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Research Article

Evaluating Sensitivity of the Ranking of Forest Fuel Treatments to Manager's Risk Attitudes and the Importance of Treatment Objectives, Montana, USA

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This study develops a conceptual framework for evaluating the sensitivity of the ranking of forest fuel treatment strategies (FTSs) to variation in managers' risk attitudes and the importance ratings managers assign to fuel treatment objectives and demonstrates the application of the framework using a case study. The conceptual framework involves (1) defining a utility function on an index that is a weighted average of fuel treatment objectives and incorporates a manager's risk attitude; (2) using the utility function to calculate utility values for FTSs; (3) applying the stochastic efficiency with respect to a function method to utility values to obtain certainty equivalents (CEs); and (4) ranking FTSs based on statistically significant differences in median CEs for pairs of FTSs. The case study involves three (federal, state, and private) forested areas in Flathead County, Montana, USA, three FTSs (i.e., Community Wildfire Protection Plan (CWPP) Priority; CWPP & Wildland-Urban Interface Priority; and No Priority), three treatment objectives (i.e., minimizing expected residential monetary losses from wildfire, minimizing expected deviation of forest ecological conditions from their historic range and variability, and maximizing expected net returns from timber harvesting associated with fuel treatment), two risk attitudes (i.e., almost risk neutral and highly risk averse), and 35 weight scenarios for treatment objectives. Case study results are used to test the hypothesis that the ranking of FTSs is sensitive to manager's risk attitudes and the importance ratings for management objectives. The ranking of FTSs for the three forested areas was insensitive for an almost risk neutral manager and sensitive for a highly risk averse manager. In general, the case study indicates that the ranking of FTSs is sensitive to both a forest manager's risk attitudes and the importance ratings assigned to fuel treatment objectives.

1. Introduction

Higher fuel loads, population growth in the WUI (wildland-urban interface), and climate change (i.e., warmer summers, lower precipitation, and milder winters) in the western U.S. and elsewhere continue to drive an increase in wildfire intensity and wildfire-related losses, especially for residential properties located near public lands [1, 2]. In addition, the ecological health of forest ecosystems has declined, as evidenced by high departures of forest ecological conditions from their historic range and variability [3]. One source of these departures is the accumulation of fuels due to wildfire suppression and reduced timber harvesting. For example, harvest rates in U.S. national forests have declined from 26.7 million cubic meters (mcm) in FY (fiscal year)-1987 to 6.8 mcm in FY-2016, or 75% [4], and current harvest rates are considerably below their estimated long-term, sustainable capability of 29.9 mcm [5].

Fuel reduction treatments have the potential to decrease wildfire intensity or severity, yet the variable application or prioritization of these treatments across the landscape is necessary in order to efficiently reduce the adverse impacts of wildfire [6–14]. For example, at a briefing in Florence, Montana, USA, on August 24, 2017, the secretaries of Agriculture and Interior announced that their departments will be working together to remove fuel from the nation's forests and reduce the threat of catastrophic wildfires. During the briefing, Interior Secretary Ryan Zinke said: "The issue before us is . . . making sure we have healthy forests, and going back to reduce fuel so we don't have these catastrophic events year after year" [15].

A variety of fuel treatments have been promoted as a means of restoring fire-dependent forests to conditions that better resemble historical and healthy conditions that existed prior to long-term fire suppression [16–20]. However, several experts point out that it may not be financially, politically, and/or physically feasible to decrease fuel loads enough to significantly reduce wildfire losses [12, 21, 22]. This situation implies that selective and efficient placement of fuel reduction treatments is important.

A potentially important issue not addressed in previous studies and addressed in this study is the extent to which managers' risk attitudes and the importance that they assign to fuel treatment objectives influence forest management decisions regarding preferred fuel treatments. For instance, some managers may prioritize the reduction of future wildfire hazards to private properties and structures over restoration of forest stands, which would modify the conflagration, and the types or amount of treatments on forest lands.

This study has two overarching objectives: (1) to develop a conceptual framework for evaluating the sensitivity of the ranking of fuel treatment strategies (FTSs) to variation in managers' risk attitudes and the weights assigned to treatment objectives; (2) to demonstrate the application of the framework using a case study. The case study involves three distinct FTSs, three fuel treatment objectives, two risk attitudes, and several scenarios for the importance of fuel treatment objectives.

2. Previous Research

This section summarizes several studies exploring efficient fuel treatment decisions, including (1) the effects of forest fuel treatments on fuel and wildfire hazard; (2) the optimal spatial arrangement of fuel treatments on a landscape for decreasing wildfire losses; or (3) use of multiple objective/attribute decision criteria to rank management alternatives.

Several studies have examined the design and efficacy of different forest FTSs. Those studies indicate that a variety of factors influence forest managers' placement of fuel treatments on the landscape, including (1) priorities or considerations outlined in policies, such as the Healthy Forests Restoration Act and the Collaborative Landscape Restoration Program; (2) the economic viability of treatments; (3) prioritization of sensitive wildlife habitat; (4) limitations on management efforts due to protected area designation; and (5) the extent to which fuel treatments can help restore forest stands to healthier conditions [23–27]. Taken together, these factors create a complex set of decision parameters for managers or collaboratives designing landscape-level fuel treatments.

Design and implementation of fuel treatments for a forested landscape can be influenced by variation in risk attitudes and the importance of fuel treatment objectives among forest managers. For instance, psychological theory and wildfire research both indicate that some managers may be more risk averse when prioritizing wildfire management actions that reduce losses to private property, while others may be more focused on landscape restoration [28–31].

There have been a number of research efforts that seek to evaluate and prioritize fuel treatments based on multiple management objectives. For instance, Wei et al. [32] developed a mixed-integer programming model that allocates fuel treatments across a landscape based on spatial information for fire ignition risk, conditional probabilities of fire spread between raster cells, fire intensity levels, and values at risk from fire. Bradstock et al. [33] estimated the percent of a landscape that would need to be treated with prescribed burning to reduce wildfire hazards to people and property in Australian eucalypt forests based on 2050 climate change scenarios. Ferreira et al. [34] developed a stochastic dynamic programming model to determine the impact of wildfire risk on the optimal stand management schedule for maximizing expected discounted net revenue for a Maritime pine forest in Leiria National Forest, Portugal. He et al. [35] used the fuel module in LANDIS to simulate the impacts of alternative fuel treatments on fire risk dynamics. Fire risk was measured by potential fire intensity and fire probability.

Lessons from the above literature indicate that various management objectives have been used to evaluate and determine preferred fuel treatments. For instance, Ager et al. [24] evaluated fuel treatment prioritization to maximize protection and conservation of old growth ponderosa pine (*Pinus ponderosa*) stands and found that outcomes were sensitive to trade-offs in parameters related to fire intensity and treatment size. Hessburg et al. [36] noted how protection of watersheds and areas near private development influenced the structure and placement of fuel treatments in their prioritization scheme. Konoshima et al. [37] applied a dynamic optimization model to a hypothetical landscape to evaluate how various biophysical and socioeconomic characteristics influence optimal fuel treatments, including weather, slope, and treatment costs under a variety of discount rates. They found that the net value of timber and the probability of loss to timber value interacted to influence fuel treatment optimization.

The variety of objectives that influence optimal fuel treatments and the complex nature of the trade-offs facing managers when selecting fuel treatments pose a significant challenge for forest managers [27, 30, 38]. Multiple criteria decision-making (MCDA) techniques have emerged as a popular approach for addressing natural resource management decisions in a way that balances the trade-offs between economic, environmental, and social values or preferences of stakeholders [39]. Numerous multiple objective/criteria decision-making methods have been used to address natural resource management issues, including multiple objective/attribute utility theory [40], multiple objective/attribute value theory [41], ELECTRE [42], Analytic Hierarchy Process [43], balancing and ranking method [44], and fuzzy Technique for Order Preference by Similarity of Ideal Solution [45, 46]. These methods essentially determine preferred management alternatives for a natural resource system by taking into account multiple management objectives and the importance of those objectives.

This study builds on the work cited above to quantify the outcomes of FTSs using a multiple objective utility function and uses those outcomes to evaluate the extent to which different risk attitudes and weights for management objectives influence the ranking of FTSs.

An increasing number of studies use MCDA approaches to design or research optimal fuel treatments. For instance, Ohlson et al. [47] evaluated the influence of fuel management on wildfire risk accounting for uncertainty about multiple attributes of fuel management alternatives as measured by the expected value and risk profile (probability distributions) for those attributes. Their study compared four FTSs based on six fuel treatment objectives. Prato and Paveglio [46] evaluated the effects of three FTSs on three fuel treatment objectives (i.e., expected residential property losses due to wildfire, expected deviation of ecological conditions from their historic range and variability, and expected net returns from timber harvesting associated with fuel treatment). Driscoll et al. [48] used multiattribute utility theory to assess outcomes of 22 prescribed fire scenarios on eight management objectives including home loss and minimizing soil loss. They found a small number of solutions that minimized conflicts among objectives, but noted that no scenario improved outcomes for all objectives. Schroder et al. [49] used multiple objective optimization techniques to evaluate trade-offs between fire hazard reduction, wildlife habitat, and sediment delivery in an Oregon municipal watershed.

Marques et al. [50] used multiple criteria decision-making methods to incorporate wildfire risk in a multiple objective planning framework that generates information about trade-offs among multiple objectives. Ferreira et al. [51] developed a forested landscape management scheduling model that addresses the risk of wildfires as measured by wildfire occurrence and damage probabilities and tested the model by using a mixed-integer programming to determine the location and timing of management options (e.g., fuel treatment, thinning, and clearcut) that maximize expected net revenues for the Leiria National Forest in central Portugal.

Although research about fuel treatments has addressed complex trade-offs facing forest managers, there is less understanding about how managers' risk attitudes influence their fuel treatment decisions. Most studies prescribe "optimal" treatment solutions and expect managers to implement those solutions. This approach does not necessarily reflect a decision environment where managers face political and public pressure to implement fuel treatments, including pressure to protect private property and ecological values, or reduce firefighting costs [28, 29, 38]. In summary, although the studies described above and other studies have contributed to an understanding of efficient fuel treatment decisions, no studies have explicitly examined the sensitivity of the ranking of FTSs to forest managers' risk attitudes and the importance of fuel treatment objectives as done in this study.

3. Materials and Methods

3.1. Conceptual Framework. The conceptual framework developed here (1) selects an outcome that the forest manager desires more of, designated as c; (2) defines a utility function in terms of c, namely, U(c); (3) calculates certainty equivalents (CEs) for decision alternatives based on that utility function; and (4) uses CE values to rank decision alternatives. Existing theoretical (e.g., [52]) and empirical (e.g., [53, 54]) studies of risky alternatives usually define c as wealth or income. However, wealth or income may not be an appropriate variable for forest managers that need to balance multiple values for a landscape. Accordingly, the framework presented here defines c in terms of three attributes of management objectives: (1) wildfire risk to private properties; (2) forest health; and (3) net returns from timber harvesting. In general, CE is the guaranteed amount of money that would yield the same exact expected utility as a given risky asset with absolute certainty [55, 56]. In this study, CV is defined as the amount of compensation a forest manager is willing to receive in order to accept the variability in utility associated with an FTS (adapted from [56]). The conceptual framework defines c_j as a weighted sum of the estimated values of FTS objectives, namely, $c_j = \sum_{i=1}^{n} w_i V_{ij}$, where $i = 1, \ldots, n$ where n is the number of fuel treatment objectives, $j = 1, \ldots, m$ where m is the number of risky FTSs being ranked, w_i is the weight for the ith objective, V_{ij} is the estimated value of the ith objective for the jth FTS, and $\sum_{i=1}^{n} w_i = 1$. FTSs are risky alternatives when w_j and/or V_{ij}, and hence c_j, are stochastic. The conceptual framework described in this section does not make reference to time periods. However, in empirical applications (see Section 3.2), the values of w_i and/or V_{ij} can be varied over time periods, which causes the values of c_j to vary over time periods.

FTSs are ranked based on CEs, and CEs are derived from utility values obtained by substituting the values of c_j into a utility function, namely, $U(c_j)$. Based on Hardaker et al. [52], the probability density functions describing the g stochastic outcomes of FTS_j are $f_1(c_j), f_2(c_j), \ldots, f_g(c_j)$, and the corresponding cumulative distribution functions are $F_1(c_j), F_2(c_j), \ldots, F_g(c_j)$. The subjective expected utility hypothesis states that $U(c_j) = EU(c_j) = \int U(c_j) f(c_j) d(c_j) = \int U(c_j) dF(c_j)$, where $EU(c_j)$ is the expected value of $U(c_j)$ [54]. In other words, the utility of c_j is its expected value.

A limitation of the above utility framework in empirical applications is that it requires knowledge of the exact shape of the forest manager's utility function and hence the manager's risk attitudes. Some studies have elicited decision makers' risk attitudes (e.g., [57]) and others have used hypothetical attitudes [58]. The Stochastic Efficiency with Respect to a Function (SERF) method [52] used in the framework presented here addresses this limitation by ranking FTSs for an absolute, relative, or partial risk aversion coefficient r(c) ϵ $[r_L(c), r_U(c)]$, where $r_L(c)$ is the lower bound and $r_U(c)$ is the upper bound of the coefficient. That method assumes the values of r(c) are the same for all FTSs and uses a discrete approximation of the utility function and a specific form of the utility function. The utility function used in this study is $U[c_j, r(c)] = \sum_{i=1}^{m} U[c_i, r(c)]p(c_{ij})$, where $p(c_{ij})$ is the probability of the ith outcome for the jth FTS. This discrete utility function is used to calculate utility values for discrete values of r(c) selected from $[r_L(c), r_U(c)]$. The partial ordering of FTSs based on $U[c_j, r(c)]$ and CE values is the same. In particular, $CE[c_j, r(c)] = U^{-1}[c_j, r(c)]$, where $U^{-1}[c_j, r(c)]$ is the inverse utility function.

3.2. Case Study. This section presents an empirical case study that demonstrates the application of the conceptual framework. Case study results are used to test the hypothesis that the ranking of FTSs is sensitive to manager's risk attitudes and the importance ratings for management objectives. The case study ranks three FTSs for three forested areas in Flathead County, Montana, using site-specific, empirical data for FTSs, climate change, economic growth, residential development patterns, and risk evaluation. Holding these elements constant in the case study allows us to determine the influence of variation in managers' risk attitudes and the importance of management objectives on the ranking of FTSs. The remainder of this section describes the forested areas, three FTSs, and three fuel treatment objectives used to rank FTSs for the case study. It also explains the methods used to evaluate the sensitivity of the ranking of FTSs to managers' risk attitudes and the weights assigned to treatment objectives.

3.2.1. Forested Areas, FTSs, Time Periods, and Fuel Treatment Objectives. This study utilizes data on forested areas, FTSs, time periods, and fuel treatment objectives collected or simulated for Flathead County as part of a broader study (see [46, 59, 60]). The three forested areas and sizes of those areas are (1) the Flathead National Forest, which is managed by the U.S. Forest Service (FS) and covers 290,135 ha; (2) Montana Department of Natural Resources and Conservation (DR) forests that encompass 44,540 ha; and (3) former Plum Creek Timber Company (PC) forests that contain 75,178 ha. All three forests are located in Flathead County, Montana, USA. Figure 1 illustrates the location of the three forests.

Three FTSs were ranked for each forested area: (1) Community Wildfire Protection Plan (CWPP) Priority; (2) CWPP & WUI Priority; and (3) No Priority (NP). FTSs rankings for each forested area were obtained using data for five time periods: 2010–2019; 2020–2029; 2030–2039; 2040–2049; and 2050–2059. These data were used to calculate values of c_i for each of the five time periods. Using data for multiple time periods causes the value of V_{ij}, and hence c_i, to vary over time periods. The values of c_i for the five time periods were then used to rank FTSs. The five time periods are the same ones used in the broader study. A CWPP is a planning tool and process that originated with the Healthy Forests Restoration Act and is a popular means for conducting wildfire planning and incentivizing fuel reduction actions [19, 33]. Each FTS specifies the forest stands prioritized for fuel treatment as simulated in previous studies (see [46, 59–61] for details). The CWPP Priority FTS targets forest stands for fuel treatment based on priorities established by local stakeholders in Flathead County [62, 63]. Priority forest

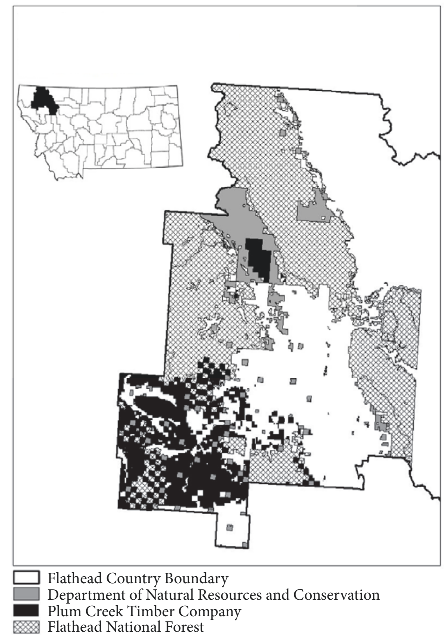

Figure 1: Location of three forests in Flathead County, Montana, 2010.

stands are stands in which wildfire would pose a hazard to communities in the WUI, or the area where private properties and structures are adjacent to or intermixed with flammable wildland vegetation. The geographical extent of the WUI used in this study was simulated in a previous study and accounts for wildfire hazard reduction targets for the United States (see [61] for parameters).

The CWPP & WUI Priority FTS targets forest stands for treatment based on whether they have a CWPP Priority and are in the WUI. Stands without a CWPP Priority or outside the WUI are not treated until all eligible CWPP & WUI priority stands are treated.

The NP FTS is the control FTS. It randomly selects eligible forest stands for treatment until the maximum area treated in each time period is attained or no more stands are eligible for treatment. FTSs incorporate three fuel treatment practices: (1) heavy partial thinning; (2) light partial thinning; and (3) prescribed burning. The parameters of each practice, including species harvested or retained, size of treatments, amount of biomass removed, and amount of biomass retained for each individual treatment, vary and are described in Prato et al. [59].

The three fuel treatment objectives used in this study are: (1) minimizing expected residential monetary losses from wildfire (ERLW); (2) minimizing expected deviation of forest ecological conditions from their historic range and variability (EDRV); and (3) maximizing expected net returns from timber harvesting associated with fuel treatment (ENRH). ERLW, EDRV, and ENRH are referred to as the attributes of FTSs.

ERLW was simulated based on: (1) the number of residential properties on parcels; (2) the probability that parcels burn; (3) the probability of wildfire-related losses for residential structures on properties given the parcels on which those properties are located burn; (4) the average percentage of wildfire-related losses in aesthetic values of residential properties; and (5) the total value (structures plus land) of residential properties [60]. The probability components of ERLW were simulated using the FireBGC model [64] and the Intergovernmental Panel on Climate Change's (IPCC's) A2 emission scenario [65]. The numbers of residential properties in each parcel and time period were stimulated using the RECID2 model and the land use policy that existed in Flathead County in 2010 (see [59, 61, 66] for parameters and simulation outcomes).

EDRV measures the extent to which the simulated values of basal area, leaf area index, and fuel load for each forested area, FTS, and time period deviated from the historic range and variability (HRV) for those variables as outlined in Keane et al. [3] and Prato and Paveglio [46]. HRV simulations of the three variables were conducted using FireBGC.

ENRH depends on: (1) the number of tree stands harvested in each forested area for a particular FTS and time period simulated using FireBGC; (2) the merchantable cubic meters harvested in each stand, forest, and time period with a particular FTS simulated using FireBGC; and (3) the average cost per cubic meter of harvesting and hauling timber to the sawmill for each stand, forest, and time period. Average cost per cubic meter for each FTS was estimated using the Harvest Cost Model [67], and average annual mill-delivered log price weighted by volume of sawlog species for the period 1989–2009 in northwest Montana sawmills [68]. Those models utilized site-specific GIS data on transportation capacity and access for each forest landowner included in the study. Attributes of FTSs were simulated assuming that only one FTS is used per time period and the same FTS is used across time periods. The models used in the broader study simulate only one value for the variables needed to estimate ERLW, EDRV, and ENRH for each FTS and time period. Therefore, it was not possible to make the V_{ij}s stochastic.

3.2.2. Sensitivity to Risk Attitudes. The c_j values are a weighted sum of the simulated values of the treatment objectives, namely, $c_j = \alpha_{\mathrm{ERLW}}\ (1 - \mathrm{ERLW}_j*) + \alpha_{\mathrm{EDRV}}\ (1 - \mathrm{EDRV}_j*) + \alpha_{\mathrm{ENRH}}\ \mathrm{ENRH}_j$. ERLW_i* is expected normalized monetary residential losses due to wildfire for the jth FTS, EDRV_j* is expected normalized deviation of ecological conditions from their historic range and variability for the jth FTS, ENRH_j is expected net revenue from timber harvesting for the jth FTS. α_{ERLW}, α_{EDRV}, and α_{ENRH} are the weights assigned to fuel treatment objectives involving ERLW, EDRV, and ENRH, respectively, and $\alpha_{\mathrm{ERLW}} + \alpha_{\mathrm{EDRV}} + \alpha_{\mathrm{ENRH}} = 1$. Because attributes are measured in different units (i.e., ERLW and ENRH in dollars and EHRV in numbers in the interval [0, 1]), ERLW and ENRH were normalized to the interval [0, 1] to obtain ERLW$*$ and ENRH$*$. In addition, ERLW$*$ and EDRV$*$ were adjusted by subtracting their normalized value from one. As a result of the normalizations and/or adjustments, $1 - \mathrm{ERLW}_j*$, $1 - \mathrm{ERDV}_j*$, and ENRH_j* are positive objectives, meaning each objective is positively related to c_j. That is, increases (or decreases) in $1 - \mathrm{ERLW}_j*$, $1 - \mathrm{ERDV}_j*$, and ENRH_j* cause increases (or decreases) in c_j. The resulting c_j values are the raw data used in the SERF method to rank FTSs.

Calculation of the values of the utility function $U(c_j)$ requires the user to specify an equation for that function. The case study calculates utility values for each FTS and time period based on an exponential utility function, namely, $U(c_j) = (1 - e^{-rcj})$. r is the absolute risk aversion coefficient (ARAC) for a forest manager defined as $r = -U''(c_j)/U'(c_j)$, where $U''(c_j)$ is the second derivative and $U'(c_j)$ is the first derivative of $U(c_j)$ with respect to c_j. r is independent of c for an exponential utility function, which implies constant absolute risk aversion. Using an exponential utility function requires the user to specify an interval for ARAC, namely, $[r_L, r_U]$.

Data from previous simulation and wildfire management studies by Prato and Paveglio [46, 60] provide an opportunity to explore the sensitivity of FTS rankings to variable risk attitudes. We evaluated two divergent ARAC intervals (or risk attitudes) in this study: (1) almost risk neutral for $r \in [-.005, .005]$ and (2) highly risk averse for $r \in [.02, .04]$. Both intervals are consistent within the intervals for almost risk neutral and highly risk averse attitudes used in other studies of risky alternatives [69].

Utility values for FTSs and ARAC intervals were used in the Simetar version of the SERF method [70] to obtain 25 CE values, one for each of the 25 values of r(c) that Simetar selects from the ARAC interval. The resulting 25 CE values for each FTS are then used to rank FTSs.

3.2.3. Sensitivity to Attribute Weights. The sensitivity of the ranking of FTSs to attribute weights was evaluated by specifying 35 attribute weight scenarios for α_{ERLW}, α_{EDRV}, and α_{ENRH}, then ranking the FTSs for every weight scenario and ARAC interval using the SERF method and attribute data for the five time periods. Weight scenarios were determined by increasing or decreasing individual weights for attributes relative to their baseline values collected in a previous study (see [58]). Decision makers for the three forests in that study were asked to assign weights to the three attributes used in the study. The resulting weights, given in Table 1, represent the importance of the three attributes.

Assigned weights for the three attributes and three forested areas were converted to baseline weights by normalizing weights to the [0, 1] interval (see Table 1). The 15 weight scenarios for FS and 10 weight scenarios for DR and PC were derived by increasing or decreasing the baseline attribute weights by the amounts indicated in Table 2. For example, the weights for FS1 are derived by increasing the weight for ERLW by .08 and decreasing the weights for EDRV and ENRH by .04 relative to the baseline weights. Weight scenarios are balanced in the sense that the weights for a higher numbered scenario are determined by increasing the weight for one attribute by x and decreasing the weights for each of the other two attributes by x/2 relative to their values in the next lower numbered scenario. This process ensured variation in the weights used to explore the sensitivity of FTS rankings.

TABLE 1: Derivation of baseline weights for attributes of FTSs for Forest Service (FS), Department of Natural Resources and Conservation (DR), and Plum Creek Timber Company (PC).

Attribute[a]	Rating scores for attributes[b]			Weights[c]		
	FS	DR	PC	FS	DR	PC
ERLW	5	3	2[d]	.42	.3	.2
EDRV	4	3	4	.33	.3	.4
ENRH[e]	3	4	4	.25	.4	.4

a. ERLW is expected residential monetary losses from wildfire, EDRV is expected deviation of forest ecological conditions from their historic range and variability, and ENRH is expected net returns from timber harvesting associated with fuel treatment.
b. Very low = 1, low = 2, moderate = 3, high = 4, and very high = 5.
c. Weights for each agency obtained by dividing each attribute score by the sum of the scores.
d. Because PC managers did not indicate the importance of ERLW, a weight of .2 (low importance) was assigned to ERLW for PC land.
e. Based on rating assigned to importance of commercial timber losses from survey of three forest landowners.

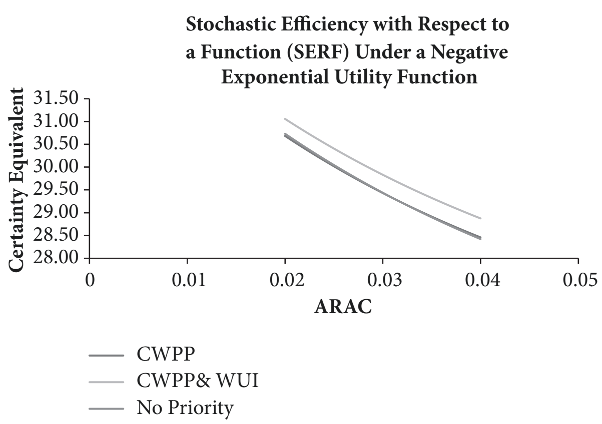

FIGURE 2: Plot of CE values for Plum Creek for weight scenario PC1 and ARAC interval [.02, .04].

4. Results

SERF ranks risky alternatives based on their CE values. Our results indicated very similar CE values for two FTSs. For example, Figure 2 plots Plum Creek CE values for the three FTSs, weight scenario PC1, and highly risk averse attitudes (i.e., ARAC values in the interval [.02, .04]). In this case, the CE values for CWPP Priority and NP (the two lowest curves in Figure 2) have very similar CE values, making it difficult to determine whether CWPP Priority outranks NP or vice versa. To avoid such ambiguities, a statistical test was used to determine whether CE values for the three pairs of FTSs (i.e., CE_{CWPP} versus CE_{NP}, $CE_{CWPP\&WUI}$ versus CE_{NP}, and CE_{CWPP} versus $CE_{CWPP\ \&\ WUI}$) were significantly different from one another.

CE values for FTSs were not normally distributed with respect to the values of ARAC. For that reason, it was inappropriate to perform a t-test for significant differences in the mean CE values for pairs of FTSs. Therefore, a nonparametric test was used. Two nonparametric tests were considered for this purpose: Mood's Median Test and Mann–Whitney U Test. The null and alternative hypotheses for both tests are H_0: $\eta_j = \eta_{j'}$ versus H_a: η_j < or > $\eta_{j'}$, where η_j and $\eta_{j'}$ are the median CE values for the jth and j'th FTSs, respectively. A Mann–Whitney U Test assumes the variances of CEs for all FTSs are the same. Mood's Median Test does not make this assumption. Mood's Median Test could not be used because there were not enough CE values greater than the median. Therefore, equality of median CE values for pairs of FTSs was tested using the Mann–Whitney U test. An α value, or type I error, of .05 was used for all Mann–Whitney U tests. Table 3 contains the results of the Mann–Whitney U tests for the 35 attribute weight scenarios, two risk attitudes, and three forested areas.

FTSs are ranked based on the test results in Table 3. Test results in Table 3 are interpreted as follows. For example, the test results for Forest Service (FS) managers with almost risk neutral attitudes are: (1) reject H_0: $\eta_{CWPP} = \eta_{NP}$ versus H_a: $\eta_{CWPP} > \eta_{NP}$; (2) reject H_0: $\eta_{CWPP\ \&\ WUI} = \eta_{NP}$ versus H_a: $\eta_{CWPP\ \&\ WUI} > \eta_{NP}$; and (3) reject H_0: $\eta_{CWPP} = \eta_{CWPP\ \&\ WUI}$ versus H_a: $\eta_{CWPP} > \eta_{CWPP\ \&\ WUI}$, where η is the median CE value for an FTS. The null hypothesis for test results (1) is that the median CE value for the CWPP and NP FTSs are equal and the alternative hypothesis is that the median CE value for the CWPP FTS exceeds the median CE value for the NP FTS. The null hypothesis for test results (2) is that the median CE values for the CWPP & WUI and NP FTSs are equal and the alternative hypothesis is that the median CE value for the CWPP & WUI FTS exceeds the median CE value for the NP FTS. The null hypothesis for test results 3 is that the median CE values for the CWPP and CWPP & WUI FTSs are equal and the alternative hypothesis is that the median CE value for the CWPP FTS exceeds the median CE value for the CWPP & WUI FTS. Therefore, for Forest Service (FS) managers with almost risk neutral attitudes, the ranking of FTSs is CWPP Ƥ CWPP & WUI Ƥ NP, where Ƥ stands for "preferred to". This same ranking is implied by the test results for FS managers with almost risk neutral attitudes for all weight scenarios except FS14, for which the ranking is CWPP Ƥ NP and CWPP & WUI Ƥ NP.

For FS managers with highly risk averse attitudes, the ranking is CWPP Ƥ NP Ƥ CWPP & WUI for weight scenarios FS1 through FS5, and CWPP Ƥ CWPP & WUI Ƥ NP for weight scenarios BFS and FS6 through FS10. Rankings vary for weight scenarios FS11 through FS15. These results indicate that the FTS ranking is not sensitive to the weight scenarios for FS managers with almost risk neutral attitudes, but is sensitive to weight scenarios for FS managers with highly risk averse attitudes.

For Department of Natural Resources (DR) managers with almost risk neutral attitudes, the ranking of FTSs is: (1) CWPP & WUI Ƥ NP Ƥ CWPP for weight scenarios BDR, DR2, and DR4 through DR10; (2) NP Ƥ CWPP & WUI Ƥ CWPP for weight scenario DR1; and (3) NP Ƥ CWPP Ƥ CWPP & WUI for DR3. These results imply that ranking of FTSs is rather insensitive to the weight scenarios for DR managers having almost neutral risk attitudes. For DR managers with highly risk averse attitudes, the ranking of

Table 2: Attribute weight scenarios for ERLW, EDRV, and ENRH.

U.S. Forest Service (FS)					
Increase ERLW weight by .08 and decrease EDRV and ENRH weights by 0.04					
Attribute	FS1	FS2	FS3	FS4	F5
ERLW	.5	.58	.66	.74	.82
EDRV	.29	.25	.21	.17	.13
ENRH	.21	.17	.13	.09	.05
Increase EDRV weight by .08 and decrease ERLW and ENRH weights by 0.04					
	FS6	FS7	FS8	FS9	FS10
ERLW	.38	.34	.3	.26	.22
EDRV	.41	.49	.57	.65	.73
ENRH	.21	.17	.13	.09	.05
Increase ENRH weight by .08 and decrease ERLW and EDRV weights by 0.04					
	FS11	FS12	FS13	FS14	FS15
ERLW	.38	.34	.3	.26	.22
EDRV	.29	.25	.21	.17	.13
ENRH	.33	.41	.49	.57	.65
Department of Natural Resources and Conservation (DR)					
Increase ERLW weight by .08 and decrease EDRV and ENRH weights by 0.04					
	DR1	DR2	DR3	DR4	DR5
ERLW	.38	.46	.54	.62	.7
EDRV	.26	.22	.18	.14	.1
ENRH	.36	.32	.28	.24	.2
Increase ENRH weight by .08 and decrease ERLW and ENRH weights by 0.04					
	DR6	DR7	DR8	DR9	DR10
ERLW	.26	.22	.18	.14	.1
EDRV	.26	.22	.18	.14	.1
ENRH	.48	.56	.64	.72	.8
Plum Creek Timber Company (PC)					
Increase ENRH weight by .08 and decrease ERLW and EDRV weight by .04					
	PC1	PC2	PC3	PC4	PC5
ERLW	.16	.12	.08	.04	0
EDRV	.36	.32	.28	.24	.2
ENRH	.48	.56	.64	.72	.8
Increase ERLW weight by .08, and reduce ENRH and EDRV weights by .04					
	PC6	PC7	PC8	PC9	PC10
ERLW	.28	.36	.44	.52	.6
EDRV	.36	.32	.28	.24	.2
ENRH	.36	.32	.28	.24	.2

FTSs is (1) NP Ƥ CWPP & WUI Ƥ CWPP for weight scenarios DR1, DR5, DR9, and DR10; (2) CWPP & WUI Ƥ NP Ƥ CWPP for weight scenarios BDR, DR2, and DR4; (3) NP Ƥ CWPP Ƥ CWPP & WUI for weight scenario DR3; and (4) NP Ƥ CWPP and CWPP & WUI Ƥ CWPP for weight scenarios DR6 through DR8. These results imply that FTS rankings for DR managers with highly risk averse attitudes are highly sensitive to the weight scenarios.

Compared to the test results for FS and DNR, the test results for Plum Creek (PC) indicate that the rankings of FTSs are more sensitive to risk attitudes and attribute weights. In particular, test results for PC land managers with almost risk neutral attitudes indicate: (1) no ranking of FTSs (i.e., the three FTSs are equally preferred) for PC2, PC3, PC5, PC7, PC9, and PC10; (2) CWPP & WUI Ƥ NP for BPC; (3) CWPP & WUI Ƥ CWPP for BP and PC1; (4) CWPP & WUI Ƥ NP for BPC; (5) CWPP Ƥ NP and CWPP Ƥ CWPP & WUI for PC4 and PC6; and (6) NP Ƥ CWPP and CWPP Ƥ CWPP & WUI for PC8. The rankings for Plum Creek (PC) land managers with strongly risk averse attitudes are: (1) CWPP & WUI Ƥ

Table 3: Results of Mann-Whitney U tests of equality of median certainty equivalents for three pairs of fuel treatment strategies for two risk attitudes and three managers.

Weight	Almost Risk Neutral (ARAC ϵ [-.005, .005])			Highly risk averse (ARAC ϵ [.02, .04])		
scenario	CWPP vs. NP	CWPP & WUI vs. NP	CWPP vs. CWPP & WUI	CWPP vs. NP	CWPP & WUI vs. NP	CWPP vs. CWPP & WUI
			U.S. Forest Service (FS)			
BFS	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[b]	Reject[c]
FS1	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[d]	Reject[c]
FS2	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[d]	Reject[c]
FS3	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[d]	Reject[c]
FS4	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[d]	Reject[c]
FS5	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[d]	Reject[c]
FS6	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[b]	Reject[c]
FS7	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[b]	Reject[c]
FS8	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[b]	Reject[c]
FS9	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[b]	Reject[c]
FS10	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[b]	Reject[c]
FS11	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Do not reject[b]	Do not reject[c]
FS12	Reject[a]	Reject[b]	Reject[c]	Do not reject[a]	Do not reject[b]	Do not reject[c]
FS13	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Do not reject[b]	Reject[f]
FS14	Reject[a]	Reject[b]	Do not reject[f]	Reject[a]	Reject[b]	Reject[f]
FS15	Reject[a]	Reject[b]	Reject[c]	Reject[a]	Reject[b]	Reject[f]
			Department of Natural Resources and Conservation (DR)			
BDR	Reject[e]	Reject[b]	Reject[f]	Do not reject[e]	Reject[b]	Reject[f]
DR1	Reject[e]	Reject[d]	Reject[f]	Reject[e]	Reject[d]	Reject[f]
DR2	Reject[e]	Reject[b]	Reject[f]	Reject[e]	Reject[b]	Reject[f]
DR3	Reject[e]	Reject[d]	Reject[c]	Reject[e]	Reject[d]	Reject[c]
DR4	Reject[e]	Reject[b]	Reject[f]	Reject[e]	Reject[b]	Reject[f]
DR5	Reject[e]	Reject[b]	Reject[f]	Reject[e]	Reject[b]	Reject[f]
DR6	Reject[e]	Reject[b]	Reject[f]	Reject[e]	Do not reject[d]	Reject[f]
DR7	Reject[e]	Reject[b]	Reject[f]	Reject[e]	Do not reject[d]	Reject[f]
DR8	Reject[e]	Reject[b]	Reject[f]	Reject[e]	Do not reject[d]	Reject[f]
DR9	Reject[e]	Reject[b]	Reject[f]	Reject[e]	Reject[d]	Reject[f]
DR10	Reject[e]	Reject[b]	Reject[f]	Reject[e]	Reject[d]	Reject[f]
			Plum Creek Timber Company (PC)			
BPC	Do not reject[e]	Reject[b]	Reject[f]	Do not reject[e]	Reject[b]	Reject[f]
PC1	Do not reject[e]	Do not reject[b]	Reject[f]	Do not reject[e]	Reject[b]	Reject[f]
PC2	Do not reject[e]	Do not reject[b]	Do not reject[f]	Do not reject[e]	Reject[b]	Reject[f]
PC3	Do not reject[e]	Do not reject[b]	Do not reject[f]	Do not reject[a]	Reject[b]	Do not reject[f]
PC4	Reject[a]	Do not reject[d]	Reject[c]	Reject[a]	Do not reject[d]	Reject[c]
PC5	Do not reject[e]	Do not reject[d]	Do not reject[c]	Do not reject[a]	Reject[b]	Do not reject[f]
PC6	Reject[a]	Do not reject[b]	Reject[c]	Reject[a]	Reject[b]	Reject[c]
PC7	Do not reject[e]	Do not reject[b]	Do not reject[c]	Do not reject[e]	Reject[b]	Reject[f]
PC8	Do not reject[e]	Reject[d]	Reject[c]	Do not reject[e]	Reject[d]	Reject[c]
PC9	Do not reject[e]	Do not reject[b]	Do not reject[f]	Do not reject[a]	Do not reject[b]	Reject[c]
PC10	Do not reject[e]	Do not reject[d]	Do not reject[f]	Do not reject[a]	Do not reject[b]	Do not reject[f]

NP for BPC, PC1, PC2, PC5, PC6, and PC7; (2) CWPP & WUI Ƥ CWPP for BPC, PC1, PC2, PC5, PC6, and PC7; (3) CWPP Ƥ NP for PC4 and PC6; (4) CWPP Ƥ CWPP & WUI for PC4, PC8, and PC9; (5) NP Ƥ CWPP & WUI for PC8; and (6) no ranking for PC10.

Mann–Whitney test results led to considerably more "do not reject the null hypothesis" decisions for PC managers than for FS and DR managers. In particular, 59% of the Mann–Whitney U tests for PC support nonrejection of the null hypothesis compared to 6% for DR and 6.7% for FS. In cases where the null hypothesis is not rejected for one or two of the three pairwise tests for equality in the median CE values, it is not possible to establish a complete ranking of the three FTSs. For example, the PC results for almost risk neutral attitudes are "do not reject" for CWPP and NP; and reject for CWPP & WUI and NP, and CWPP and CWPP & WUI. These results justify two rankings: CWPP & WUI Ƥ NP; and CWPP & WUI Ƥ CWPP. PC results for almost risk neutral attitudes are "do not reject" for CWPP and NP and CWPP & WUI and NP, and reject for CWPP and CWPP & WUI. In this case, only one ranking is possible, namely, CWPP & WUI Ƥ CWPP.

5. Discussion

Case study results build upon previous research in the same region [59] by indicating that the ranking of the three FTSs is sensitive to the risk attitudes and attribute weights evaluated here, and the degree of sensitivity varies across forested areas. This result is significant because it implies that failure to account for such sensitivity might result in an incorrect ranking or prioritization of fuel treatments and, hence, misidentification of a preferred fuel treatment for a forest. Stated differently, while other studies have prioritized FTSs using multiple management objectives and modeling results [e.g., [46]], rarely do they consider the human influence on well-informed decision-making. Our efforts to incorporate and evaluate the influence of variable risk attitudes on FTS prioritization demonstrate that modelers and policymakers might be well served to consider how simulated information is considered by managers and later acted upon. It also implies that variation in managers' risk attitudes may influence the ranking of management actions.

This implication is illustrated using two examples in which two analysts rank three FTSs (i.e., FTS$_1$, FTS$_2$, and FTS$_3$) using the same utility and CE values for fuel treatments and the same ranking procedure. In the first example, both analysts use the same weights for management objectives. The first analyst ranks FTSs without considering the forest manager's risk attitudes and obtains a ranking of FTS$_2$ Ƥ FTS$_3$ Ƥ FTS$_1$, where Ƥ stands for *preferred to*. Based on this ranking, the first analyst concludes FTS$_2$ is the preferred FTS. A second analyst ranks the three FTSs accounting for the manager's risk attitudes and obtains a ranking of FTS$_3$ Ƥ FTS$_2$ Ƥ FTS$_1$. Based on this ranking, the second analyst concludes FTS$_3$ is the preferred FTS. The first example shows that neglecting a forest manager's risk attitudes can result in misidentification of the preferred FTS. In other words, the first analyst commits a decision error by concluding that FTS$_2$ instead of FTS$_3$ is the preferred FTS.

In the second example, both analysts assume the same risk attitudes but use different attribute weights. The first analyst ranks FTSs based on a fixed set of assumed weights and obtains a ranking FTS$_3$ Ƥ FTS$_2$ Ƥ FTS$_1$, which implies FTS$_3$ is the preferred FTS. The second analyst ranks the three FTSs based on a range of attribute weights, as done in this study, and determines that, for most weights in the range, the ranking is FTS$_2$ Ƥ FTS$_3$ Ƥ FTS$_1$, which implies FTS$_2$ is the preferred FTS. This example illustrates that ignoring variation in attribute weights in ranking FTSs can result in misidentification the preferred FTS, which is a decision error.

The two examples do not imply that accounting for variations in managers' risk attitudes and/or variation in weights for objectives will always result in a different ranking of FTSs. Rather, it implies that it is possible for variation in risk attitudes and weights to influence the ranking of FTSs.

The case study assumes two risk attitudes and specifies 35 weight scenarios by modifying empirical baseline weights obtained for the three forest landowners. There are hundreds of possible risk attitudes (i.e., ARAC intervals) and weight scenarios that could be evaluated. The two risk attitudes and 35 weight scenarios used here represent a subset of the full range of possible risk attitudes and weights. Using other risk attitudes and weights could result in different rankings of FTSs than the ones obtained in the case study, and hence different conclusions about the sensitivity of the ranking of the three FTSs to risk attitudes and weights and the likelihood of committing decision errors in ranking FTSs.

Future research could explore a wider range of risk attitudes and weights to determine the extent to which the prioritization of fuel treatments is sensitive to variation in risk attitudes and weights for other forested areas. High sensitivity would imply a high likelihood and low sensitivity would imply a low likelihood of misidentifying the preferred FTS. It would also be worthwhile to evaluate whether risk attitudes and the importance of fuel treatment objectives, even for the same forest manager, is changing over time in response to more frequent and intense wildfires. In addition, the estimated values of the management objectives for FTSs (i.e., V_{ijt}s) can be made stochastic to explore the extent to which the ranking of management actions is sensitive to stochastic variation in those values. However, in order to isolate the effects of stochastic variation in V_{ijt}s on the ranking, it would be necessary to hold the weights assigned to management objectives (i.e., w_is) constant.

Many forest managers may not have the time or resources to simulate attribute values using the models employed by Prato and Paveglio [60]. Likewise, they may not have access to data or expertise needed to parameterize those models. This condition can be alleviated by using less complex models to simulate the attributes of FTSs. For example, instead of using the RECID3 model [59] to simulate the number of new residential properties developed in each time period, which is one of the variables that determines ERLW, that number can be simulated by multiplying population projections for each time period by the average number of persons per housing unit for the study area. Similarly, instead of simulating intertemporal changes in forest vegetation in response to climate change using FireBGC [64], vegetation dynamics can be simulated using the Climate-Forest Vegetation Simulator [71], or the ENVISION model [72].

Much of the existing science and research on fuel treatment assume that forest prioritization models will provide forest managers with a dominant or singular "answer" and that they will always heed science-based answers. However, our findings indicate that a forest manager's choice of fuel treatments for a landscape can be sensitive to the manager's risk attitudes and the weights for fuel treatment objectives. Therefore, there appears to be a need for additional study to explore how forest managers use science- or model-based results in prioritizing fuel treatments and the extent to which their final decisions match modeled outcomes. Studying these factors can help forest managers and scientists better understand and improve management practices or decision-making by acknowledging the trade-offs they face in dynamic environments and the thought processes they use when employing the results of science-based studies and/or decision-making tools.

6. Conclusion

The case study shows that the ranking of FTSs is sensitive to the risk attitudes and weights for fuel treatment objectives parameterized for a case study landscape and land managers in Flathead County, Montana. This result implies that it is important to consider both factors in ranking FTSs because ignoring them could result in misidentification of the preferred FTS and, hence, less efficient achievement of fuel treatment objectives.

Acronyms

ARAC: Absolute risk aversion coefficient
CE: Certainty equivalent
CWPP: Community wildfire protection plan
DR: Montana Department of Natural Resources and Conservation
EDRV: Expected deviation of ecological conditions from their historic range and variability
ENRH: Expected net revenue from timber harvesting associated with fuel treatment
ERLW: Expected monetary residential losses due to wildfire
FS: U.S. Forest Service
FTS: Fuel treatment strategy
HRV: Historic range and variability
NP: No priority
$\mathcal{P}$: Preferred to
PC: Plum Creek Timber Company
SERF: Stochastic efficiency with respect to a function
WUI: Wildland-urban interface.

Data Availability

The data set used in the paper is very large and maintained by multiple institutions. Therefore, it is not feasible to make that data set available.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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