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Analysis

Incorporating Ecosystem Health and Fire Resilience Within the Unified Economic Model of Fire Program Analysis☆

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ABSTRACT

We expand on a budget constrained, wildfire program optimization model to include a decision variable input for ecosystem health and fire resilience (*H*). With ecosystem health and fire resilience as a decision variable, two ecosystem states are delineated; the ecosystem can be within or outside its range of variability. The Southwest ponderosa pine ecosystem is used to illustrate the effects of fuels or restoration treatments on the decision variable input *H* within the probabilistic production function for wildfire losses. To estimate the health and fire resilience of the ecosystem, a short-term metric of ecosystem health (trees per acre for Southwest ponderosa pine) is used. Analysis of how the state of the ecosystem affects the optimization of the probabilistic production function for wildfire loss is carried out on the two ecosystem states. Results indicate that if the ecosystem is outside its range of variability, optimization of the objective function cannot be achieved. However, if the ecosystem is within its range of variability or if the ecosystem is transitioned within its range of variability through fuels or restoration treatments, the objective function can be optimized with respect to the decision input variables.

1. Introduction

The economics of wildfire has its beginnings in the United States with early works published at the start of the 20th century. Understanding of how fire affects natural capital stocks and social welfare has evolved since its early inception into the decision-making process. This paper focuses on how the health of the ecosystem affects the probability of losses associated with wildfire. Additionally, the dynamics of restoration and fuels treatment in altering the ecological state are introduced into predicting the probability of loss.

A recent USDA report shows wildfire suppression expenditure rising from 16% of the Forest Service budget in 1995 to 52% of the budget in 2015 (USDA, 2015). Current estimates for 2017's wildfire suppression expenditures are surpassing $2 billion, making 2017 the most expensive year ever in terms of wildfire suppression costs. With increased expenditure on wildfire suppression costs, expenditures on other non-fire related programs within the Forest Service's budget are being reduced. For example, the Vegetation and Watershed Management Program is responsible for restoration, enhancement, and post-fire restoration on National Forest System lands. Over the past 15 years the Vegetation and Watershed Management Program's budget has been reduced by 24%. Although classified as a non-fire program, the Vegetation and Watershed Management Program plays a significant role in shaping the landscape where potential wildfires may occur. Are current budgets for the wildfire suppression program not accounting for other programs that impact expenditures or losses resulting from wildfires? Showing that expenditures can be made to change ecosystem health and fire resilience within a fire program to alter expected wildfire loss is a focal point of analysis within this paper.

We begin with a history of wildfire economics in the United States and the management policies that coincided with the understanding of wildfire economics during that time to lay the foundations of where wildfire economics has progressed to today. Then, an outline of the Unified Economic Model of Fire Program Analysis (Rideout et al., 2008), which summarizes a current understanding of wildfire economics, is presented. We adapt Rideout et al.'s (2008) formulation of the objective function within the Unified Economic Model of Fire Program Analysis for further analysis by introducing a decision input variable that represents ecosystem health and fire resilience into. With this expansion, the framework can be used to analyze optimizing a fire program model when the ecosystem's health and fire resilience is both within and outside a range of variability. Discussion of the management implications stemming from the results concludes the analysis.

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1.1. History of Wildfire Economics

The effects of the 1910 fire season within the Northern Rocky Mountains have had lasting management and policy implications for the United States (Pyne, 1997). Prescribed burning and the use of fire as a management tool was one such issue. Naturalists of the time argued for fire's place in the ecosystem based on what they observed as the fire ecology of their location. A group of Californian loggers was particularly adamant in using low intensity fire as a management tool and brought it up for public debate in August of 1910. However, their timing coincided with one of the largest fire seasons in U.S. history and faced strong opposition from the Forest Service. The idea of using low intensity fire as a management tool failed to gain public support and was not considered by the Forest Service until the mid-1940.

The aftermath of the 1910 fire season fell on the recently created Forest Service and its chief, Gifford Pinchot. The U.S. Forest Service and the general public had little incentive to tolerate any fire on the landscape following these events. The notion of using prescribed fire as a management tool was squelched and fire suppression was the management objective. The first three chiefs of the U.S. Forest Service were all involved with the 1910 fire season and the policy of zero tolerance for fire or prescribed burns on the landscape did not change until Lyle Watts was appointed chief in 1943. With a strict regime of fire suppression being implemented, a natural social question to arise was, “How much fire suppression is optimal?”

In 1916 the first publications addressing the economics of fire suppression were put forth by Parish Lovejoy (1916) and Roy Headley (1916). Given a policy of fire suppression implemented by the Forest Service following the 1910 fire season, Lovejoy (1916) and Headley (1916) laid the first academic foundation for the least cost-plus damage method of determining expenditures for wildfire suppression (Pyne, 1997). In Lovejoy's (1916) and Headley's (1916) analysis, the damages associated with fire were assessed in terms of timber loss, watershed damage, and the loss of human infrastructure. Following this initial analysis of the economics of wildfire suppression, the least cost-plus damage method was expanded and graphically illustrated by Sparhawk (1925). Sparhawk's (1925) model included the independent variable protection costs (“presuppression”) that determined the suppression costs and damages (“total liability”). Total liability was assumed to be inversely related to presuppression expenditures with the objective function seeking to minimize the sum of total liability and presuppression costs. This framework guided the rationale for fire suppression policies across much of the United States. While the goal of early works sought to minimize the costs associated with fire suppression plus the damages incurred by the fire, management of wildfire gave little to no consideration of total liability damages. It was argued by forest managers that suppression costs were being kept to a minimum by quickly and efficiently containing wildfires once they were spotted. Little regard to the potential loss of assets (timber, watersheds or human infrastructure) was considered in determining which wildfires to suppress under the zero tolerance policies.

The inclusion of positive benefits associated with wildfire occurrence has more recently been incorporated into the least cost (LC) plus damage or loss (L) model to produce an objective function minimizing the cost of fire suppression (C) plus net value change (NVC) to the landscape (C + NVC). Rather than viewing wildfire as a destructive event producing only losses, NVC incorporates benefits wildfire provides society (e.g. fuel load reductions). Donovan and Rideout (2003) analyzed Sparhawk's least cost-plus loss model (LC + L) and argued the model contains two errors in its formulation. First, suppression expenditure is being incorrectly modeled as a model output rather than a decision variation or an input. Second, presuppression and suppression efforts are modeled as substitutes (i.e. increase in one implies decrease in the other). They argued that both suppression and presuppression expenditures should be modeled as independent inputs to optimize the net value change, which is the output. Their analysis expands on the earlier results of Rideout and Omi (1990) which demonstrated that suppression and presuppression efforts/expenditures are not necessarily negatively correlated (Donovan and Rideout, 2003).

Our analysis of the economics of a fire management program builds on the theory established in C + NVC framework. The unified economic model of fire program analysis presented by Rideout et al. (2008) is the base theoretical model that input variables are expanded on. The decision variable input of “fuels” (a proxy for fuels treatments or presuppression activities) used in the probabilistic production function in Rideout et al. (2008) is expanded on to incorporate the use of fuels treatments or restoration to change the state of the ecosystem and its fire resilience. It is then the state of the ecosystem after the fuels treatments or restoration which becomes a decision variable in the probabilistic production function rather than fuels treatments itself. Relating the state of the ecosystem to the Southwest ponderosa pine ecosystem and using the pre-European state of the ecosystem as a benchmark for ecosystem health and fire resilience, analysis of the probabilistic production function when the ecosystem is either within or outside of its historical range of variability is conducted. Incorporating the state of the ecosystem into the probabilistic production function allows for the analysis of the marginal productivity of fuels treatments or restoration. This distinction demonstrates why marginal analysis fails to produce an optimal solution when the ecosystem is outside its historical range of variability.

2. The Unified Economic Model of Fire Program Analysis

Rideout and Omi (1990) offered a more in-depth analysis of the C + NVC model by allowing decision inputs (suppression and presuppression) to interact as complements or substitutes with each other. Building on the analysis of the C + NVC model, Rideout et al. (2008) formulated a unified economic model of fire program analysis. Two key elements of a fire program are built in this model. First is the inseparability of the cost components that comprise the fire program. This point is highlighted in the cost function with the inclusion of a joint cost component. Many components of a fire program, both suppression and presuppression activities, share costs. Thus, analysis of the fire program cannot take place by analyzing the sum of the parts. Second is setting up the loss function with two key decision inputs, “suppression” and “presuppression”. The loss function allows for the marginal analysis of decision inputs and the corresponding effects marginal changes have on the other decision input when optimizing the objective function. The most general structure of this model is presented in Eq. (1) (Rideout et al., 2008).

$$Min\ Z = \Lambda[P(F,S)] + \lambda[B - C(F,S)] \tag{1}$$

where:

Λ denotes a general loss function of burn probability P across the program
$P(F,S)$ denotes the probabilistic production function for the program
$C(F,S)$ denotes the cost function of the fire program
F denotes the fuels decision variable
S denotes the suppression decision variable
B denotes the fire program budget
λ denotes the Lagrange multiplier for the program budget constraint.

To further analyze the benefits wildfire provides within the framework of Rideout et al.'s (2008) probabilistic production function, the use of an input variable to represent the ecosystem's health and fire resilience (H) is introduced. The use of this input in the probabilistic production function furthers the ability to assess the beneficial and negative impacts of fire on the landscape in terms of changes to the overall loss function. In addition, it allows us to analyze the most efficient allocations of restoration or fuels treatment investment given the state of the ecosystem. Fire impacts an ecosystem in different ways depending on the state of that ecosystem. Investment in ecosystem management to change potential fire behavior is effective depending on the current state of the ecosystem's health and fire resilience. By introducing the input variable *H*, the state of the ecosystem's health and fire resilience impacts (beneficial or harmful) the effects of fire measured by the NVC calculation. The use of *H* allows us to analyze marginal productivity of each input and optimal allocation among decision variables under a given output.

In Eq. (1), *F* denotes the fuels decision variable. We separate it into two components (*E* and *H*) in this analysis. *E* represents a presuppression decision variable that includes expenditures on administrative and resource allocation placement, along with fire season and weather predictions and modeling. *E* does not include restoration or fuels treatment decisions affecting *H*. Expenditures on fuels treatments or restoration are captured in the decision input variable *H* which have a direct impact on the state of the ecosystem's health and fire resilience. The state of ecosystem's health and fire resilience changes depending on natural occurrences, restoration or fuels treatment, and other human impacts. The treatment costs depend on the desired level of health and fire resilience to be achieved. For example, a full restoration treatment aiming to recover a reference condition is usually much more expensive than a fuels treatment aiming solely to reduce fuel loads. Eq. (2) includes the substitution of the decision input variables *E* and *H* for *F*.

$$Min\ Z = \Lambda[P(E,S,H)] + \lambda[B - C(E,S,H)] \quad (2)$$

where:

Λ denotes a general loss function of burn probability *P* across the program
$P(E,S,H)$ denotes the probabilistic production function for the program
$C(E,S,H)$ denotes the cost function of the fire program
E denotes the presuppression decision variable (not including restoration or fuels treatments)
S denotes the suppression decision variable
H denotes the ecosystem's health and fire resilience
λ denotes the Lagrange multiplier for the program budget constraint.

Following Rideout et al. (2008), we assume risk neutrality for fire management ($\partial\Lambda/\partial P = L$ and $\partial^2\Lambda/\partial P^2 = 0$) and substitute *L*, the constant price of fire risk, for Λ, to arrive at the following equation:

$$Min\ Z = L\cdot[P(E,S,H)] + \lambda[B - C(E,S,H)] \quad (3)$$

Risk adverse behavior is more common in a fire management program (e.g. rules and regulations limiting fuel treatment activities in the wildland urban interface and urban centers). However, the risk neutrality assumption allows for a constant price of fire risk and a focus on the decision input variables. Expanding the cost function of the fire program to show separable and joint costs of the input components yields:

$$C(E,S,H) = SCE(E) + SCS(S) + SCH(H) + JC(E,S,H) \quad (4)$$

The separation of the cost function into the individual and joint components helps demonstrate the connectedness of the individual parts within a fire program. Certain investments in resources and infrastructure that are shared among the components are included in the cost function as joint costs ($JC(\cdot)$). Costs that are specific to a given component are captured by the separable cost related to that component ($SCx(x)$). The inclusion of the joint costs in this model underscores the relationships between fire program components and the need to examine the fire program as a whole rather than the sum of its individual parts. However, the introduction of the *H* variable and its separate cost component make it an explicit factor changing the state of ecosystem's fire resilience which requires additional and separate investment.

Substituting Eq. (4) into Eq. (3) gives the following expanded economic model of fire program analysis equation with the properties of the probabilistic production function, the assumption of risk neutrality (e.g. the corresponding constant price of fire risk (*L*)), and the separable and joint aspects of the cost function:

$$Min\ Z = L\cdot[P(E,S,H)] + \lambda[B - (SCE(E) + SCS(S) + SCH(H) + JC(E,S,H))] \quad (5)$$

The inclusion of *H* adds complexity to the probabilistic production function. Fulé et al. (2001) used fire models to show how effective different treatment intensities were at changing crowning indices within a Southwest ponderosa pine forest. Their results indicate that the more intensive the treatment (e.g. the more trees removed) the higher the wind the speed needed to make an active crown fire possible. For certain states of the ecosystem, increased investment to improve *H* results in the decrease of expected losses with decreasing returns to scale. However, for other states of the ecosystem (specifically, those beyond the historic range of variability), increased investment in *H* results in the decrease in expected losses with increasing returns to scale. Determining the current state of the ecosystem's fire resilience compared to its historical range of variability is a key component of determining the optimal investment in altering the state of *H* via restoration or fuel treatments. The following sections describe the input variable *H* and how to determine the optimal level of investment for improving *H*.

3. Describing the *H* Input Variable

The Southwest ponderosa pine forest is used as an example of how *H* describes the health and fire resilience of an ecosystem. Many factors go into determining the health and fire resilience of an ecosystem. A simplified, abstract model is presented to account for the factors affecting an ecosystem's health and fire resilience. From this model, the effects humans can have on the health and fire resilience of an ecosystem through restoration or fuels treatments are highlighted. We propose separating factors that affect the ecosystem into two vectors for analysis. One vector contains factors society has direct impacts on through management actions (***d***), such as fuels treatments and restoration. The other vector contains factors society has no direct impact on (***i***), such as years since the previous wildfire (Fitzgerald, 2005), current and past weather conditions, current and past disease and beetle outbreaks, and measures of species diversity and richness. Eq. (6) demonstrates the function of ecosystem health and fire resilience (*H*). Restoration treatments implemented in Southwest ponderosa pine forests seek to restore ecosystems within their historical range of variability of pre-European settlement conditions (Fulé et al., 1997; Moore et al., 1999, and Bailey and Covington, 2002). In contrast, fuels treatments aim to alter short-term potential fire behavior with no regard for achieving a historical forest structure. Both are included as factors in the vector of direct impacts society has on influencing *H*. Because of the dynamic progression of an ecosystem, a fuels or restoration treatment's benefits are effective for a limited time. While the longevity and effectiveness of the treatment varies over time with respect to a variety of factors (e.g. size, intensity, climate) the effectiveness of a restoration or fuels treatment can range significantly between 4 and 15 years for western pine forests (Pollet and Omi, 2002; Agee and Skinner, 2005, and Safford et al., 2012). Incorporating this temporal aspect of restoration or fuels treatments is noted in the vector of direct impacts in Eq. (6). A temporal aspect for weather and disease outbreaks within the no direct impact vector (***i***) is also incorporated. While both vectors play a role in determining the overall health and fire resilience of an ecosystem, the focus of analysis is on the ecological state influenced by the direct human impact vector ***d***. In this setting, ***d*** only includes treatments and their temporal attributes. To incorporate the dynamic nature of an ecosystem, if R_0 is a treatment implemented in today and R_{10} is a treatment implemented in a time period 10 years ago, both are incorporated in the ***d*** vector. Given the treatments were of equal impact on H at time 0, because of temporal dynamics, R_0 has a greater marginal impact on H than the R_{10} treatment. Within Eq. (6), the estimated coefficient for R_0 would be greater than the estimated coefficient for R_{10} all else equal.

$$H = f(\boldsymbol{d}, \boldsymbol{i}) \tag{6}$$

where:

H = state of ecosystem health and fire resilience
d = vector of direct impacts humans can implement to influence ecological state of forest
i = vector of indirect impacts humans have no or an indirect impact on influencing the ecological state of forest.

It would be difficult to measure H in terms of all ***d*** and ***i*** relationships and interactions. A surrogate variable is therefore implemented to represent health and fire resilience. Similar structures have been used in assessing ecosystem resilience (Walker et al., 2010; Wu and Kim, 2013). However, rather than focusing on irreversible change of an ecosystem due to loss of resilience, we examine the Southwest ponderosa pine ecosystem in terms of exhibiting a continuous change in ecosystem health and fire resilience based on a surrogate variable rather than Eq. (6). In the case of the Southwest ponderosa pine ecosystem, trees per acre has been used as a viable metric for assessing ecosystem health in relation to its historical range of variability (Fulé et al., 1997 and Wu and Kim, 2013). While other factors (e.g. the spatial distribution of trees over the landscape) are important for determining a historical benchmark for restoration treatments to try and replicate, the general metric of trees per acre is used in this analysis. Figs. 1 and 2 are conceptual functions of trees per acre predicting ecosystem health. The relationship between the surrogate variable and ecosystem health and fire resilience could take many different forms. However, Figs. 1 and 2 highlight two key limits and a point of interest within the function.

3.1. Maximum and Minimum Levels of H

Fig. 1 highlights a maximum level of H (denoted as $H_{\max}$) that can be attained by a Southwest ponderosa pine ecosystem. $H_{\min}$ represents a minimum level of ecosystem health and fire resilience that is approached as the ecosystem suffers from degradation. As the ecosystem approaches $H_{\min}$, the ecosystem is more prone to transition to an alternative ecosystem stable state (ecosystem type). However, some shock to the ecosystem would be needed to initiate this transition. As a Southwest ponderosa pine ecosystem increases in trees per acre, it loses its ability to recover from shocks (e.g. fire) leading to the possibility of

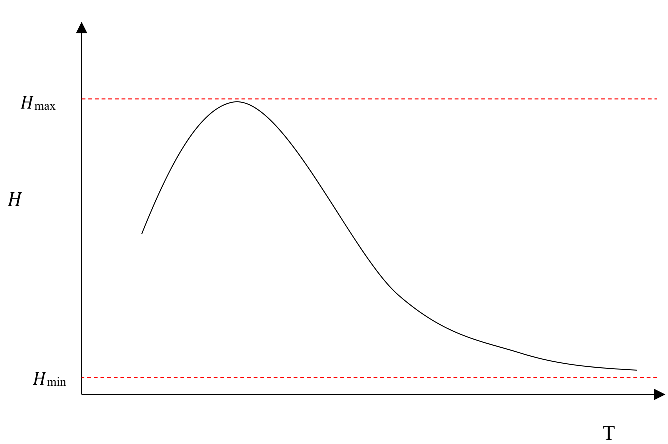

Fig. 1. A conceptual model of ecosystem health and fire resilience as a function of trees per acre.

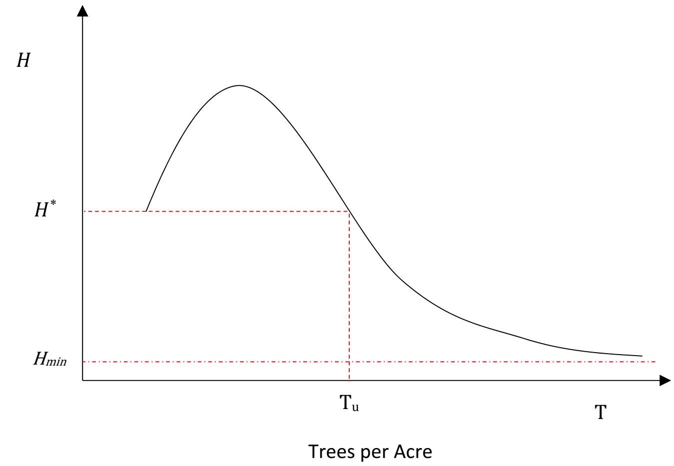

Fig. 2. A conceptual measure of ecosystem health and fire resilience shown at the upper range of variability for trees per acre (T_u) for a given landscape.

an ecosystem regime change. A minimum number of trees per acre is required for the landscape to be considered a ponderosa pine ecosystem; therefore, the function does not start at 0 trees per acre. If the ecosystem was to fall below that threshold number of trees per acre, it is no longer functioning as a ponderosa pine ecosystem. With the inclusion of H in the probabilistic production function (5), a focus for optimization is determining if the landscape is within or outside its historical range of variability with respect to the short-term measure for ecosystem health and fire resilience. If the landscape is within this historical range of variability, then fire behavior characteristics are more likely to be within their historical norm of low severity surface fires. If the landscape is outside its historical range of variability, then extreme fire behavior characteristics are more likely to result with higher proportions of mixed and high burn severity. Fig. 2 demonstrates a number of trees per acre that acts as an upper bound for a historical range of variability for a given landscape.

3.2. The Inflection Point on the H Function

In Fig. 2, the point (T_u, H^*) represents an inflection point where H is strictly concave ($\frac{\partial^2 H}{\partial T^2} < 0$) for the range of $T < T_u$. For $T > T_u$ the H function is strictly convex ($\frac{\partial^2 H}{\partial T^2} > 0$) with respect to trees per acre. While T_u changes between different stands or landscapes within the Southwest ponderosa pine ecosystem, the H function always has the property of an inflection point evaluated at (T_u, H^*). The upper range of variability, measured in terms of trees per acre, for the Southwest ponderosa pine ecosystem acts as a threshold for determining where the H function stops decreasing at a decreasing rate and starts decreasing at an increasing rate. Depending on how far the current state of the ecosystem is from its historical range of variability, increases in H affect the probabilistic production ($P(E,S,H)$) in Eq. (3) at different rates. For values of T below or at the inflection point T_u, the state of the ecosystem in a Southwest ponderosa pine landscape is in a state where fire behavior exhibits its historical, low intensity surface fires behavior. Since the ecosystem is in a state better suited for fire disturbance, additional investment in fuels or restoration treatments have decreasing marginal impacts on improving H. For $T \leq T_u$ and $H \geq H^*$, the H function exhibits diminishing returns to scale in the probabilistic production function since the ecosystem can withstand, and even prosper, from fire disturbances.

On the other hand, when $T > T_u$, fire behavior demonstrates characteristics that are outside its historical range of variability with greater proportions of landscape burning at higher severities. In this state, the ecosystem has a reduced resilience to potential wildfires outside the historical range of variability causing an increase in loss. The corresponding fire behavior characteristics continue to return to their historical norm of variability until they finally do so when the surrogate measure of trees per acre is within its historical range of variability. Investment in fuels or restoration treatments have larger impacts on the ecosystem's health and fire resilience over some ranges but minimal change in *H* over others. When the ecosystem is within the historical range of variability of trees per acre, *H* ranges from H^* to H_{max}. When the ecosystem is outside its historical range of variability of trees per acre, *H* ranges from the H_{min} limit to H^*.

The implications of *H*'s effect on the expanded probabilistic production function are shown with the first and second order conditions in Eqs. (7.1) and (7.2). For values of *H* within its historical range of variability, decreasing returns to scale are implemented for ecosystem's health and resilience on the loss function. For values of *H* outside its historical range of variability, the loss function decreases with fuels or restoration treatments but at an increasing return to scale. Increasing returns to scale are used with ecosystems outside their historical range of variability based on results from Johnson et al. (2011) and Fulé et al. (2001). In their analysis, Johnson et al. (2011) show proportions of the landscape burning as surface fires increasing with more intensive reductions in trees per acre in forest types of western North America (Central Rockies Forest Vegetation Simulator (FVS) variant). However, the rates of change in proportion of the landscape burning as surface fires change between treatment intensities. Fulé et al. (2001) demonstrate different changes in crowning indices based on three restorations at different intensities. From these results, we implement the following first and second order conditions:

If $H \geq H^*$ relating to $T \leq T_u$:

$$\frac{\partial P}{\partial H} \leq 0; \qquad \frac{\partial^2 P}{\partial H^2} \geq 0 \tag{7.1}$$

If $H < H^*$ relating to $T > T_u$:

$$\frac{\partial P}{\partial H} < 0; \qquad \frac{\partial^2 P}{\partial H^2} < 0 \tag{7.2}$$

4. Implications of H on the Unified Economic Model of Fire Program Analysis

The following are the first order partial derivative conditions for the minimization of Eq. (5):

$$Z_S = L \cdot P_S - \lambda\,(SCS_S + JC_S) = 0 \tag{8.1}$$

$$Z_E = L \cdot P_E - \lambda\,(SCE_E + JC_E) = 0 \tag{8.2}$$

$$Z_H = L \cdot P_H - \lambda\,(SCH_H + JC_H) = 0 \tag{8.3}$$

$$Z_\lambda = B - (SCE(E) + SCS(S) + SCH(H) + JC(E, S, H)) = 0 \tag{8.4}$$

Eqs. (8.1)–(8.4) state the first order conditions of the economic model of fire program analysis. Eqs. (8.1)–(8.3) show the marginal benefit-cost condition. Eq. (8.3) states the marginal benefit-cost condition for a change in expected loss with respect to *H*. For loss minimization, ($L \cdot P_H$) equals the marginal cost of the program cost component with respect to *H* adjusted for the shadow price (λ). Rewriting Eq. (8.3) yields the following expression of the marginal benefit-cost condition:

$$L \cdot P_H = \lambda\,(SCS_H + JC_H) \tag{8.3.1}$$

Because increases in all decision variable inputs (*S*, *E*, *and H*) are expected to reduce expected loss and *L* is assumed constant from risk neutrality, P_S, P_E, and P_H must be negative. In addition, with all costs being positive and increasing as investment in the decision variable inputs increases, λ must be negative. This result reflects the marginal value of an increase in the budget, with the assumption that all increases in the budget are allocated to program components. Marginal changes in the budget then have the overall result of reducing the fire program loss by λ ($\partial Z/\partial B = \lambda$).

4.1. Impacts of H on the Probabilistic Production Function

Increases in the decision variable of ecosystem health and resilience (*H*) result in decreases of expected loss at different rates depending on the condition of the ecosystem. If the ecosystem is within its historical range of variability, an intensive restoration expenditure would not have the same effect as implementing an intensive restoration expenditure on an ecosystem that is outside its historical range of variability. Changes in wildfire behavior and the associated probability of losses would be greater in the ecosystem outside its historical range of variability. In either case, treatments would improve *H* but greater increases in loss reduction would occur where $T > T_u$ as T approaches T_u. The function ($L \cdot P(H)$) decreases at higher rates for values of T close to T_u. If using a marginal analysis approach for $T > T_u$ and T is excessively high, little marginal change in *H* occurs. The corresponding expected loss from wildfire decreases as the fire behavior characteristics are changed from high to low severity. Because of risk neutrality and a constant price for loss, improvements in *H* decrease the probabilistic production function to represent an overall reduction in loss from wildfire on the landscape. The probabilistic production function is segmented into a non-continuous function with respect to the ecosystem health decision variable (*H*). T's determination of *H* creates a limit on *H* in the probabilistic production function. More specifically, it exhibits its limits where the ecosystem health metric is at its maximum historical rate of variability (H^*).

The following are the second order partial and cross partial derivative conditions of Eq. (5):

$$Z_{SS} = L \cdot P_{SS} - \lambda\,(SCSS_S + JCS_S) \tag{9.1}$$

$$Z_{EE} = L \cdot P_{EE} - \lambda\,(SCE_{EE} + JC_{EE}) \tag{9.2}$$

$$Z_{HH} = L \cdot P_{HH} - \lambda\,(SCH_{HH} + JC_{HH}) \tag{9.3}$$

$$Z_{SE} = L \cdot P_{SE} - \lambda\,(JC_{SE}) \tag{9.4}$$

$$Z_{SH} = L \cdot P_{SH} - \lambda\,(JC_{SH}) \tag{9.5}$$

$$Z_{EH} = L \cdot P_{EH} - \lambda\,(JC_{EH}) \tag{9.6}$$

$$Z_{\lambda\lambda} = 0 \tag{9.7}$$

$$Z_{\lambda S} = -SCS_S - JC_S \tag{9.7}$$

$$Z_{\lambda E} = -SCE_E - JC_E \tag{9.8}$$

$$Z_{\lambda H} = -SCH_H - JC_H \tag{9.9}$$

Eqs. (9.1)–(9.9) represent the partial second order conditions of Eq. (5). Diminishing returns to scale are observed for suppression efforts Eq. (9.1) and resource allocation Eq. (9.2) over all ranges of decision variable inputs *S* and *E* (Z_{SS} and Z_{EE} are positive). For $H < H^*$ increasing returns to scale occurs when the ecosystem exceeds its historical range of variability in terms of trees per acre ($T > T_u$) for Eq. (9.3) (Z_{HH} is negative) (Johnson et al., 2011). At trees per acre levels highly divergent from their historical range of variability, marginal changes in trees per acre for simulated fires appears to have minimal impacts on changing wildfire behavior (Johnson et al., 2011). However, as trees per acre approaches its historical range of variability, more dramatic changes occur in fire behavior.

4.2. $H \geq H^*$

Fig. 3 illustrates Eq. (7.1) and what is derived from Eqs. (8.3) and (9.3) when the ecosystem state is within its historical range of variability. Additional investment in the health and fire resilience of the ecosystem begins to lose it effectiveness in reducing the wildfire loss function. The loss function is decreasing as the ecosystem's health

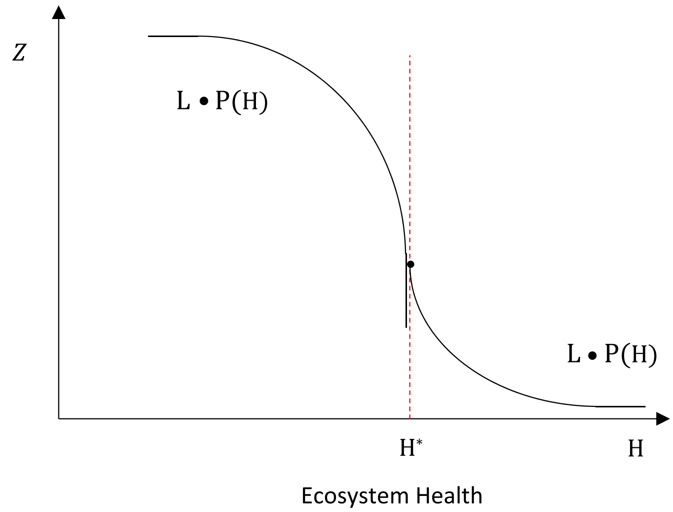

Fig. 3. Conceptual loss function with respect to ecosystem health and fire resilience for. H^* represents a limit the loss function approaches as H increases. Once equaling or exceeding H^*, diminishing returns to scale are observed.

increases (holding all other decision inputs constant) and doing so with diminishing returns to scale.

4.3. $H < H^*$

Fig. 3 further illustrates Eq. (7.2)'s implications on Eqs. (8.3) and (9.3) for the concavity of the loss function with respect to H over the range $H < H^*$. For $H < H^*$ the first order Eqs. (8.1)–(8.4) for the marginal benefit-cost conditions on the decision input variables and the budget continue to hold. However, the objective function (Eq. (5)) is a minimization problem and the first order condition of Eq. (8.3) would be expressing a maximum given the function is concave following the structure of Eq. (7.2) over the range of $H < H^*$ (Eq. (9.3) is negative for $H < H^*$). While the equi-marginal principle could produce a solution to the objective function, its practical implications would contradict wildfire loss minimization. The equi-marginal principle would hold for Eqs. (8.1) and (8.2) for of $H < H^*$. However, Eq. (8.3) over the range of $H < H^*$ is strictly concave causing the equi-marginal principle to solve a maximization problem for H while solving a minimization problem for S and E.

5. Discussion

With ecosystem health and fire resilience as a decision variable input of fire program optimization, two ecosystem states exhibiting different returns to scale with respect to (H) are analyzed. The Southwest ponderosa pine ecosystem is used to illustrate the effects of fuels or restoration treatments on the expected loss function from wildfire. In this setting, H is affected by human capital investment in ecosystem health and fire resilience (reduction of trees per acre to increase H).

In the case where the ecosystem state is within its historical range of variability ($H \geq H^*$), measured in terms of trees per acre ($T \leq T_u$), diminishing returns to scale in the probabilistic production function, with respect to H, follow from Rideout et al. (2008). In this instance, the results differ little from Rideout et al.'s (2008) results in that an optimal solution for each decision input variable can be found. The arguments regarding complementary effects or synergism between decision variable inputs hold and the minimization of the objective function (Z) has a solution for a given budget (B) with a constant rate of loss from fire L. The three decision inputs can be optimized using equi-marginal analysis where ratios in the reduction of fire probabilities equal the ratios of their marginal costs.

When the state of the ecosystem's health is outside its historical range of variability ($H < H^*$), increasing returns to scale in the objective function with respect to H are implemented. As H approaches H^*, changes in wildfire behavior are shown to shift from larger proportions of the landscape burning at high and mixed severities to surface fires or low severity wildfire (Johnson et al., 2011). Since loss is constant in this analysis, the reduction in loss is associated with the lowering of the probability of experiencing such loss through the probabilistic production function. The low intensity surface fire reflects the historical fire regime of the Southwest ponderosa pine ecosystem. The inflection point of H^*, represented by T_u in its ecological metric, is the function's limit for $H < H^*$ and the objective function continues to decrease and approach H^* (H^* is the limit the function is approaching). Although the equi-marginal principle doesn't produce a rational solution in the range of $H < H^*$, there still exists applications for the marginal analysis of the loss function. When the absolute value of the first order condition of the loss function with respect to H is > 1 there is increasing incentive for investment in H. Holding all other input decision variables constant, the loss function continues to approach its limit as H approaches H^*. This corresponds to large reductions in the expected loss from marginal changes in H as H approaches H^*. Two additional aspects of the marginal loss function with respect to ecosystem health are worth further examination when the ecosystem is outside its historical range of variability in terms of health and sustainability:

1) At what point is the first order condition of the expected loss $|P_H| \geq 1$ for $H < H^*$?
2) How is the corresponding H for the first order condition of the expected loss

$|P_H| \geq 1$ represented in the physical world?

Matching the metric for ecosystem health and fire resilience to the corresponding partial derivative of the objective function is critical for establishing thresholds that must be met before economic optimization of the fire program can occur. In this study, we hypothesized the upper range of variability for pre-European trees per acre in Southwest ponderosa pine to be synonymous with the infliction point (H^*) for the partial derivative of objective function (Eq. (5)) with respect to H. However, relaxing H^* as a threshold, the point where $|P_H| = 1$ (for $H < H^*$) becomes an important ecosystem state for optimization of the objective function. From a marginal analysis perspective, $|P_H| \geq 1$ supports additional investment in ecosystem health and fire resilience as a unit investment in H brings about a greater than one unit decrease in expected loss. Determining the associated ecosystem health and fire resilience metric that corresponds to $|P_H| = 1$ for $H < H^*$ or H^* is needed for fire program optimization. However, for $|P_H| < 1$ and $H < H^*$, marginal invest in H is not supported as the objective function would be optimizing P_H at a maximum rather than a minimum. Collaboration between forest ecologists and social scientists is needed to determine threshold metrics of H that need to be achieved before optimization of the objective function can occur.

From a management perspective, the results of using the ecosystem's health and fire resilience as a decision variable have several implications. If H is within its historical range of variability ($H \geq H^*$) then the equi-marginal analysis for the optimization of the objective function (Eq. (5)) is an appropriate tool for optimizing the decision input variables for a given budget constraint in a fire optimization program. Relating this range of H to trees per acre, the range of trees per acre in the Southwest ponderosa pine ecosystem would be $T \leq T_u$. When H is outside its historical range of variability, land managers should focus on getting the landscape back to within its historical range of variability or to the corresponding point where $|P_H| = 1$ for $H < H^*$ before considering marginal analysis with respect to fire program optimization. In this instance, the probabilistic loss function is exhibiting increasing returns to scale from investment in restoration or fuels treatments. As T decreases from restoration or fuels treatments and approaches T_u, fire regimes change and start approaching the low intensity surface fires associated with the Southwest ponderosa pine ecosystem being within its historical range of variability. If the ecosystem is outside its historical range of variability, the objective function of the fire program cannot be optimized. Thus, marginal analysis does not support investment in the ecosystem state. In the instance where H is outside its historical range of variability, land managers should focus on returning the landscape to within its historical range of variability before undertaking any form of optimization with respect to a fire program.

6. Conclusions

Largescale restoration project goals of Southwest ponderosa pine reflect economic optimization of reducing trees per acre to pre-European forest structure to increase ecosystem health and fire resilience (Brown et al., 2004, Noss et al., 2006, and United States Department of Agriculture (USDA), 2013). Our results highlight the situations where large restoration projects need to be taken before marginal analysis can be used for optimization of wildfire programs. Economics has a strong foundation in marginal analysis to determine optimal outcomes. However, if an ecosystem well outside its range of variability, marginal analysis may fail at producing an optimal outcome. Under these circumstances, more emphasis and expenditure will be placed on wildfire suppression rather than increasing ecosystem health and fire resilience. Current budget patterns seem to be showing support of this occurrence but are large, non-marginal investments in restoring ecosystem health the reason?

This analysis is based on the assumptions of constant loss. These assumptions were used to focus on the marginal impacts of the decision variable inputs with the probabilistic production function portion of the objective function. However, these assumptions rarely hold in real world situations. The 2017 wildfire season in California exemplified how loss from wildfire is not constant and that homogeneous landscapes where wildfires burn do not exist. Human infrastructure, particularly expansion of the wildland urban interface (WUI) into fire prone ecosystems, and ecosystem goods and services vary across the landscape. Bostwick et al. (2011) and Loomis (2018) examine the connections between wildfire suppression expenditures and human infrastructure damaged by wildfire. In addition, Fitch et al. (2018) examined how changing wind conditions and location of the wildfire affects fire behavior and wildfire suppression costs. Functions to estimate the loss from wildfire are addressed using a variety of variables; however, estimating loss from wildfire is an area for further analysis.

Risk neutrality on behalf of the program managers was also used to achieve a constant loss function. Given the potential for losses from restoration, fuel treatments, or extreme wildfire conditions, program managers tend to exhibit more risk adverse behavior. For instance, prescribed burns are not permitted in WUI areas because of the risk of the fire damaging human infrastructure. Preservation of human life will also cause management decisions to be made under risk adverse rather than risk taking behavior. Further studies into risk management within wildfire programs would be a significant contribution to wildfire economics.

Further areas of collaboration between natural and social scientists in fire program optimization could examine the physical states of the ecosystem to their corresponding relevance in determining threshold states for management. How physical states of ecosystems relate to metrics of ecosystem health and fire resilience, as a decision input variable for fire program optimization, would be beneficial to land managers. These metrics and tools would give land managers the ability to determine threshold states to transition the landscape toward fire program optimization.

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