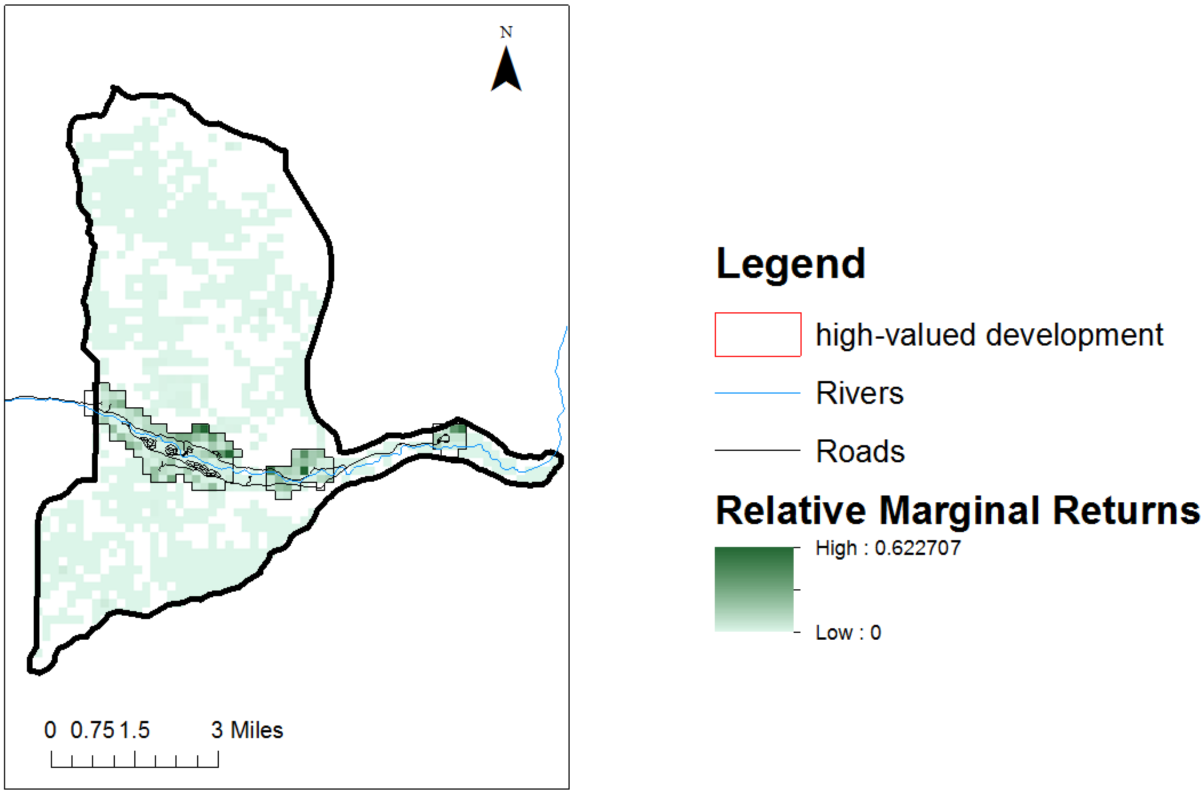

Figure 4 – Expected Relative Marginal Returns on Prescribed Fire investments at the King's Basin study site

3.4 Additional spatial data obtained for the test case

In addition to the spatially explicit expected relative marginal return data, additional spatial data describing each cell's emissions potential is needed to reprioritize the optimal treatment pattern. The fuel model (F_i) contributes to a landscape's emissions potential as indicated by results from simulations of the First Order Fire Effects Model (FOFEM). FOFEM 4.0 simulations previously conducted at the case study site indicate there is a positive relationship between emissions of fine particulate matter and the fuel model value (U.S. National Parks Service, 2004). Relative emissions potential for fine particulate matter can be measured by an average emissions factor (Hardy et al., 2000) or "emissions production coefficient" as it will be referred to here. For this decision application, a constant fuel combustion efficiency is assumed across all prescribed burns. Fuel models of the grass type ($121 \leq F_i \leq 124$ and $101 \leq F_i \leq 109$) show to release approximately 5% of the mass of particulate matter released by the tree types ($180 \leq F_i \leq 204$), while shrub type fuels ($140 \leq F_i \leq 179$) release approximately 21% of the particulate matter released by tree types (U.S. National Parks Service, 2004). These relative emissions quantities can be represented by the following formula:

$$E_i(F_i) = \begin{cases} 1.00 & \text{for } 180 \leq F_i \leq 204 \\ 0.21 & \text{for } 140 \leq F_i \leq 179 \\ 0.05 & \text{for } 101 \leq F_i \leq 124 \end{cases} \tag{3.2}$$

The fuel model was mapped at the study site and relative quantities of emissions were obtained using ArcMap's "raster algebra" feature by adhering to equation [3.2]. Emissions production coefficients are given by the term "E_i" and are summarized by the map shown in Figure 5.

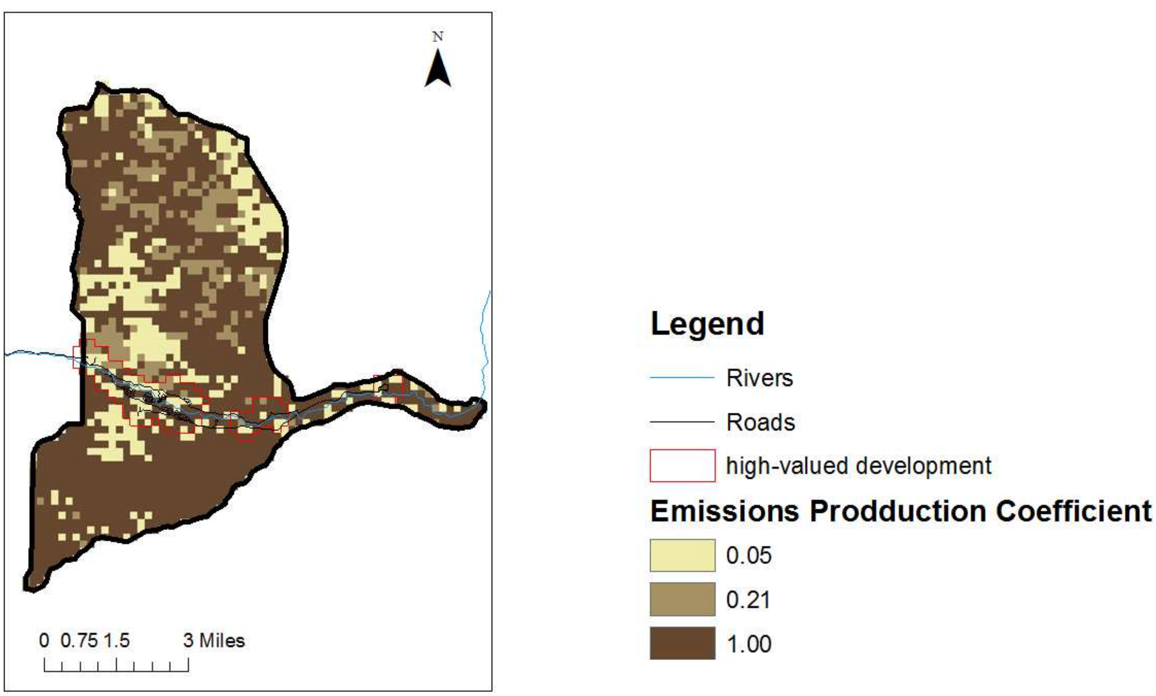

Figure 5 – Emissions Production Coefficients at the King's Basin study site (E_i)

An ordinal estimate of social impact (M_i) defines the fire manager's preference to avoid smoke emissions due to the likely impacts on nearby human populations. Fire managers at both Sequoia and King's Canyon National Parks have previously identified an ordinal estimate of social impact across both parks (shown in Figure 6). Areas of high social impact are given a social impact factor of 2, while medium social impact and low social impact are given a factor of 1 and 0 respectively.

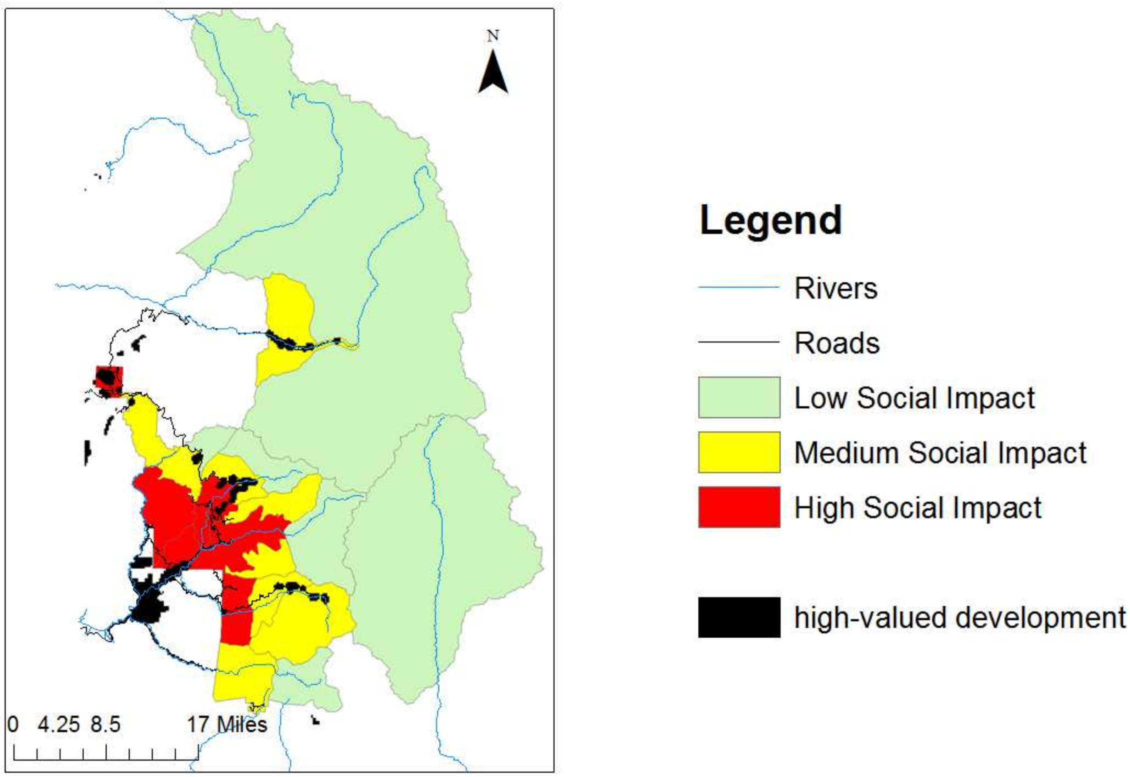

Figure 6 – Ordinal social impacts of smoke defined by fire managers at Sequoia and King's Canyon National Parks (M_i)

Using the ordinal ranking of social smoke impacts as a limited dependent variable, a generalized least squares model (GLS) is used to obtain a more continuous estimate of social impact ($\widehat{M}_i$) across the King's Basin study site. Smoke impact per cell is given by an estimated regression equation which relates the level of social impact (M_i) to elevation measured in meters (L_i) and Euclidean distance (in meters) to the nearest area of high-valued development (D_i):

$$\widehat{M}_i = \hat{\beta}_0 + \hat{\beta}_1(L_i) + \hat{\beta}_2(D_i) + \hat{\varepsilon}_i = 2.8264 - 0.000011631(L_i) - 0.000042787(D_i)$$

[3.3]

Elevation is included as a predictor of social impact due to the liklihood for smoke to settle in a valley and pose a health or visibility threat to human populations (Schweizer and Cisneros, 2014). The estimated regression equation [3.3] is used to generate a smoothed surface of social impact ($\widehat{M}_i$) across the study site so that different weights on emissions production can be analyzed in the decision model. Information about the estimated generalized linear regression model are summarized in Appendix A. Both the Euclidian distance to the nearest area of high-valued human developments and the elevation were shown to be highly significant determinants of the fire manager's ordinal estimate of smoke impact. There are no multicollinearity problems between the two explanatory variables, but the uncorrected GLS exhibits heteroscedasticity and spatial autocorrelation. To overcome this problem and determine if the chosen predictors (L_i and D_i) are truly significant, a series of weighted least squares estimators were obtained. Heteroscedasticity and autocorrelation robust standard errors are reported in Appendix A. Newey-West standard errors (Newey and West, 1987) are obtained using the "sandwich" package for the R statistical programming language (Zeileis, 2006; Zeileis, 2004) to ensure that the estimated regression parameters ($\hat{\beta}_0$, $\hat{\beta}_1$, and $\hat{\beta}_2$) are efficient. Additional attempts to correct the efficiency of estimators used a Gaussian variogram transformation of the variance-covariance matrix and an estimation of a spatial error model (also shown in Appendix A). These additional attempts to correct the efficiency of GLS results indicate that the estimated regression parameters are still significant and their estimated coefficients are statistically different from zero, but spatial autocorrelation of GLS residuals remains (which may lead to inflated test statistics for the estimated GLS parameters). However, ignoring the presence of autocorrelation in a least squares model does not generate any bias in the estimated parameters like those obtained for equation [3.3] (Ward and Gleditsch, 2008).

Extrapolations of the estimated GLS model [3.3] are used to obtain a spatial data layer describing the social impact with less heterogenei across the study site than could be obtained from a kernel smoother- although alternative parameters in the smoothing function were not tested. This is important for assessing the relative changes in social impact across grid cells at alternative distances from areas of high-valued development. The predicted surface of social impact across the King's Basin study site is shown in Figure 7.

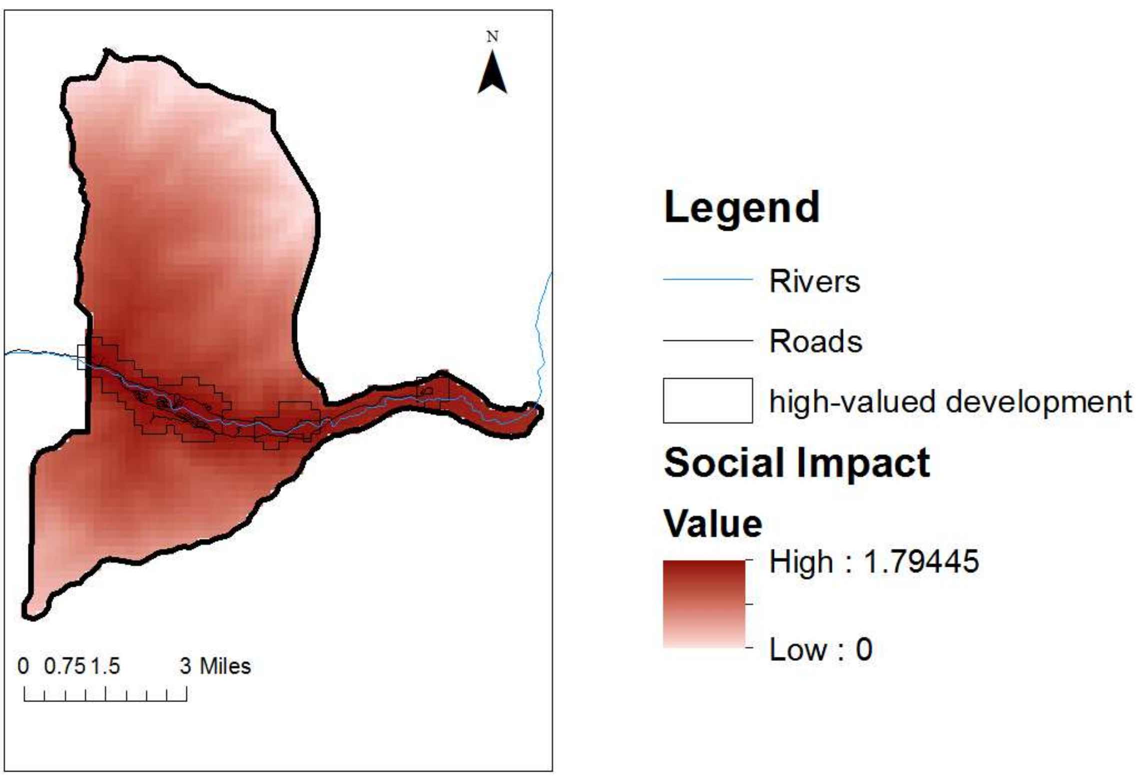

Figure 7 – Interpolation of Social Impact at the King's Basin study site ($\widehat{M}_i$)

I use the predicted social impact layer $(\widehat{M}_i)$ along with the measure of relative emissions quantity (E_i) to obtain an estimate of smoke impact at each cell across the management zone (Figure 8). Since the social impact $(\widehat{M}_i)$ represents the relative marginal social impact of smoke emissions generated from each cell, and the relative quantity of such emissions released from a burn at each cell is represented by E_i, then the smoke impact is given by the product in equation [3.4]:

$$S_i = \widehat{M}_i \cdot E_i(F_i) \tag{3.4}$$

Figure 8 shows how the smoke impact varies across the region.

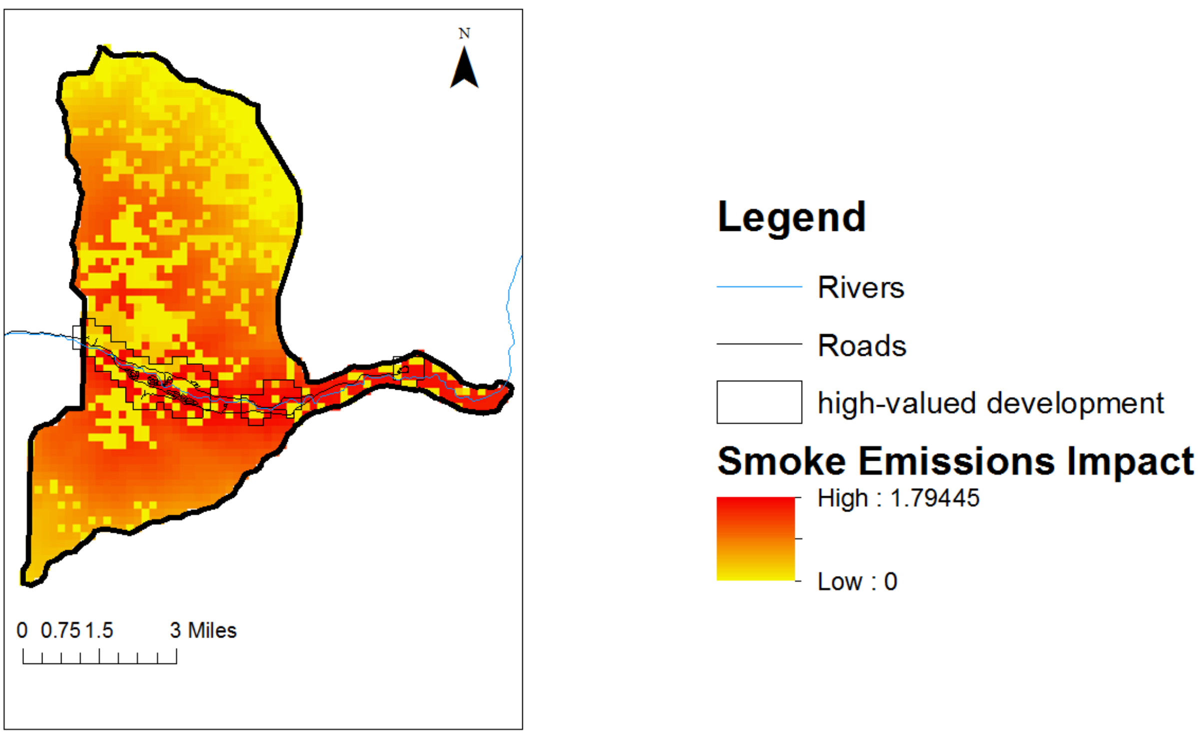

Figure 8 – Smoke Impact at the King's Basin study site (S_i)

3.5 Definition of the smoke impact constraint and the derivation of marginal smoke cost

Using the methods described in section 2 and the spatial data outlined in section 3, the marginal cost of the smoke constraint was derived. All raster data were read into the R statistical programming environment using the “rgdal” package (Bivand et al., 2015). The script used to conduct the discrete derivation of λ^* is given in Appendix B.

Manager’s at King’s Canyon identified that no more than 87 acres at the King’s Basin study region can be burned in a typical fire season before meeting the regional and national air quality standards for fine particulate matter. 87 acres is equivalent to approximately 352,077 square meters. Under this spatial constraint, the manager is limited to the employment of prescribed burns on only 6.11 grid cells for a total area of 57,600 square meters. Under this constraint, the estimated sum of smoke impact ($\sum S_i$) across the ordered set of landscape cells is 0.7519 units. A tightening of the smoke impact constraint from 0.7519 to 0.7518 units yields a shadow price (λ^*) of 0.2382. Using this shadow price as an estimate of the marginal cost of the smoke impact constraint, alternative estimates of marginal return on prescribed fire investment are generated across the management zone.

3.6 Re-prioritizing areas on the landscape for prescribed burning investments

The added marginal cost of prescribed burns due to smoke impact is given by multiplying the derived marginal cost (λ^*) by the potential emissions at each cell (E_i) and its impact ($\widehat{M}_i$). The derivation of the shadow price gives these estimates of marginal cost in the same units as the objective funcction, so they are subtracted from each cell’s estimate of relative marginal return:

$$R'_i = \frac{V_i}{W_i} - \lambda^* \cdot \widehat{M}_i \cdot E_i = \frac{V_i}{W_i} - 0.2382 \cdot S_i \qquad [3.5]$$

An alternative marginal return schedule is generated using the derived marginal cost from an infenetesmal change in the smoke impact constraint. Consequently, the spatial optimization process can now target landscape cells with the highest relative marginal return from which the added social impacts of smoke emissions have been subtracted. Differences in maps based off equation [3.1] and [3.5] are assessed for their potential to re-prioritize the optimal prescribed fire strategy across a fire season. Figure 9 describes the spatial arrangement of cells characterized by equation [3.5].

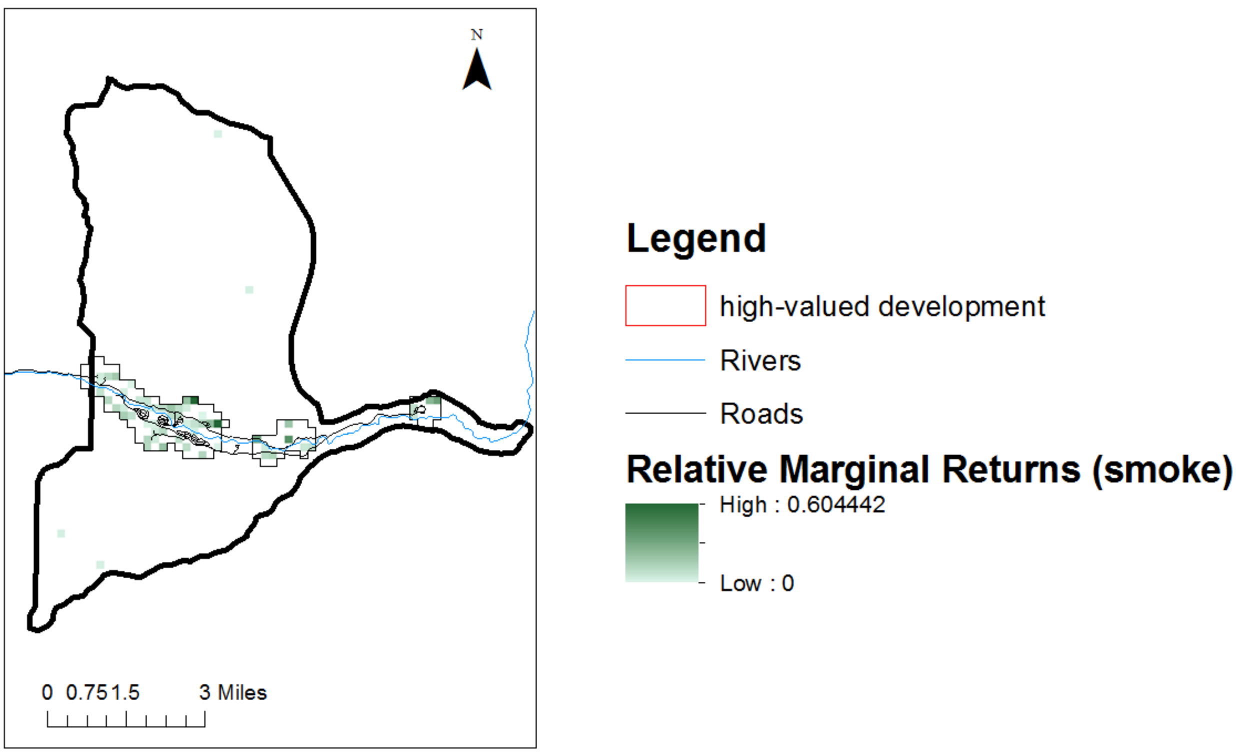

Figure 9 – Expected Relative Marginal Returns on Prescribed Fire Investments at the King's Basin study site after accounting for smoke costs

4. Results of the test case

Results indicate that 933 fewer grid cells are optimal for the selection of a controlled burn relative to the unconstrained solution. Under the "smoke-informed" calculations of marginal return, 59 cells across the landscape would be targeted for treatment if the fire manager were not constrained by air quality regulations. The selection of cells under the smoke-informed plan fall within the set of cells that would have originally been selected with an unbinding fuels budget. Yet, under a targeting strategy where the cells with the largest marginal returns are given priority for treatment, the order in which the cells would be selected changes under the smoke-informed plan. Figure 10 shows how the total return schedule ($\sum R_i$) compares with the total smoke costs (which are obtained by multiplying the derived marginal cost (λ^*) by the total smoke impact ($\sum S_i$) after first sorting the data in descending order of relative marginal returns). Subtracting the smoke costs from the initial estimate of total relative returns yields a net return schedule in Figure 11. However, the schedule in Figure 11 does not represent the efficient prioritization that would occur from first targeting the cells with the largest marginal return. Figure 12 depicts a negative shift of the total return schedule after a reprioritization of cells based on the adjusted social returns (from ($\sum R_i$) to ($\sum R_i'$)).

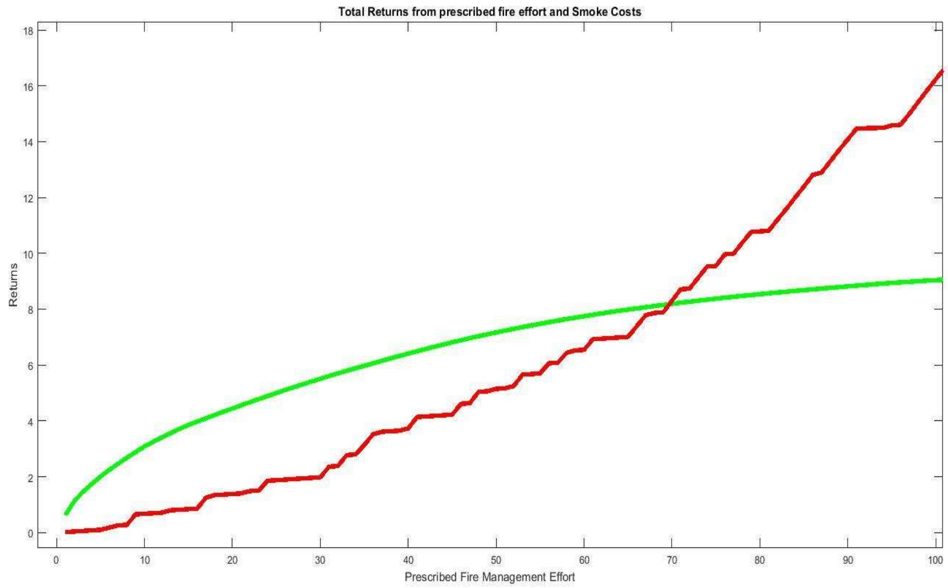

Figure 10 – Total Returns and Total Smoke Costs

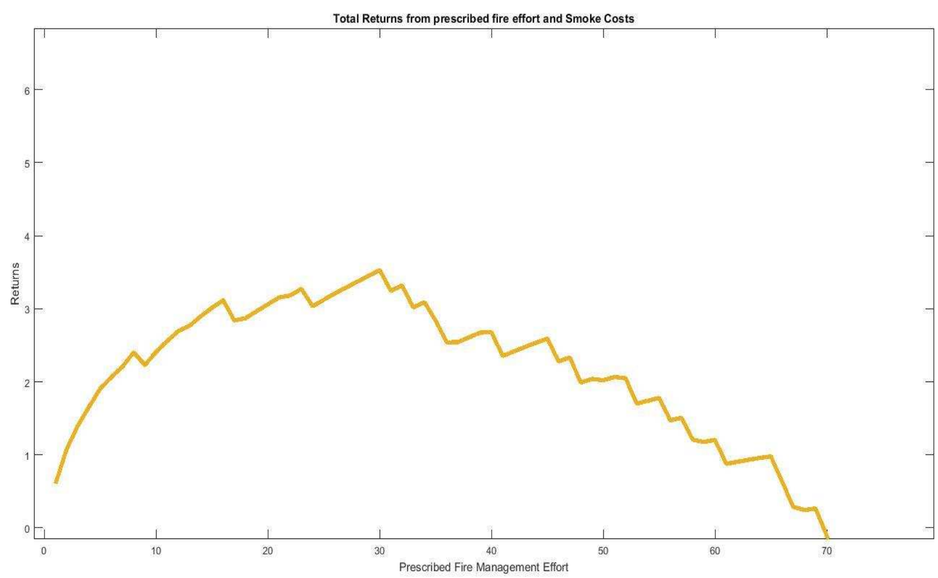

Figure 11 – Relative total returns on prescribed fire effort (after accounting for smoke costs)

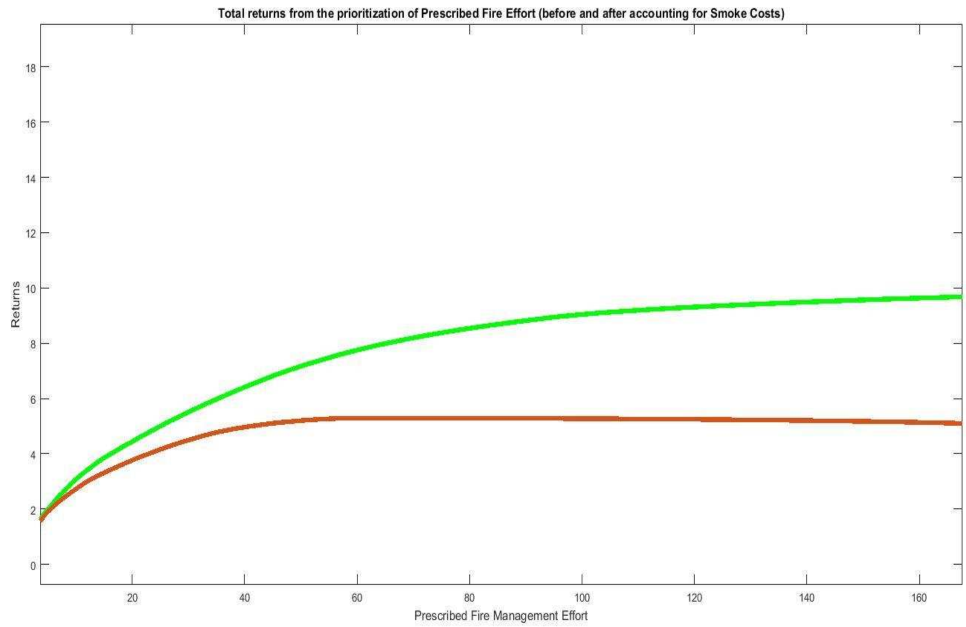

Figure 12 – Ordered Relative Total Returns from Prescribed Fire Effort (before and after accounting for smoke costs)

When the smoke constraint (expressed in acres) is applied to the decision process, it is revealed that one alternative cell would be selected for treatment compared to the optimal selection of cells ordered according to the original total return schedule. Less than 7 cells can be targeted under the smoke impact constraint, yet an alternative menu of cells are optimal for selection after accounting for smoke costs. Figure 13 shows this slight change to the optimal spatial pattern of prescribed fire management efforts under this constraint. Figure 14 shows the optimal pattern if, instead, 18 cells could be selected before the smoke impact constraint is met.

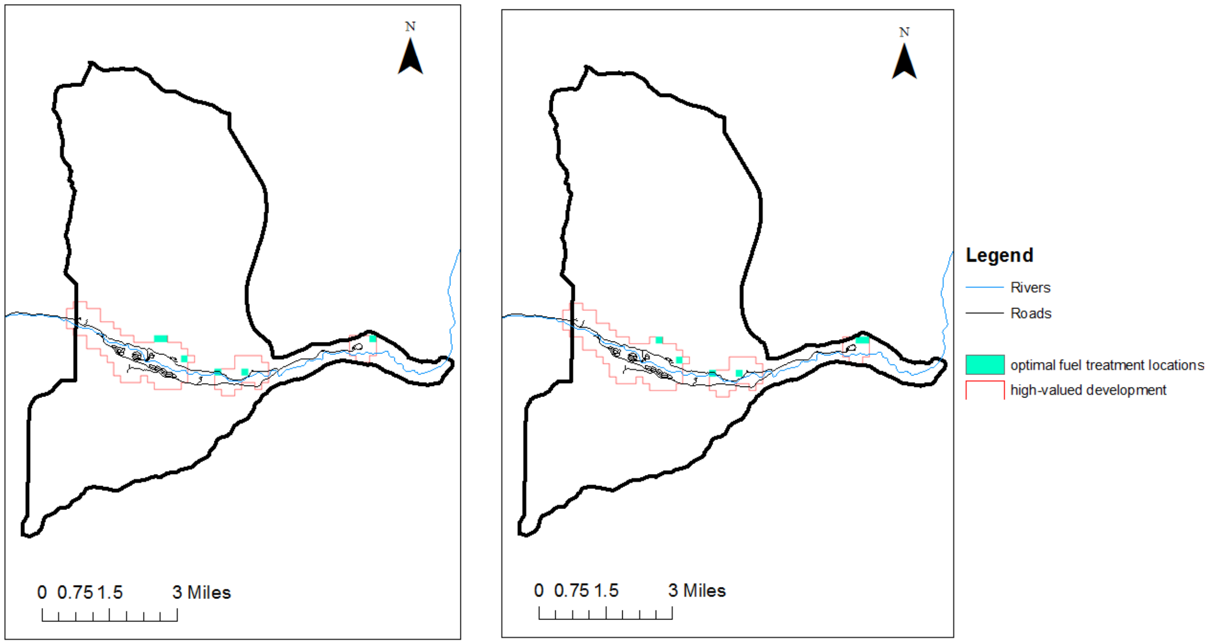

Figure 13 – Optimal constrained selection of landscape grid cells under the original marginal return schedule (left) and the smoke-informed marginal return schedule (right)

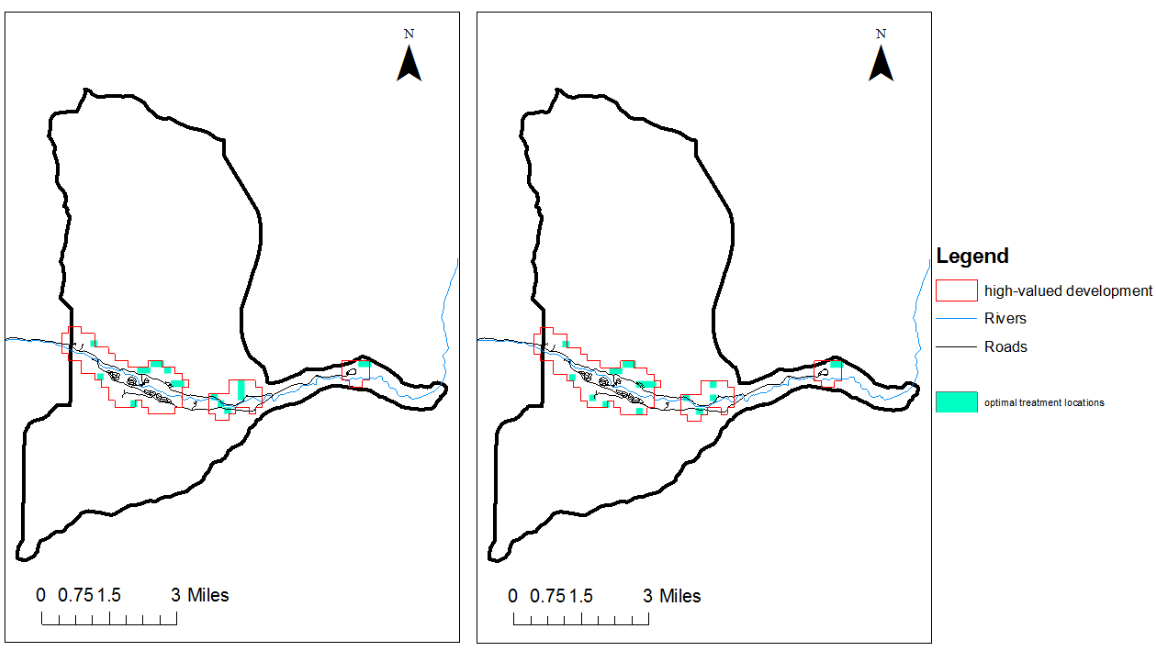

Figure 14 – Optimal constrained selection of landscape grid cells under the original marginal return schedule (left) and the smoke-informed marginal return schedule (right)

5. Conclusions and discussion

The static analysis shown in the test case demonstrates how the optimal pattern of fuel treatment sites are selected under alternative estimates of marginal social returns. The total return schedule is shifted using an optimization model to incorporate the added cost of smoke impacts. When the shadow price associated with each grid cell's relative emission potential is internalized, the relative marginal return on prescribed burn effort at each cell decreases by a different value, depending on its emissions potential and social impact. This information is utilized to re-prioritize landscape cells for targeting strategic fuels management efforts through an adjustment of each cell's relative marginal return from the employment of prescribed fire effort. These calculations are helpful for fire managers who seek to strategically evaluate locations on a complex landscape for generating the desired ecosystem service flows from fuels management efforts.

Using data from King's Canyon National Park, a function for deriving the marginal cost of smoke emissions (λ^*) was developed that is consistent with the methods described in section 2. Applying the marginal cost of smoke emissions to each calculation of expected relative marginal return from prescribed fire investment at each cell shows a slight change to the menu of cells that are optimal to target under the smoke constraint. This study represents a novel application of the shadow pricing literature to the social costs created from prescribed fire actions. A decision model constrained by air quality regulations is applied to the fire manager's decision process to evaluate the changes to an optimal landscape-scale collection of prescribed fire efforts. The decision process was able to evaluate these social costs in the same units that are used to prioritize landscape-scale prescribed fire alternatives and the results indicate a less impactful fuels targeting strategy.

In further applications of this model (perhaps on different landscapes), it may be worthy to note how the optimal list changes after adjusting the marginal return calculations. In cases where the initial marginal return estimates (R_i) are highly correlated with marginal smoke impacts (S_i), the optimal menu of cells to target for treatment may not change. However, in cases where there is little to no correlation between marginal returns (R_i) and marginal smoke impacts (S_i), calculating the new measure of marginal returns (R_i') is likely to alter the spatial design of targeted cell.

In a follow-up study, a new schedule of expected relative marginal values from prescribed fire could be found under the new optimal treatment plan. Burn probability measures can be expected to change in light of the smoke-informed prescribed fire strategy, thereby altering estimates of expected marginal benefits (say V_i'). Using dynamic fire spread simulations to create the expected relative marginal benefits would yield new estimates of marginal returns. Future modeling efforts may also extend the analysis to consider the land manager's employment of a preparedness input which does not produce smoke (such as mechanical thinning treatments or mastication). This extended analysis would consider the degree of substitutability between mechanical thinning efforts and prescribed burns in light of the revealed cost increase for prescribed burning efforts. As the price of generating returns from prescribed fire increases, the optimal solution may be to substitute into alternative fuel treatment strategies. This would, however, require an alternative estimate of expected marginal benefit from each type of fuels management action.

References

Arbaugh, M., Procter, T., & Esperanza, A. 2009. Managing Air Pollution Impacted Forests of California. In A. Bytnerowicz, M. Arbaugh, A. Riebau, & C. Andersen (Eds.), "Developments in Environmental Science" (Vol. 8, pp. 567–582). Amsterdam, Netherlands: Elsevier.

Barrett, T., Jones, J., & Wakimoto, R. (2000). Forest Service spatial information use for planning prescribed fires. *Western Journal of Applied Forestry* 15(4): 200–207.

Bivand, R., Keitt, T., & Rowlingson, B. (2015) "rgdal: Bindings for the Geospatial Data Abstraction Library." R package version 1.0-4. http://CRAN.R-project.org/package=rgdal.

Boardman, A., Greenberg, D., Vining, A., & Weimer, D. 1996. Cost-Benefit Analysis: concepts and practice. Upper Saddle River, NJ: Prentice Hall.

Brunson, M.W. & Evans, J. (2005). Badly Burned? Effects of an Escaped Prescribed Burn on Social Acceptability of Wildland Fuels Treatments. *Journal of Forestry* 103(3): 134-138.

Core, J. (2001). Visibility. In "Smoke Management Guide for Prescribed and Wildland Fire" (p. 35-39). Boise, ID: National Wildfire Coordination Group.

Core, J., & Peterson, J. (2001). Public Health and Exposure to Smoke. In "Smoke Management Guide for Prescribed and Wildland Fire" (p. 27-33). Boise, ID: National Wildfire Coordination Group.

Daniel, T.C. 1988. Social/Political Obstacles and Opportunities in Prescribed Fire Management. Panel paper presented at the conference: "Effects of Fire in Management of Southwestern Natural Resources, November 14-17. Tuscon, AZ.

Ferraro, P. (2003) Assigning priority to environmental policy interventions in a heterogeneous world. *Journal of Policy Analysis and Management* 22(1): 27-43.

Fox, D. & Riebau, A. 2009. Effects of Forest Fires on Visibility and Air quality. In "Developments in Environmental Science" (Vol. 8, pp. 171-195). A. Bytnerowicz, M. Arbaugh, A. Riebau, & C. Andersen (Eds.), Amsterdam, Netherlands: Elsevier.

Gonzalez-Caban, A. (1997). Managerial and Institutional Factors Affect Prescribed Burning Costs. *Forest Science*, *43*(4): 535–543.

Hall, A.J. 1972. Forest fuels, prescribed fire, and air quality. Portland, OR: U.S. Department of Agriculture, Forest Service, Pacific Northwest Forest and Range Experiment Station. 47 p.

Hardy, C.C., Burgan, R.E., & Ottmar, R.D. (2000) A database for spatial assessments of fire characteristics, fuel profiles, and PM10 emissions. *Journal of Sustainable Forestry* 11(1): 229-244.

Hesseln, H. (2000). The Economics of Prescribed Burning: A Research Review. *Forest Science* 46(3): 322–334.

Kline, J . 2004. Issues in evaluating the Costs and Benefits of Fuel treatments to Reduce Wildfire in the Nation's Forests. U.S. Department of Agriculture, Forest Service, Pacific Northwest Forest and Range Experiment Station. 48 p.

Lavdas, L. (1996). Improving Control of Smoke from Prescribed Fire Using Low Visibility Occurrence Risk Index. *Southern Journal of Applied Forestry* 20: 10–14.

Newey, W. & West, K. (1987). A simple Positive Semi-Definite Heteroskedasticity and Autocorrelation Consistent Covariance Matrix. *Economterica* 55: 703-708.

Peterson, J. (2001). Regulations for Smoke Management. In "Smoke Management Guide for Prescribed and Wildland Fire" (p. 61-74). Boise, ID: National Wildfire Coordination Group.

Quinn-Davidson, L. N., & Varner, J.M. (2011). Impediments to prescribed fire across agency, landscape and manager: an example from northern California. *International Journal of Wildland Fire* 21(3): 210-218.

Reinhardt, E., & Dickinson, M. (2010). First-Order Fire Effects Models for Land Management: Overview and Issues. *Fire Ecology* 6(1): 131-142.

Reinhardt, E., Keene, R., & Brown, J. (2001) Modeling Fire Effects. *International Journal of Wildland Fire* 10(4): 373-380.

Rideout, D., Ziesler, P., & Kernohan, N. (2014). Valuing Fire Planning Alternatives in Forest Restoration: Using Derived Demand to Integrate Economics with Ecological Restoration. *Journal of Environmental Management* 141: 190–200.

Rideout D., Ziesler, P., Kling, R., Loomis, J. & Botti, S. (2008). Estimating rates of substitution for protecting values at risk for initial attack planning and budgeting. *Forest Policy and Economics* 10: 205-219.

Rideout, D., Loomis, J., and Omi, P. 1999. Incorporating Non-Market Values in Fire Management Planning. Gen Tech. Rep. Fort Collins, CO. PSW-GTR-173.

Rideout D., & Wei, Y. (2013). A Probabilistic Landscape Analysis Supporting the Management of Unplanned Ignitions at Sequoia and Kings Canyon National Parks. *Journal of Sustainable Forestry* 32: 437-455.

Riebau, A., & Fox, D. (2001). The New Smoke Management. *International Journal of Wildland Fire*. 10(4): 415-427.

Sandberg, D.V., Ottmar, R.D., Peterson, J.L. and Core, J. 2002. Wildland fire in ecosystems: Effects of fire on air. Gen. Tech. Rep. Ogden, UT. RMRS-GTR-42-V5

Scott, J. 2006. An Analytical Framework for Quantifying Wildland Fire Risk and Fuel Treatment Benefit. In P. Andrews and B. Butler, (comps), "Fuels Management – How to Measure Success: Conference Proceedings" Portland, OR. Gen. Tech. Rep. RMRS-P-41.

Scott, J., Burgan, R., 2005. Standard fire behavior fuel models: a comprehensive set for use with Rothermal's surface fire spread model. Fort Collins, CO. Gen. Tech. Rep. RMRS-GTR-153.

Schweizer, D. & Cisneros, R. (2014). Wildland fire management and air quality in the southern Sierra Nevada: Using the Lion Fire as a case study with a multi-year perspective on $PM_{2.5}$ impacts and fire policy. *Journal of Environmental Management* 144: 265-278.

U.S. Department of the Interior. 2012. "Wildland Fire Management Program Benefit-Cost Analysis: A Review of Relevant Literature, p. 70. Washington D.C.

U.S. Environmental Protection Agency. 1998 "Interim Air Quality Policy on Wildland and Prescribed Fires." Washington, D.C.

U.S. Environmental Protection Agency. 1990. "Air quality criteria for particulate matter: Volume II of III." Washington, D.C.

U.S. National Parks Service 2004. "Sequoia and Kings Canyon National Parks: Environmental Assessment."

Varian, H. 1992. Microeconomic Analysis. 3rd Ed. W.W. Norton and Company, Inc. New York, NY.

Wain A., Mills, G., McCaw, L., & Brown, T. 2009. Managing Smoke from Wildfires and Prescribed Burning in Southern Australia. In A. Bytnerowicz, M. Arbaugh, A. Riebau, & C. Andersen (Eds.), "Developments in Environmental Science" (Vol. 8, pp. 535–550). Amsterdam, Netherlands: Elsevier.

Ward, M.D., & Gleditsch, K.S. 2008. Spatial Regression Models. Thousand Oaks, CA: Sage.

Ward, D., & Hardy, C. (1991). Smoke emissions from wildland fires. *Environmental International* 17: 117-134.

Weise, D. Kimberlin, R., Arbaugh, M., Chew, J., Jones, G., Merzenich, J., Wiitala, M., Keane, R., Schaaf, M., & Wagtendonk, V. 2003. Comparing potential fuel treatment trade-off models: Initial Results. In "Systems Analysis in Forest Resources. G. Arthaud and T. Barrett (Eds.).Printed in the Netherlands: 15-25.

Winter, G., Vogt, C., & Fried, J. (2002). Fuel Treatments at the Wildland-Urban Interface: Common Concerns in Diverse Regions. *Journal of Forestry* 100(1): 15-21.

Yokelson, R., Goode, J., Ward, D., Baker, S., Susott, R., & Hao, W. (2000). The chemistry of fire and smoke: the composition, amount, and fate of smoke from residual smoldering combustion. In L. Neuenschwander, K. Ryan, G. Gollberg, J. Greer, "Proceedings from the joint fire science conference and workshop", Boise, ID. p. 112-113.

Zeileis, A. (2006). Object-Oriented Computation of Sandwich Estimators. *Journal of Statistical Software* 16(9): 1-16.

Zeileis, A. (2004) Econometric Computing with HC and HAC Covariance Matrix Estimators. *Journal of Statistical Software* 11(10): 1-17.

Appendix A – (Results of the Generalized Least Squares Model of smoke impact)

Table 1 - Summary Statistics for data used in the GLS

16,398 observations	**Mean**	**St. Dev.**	**Min**	**Max**
M_i	1.017	0.7462	0.0	2.0
L_i	139647 meters	2832.746	26929 meters	237779 meters
D_i	4314 meters	43404.61	0.0 meters	15956 meters

Table 2 – GLS results with Newey-West corrected standard errors and p-values

Dependent variable: M_i	**Coefficient**	**St. Error**	**z-statistic**	**p-value**
(intercept)	2.8264	0.053942	52.3969	<0.0001
L_i	-0.000011631	0.00000043589	-26.6833	<0.0001
D_i	-0.000042878	0.0000076085	-5.6355	<0.0001
AIC = 23958				

Table 3 – SEM results with row-standardized inverse distance spatial weights matrix

Dependent variable: M_i	**Coefficient**	**t-statistic**	**p-value**
L_i	-0.000001514	-58.3984	<0.0001
D_i	-0.000002901	-0.6380	0.5235
$\varepsilon_i = \rho\mathbf{W}\varepsilon_i + u_i$ $\rho = 0.9900^{***}$ AIC = -11.7367			

Appendix B – (R SCRIPT)

```
#######################
#READ IN THE ROI LAYER#
#######################
library(sp)
library(spdep)
library(rgdal)
library(raster)

# read in the baseline data for expected treatment benefits/relative
    #treatment cost
LA_baseline = readGDAL("E://SmokeData//zone4//bcr_zone4.txt")
projection(LA_baseline)= "+proj=utm +zone=19 +datum=NAD83"
#LA_baseline$band1[is.na(LA_baseline$band1)] = 0


########################
#READ IN THE SMOKE DATA#
########################
# SMOKE IMPACT FACTOR
SIF_zone4 = readGDAL("E://SmokeData//zone4//smkimpct_zone4.txt")
projection(SIF_zone4) ="+proj=utm +zone=19 +datum=NAD83"
#SIF_zone4$band1[is.na(SIF_zone4$band1)] = 0
x = coordinates(SIF_zone4)[,1]
y = coordinates(SIF_zone4)[,2]
# EMISSIONS COEFFICIENT
EmCoef = readGDAL("E://SmokeData//zone4//emcoef_zone4 (2).txt")
projection(EmCoef) ="+proj=utm +zone=19 +datum=NAD83"
```

```
#############################################
#############################################
#~~~~CALCULATE THE SHADDOW PRICE OF SMOKE~~~~#
#############################################
#############################################
########################
#BASELINE FUELS  BUDEGT#
########################
library(dplyr)

S = EmCoef$band1*SIF_zone4$band1
R0 = LA_baseline$band1 #LA VALUES UNDER THE BASELINE BUDGET
#R0 = (LA_baseline_POS$band1 + LA_baseline_NEG$band1)
df0 = data.frame(R0,EmCoef$band1,SIF_zone4$band1,S)
df0 = na.omit(df0)

df0 = arrange(df0,-R0)  #df0 = df0[order(-df0$V0),])
df0 = arrange(df0,-R0,S) #df0 = df0[order(df0$S),]
df0$sumS = cumsum(df0$S)
df0 = df0[is.finite(df0$R0),]    #replace all non-finite values with 0
df0$effort = 1:length(df0$R0)   # add a vector which describes the level of
effort
head(df0)

############################
#CALCULATE THE SHADOW PRICE#
############################
L <- function(B){   #B defines the Smoke Impact Constraint (expressed in
    terms of sumS)
  ROI <- as.numeric((df0$sumS < B))*df0$R0
  cat(sum(ROI),'is the total return on investment')
}
L(0.7519)
L(0.7518)

## CALCULATE L(0.7519) - L(0.7518) TO FIND THE SHADOW PRICE ##
```

```
######
#PLOT#
######
plot(df0$effort[1:150],cumsum(df0$R0)[1:150],col="green",type="l",xlab="Presc
ribed Fire Management Effort",ylab="Return")
points(df0$effort[1:150],(df0$sumS*0.2382)[1:150],col="red",type="l")
title("Total Return on Prescribed Fire Effort and Total Smoke Cost")

df0$NB = df0$R0 - (0.2382*df0$S)

plot(df0$effort[1:70],cumsum(df0$NB)[1:70],,col="green",type="l")
title("Total Returns on Prescribed Fire investments after subtraction of
Smoke Costs (non-prioritized)")


plot(df0$effort,sort(df0$R0,decreasing=TRUE),col="orange",ylab="Marginal
Return on Investment",xlab="Prescribed Fire Management Effort",type="l")
points(df0$effort,sort((df0$R0-
(0.2382*df0$E)),decreasing=TRUE),col="green",ylab="Marginal Return on
Investment (ROI)",type="l")
title("Marginal Return on Investment from Prescribed Fire Effort before and
after accountign for smoke costs")
legend(100,0.55,c("Marginal Return On Prescribed Fire Investment","Marginal
Return on Prescribed Fire Investment after accounting for Smoke
Costs"),col=c("orange","green"),lwd=c(2.5,2.5))


plot(1:120,cumsum(df0$R0)[1:120],col="blue",type="l",xlab="Prescribed Fire
Management Effort",ylab="Returns")
points(1:120,cumsum(df0$NB)[1:120],col="green",type="l")
title("Total Return on Investment from Prioritizing Prescribed Fire Effort
before and after accounting for smoke costs")

df0 = arrange(df0,-NB)

plot(1:120,cumsum(df0$R0)[1:120],col="blue",type="l",xlab="Prescribed Fire
Management Effort",ylab="Returns")
points(1:120,cumsum(df0$NB)[1:120],col="green",type="l")
title("Total Return on Investment from Prioritizing Prescribed Fire Effort
before and after accounting for smoke costs")

#############################################################
#HOW MANY FEWER CELLS SELECTED FOR TREATMENT (UNCONSTRAINED)#
#############################################################
numOPTIMALcells = sum(df0$R0>0) # number of cells selected before accounting
for smoke costs
numOPTIMALcells
numOPTIMALcells_smoke = sum((df0$R0-(0.2382*df0$S)) > 0) # number of cells
select after accounting for smoke costs
numOPTIMALcells_smoke
numOPTIMALcells -  numOPTIMALcells_smoke #fewer number of cells selected
after accounting for smoke costs
```

```
################################
#INTERPOLATION OF SMOKE IMPACT#
################################
Spatial_start()
##########################
#READ IN THE SPATIAL DATA#
##########################
library(rgdal)
SIF = readGDAL("E://ParkData//SEKI//Smoke//smokeimpactfactor240.asc.txt")
WUIdist = readGDAL("E://ParkData//SEKI//Smoke//wuidist.txt") #this layer
measures the euclidian distance from each cell to the nearest WUI area
SmokeZone = readGDAL("E://ParkData//SEKI//Smoke//smokezones240.txt")
elevation = readGDAL("E://ParkData//SEKI//Topography//sekielev240.txt")
boundary = readGDAL("E://ParkData//SEKI//Attributes//siteboundary.asc")

x =  coordinates(WUIdist)[,1]
y =  coordinates(WUIdist)[,2]

########################
#CONSTRUCT A DATA FRAME#
########################
df =
data.frame(x,y,SIF$band1,WUIdist$band1,elevation$band1,SmokeZone$band1,bounda
ry$band1)
df = na.omit(df) #remove observations with NA data
summary(df)
dim(df)
#use sub-sample of data for estimation of smoke impact (zones 1 & 5)
df = df[which(df$SmokeZone.band1 == 1 | df$SmokeZone.band1 == 5),]
summary(df)
head(df)
dim(df)

######################
#LOAD SPATIAL LIBRARY#
######################
plot(df$elevation.band1,df$SIF.band1)
plot(df$WUIdist.band1,df$SIF.band1)
elev2 = df$elevation.band1^2
##GENERALIZED LEAST SQUARES##
model.glm = glm(df$SIF.band1~df$elevation.band1+df$WUIdist.band1,data=df)
summary(model.glm)
library(lmtest)
library(sandwich)
coeftest(model.glm,vcov=NeweyWest(model.glm))
plot(model.glm)
hist(model.glm$resid)
qqnorm(model.glm$resid)
qqline(model.glm$resid)
plot(df$WUIdist,model.glm$resid)
plot(df$elevation,model.glm$resid)
confint(model.glm)
library(aod)
wald.test(b=coef(model.glm),Sigma=vcov(model.glm),Terms=1:2)

# test for spatial autocorrelation of GLS residuals
```

```
# first need to sample the data and run the GLS model again in order to build
a weights matrix
sample = df[sample(nrow(df),4000),]
summary(sample)
head(sample)
dim(sample)

w = spwtdist(sample$x,sample$y) #proximity matrix based on distance between
sampled grid cells
morani(model.glm$residuals,w) #Moran's I test for Spatial autocorrelation of
GLS residuals
#there is still spatial autocorrelation in the model resiudals

model.glm.s =
glm(sample$SIF.band1~sample$elevation.band1+sample$WUIdist.band1,data=sample)
summary(model.glm.s)
coeftest(model.glm.s,vcov=NeweyWest(model.glm.s))

############################################################################
#RESIDUAL KRIGING TO ENSURE THAT SPATIAL AUTOCORRELATION DOES NOT CAUSE A
#PROBLEM FOR SIGNIFICANCE OF GLS PARAMETERS#################################
############################################################################
## fit a gaussian variogram model to the residuals from the GLS model
SEKI.var.gau =
variogrm(sample$x,sample$y,model.glm.s$residuals,30,dmax=30000)
SEKI.fitvar.gau = fitvar(SEKI.var.gau,0,90,2000,wt=T,model="gau")
title("Gaussian Variogram Model of GLS residuals")
xlab("Distance lag (meters)")
ylab("Spatial Dis-similarity")
## fit an exponential variogram model to the residuals from the GLS model
SEKI.var.exp =
variogrm(sample$x,sample$y,model.glm.s$residuals,30,dmax=30000)
SEKI.fitvar.exp = fitvar(SEKI.var.exp,0,90,2000,wt=T,model="exp")
title("Exponential Variogram Model of GLS residuals")
xlab("Distance lag (meters)")
ylab("Spatial Dis-similarity")
## fit a spherical variogram model to the residuals from the GLS model
SEKI.var.sph =
variogrm(sample$x,sample$y,model.glm.s$residuals,30,dmax=30000)
SEKI.fitvar.sph = fitvar(SEKI.var.sph,0,90,2000,wt=T,model="sph")
title("Spherical Variogram Model of GLS residuals")
xlab("Distance lag (meters)")
ylab("Spatial Dis-similarity")

# gaussian model fits best, (lowest AIC) #

#calculate the spatial covariance matrix
x.mat = matrix(sample$x,,ncol=2000,nrow=2000,byrow=FALSE)
y.mat = matrix(sample$y,ncol=2000,nrow=2000,byrow=FALSE)
dst = sqrt((x.mat-t(x.mat))^2 + (y.mat-t(y.mat))^2)
# calculate the variance-covariance matrix using the fitted Gaussian
variogram model
alpha = 0.035137
sill = 0.272162
range = 7632.442
cov = (1-alpha)*sill*exp((-3*(dst/range)^2))
diag(cov) = sill
```

```
cov = round(cov,6)
corr = cov/sill
# take the inverse of the spatial covariance matrix then apply Cholesky
decomposition
VI = solve(cov)
L.inv = t(chol(VI))
# create a new design matrix  of explanatory variables which includes an
intercept term
X = cbind(sample$elevation.band1,sample$WUIdist.band1)
M = sample$SIF.band1
# Transform the model variables
X.tran = L.inv %*% as.matrix(X)
M.tran = L.inv %*% M
#define the new variables as the new sample data frame
sample = data.frame(cbind(M.tran,X.tran))

# fit a new GLS model with the transformed data
model.glm.s = glm(M.tran~X.tran,data=sample)
summary(model.glm.s)
#retest residuals for spatial AC
morani(model.glm.s$residuals,w) #still a problem, but parameters still
unbiased

coeftest(model.glm.s,vcov=NeweyWest(model.glm.s))
coeftest(model.glm.s,vcov=cov)

#####################
#SPATIAL ERROR MODEL#
#####################
sample = df[sample(nrow(df),2000),]
summary(sample)
X = cbind(sample$WUIdist.band1,sample$elevation.band1)
w = spwtdist(sample$x,sample$y,a=1,)
model.SEM = spatar2(sample$SIF.band1,X,w)
morani(model.SEM$residuals,w)
```