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Determining preferred forest management plans under ecosystem driver uncertainty: A conceptual framework

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ABSTRACT: *Forest managers desiring to maintain the long–term sustainability of forests face the important and challenging task of developing forest management plans that account for uncertainty about future changes in ecosystem drivers (i.e., driver uncertainty). The conceptual framework proposed here is important because forest managers can use it to achieve this task. The framework has seven analytical components: (1) selecting ecosystem services and management objectives; (2) choosing management plans; (3) specifying ecosystem drivers and scenarios for future changes in drivers; (4) evaluating management objectives achieved by management plans; (5) identifying the weak or strong sustainability of management plans; (6) using a fuzzy decision–making technique to determine preferred sustainable management plans for driver scenarios; and (7) using the minimax regret criterion to identify preferred sustainable management plans across planning periods. Noteworthy contributions of the framework are that it: (1) incorporates multiple management plans, ecosystem drivers, management objectives, and planning periods; (2) accounts for uncertainty about future changes in ecosystem drivers; (3) characterizes and evaluates management plans in terms of multiple objectives; (4) accommodates single– or multi–valued objectives; and (5) handles quantitative and qualitative management objectives. Implementation of certain analytical components of the framework, particularly quantitative or qualitative evaluation of the effects of forest ecosystem drivers on the objectives achieved by management plans, would most likely require assistance from professionals with expertise in that area.*
Keywords *- Sustainable forest management planning, uncertainty, multiple ecosystem drivers*

I. INTRODUCTION

Forest managers desiring to maintain the long–term sustainability of forests face the important and challenging task of accounting for uncertainty about future changes in ecosystem drivers (i.e., driver uncertainty) in forest planning. An ecosystem driver "is any natural or human–induced factor that directly or indirectly causes a change in an ecosystem" ([1]). Typically, there is uncertainty about future changes in socioeconomic and biophysical drivers. Both types of drivers have the potential to reduce forest sustainability by impairing the supply of ecosystem services [2]. The latter include the "… full suite of goods and services that are vital to human health and livelihood" [3], including wildlife habitat and diversity, watershed services (e.g., erosion control and water purification), carbon storage, scenic landscapes, and recreational opportunities [2,4].

This paper evaluates the effects of three ecosystem drivers on forest sustainability, namely landscape fragmentation from residential development in or adjacent to forests, intertemporal growth in recreational use, and climate change. Landscape fragmentation from residential development is an important socioeconomic driver of forest sustainability that can degrade the suitability of wildlife habitat [5], especially for species intolerant to human disturbance [6]. Also, landscape fragmentation hinders the ability to manage national forests and private lands for public benefits and ecosystem services [7]. Impacts of other drivers of landscape fragmentation can also be evaluated using the framework described here, such as the spatial pattern and intensity of harvesting, road construction, and natural disturbance (e.g., wildfire, native and invasive pests, and blowdown).

Intertemporal growth in recreational use is another important socioeconomic driver of forest sustainability. Such growth can increase soil erosion, especially along hiking trails and at campsites. In particular, increased use of recreational areas can negatively impact soil and vegetation properties of forest ecosystems [8,9,10]. Increased soil erosion escalates sediment transport to water bodies, negatively impacting the quality of aquatic habitat. In addition, growth in recreational forest use can diminish the quality of recreational experiences by reducing solitude.

Climate change is an important biophysical driver of forest sustainability that can decrease the capacity of forests to provide ecosystem services, especially forests experiencing lower precipitation and/or higher temperatures due to climate change [11]. Higher temperatures and/or lower precipitation can increase the frequency, size, and intensity of wildfires, thereby degrading habitat for some wildlife species and diminishing recreational opportunities, and increasing residential property damages, personal injuries, or disruptions to local economies and their residents [12,13]. Some studies obviate the need to address climate change uncertainty in forest management planning by assuming that local climatic conditions remain constant [11]. Such an assumption is unrealistic.

Forest planners and managers (managers for short) could benefit from a conceptual framework that allows them to evaluate the sustainability of forest management plans when there is uncertainty about future changes in multiple ecosystem drivers. This study develops such a framework.

II. PREVIOUS RESEARCH

Existing conceptual frameworks have several limitations relative to evaluating the sustainability of forest management plans under driver uncertainty. The assessment framework developed by Jabareen [15] to help cities cope with climate change applies various concepts of sustainability to a management plan in a qualitative manner. It does not integrate those concepts in a manner that allows determination of the most preferred sustainable management plan. Conceptual frameworks developed to assess the sustainability of forest fuel reduction treatments [16] and adaptively manage coupled natural–human systems [17] consider only one ecosystem driver, namely climate change. In contrast, the conceptual framework presented here accounts for uncertainty about multiple ecosystem drivers.

Several studies have determined optimal fuel treatment plans for forests based on one management objective. Finney et al. [18] simulated the effects of landscape–level fuel treatments on large wildfires. Wei et al. [19] used an optimization model to determine landscape–scale fuel treatments for reducing expected fire losses. Young–Hwan and Pettinger [207] evaluated whether fuel treatments are effective in reducing wildfire size or severity. Chung et al. [21] determined the locations and timing of fuel treatments that minimize total expected wildfire loss for a landscape. Garcia-Gonzalo [22] evaluated the effect of climate change uncertainty on timber yield. Unlike these previous studies, this study incorporates multiple forest management objectives. The latter is advantageous, especially for public land managers in the U.S. that are required by law (e.g., the Multiple Use–Sustained Yield Act of 1960 and the National Forest Management Act of 1976 in the USA) to manage forests based on multiple objectives.

Several studies optimize forest treatments spatially and temporally based on multiple objectives and constraints. Examples include the Multiple–resource Analysis and Geographic Information System (MAGIS) [20]. Similarly, the OptFuels decision support system [24] determines the spatial and temporal locations of fuel treatments in a forest that maximize objectives related to management costs and value of products produced by treatments (e.g., timber revenue) subject to constraints related to financial budgets, area available for treatment, road accessibility, and others. Unlike previous studies that determine the optimal forest management plans over space and/or time, the conceptual framework presented here determines which of several preselected forest management plans is most preferred over a multi–period planning horizon. In particular, the framework does not incorporate optimization models and, as such, would be useful, for example, in environmental impact assessments of alternative forest management plans.

III. METHODS AND RESULTS

This study proposes a conceptual framework to determine preferred sustainable forest management plans. For that reason, there are no empirical results. The results of the study consist of the various methods incorporated in the framework.

III.1 Overview of conceptual framework

The conceptual framework consists seven analytical components: (1) selecting ecosystem services and management objectives for evaluating management plans; (2) choosing management plans; (3) specifying ecosystem drivers and scenarios for future changes in drivers; (4) quantitatively estimating or qualitatively evaluating management objectives achieved by management plans; (5) identifying sustainable management plans; (6) determining preferred sustainable management plans for driver scenarios within multi–year planning periods; and (7) identifying preferred sustainable management plans for planning periods. The framework incorporates multiple management plans, ecosystem drivers, management objectives, and planning periods, and handles any spatial scale, number and length of planning periods, and private or public forests. Fig. 1 is a diagram of the conceptual framework. Of the three types of forest planning methods (i.e., strategic, tactical, and operational), the conceptual framework described here is for strategic planning.

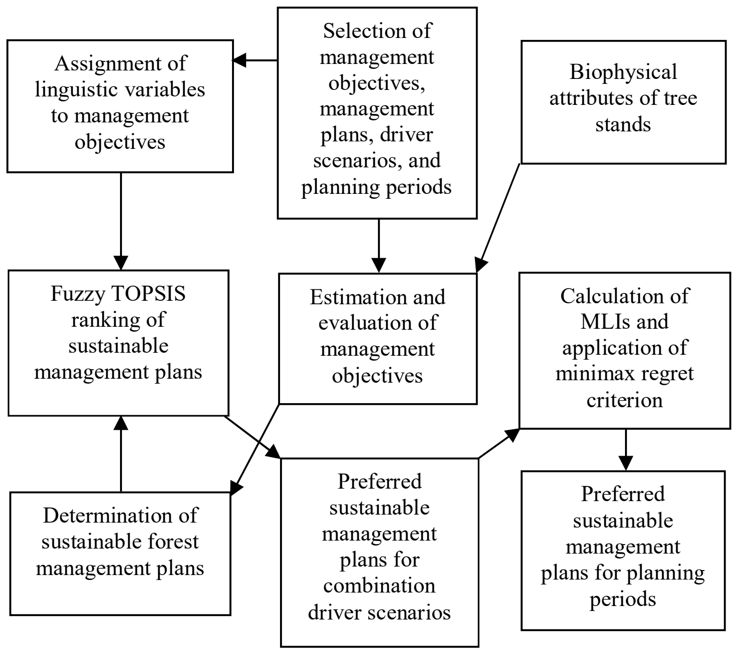

Fig. 1. Diagram of conceptual framework

To facilitate understanding of the proposed framework, it is explained in terms of three ecosystem drivers, five ecosystem services, and five management objectives, as follows:

- Ecosystem drivers: climate change; landscape fragmentation associated with residential development; and recreational use
- Ecosystem services: soil erosion control; water quality; wildlife habitat and diversity; net revenue from timber production; and recreational opportunities.
- Management objectives expressed in terms of ecosystem services: minimizing soil erosion; maximizing water quality; maximizing wildlife habitat and diversity; maximizing net revenue for timber production; and maximizing recreational opportunities.

3.2 Selecting ecosystem services and management objectives

The framework evaluates the effects of forest management plans on management objectives for forest planning selected by managers, possibly, in cooperation with stakeholders. Objectives are expressed in terms of supporting, provisioning, regulating, and/or cultural ecosystem services [2]. The U.S. Forest Service defines ecosystem services as the "… full suite of goods and services that are vital to human health and livelihood" [3, p.1], including wildlife habitat and diversity, watershed services (e.g., erosion control and water purification), carbon storage, scenic landscapes, and recreational opportunities [3,4].

The ecosystem services listed above do not include timber production, which is a provisioning service of forests. Timber production is a product obtained from a forest that generates timber revenues, creates jobs and income for forest workers, and revenue for forest–dependent communities via the Secure Rural Schools Program [25]. Not all forest services are equally important to managers and stakeholders. For example, private timber companies primarily manage forests to maximize revenue from the sale of wood products. In contrast, public forest land managers, such as the U.S. Forest Service, are required by law to manage forests for multiple uses or ecosystem services. Management objectives included in the framework pertain to: (1) soil erosion; (2) water quality; (3) wildlife habitat and diversity; (4) net revenue from timber production; and (5) recreational opportunities.

The conceptual framework requires managers, possibly in cooperation with stakeholders, to rate the importance of objectives. Management objectives for the i^{th} forest are designated by $\{O_{i1}, \ldots, O_{ik}\}$, where k is the number of management objectives. That number is less than or equal to five, which is the number of management objectives used to illustrate the framework. In general, the framework can handle any number of management objectives.

3.3 Choosing management plans

Like management objectives, the pre–selected management plans are likely to vary across forests and, possibly, planning periods. Management plans for the i^{th} forest and t^{th} planning period are designated by $\{M_{i1t}, \ldots, M_{irt}\}$. These plans must be capable of achieving the management objectives for each forest and consistent with each forest's personnel and budget constraints for planning periods, management plans implemented in previous planning periods (e.g., tree stands harvested in one planning period are not eligible for harvesting until they reach maturity in subsequent planning periods), and biophysical attributes of forest stands (e.g., land slope, road access, designated habitat for threatened and endangered species, etc.). Management plans are spatial because they specify the forest management practices applied to various tree stands.

3.4 Specifying ecosystem drivers and driver scenarios

Ecosystem drivers for a forest influence the management objectives achieved by management plans. For instance, if the management objectives for the i^{th} forest pertain to soil erosion control, water quality, wildlife habitat and diversity, net revenue from timber production, and recreational opportunities, and those objectives are influenced by climate change (CC), landscape fragmentation (LF), and recreational use (RU), then CC, LF, and RU are the relevant ecosystem drivers.

Uncertainty about future changes in the ecosystem drivers is handled by specifying multiple scenarios for each type of driver, as follows:

- Climate change: $\{CC_1, \ldots, CC_f\}$;
- Landscape fragmentation: $\{LF_1, \ldots, LF_g\}$; and
- Recreational use: $\{RU_1, \ldots, RU_h\}$.

A combination driver scenario (e.g., CC_1–LF_3–RU_5) specifies the value of each driver in each year of the planning period. Preferred sustainable management plans are determined for each combination driver scenario and planning period. Since there are f CC scenarios, g LF scenarios, and h RU scenarios, there are a total of fgh combination driver scenarios.

CC scenarios can be specified based on the Intergovernmental Panel on Climate Change's (IPCC's) global climate projections. The IPCC's projections for the fifth and most recent assessment are: RCP8.5; RCP6; RCP4.5; and RCP2.6 [23]. RCP stands for representative concentration pathway. The number associated with each RCP is the radiative forcing (global energy imbalances) measured in watts per square meter by the year 2100.

NASA Earth Exchange (NEX) (https://nex.nasa.gov/nex/resources/264/) has produced spatially downscaled IPCC's global climate projections for monthly average maximum temperature, minimum temperature, and precipitation to 800–meter spatial resolution. Monthly climate projections for each biophysically distinct area of a forest can be determined using the projections for the 800–meter pixels covering each area.

There are no LF projections for all forests. LF projections can be developed using the following two–step procedure. First, a GIS–based, land development simulation model, such as RECID3 [27], is used to simulate the number of new houses required to support the low, medium, or high projection of population growth and the location of new houses for each planning period. Second, landscape metrics for each LF scenario are computed using programs such as FRAGSTATS [28] or APACK [29].

Regional RU projections for forests have been made in terms of participation and consumption, in days and trips, in 10–year intervals from 2000 to 2050 [30]. Similar projections do not appear to be available for all individual forests. Furthermore, application of the proposed conceptual framework requires multiple scenarios or projections of future RU for a forest. If projections of future RU are available for a forest, then those projections can be designated as the medium RU scenario. A low (or high) RU scenario can be constructed by decreasing (or increasing) the medium RU scenario by a fixed percentage (e.g., -20% for the low RU scenario and +20% for the high RU scenario). If projections of future RU are not available for the forest, then the manager has to develop them using a different procedure.

A problem with specifying RU scenarios is that the number of recreational days and the form of recreation (e.g., frontcountry camping vs. backcountry camping) influence the management objectives achieved by a plan. Projections for different types of recreational uses do not exist for all forests. One way to handle this problem is to assume that the future proportion of total recreational days in each type of recreational use is the same as the current proportion, or that the proportions change in a particular way across planning periods. Based on such assumptions, it is possible to disaggregate projections of total days of recreational use to projections of total days of recreational use for each type of recreation.

3.5 Quantitative estimation of management objectives

Quantitative and/or qualitative methods are used to estimate the effects of management plans on management objectives for each combination driver scenario and planning period. This section describes quantitative methods and the next section describes qualitative methods used to estimate these effects.

3.5.1 Soil erosion and water quality

Forest management plans, particularly harvesting methods, influence vegetative cover for a forested landscape, which in turn affects soil erosion, runoff rates, and sedimentation of waterbodies located downslope of harvested areas. For instance, higher rates of biomass removal from tree stands typically result in higher soil erosion and sedimentation of downslope waterbodies than lower rates. Sediment loads to waterbodies affect the quality of aquatic habitat. Biophysical models are well suited for estimating soil erosion rates and water quality impacts of forest management plans. For example, the Soil and Water Assessment Tool (SWAT) has been widely used to simulate the effects of forest management practices on soil erosion, hydrology (i.e., runoff volume), water quality (e.g., sediment and nutrient loads to receiving waters), and ecosystem services [31,32].

3.5.2 Wildlife habitat and diversity

Management plans are likely to influence the suitability of habitat for a wide range of wildlife species. For instance, management plans that increase the amount of sunlight reaching the forest floor stimulate the production of grasses and shrubs, which benefits herbivores, such as deer and elk. Opening logging roads in prime habitat areas for grizzly bears (*Ursus arctos* ssp.) increases interactions between humans and bears and, hence, bear mortality [33]. Therefore, temporarily or permanently closing logging roads is likely to reduce grizzly bear mortality.

Effects of management plans on wildlife habitat are assessed by combining the landscape metrics calculated using the procedures described above and species distribution and persistence models that explain how changes in landscape metrics are likely to influence habitat suitability for various species (e.g., [34,35,36]).

3.5.3 Net revenue

The net revenue provided by a management plan equals the present value of the total revenue from the sale of marketable biomass removed by the plan, if any, plus recreational fees, if any, minus the present value cost of developing and implementing the plan. Calculation of net revenue requires selecting an appropriate discount rate, projecting wood product prices and costs of the forest management practices (e.g., light partial thinning) used in a plan. Wood product prices in a given year are likely to be the same for forests that sell timber in the same market. The cost of a forest management plan is the present value of the product of the per hectare cost of each management practice and the number of hectares treated with that practice, summed over all practices employed in that plan. Per hectare practice costs are likely to vary within a forest, even for the same practice, due to spatial variability in slope, aspect, initial forest biomass, forest biomass removed, new road construction (if any), hauling distances, labor and equipment requirements, and other factors. Programs, such as the harvest cost model developed by Hayes [37], can be used to estimate the cost of forest management plans.

3.5.4 Recreational opportunities

Managers can estimate how management plans influence recreational opportunities using various methods, such as the recreation opportunity spectrum [38] and the Delphi method [39].

3.5.5 Qualitative evaluation of management objectives

Qualitative methods for evaluating the effects of management plans on management objectives need to be used when a manager is unable or unwilling to quantitatively estimate those effects. The qualitative method proposed here requires a manager to assign linguistic variables to the effects of management objectives on management plans. The linguistic variables used to determine the preferred sustainable management plan for a combination driver scenario and planning period can be used for this purpose. Table 1 illustrates the qualitative method.

Table 1. Example of assigning linguistic variables to management objectives for three management plans for a given combination driver scenario and planning period

Management plan	Soil erosion	Water quality	Wildlife habitat and diversity	Net revenue	Recreational opportunities
P_1	Very low	Very high	High	Low	Very high
P_2	Moderate	Low	Moderate	Moderate	Moderate
P_3	Very high	Very low	Very low	High	Low

Qualitatively evaluating management objectives with the above procedure requires managers to have sufficient information and/or knowledge to assign linguistic variables to management objectives achieved by all sustainable management plans. If the assignment of linguistic variables to management objectives is done by the management team as a whole, then consensus assignments can be determined using the Delphi method. Fuzzy numbers are then assigned to the resulting linguistic variables based on, for example, a triangular probability distribution (Table 2). Alternatively, if each individual member of a management team assigns linguistic variables to management objectives, then fuzzy numbers are assigned to the linguistic variables assigned by each member and the resulting fuzzy numbers for each management objective are averaged to obtain an overall average fuzzy number for that objective. The resulting fuzzy numbers for management objectives are used in the fuzzy technique for preference by similarity to the ideal solution (fuzzy TOPSIS) to rank management plans.

3.5.6 Identifying sustainable management plans

The sustainability of management plans can be evaluated using a weak or strong sustainability criterion.

Weak sustainability allows decreases in one objective to be offset by increases in another objective, implying that objectives are substitutes. In contrast, strong sustainability asserts that decreases in one objective are not necessarily offset by increases in another objective, implying that objectives are complements [39]. Application of both sustainability criteria are demonstrated below for: (1) quantitatively estimated management objectives (case 1) and qualitatively evaluated management objectives (case 2).

Table 2. Assignment of fuzzy numbers to linguistic variables based on the triangular probability distribution

Linguistic variable	Triangular fuzzy number[a]
Very low	(0.05, 0.05, 1)[b]
Low	(0.05, 1, 3)
Moderate	(3, 5, 7)
High	(7, 9, 10)
Very high	(9, 10, 10)

a. Adapted from Chen [40] and Prato [41].
b. The first number in parentheses is the minimum value, the second number is the mode, and the third number is the maximum value for a triangular probability distribution.

3.5.6.1 Case 1

When objectives are quantitatively estimated, a management plan is weakly sustainable if the index of management objectives for that plan (defined below) exceeds a minimum acceptable value chosen by the manager, possibly in consultation with stakeholders. For example, if there is only one estimated value for each objective, the objectives are positive (i.e., more of every objective is desirable), then the j^{th} management plan is weakly sustainable if $I_{jt} = \sum_{r=1}^{5} \alpha_r I_{rjt} \geq I'_t$, where α_r is the weight assigned to the r^{th} objective, $\sum_{r=1}^{5} \alpha_r = 1$, I_{rjt} is an index for the estimated value of the r^{th} objective for the j^{th} plan and t^{th} planning period, $0 \leq I_{rjt} \leq 1$, I'_t is the minimum acceptable value for an aggregate index of the five management objectives for the t^{th} planning period chosen by the manager, and $0 \leq I'_t \leq 1$. If there are multiple values for each objective, then I_{rjt} is defined as an index of the average estimated value of the r^{th} objective for the j^{th} plan and t^{th} planning period. The higher (or lower) the value of I'_t, the less (or more) likely it is that a forest management plan will be judged sustainable.

If there is just one estimated value for each objective and all of the management objectives are positive, then a management plan is strongly sustainable if $x_{rjt} \geq x'_{rt}$ for all r, where x_{rjt} is the measured value of the r^{th} objective for the j^{th} plan and t^{th} planning period, and x'_{rt} is the minimum acceptable value of the r^{th} objective for the t^{th} planning period. If there are multiple values for each objective, then a management plan is strongly sustainable if: (1) $pr(x_{rjt} \geq x'_{rt}) \geq 1 - \beta_r$ for r = 1, …,5, where pr stands for probability, x'_{rt} is the minimum acceptable level of the r^{th} objective for the t^{th} planning period, $1 - \beta_r$ is the reliability level for the probability statement for the r^{th} objective, and $0 \leq \beta_r \leq 1$. Probabilities for objectives (e.g., $pr(x_{rt} \geq x'_{rt})$) are calculated using the probability distributions that best fit the estimated values of each objective. In general, the more serious the consequences of falling short of the minimum acceptable level for a positive objective, the lower the values of β_r. Similar statements can be made about the conditions that must be satisfied for weak or strong sustainability of management plans that involve quantitatively–estimated negative objectives (i.e. less of the objective is desirable).

3.5.6.2 Case 2

When the five objectives are qualitatively evaluated and positive, a management plan is weakly sustainable if $L_{jt} = \sum_{r=1}^{5} \alpha_r L_{rjt} \geq L'_t$, where α_r is the weight assigned to the r^{th} objective, $\sum_{r=1}^{5} \alpha_r = 1$, L_{rjt} is the numerical score for the linguistic variable assigned to the r^{th} objective for the j^{th} plan and t^{th} planning period, L'_t is the minimum acceptable aggregate numerical score for the five management objectives for t^{th} planning period, where $0 \leq L'_t \leq$

5. Numerical scoring is done by the manager using a scheme, such as: 1 for very low; 2 for low; 3 for moderate; 4 for high; and 5 for very high.

A management plan is strongly sustainable if $L_{rjt} \geq L'_{rt}$, where L_{rjt} is the numerical score for the linguistic variable assigned to the r^{th} objective for the j^{th} plan and t^{th} planning period, and L'_{rt} is the minimum acceptable numerical score for the r^{th} objective for the t^{th} planning period. The sustainable management plans for the i^{th} forest, d^{th} combination driver scenario, and t^{th} planning period are: $\{M_{i1dt}, \ldots, M_{ikdt}\}$, where $k \leq r$. Similar statements can be made about the conditions that must be satisfied for weak or strong sustainability of management plans that involve qualitatively–evaluated negative objectives.

3.5.7 Determining preferred sustainable management plans for driver scenarios

The steps for determining preferred sustainable management actions for driver scenarios and planning periods are described in this section and the next section, respectively. Figure 2 is a schematic of the both steps for a single planning period (i.e., planning period t).

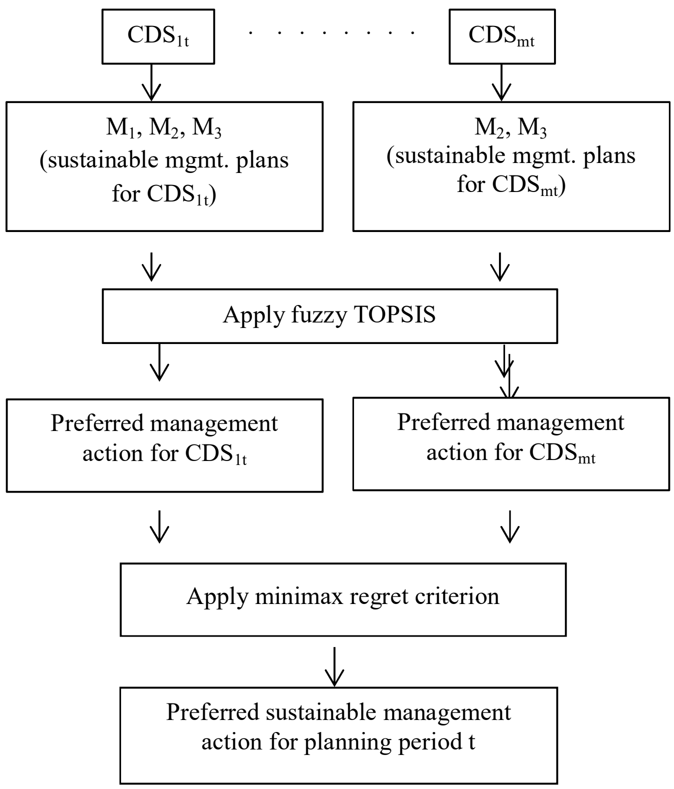

Fig. 2. Schematic of procedure for determining preferred management actions for driver scenarios and planning period t (CDS stands for combination driver scenario)

The first step requires ranking the sustainable management plans (i.e., $\{M_{i1dt}, \ldots, M_{ikdt}\}$) for each combination driver scenario and planning period using fuzzy TOPSIS. Management plans are ranked based on their closeness coefficients [16,40,41,43]. A closeness coefficient measures how close the values of the objectives for a sustainable management plan are to the values of the objectives for the fuzzy positive–ideal plan and how far away they are from the values of the objectives for the fuzzy negative–ideal plan. The fuzzy positive–ideal plan has the most desirable values of the objectives and the fuzzy negative–ideal plan has the least desirable values of the objectives.

Fuzzy TOPSIS has three advantages relative to more conventional multiple–objective evaluation methods. First, it requires decision–makers to state their preferences for the values and importance of objectives using linguistic variables, which is relatively straightforward. Second, fuzzy TOPSIS does not assume utility independence of objectives as do multiple–objective evaluation methods that employ an additive utility function to rank decision alternatives. Utility independence implies that the marginal utility of one objective is independent of the amounts of all other objectives. Third, fuzzy TOPSIS does not impose restrictions on the decision–maker's risk preferences (i.e., risk averse, risk neutral, or risk loving).

Fuzzy TOPSIS ranking of sustainable forest management plans involves the following general steps:

- If management objectives are quantitatively estimated, then managers assign linguistic variables to non–overlapping intervals for the estimated values of the objectives for sustainable management plans and the importance of objectives. For example, suppose a manager assigns the following linguistic variables to non–overlapping intervals for an estimated objective whose range of estimated values is $[O_1, O_{10}]$: (1) 'very low' for $[O_1, O_2]$; (2) 'low' for $[O_3, O_4]$; (3) 'moderate' for $[O_5, O_6]$; (4) 'high' for $[O_7, O_8]$ and (5) 'very high' for $[O_9, O_{10}]$. The range $[O_1, O_{10}]$ is defined based on the estimated values of the objectives across all planning periods and combination driver scenarios for a given forest. Intervals can differ across objectives. When management objectives are qualitatively evaluated, linguistic variables are directly assigned to management objectives.
- Managers assign linguistic variables (e.g., very low, low, moderate, high, and very high) to the importance of objectives.
- Fuzzy numbers are assigned to linguistic variables for the estimated values and importance of objectives using a scheme like the one illustrated in Table 2.
- Fuzzy numbers assigned to the estimated values and importance of management objectives are used to rank sustainable management plans for each combination driver scenario and planning period. The preferred sustainable management plan for a forest, combination driver scenario, and planning period is the top–ranked sustainable management plan for that forest, combination driver scenario, and planning period.

Methods other than fuzzy TOPSIS can be used to determine preferred sustainable management plans for combination driver scenarios and planning periods. Examples of alternative methods include multiple objective programming, goal programming, multiple attribute utility theory, and the Analytic Hierarchy Process [44,45,46].

3.5.8 Identifying preferred sustainable management plans for planning periods

The preferred sustainable management plan for a planning period is determined by applying the minimax regret criterion (MRC) to the preferred sustainable management plans for the combination driver scenarios for that planning period. With the MRC, the preferred sustainable management plan for a planning period is the one that minimizes the maximum loss index (MLI) across combination driver scenarios for that planning period. This process results in preferred sustainable management plans for all planning periods.

For quantitatively–estimated management objectives, MLIs for each management plan are calculated as follows:

$$MLI_{idt} = \sum_{i=1}^{5} w_{ir}(O^{*}_{irt} - O^{*}_{irdt}), \tag{1}$$

where:

MLI_{idt} = maximum loss index for the ith forest, dth combination driver scenario, and tth planning period;

w_{ir} = weight assigned to the rth objective for the ith forest;

O^{*}_{irt} = normalized value of the rth objective for the ith forest, and tth planning period when there are no changes in drivers across planning periods; and

O^{*}_{irdt} = normalized value of the rth objective for the ith forest, dth combination driver scenario, and tth planning period ($0 \le O^{*}_{irdt} \le 1$).

Since O^{*}_{irt} is expected to exceed O^{*}_{irdt}, $(O^{*}_{irt} - O^{*}_{irdt}) > 0$. Managers can select the weights for the objectives in collaboration with stakeholders.

The same procedure used to estimate the values of the objectives for a combination driver scenario can be used to estimate the values of objectives when the drivers do not change across planning periods. To avoid biases in the index caused by differences in the units of measurement for objectives, normalized objectives are used to calculate MLIs. Weights for objectives are derived from the linguistic variables assigned to objectives using the procedure illustrated in Table 3.

Table 3. Example of procedure for weighting objectives

Objective	Linguistic variable assigned to objective by landowner	Numerical value assigned to linguistic variable[a]	Weight
1	High	5	5/10 = .5
2	Low	2	2/10 = .2
3	Moderate	3	3/10 = .3

a. Very high = 5, high = 4, moderate = 3, low = 2, and very low = 1 (sum of weights = 10)

IV. DISCUSSION

The conceptual framework presented here is similar to hybrid methods of forest management planning that integrate several techniques and sources of information, such as multiple–objective decision–making, uncertainty analysis, geographic information systems (GIS), optimization, stakeholder knowledge, and others [46,47]. In particular, selection of the preferred sustainable management plans for each combination driver scenario involves application of a fuzzy multiple–objective technique and accounts for uncertainties regarding drivers. Simulation of residential development across planning periods makes extensive use of a GIS. Selection of the preferred sustainable management plans for planning periods is done using the minimax regret criterion, which is essentially an optimization routine. Managers can incorporate stakeholder knowledge in implementation of the conceptual framework. Specifically, managers can solicit stakeholders' opinions about which: (1) management objectives, plans, and driver scenarios to evaluate; (2) linguistic variables to assign to management objectives and their importance; and (3) minimum or maximum acceptable values for objectives and the weights for objectives to use in calculating the MLIs.

The proposed conceptual framework is admittedly complex and has relatively high data/information requirements, especially for quantitative simulation and/or qualitative evaluation of management objectives when the objectives have multiple values per year. The qualitative evaluation of management objectives avoids the need to apply simulation models. However, for that method to be reliable, managers must be able to accurately assign linguistic variables to management objectives. Most managers are likely to require the assistance of professionals to apply the more complex elements of the conceptual framework.

The task of applying fuzzy TOPSIS is simplified by using a spreadsheet developed by the author. The spreadsheet ranks management plans based on the linguistic variables and associated fuzzy numbers assigned to management objectives achieved by management plans and the importance of objectives. Application of the MRC is straightforward once the MLIs have been calculated.

The remainder of this section discusses four issues pertaining to the application of the conceptual framework: (1) handling negative management objectives in fuzzy TOPSIS; (2) evaluating weak and strong sustainability of management plans when some objectives are quantitatively estimated and others are qualitatively evaluated (i.e., mixed objectives); (3) determining preferred management plans for combination driver scenarios with mixed objectives; and (4) estimating MLI with mixed objectives.

The aforementioned description of fuzzy TOPSIS uses positive objectives. Not all management objectives are positive. Of the five management objectives used to illustrate the conceptual framework, four are positive (i.e., maximizing water quality, maximizing wildlife habitat and diversity, maximizing net revenue from timber production, and maximizing recreational opportunities), and one is negative (i.e., minimizing soil erosion). Linguistic variables for negative objectives can be converted to linguistic variables for positive objectives. For instance, Table 4 illustrates how to convert linguistic variables for soil erosion to linguistic variables for soil conservation. The latter is a positive objective. This transformation translates the objective of minimizing soil erosion to the objective of maximizing soil conservation.

Mixed objectives are not problematic when applying the strong sustainability criterion because management objectives are evaluated separately. However, an adjustment is required in order to apply the weak sustainability criterion (i.e., $L_{jt} = \sum_{r=1}^{5} \alpha_r L_{rjt} \geq L'_t$) to mixed objectives. The adjustment involves converting the quantitative objectives to qualitative objectives by assigning linguistic variables to the quantitative objectives and numerical scores to the resulting linguistic variables using the numerical scoring scheme described earlier.

Table 4. Conversion of linguistic variables for soil erosion to linguistic variables for soil conservation

Soil erosion	Soil conservation
Very low	Very high
Low	High
Moderate	Moderate
High	Low
Very high	Very low

Applying fuzzy TOPSIS with mixed objectives is not problematic because linguistic variables must be assigned to all objectives regardless of whether they are quantitatively estimated or qualitatively evaluated.

Estimating MLI with mixed objectives is accomplished using the following three–step procedure. First, the linguistic variables assigned to quantitatively–estimated management objectives are converted to numerical scores using the scoring scheme described earlier. Second, the same scoring scheme is applied to the linguistic variables assigned to qualitatively–evaluated management objectives. Third, numerical scores for all management objectives are entered into the MLI equation for each management plan: $MLI_{irdt} = \sum_{r=1}^{5} w_{ir}(S_{irt} - S_{irdt})$, where w_{ir} is the weight assigned to the r^{th} objective for the i^{th} forest, S_{irt} is the numerical score for the i^{th} forest, r^{th} objective, and t^{th} planning period when the individual drivers do not change across planning periods, and S_{irdt} is the numerical score for the i^{th} forest, r^{th} objective, d^{th} combination driver scenario, and t^{th} planning period. S_{irt} is expected to exceed S_{irdt}. Therefore, $(S_{irt} - S_{irdt}) > 0$.

V. CONCLUSION

Future changes in forest ecosystem drivers, such as climate change and residential development adjacent to or within forests, can negatively impact the long–term sustainability of those ecosystems. Managers can alleviate such impacts by using the proposed conceptual framework to identify preferred sustainable management plans for a forest. Noteworthy contributions of the framework are that it: (1) incorporates multiple management plans, ecosystem drivers, management objectives, and planning periods; (2) accounts for uncertainty about future changes in ecosystem drivers; (3) characterizes and evaluates management plans in terms of multiple objectives; (4) accommodates single– or multi–valued simulated objectives achieved by management plans; and (5) handles quantitatively–estimated or qualitatively–evaluated management objectives. Implementation of certain elements of the framework, particularly quantitative or qualitative evaluation of the effects of forest ecosystem drivers on the objectives achieved by management plans, would most likely require assistance from professionals with expertise in that area.

The conceptual framework described here is complex. As such, it would be difficult for forest managers to utilize the framework. One area of future research that could increase forest managers' access to the framework is to incorporate it in a decision support system. The latter is a computer–based system that integrates data, information, and models for the purpose of allowing decision makers to solve complex, decision problems and evaluate the consequences of alternative scenarios [48,49,50].

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Our objective here is to outline a conceptual framework for understanding ecosystem sensitivity to human influence on fire regimes with particular attention to feedbacks driving widespread forest transitions in more productive forest ecosystems. To evaluate this framework we draw upon examples from four temperate forest regions in a circum-Pacific region: the northwestern United States, southern South America, Tasmania and New Zealand. HYPOTHESES We propose that