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COMPROMISE PROGRAMMING IN FOREST MANAGEMENT

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ABSTRACT

Multi-objective decision-making (MODM) is an appropriate approach for evaluating a forest management scenario involving multiple interests. Today's land managers must accommodate commercial as well as non-commercial objectives that may be expressed quantitatively and/or qualitatively, and respond to social, political, economic and cultural changes. The spatial and temporal characteristics of a forest ecosystem and the huge number of variables involved require the management of such a system in a spatiotemporal MODM framework. The particular MODM technique used in this paper is Compromise Programming. This technique is used to determine the most satisfactory management option. Compromise Programming uses a common management response indicator to solve a forest ecosystem management scenario in a fair and equitable manner.

INTRODUCTION

Forest ecosystems in the United States present land managers and decision makers with many conflicting management objectives related to societal, ecological, environmental and economic values. These objectives include improving desirable objectives, such as aesthetic quality, forage for livestock and wildlife, recreational use, quantity and quality of water, and reducing undesirable objectives, such as fire and flood hazards, invasive exotic plant species, etc. Often these conflicting objectives are noncommensurable, and change with time and space. The goal of the forest-planning process is to reach satisfactory achievement levels of all objectives. The primary motivation for this paper is the use of a spatio-temporal multi-objective decision-making (MODM) modeling effort as a planning tool for a forest land-management planning process.

In an adaptive forest-planning process, land managers acknowledge that the ecosystem they manage will be different in the future and are willing to deal with changing circumstances (Gregory et al. 2006). However, it may be difficult to assess the achievement level of objectives through time. Objectives pertaining to both human and natural systems are interdependent, as the systems themselves are and should be treated as such (Folke et al. 2002). Consequently, it can be problematic to engage multiple decision makers with varying interests in the forest management decision-making process, especially when the future abounds with ecological and social uncertainties. It is essential to establish objectives and criteria to implement scientifically credible and defensible management alternatives that have widespread acceptance by decision makers and stakeholders. Yet, in order to achieve management goals and objectives, it is inevitable that future adjustments to management will be required. Here active adaptive management can be combined with scenario modeling to become a learning exercise and to test hypothesis (Gregory et al. 2006). With the availability of temporal and spatial software for use in forest planning and considering the complexity and number of variables involved in ecosystem management, it is appropriate to model forest management in a spatio-temporal MODM framework. Ecosystem management would be much simpler if there was only one objective of concern. But in actuality management must take into consideration multiple objectives to mitigate conflicts (Gregory et al. 2006). Adaptive decision making in forest management across spatio-temporal scales allows for exposure of long-term, cross-scale consequences.

Multi-Criteria Decision Making (MCDM) has its origin in the field of Operations Research (Zeleny 1982), which was initially developed for military use during the Second World War to optimize submarine warfare in the Atlantic Ocean (Morse 1986). Since then, MCDM has been developing into a discipline with its own concepts, approaches and methods to aid decision makers (DMs) to identify, describe, evaluate, sometimes sort, rank, and select or reject alternatives, based on evaluation processes that involve several criteria (Colson and De Bruyn 1989, Tecle and Duckstein 1994). MCDM basically is a technique that determines the performance levels of alternative management actions in achieving desired management objectives and thereby differs from other linear programming techniques used in forest management, such as goal programming (Dyer et al. 1979, Field 1973). The MCDM description is made in the form of constructing a matrix of criteria versus alternatives. The technique may be divided into two broad classes (Zimmermann 1996, Phoa and Minowa 2005): (1) Multi-attribute decision making, which evaluates a finite feasible set of alternatives and selects the best one based on the scores of a set of

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attributes; and (2) Multi-objective decision making, which selects the best alternative on the basis of its performance levels in achieving a set of conflicting objectives. Both processes can be used by a single DM or a group of DMs (Phoa and Minowa 2005).

One of the reasons MCDM techniques have not been fully exploited in natural-resource management is that managers are still unfamiliar or feel uncomfortable with the tools and methods (Pomerol and Bara-Romero 2000). The problem in forest management is mostly due to unfamiliarity with or the lack of expertise on the approach. The low number of MCDM techniques applied so far, has primarily been to determine optimal timber harvesting methods (Duerr et al. 1979, Dekluyer et al. 1980, Garcia 1990, Diaz-Balteiro and Romero 1998). While MCDM techniques have been primarily assuming homogeneity within a study area and were basically aspatial (i.e., Poff 2002, Phoa and Minowa 2005), many MCDM problems in reality vary across space (Tkach and Simonovic 1997, Malczewski 1999a).

Even though MCDM integration into GIS received considerable attention among urban planners (Carver 1991, Malczewski 1996) and in land allocation problems (Jansen and Rietveld 1990, Eastman et al. 1995, Yeh and Li 1998), relatively few studies have employed MCDM with GIS techniques in forest management planning (Phoa and Minowa 2005). In the past few years, GIS have been used to find solutions to natural-resource management and planning problems, such as the Patuxent Landscape Model (PLM 1995, Costanza et al. 2002, Voinov et al. 2003). This has opened the door for GIS-based multicriteria decision making (Ratsiatou and Stefanakis 2001), leading to the development of spatial decision support systems that incorporate forest planning models into a GIS format (Næsset 1997).

Malczewski (1999b) suggests that visualization of spatial MCDM analysis outcomes are important in attempts to integrate MCDM tools with GIS. This has led to several prototypes in the past decade (Jansen and Rietveld 1990, Carver 1991, Faber et al. 1995, Jankowski 1995, Lotov et al. 1997, Tkach and Simonovic 1997, Wu 1998, Jiang and Eastman 2000).

As with simulation software, there are three basic ways of integrating MCDM into GIS software: (1) The first one involves incorporating MCDM tools within the GIS software (Jiang and Eastman 2000), (2) the second one imbeds GIS techniques and tools within the MCDM software (Fisher et al. 1996), and (3) the third integrates both at the operating system level (Jankowski et al. 1997). According to Morris and Jankowski (2000) the main problem with MCDM-GIS integration is that the approach used to assign criterionweights is either somewhat arbitrary or assumes that the criteria are strictly Boolean.

One MCDM technique that has been successfully used with GIS to deal with spatial variability is Compromise Programming (Rogowski and Engman 1996, Tkach and Simonovic 1997, Bukenya 2000, Simonovic 2002, Thinh and Hedel 2004). However, none of these examples involve dynamic models and primarily focus on either cleaning up remotely sensed data or determining land suitability for various natural resource management problems. That is because this area of modeling involves methods that are being used to optimize some set of goals or objectives, in terms of planning, design, policy and management. Commonly planning and management processes are regarded as so complex that it is thought to be not possible to build a spatial model optimized in a fashion that meets the diversity and complexity of political aspirations of decision makers (Batty 2005). Some dynamic decision support tools that have been applied on landscape scales include the Everglades Landscape Model (ELM 1997) and the Land Use Evolution and Impact Assessment Model (LEAM 1999). These models have allowed decision makers, stakeholders and concerned citizens to visualize and test impacts of management actions on urban, environmental, social and economic systems (Maxwell and Voinov 2005). However, none of these models use the classical MCDM/MODM techniques as defined above.

Until well into the 1990s, forest management was dominated by timber production, even though multiple-use forest management had been introduced by the middle of the last century (Bengston 1994). This relatively recent paradigm shift from traditional single objective oriented forest management to ecosystem based forest management on public lands has presented land managers and DMs with multiple competing and/or conflicting objectives and values which have to be addressed in a forest-planning process. Forest management DMs need to have a tool allowing them to figure out how different forest-management prescriptions provide for these diverse values and objectives. There needs to be the ability to identify specific and groups of objectives by interest or category. This provides an opportunity to structure differences in objectives' behaviors, relations and risks. Further, it is necessary to have a common indicator that is reflective of the values of interest, be responsive to management actions/treatments, is a metric for the state of a key ecosystem driver and which can be used to create a mathematical response functions. Such a tool should allow for the assignment of different weights to different values and objectives by different interest groups and or stakeholders. Ideally there should also be a metric that allows for a variation in how these

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different interests and stakeholders are compensated for their differences. There is also a need to define the spatial and temporal extent and resolution over which these values and objectives are assessed. Is this plan for on a forest-stand scale or a watershed scale; does it span a decade or a century; does it give an opportunity for stratification? How well can DMs address uncertainty? Do the objectives and values contained in the planning and modeling process include diversity of interests and differences in response? Are created response functions mindful of interactions and thresholds? Can various scenarios be modeled that reflect natural or social regime change?

To achieve a spatiotemporal MODM modeling of forest management, which takes the factors described above into consideration, this study integrated Compromise Programming with spatial and dynamic computer algorithms to arrive at management solutions that address spatiotemporal variabilities of forest resources. The approach presented here fits into the current institutional planning process as well as adaptive management.

COMPROMISE PROGRAMMING

Compromise Programming (CP) employs the concept of distance to analyze multiple-objective problems. This distance is not limited to the geometric sense of distance between two points; it is rather used as a proxy to measure degrees of human preferences. CP selects a nondominated preferred solution from a feasible set, on the basis of the solution's closeness to an infeasible ideal point (Zeleny 1973). A nondominated solution in a MODM problem is one that cannot produce any improvement in any one of the objectives without making at least one other objective worse (Tecle et al. 1988, Tecle and Duckstein 1994), while an ideal point represents the joint location of the individual maximum values of all the objectives. Therefore, arriving at a compromise solution can be viewed as minimizing a DM's regret for not obtaining the ideal solution. The general formulation of a CP approach is expressed as follows:

$$\min\left\{ l_p = \left[\sum_{i=1}^{I} W_i^p \left(Z_i^* - Z_{ij} \right)^p \right]^{1/p} \right\}, j = 1,\ldots,J \qquad [1]$$

Here l_p is the distance metric, for any p in which $0<p<\infty$. It is the measure of a solution's closeness to the ideal point Z^*, which is the set of all the maximum values of all objective functions. Z_{ij} is the value of objective i under a specific discrete value of decision variable j. I is the number of objectives within categories and ranges from one to four. J is the number of discrete decision variable values. Z_i^* is the maximum value for objective i and it is determined using the equation:

$$f_i^* = df_i / dx \qquad [2]$$

where f_i is a response function and x is the decision variable in which f_i is expressed.

To avoid scale effects and to make all objective function values commensurable, the objective functions are normalized by dividing the right hand side by the expression $(Z_i^* - Z_i^{**})$, where Z_i^{**} is the worst value of objective i, which is also determined in equation [2].

The normalized objective functions are expressed in the following manner:

$$Z_{ij} = (Z_{ij}-Z_i^*)/(Z_i^*-Z_i^{**}), i = 1,\ldots, I \text{ and } j = 1, , J \qquad [3]$$

where the Z_{ij} on the left hand side of the equation represents the normalized elements of the original pay-off matrix Z_{ij} on the right hand side of the equation. This normalization process guarantees the Z_{ij} on the left hand side of the equation to have values between 0 and 1.

The weight W_i in equation [1] signifies the importance of objective i relative to the other objectives. The p is the metric parameter. Different values of p represent different aspects of a compromise programming algorithm. For p=1, all deviations from Z_i^* are directly proportional to their magnitude. For $2<p<\infty$, the largest deviation has the greatest influence. Varying p from 1 to ∞, allows to move from having a perfect compensation among the objectives (i.e., minimizing the sum of individual regrets) to having no compensation among the objectives in the decision making process (i.e., minimizing the maximum regret). The greater the conflict between different decision makers is, the smaller the possible compensation (Zeleny 1974, 1982; Goicoechea et al. 1982; Szidarovszky et al. 1986).

To illustrate the use of CP in forest management, the authors employ multi-objective management of the ponderosa pine forest in northern Arizona as an example. Land managers and scientists consider the southwestern ponderosa pine forest to be above its historical stand density and prone to catastrophic forest fires (Covington et al. 1997, USFS 2006). Management of the study area is further complicated by the number of stakeholders and other interested parties with strong feelings and mostly conflicting objectives in the way the forest should be managed (Tecle et al. 1995). These facts lend this forest ecosystem management challenge to be an ideal candidate for a study of the use of CP in forest management.

CP is adapted here to perform a two-level trade-off analysis of the ecosystem management problem.

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In the first level, equation [1] is used to seek a compromise solution within those objective categories that have more than one objective. In the second level, equation [4] is applied to determine the compromise solution for the objective categories:

$$\min\left\{ l_p = \left[\sum_{k=1}^{K} W_k^p \left(Z_k^* - Z_{kj} \right)^p \right]^{1/p} \right\}, j = 1,\ldots,J \qquad [4]$$

Z_{kj} is the normalized value of objective category k under decision variable level j, and Z_k^* is the best normalized value for objective category k. K is the number of objective categories and all others are as defined previously. The weight W_k in equation [4] signifies the importance of objective category k in comparison to the other objective categories.

For p=∞, the largest deviation is the only one considered and the problem becomes a min/max problem. As a result equation [4] reduces to equation [5], where:

$$l_\infty = max\{W_k (Z_k^* - Z_{kj})\},\ k = 1,\ldots,K \text{ and } j = 1,\ldots, J \qquad [5]$$

All the variables in equation [5] are as described above.

METHODOLOGY

The modeling approach in this study consists of several steps. First ecosystem management objectives that reflect the needs and aspirations of stakeholders need to be identified and structured in terms of specifications, criteria and criterion scales as shown in Table 1. After appropriate management decision variables with levels that can be evaluated are identified, a set of response functions can be developed and be used in a CP-spatiotemporal framework. A response function is a mathematical expression of a management objective or forest ecosystem component response to certain management action(s). In this study, the management objectives are linked to varying levels of forest stand densities and solved using CP, Forest Vegetation Simulator (FVS; a forest growth and yield model) and ArcGIS (a geographic information system model). FVS is an individual-tree growth model used by forest managers in the USDA Forest Service in developing land management plans. Other forest planning tools such as Remsoft or Spectrum could be used as well. ArcGIS is a geographic information system used by land managers and analysts for creating, storing, analyzing and managing spatial data and associated attributes. ArcGIS is used here as the spatial projection component of the modeling effort which assigns CP analysis results to polygons. These three components are combined to achieve one purpose: to solve a multi-objective forest management scenario in a dynamic and spatially varied framework to reflect a real world situation.

Response Functions

The management objectives described in this paper represent the interests of various stakeholders. Because the preferred values of many of these objectives are arrived at different forest stand density levels, they are in conflict with each other. Under this situation, it is impossible to optimize one objective without adversely affecting another. Hence, a trade off analysis using CP is performed to determine a preferred stand density level that will result in the most satisfactory solution with respect to all management objectives. In order to use CP, the individual management objectives are described in the form of mathematical response functions. The individual forest management objectives, their specifications, criteria and criterion scales used in this study are shown in Table 1. Tree basal area (m^2/ha) is the management variable used to develop and express the different objective functions. To be meaningful to managers the decision variable must be susceptible to alteration by management actions. Hence, all response functions in this study are expressed in terms of tree basal area (BA) that range from 6 through 45 m^2/ha. The minimum density required for the forest in the study area to qualify as "a forest" under UN guidelines (FAO 2006) is 6 m^2/ha, while 45 m^2/ha is the average upper limit density of the majority of the data available for creating the response functions (Poff 2002).

Figure 1 represents the trend curves for the 20 different management objectives expressed as response functions in Table 2. Each graph in the figure represents a change in management objective function values with varying tree basal area levels expressed in m^2/ha. The management objectives were normalized and brought into the same optimization direction before performing CP analysis.

Temporal Projection Using Forest Vegetation Simulator

The dynamic analysis part of the modeling effort is handled using the US Forest Service's Forest Vegetation Simulator (FVS). FVS is a large-scale forest management tool, which is employed to summarize current stand characteristics, and to predict future stand conditions under various management scenarios (Dixon 2002). Its output can be utilized as an input into forest planning models and other analytical and spatial analysis tools such as the geographic information systems used in this work (GIS) (McMahan et al. 2002). Refer to *Essential FVS: A User's Guide to the Forest Vegetation Simulator* (Dixon 2002) for a more detailed description.

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Table 1. *Objective categories, specifications, criteria, and criterion scales for the spatiotemporal CP analysis of the southwestern ponderosa pine forest ecosystem.*

Objective categories	Specifications	Criteria	Criterion scale
Maximize *social benefits*	Aesthetic quality	Scenic beauty index	Ordinal
	Cultural resources	Willingness to pay	US$/BA/ha
	Recreational use	Willingness to pay	US$/BA/ha
Minimize *insects and diseases*	Roundheaded pine beetle attacks	Beetle attacked trees	% of BA killed
	Bark beetle	Hazard rating	Composite stand Hazard values
	Dwarf mistletoe infection		10-yr infestation rate
Minimize *exotics*	Invasive plant reduction	Individual exotic plants	Plants/ha
Maximize *forage*	Herbage production	Amount of herbage	t/ha
Maximize *timber*	Timber growth	Timber yield	m^3/ha
Minimize *costs*	Costs	Cost of tree removal	US$/ha
Minimize *fire*	Forest fire	Crown fuel load	t/ha
		Heat intensity	kJ/m^2
		Crown fire	% crown burned
Achieve desirable *hydrological condition*	Maximize water quality	Sediment yield	t/ha/yr
	Maximize water yield	Streamflow	m^3/sec
	Minimize flood hazard	Peak flow	m^3/km^2
Optimize *wildlife habitat*	Nongame species	Abert squirrel	Ordinal
	Threatened/endangered species	Mexican spotted owl	Ordinal
	Game species	Mule deer	Ordinal
	Forest Service sensitive species	Northern goshawk	Ordinal

While FVS served as the temporal projection tool in this study, any software that performs similar functions such as Tree And Stand Simulator (TASS) (Mitchell 1975) could be used instead. FVS was chosen because it has been commonly used to simulate growth of southwestern ponderosa pine stands by forest land management agencies in the Southwest (Dixon 2002). FVS computes future forest stand density based on measured original stand density. In its most basic form FVS can be expressed as:

$$T_{i+1} = T_i + f(\text{var.}),\ i = 1, \ldots, I \qquad [6]$$

where T_i is the stand density at time step i and var. represents a set of variables ranging from physical and spatial characteristics such as slope, aspect and conditions of adjacent stands, to biological conditions such as tree mortality and management actions such as a thinning treatment.

The user defines the time scale for the growth simulation in FVS. In this analysis, a common cycle length of 10 years, a starting date of 2007, in which the selected treatment was applied, and an ending year of 2127 were chosen. FVS uses three stand density descriptors, namely basal area per acre, crown competition factor and basal area percentile. However, only tree basal area per acre was used, because it is the only decision variable used to express all the response functions in this study. To compute basal area, FVS simply sums the product of trees per acre and tree basal area across all tree records. This is then computed for each stand in the simulation (Dixon 2002).

Spatial Projection Using Geographic Information System (GIS)

ESRI's ArcGIS was used to handle the spatial projection part of the CP modeling process. The ModelBuilder extension of ArcGIS allows the user to build a model using a diagram that resembles a flowchart (Krivoruchko and Gotway-Crawford 2005, Maidment et al. 2005, Miller et al. 2005). In this feature of ArcGIS, the model consists of a set of spatial processes that convert input data into an output layer. ModelBuilder is not dynamic as of version 9.1, however, it can simulate changes with

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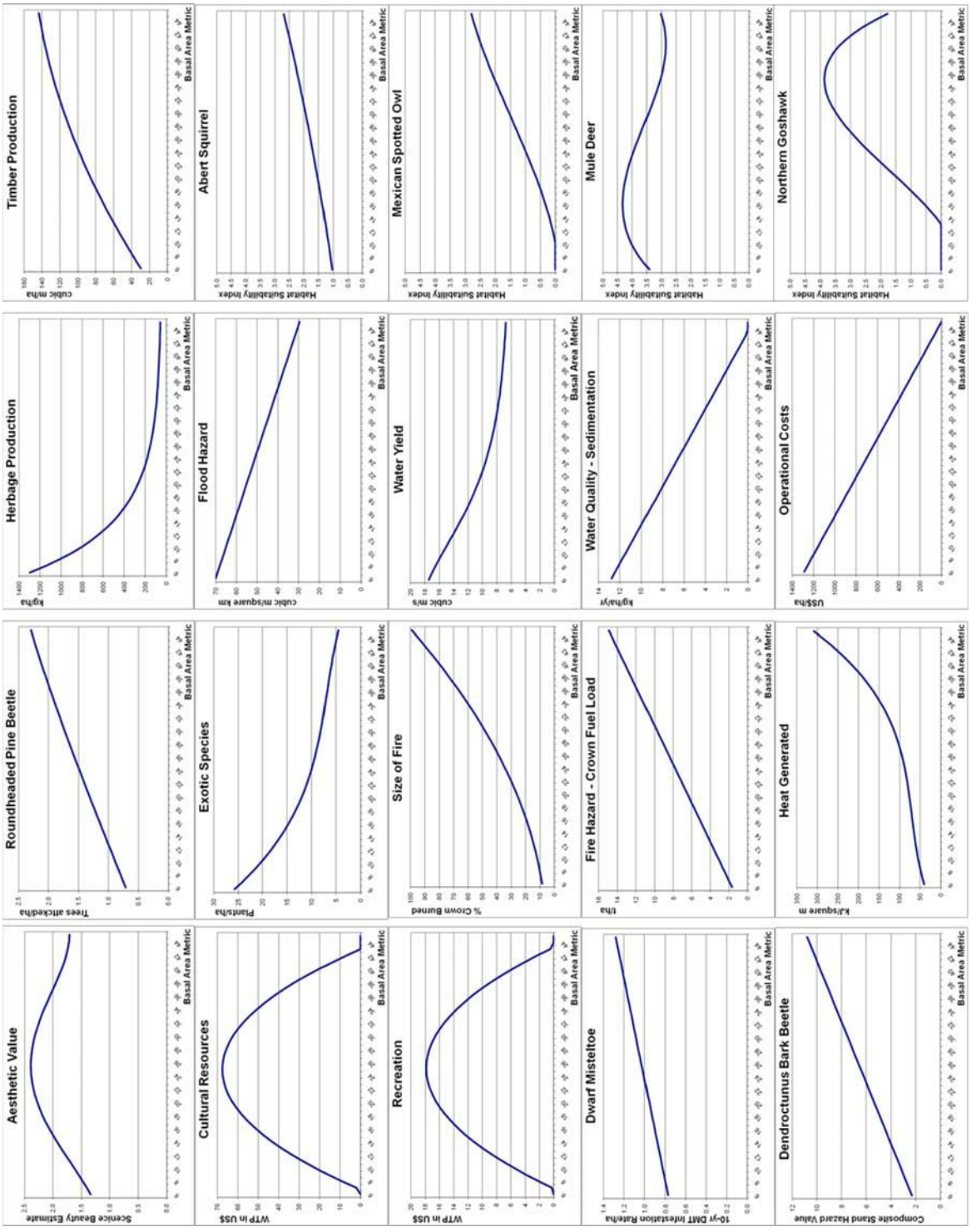


Figure 1. *Trend curves of forest management objectives versus tree basal area values.*

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Table 2. *Summary of response functions.*

Objectives (based on)	Mathematical formulations of management objective	r^2 value	Equation no.
Social concerns Aesthetic value (Brown et al. 1974,Tecle et al. 1998) Cultural resources (Loomis 1996) Recreation (Loomis 1996)	Z_1=1.144-0.001974(x/0.2296) +0.004718(x/0.2296)^2 - 0.000004356(x/0.2296)^3+0.000000001059(x/0.2296)^4 Z_2 = -59.334+10.221x-0.206x^2 Z_3 = -16.03+2.706x-0.054x^2 Where Z_1 = Scenic Beauty Index (SBE) Z_2 = Willingness to pay for forest preservation at given basal area/ha Z_3 = Willingness to pay for recreational experience in given basal area/ha x = tree basal area m^2/ha	N/A N/A N/A	8 9 10
Insects and diseases Roundheaded pine beetle (Negrón et al. 2000) *Dendroctonus* bark beetle (McMillin pers.comm.) Dwarf mistletoe infestation rate (Geils and Mathiasen 1990)	Z_4 = 0.453+0.044x-0.000025x^2-0.0000021x^3 Z_5 = 1+0.218x+0.00000000000000231x^2-0.000000000000000033x^3 Z_6 = 0.697+0.013x-0.0000007x^2 Where Z_4 = Percent ponderosa pine basal area killed from roundheaded pine beetle Z_5 = Composite Stand Hazard Values from bark beetle infestation Z_6 = 10-year dwarf mistletoe infestation rate/ha x = Tree basal area m^2/ha	0.88 1.00 N/A	11 12 13
Minimize exotic species (USFS 1999 [data, Coconino NF])	Z_7 = 36.57-2.097x+0.053x^2-0.0005x^3 Where Z_7 = Number of Scotch thistle observations/ha x = Tree basal area m^2/ha	0.55	14
Maximize herbage production (Covington and Fox 1991, Tecle et al. 1998)	Z_8 = {(45+24a/25.4+55d)(exp(-0.0289(x/0.23))}*1.1208 Where Z_8 = herbage production a = annual precipitation (= 762 mm average for study area) d = depth of soil to impedance layer (cm) (= 30 cm average for study area) x = tree basal area m^2/ha	N/A	15
Maximum timber production (Ronco et al. 1985, Tecle et al. 1998)	Z_9 = 17.06(x/0.2296)-0.03369(x/0.2296)^2*0.06997 Where Z_9 = Merchantable timber growth volume in m^3/ha x = tree basal area m^2/ha	N/A	16
Minimum operational costs (Turner and Larson 1974)	Z_{10} = 1486.35-33x Where Z_{10} = Cost of thinning to desired basal area expressed in 2000 US$ x = tree basal area m^2/ha	N/A	17
Minimum fire hazard and effects (Fulé et al. 2001a, b) Fire hazard Heat generated Size of fire	Z_{11} = -0.37+0.34x Z_{12} = 1.763+8.54x-0.398x^2+0.008x^3 Z_{13} = 5.818+0.212x+0.041x^2 Where Z_{11} = Crown fuel load (t/ha) Z_{12} = Heat generated (kJ/m^2) Z_{13} = Percent of crown burned (%)	0.96 0.75 0.52	18 19 20

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Objectives (based on)	Mathematical formulations of management objective	r^2 value	Equation no.
Hydrological concerns Water quality (Brown et al. 1974) Water yield (Rogers et al. 1984, Tecle et al. 1998) Flood hazard (Brown et al. 1974, Ffolliott and Thorud 1975, USFS 1977, Tecle 1991, Tecle et al. 1998)	Z_{14} = 14.82-0.34x Z_{15} = 1.19{-5.72+0.83Pw/25.4+42r-0.24r(Pw/25.4)$^{0.92}$-0.007Pw^2(1-exp[-(x/0.23)/45)]^3}-0.47 Z_{16} = 76.27-1.04x Where Z_{14} = Sediment yield in t/ha Z_{15} = Annual streamflow in cfs Z_{16} = m^2/km^2 of water flow Pw = Winter (1 Oct-30 Apr) precipitation (= 610 mm average for study area) R = Insolation index (= 19 INI for study area) x = tree basal area m^2/ha	N/A N/A N/A	21 22 23
Wildlife habitat condition Abert squirrel (Patton 1984, McTague 1991) Mexican spotted owl (Tecle et al. 1998, Ganey 1988) Mule deer (Wallmo and Schoen 1981, Leckenby et al. 1982, Severson and Medina 1983) Northern goshawk (Reynolds et al. 1992, Block et al. 1994)	Z_{17} = 0.857+0.02713x+0.0003027x^2 Z_{18} = 0.056-0.033x+0.0044x^2-0.00005x^3 Z_{19} = 1.659+0.386x-0.017x^2+0.0002x^3 Z_{20} = 0.459-0.295x+0.025x^2-0.0004x^3 Where Z_{17} = Abert squirrel habitat index Z_{18} = Mexican spotted owl habitat index Z_{19} = Mule deer habitat index Z_{20} = Northern goshawk habitat index x = tree basal area m^2/ha	N/A 0.47 0.74 0.86	24 25 26 27

N/A = r^2 value is not available because the original response function has been developed by respective authors and value was not given.

K = 1....K, where K = 9
Each k has 1 - 4 specific objectives, represented by I.
When I≥2 a first stage evaluation is performed using the CP algorithm given in equation 1, to arrive at a joint response function value for each objective category.
When I = 1, no first stage CP evaluation is performed on the objective category, instead each objective category's values are determined for use in the second stage CP evaluation.

time by running a model multiple times using different inputs. This was pursued in this study for each time step simulated in FVS. Using the query function in Modelbuilder eleven layers were created for each time-step output given in the FVS table. Here ArcGIS was used to assign the level of closeness to polygons based on their basal area values. This measure of closeness of CP solution to the ideal point serves as a surrogate for the achievement levels of the management problem. Each layer represents a group of forest stands with the same achievement level. This can be expressed as:

$$L_i^{TS} = \sum AL_j^{BA} \quad [7]$$

where L_i^{TS} is the layer created in time step i and AL_j^{BA} are the polygons of achievement level j given their basal area values.

There are a total of thirteen, 10-year time steps (from 2007-2127) plus pre-existing stand conditions in this simulation. The 11 layers, for each time step, are color coded in accordance to the color key given in the respective figures displaying the results of the simulation. As illustrated in Figure 7, in the results section, the user can see at a glance which forest stands in the project area have the best possible basal area that can satisfy all management objectives simultaneously. One can also easily see which stands have too high of a stand density and which stands have too little and by how much. In other words, the spatiotemporal CP output is displayed by the individual stands across the landscape in the project area using a color coded scheme to show the percentage of the achievement level.

Problem Analyses

To evaluate the different forest management alternatives with respect to their ability to achieve the desired objectives, the 20 objective response functions were categorized into nine objective categories on the basis of their similarity in addressing related issues as shown in Table 1. The process involves translating all response functions into the same optimization direction, namely maximization,

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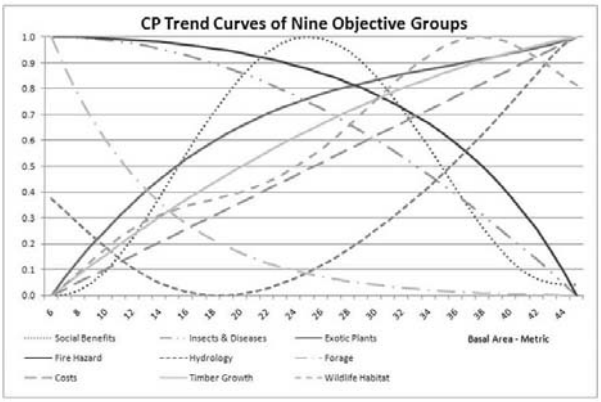


Figure 2. *Standardized response function curves for the nine objective categories in their individual desired optimization directions.*

where the higher the value of a response function, the higher the achievement level becomes.

The application of the CP algorithm in the first level leads to a compromise solution within each objective category that consists of multiple objectives. There were five objectives categories with two or more objective functions evaluated at this level. Equal weights and a *p*-metric value of 2 were used at this level of analysis to better show the difference between the individual objectives. Figure 2 shows the first level CP evaluation results for the nine different objective categories in the form of trend curves.

The second level of CP analysis involves evaluating the nine objective categories. This consists of calculating the level of closeness for each value of the decision variable, and then determining the most preferred forest stand density under three different weighting scenarios. The first case assumes all objectives to have equal weights or importance; the second case involves assigning varying weights to the different objective categories; and the third case uses extreme weights. The third indicates a situation where a particular DM is primarily interested in one of the management objective categories. In all cases the CP solutions are determined for *p*-values of 1, 2 and ∞ to show the sensitivity of the CP solution to *p*-values.

CP RESULTS AND SENSITIVITY ANALYSIS

The use of three sets of weights (W_i) and the three sets of the metric parameter *p*-values determines the sensitivity of the modeling effort to changes in the two parameters. The first set of weights consists of equal weights for each of the objective categories. The second set of weights consists of actual weights assigned by a USDA Forest Service Interdisciplinary Team on the Coconino National Forest in northern Arizona. The weights assigned to each objective category vary from 1-10, where a weight of 1 indicates least important and 10 most important. The third set of weights consists of an extreme case, where one objective category (in this case Optimization of Wildlife Habitat) was given a weight of 10, while each of the eight remaining objective categories received a weight of 1. Figures 3, 4 and 5 display the sensitivity of the CP algorithm under the three different sets of weights and for the metric values of $p = 1$, 2 and ∞, respectively. The most preferred forest density (expressed in basal area) under each weighting scheme and the three *p*-values are listed in Table 3.

In Figures 3, 4 and 5 each weighting scheme (extreme, varying and equal weights) is represented

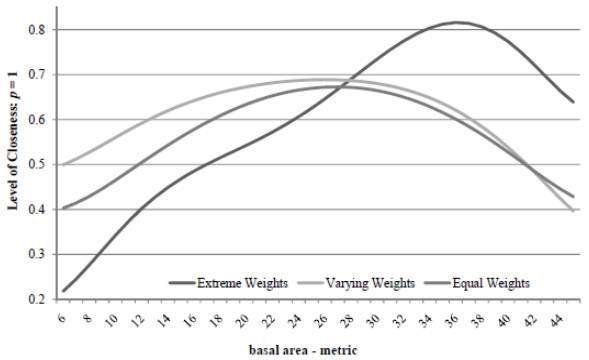


Figure 3. *The outcomes of CP analysis under the 3 different sets of W_i (equal, varying and extreme) and for p = 1.*

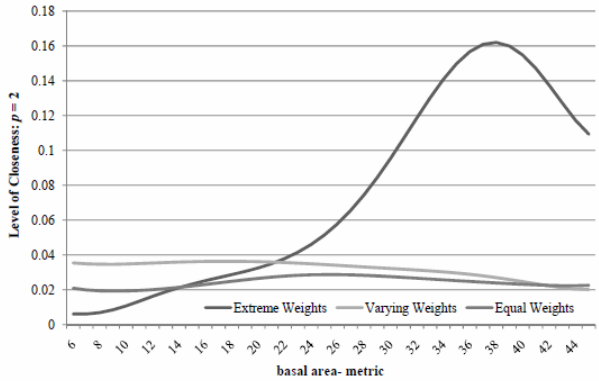


Figure 4. *The outcomes of CP analysis under the 3 different sets of W_i (equal, varying and extreme) and for p = 2.*

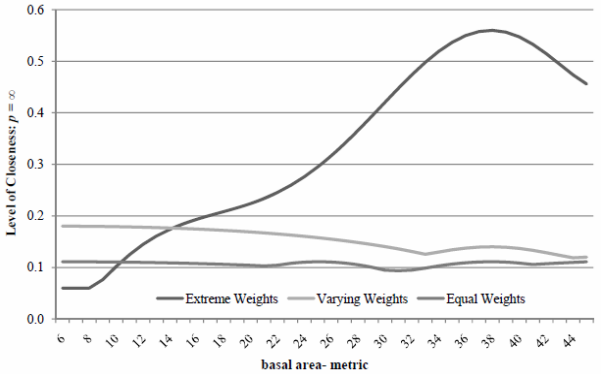


Figure 5.*The outcomes of CP analysis under the 3 different sets of Wi (equal, varying and extreme) and for p = ∞.*

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by a trend curve. The decision variable values (expressed in the form of tree basal area in m^2/ha) displayed on the x-axis serve as the vegetation management alternatives (thinning to a given level or allowing vegetation to reach a given density). The y-axis is a standardized level of closeness to the ideal point, which ranges from zero to one, where 1 represents the infeasible ideal point. The decision variable values with the highest level of closeness (i.e., the peaks of the trend curves) represent the most preferred management alternatives with respect to all objectives under the different weighting schemes. Because the level of closeness values are very small, their differences for decision making purposes are better viewed in at least three decimal places otherwise many values may round up to the same number.

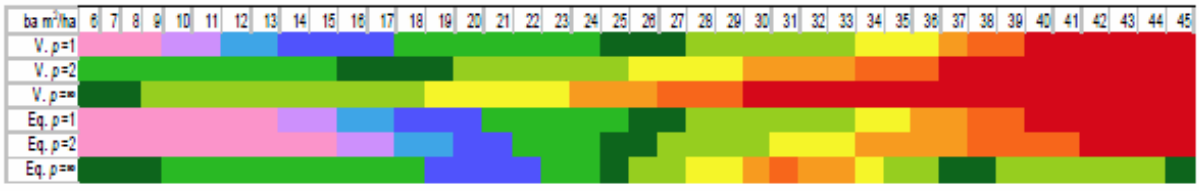
The trend curves under the extreme weighting scheme in Figures 3, 4 and 5 indicate that the CP analysis results are most robust for a metric parameter value of p=1 and most sensitive for p=2 and ∞. The extreme weighting scheme is used here only for sensitivity analysis purposes and does not necessarily represent a realistic forest management scenario.

Figure 6 displays the same results in a different manner, allowing for further interpretation of the sensitivity analysis. The CP results under extreme weighting scheme are not displayed in Figure 6 as it is not realistic to use this weighting scheme in actual decision making procedures. The columns in Figure 6 represent the management alternatives (in tree basal area) ranging from 6 to 45 m^2/ha, whereas the individual rows represent the CP results under different weighting schemes and metric parameter p-values. The most preferred vegetation management alternatives-in terms of the decision variable values-under a given weighting scheme are colored in dark green. As the colors shift from dark green to yellow and orange, the stand densities become increasingly too dense to satisfy all management objectives simultaneously. On the other side, as the colors shift from dark green to green, blue and purple, the stand densities decrease steadily and satisfies all management objectives less and less. Each change in color away from the dark green signifies a 5% decrease in the CP achievement level. Red and pink signify achievement levels of less than 80%, either on the increasing or decreasing trends in tree basal area, respectively. The same color coding is used later in the ArcGIS analysis.

The results displayed in Figures 3, 4, 5 and 6 indicate that the MODM technique employed in this modeling effort is sensitive to both the decision makers' preference structure (expressed in the form of weights) and the p-metric values. This is especially true for p=2 and ∞ and all weighting schemes. At the same time the technique is robust because it does not allow one set of weights to strongly influence any solution under p=1. Figures 3 to 6 in particular, show using p=∞ is not useful in determining a particular most preferred vegetation management alternative that satisfies all 20 objectives simultaneously.

ILLUSTRATIVE EXAMPLE RESULTS

To illustrate the application of the modeling effort presented in this paper, the most robust parameter value of p=1 and equal objective weights were used to analyze the forest management example using CP. The CP analysis suggests a most preferred tree basal area of 27 m^2/ha (see Fig. 6 and Table 3). Table 4 lists the resulting objective



Color Key:	
	: below 80 % of most preferred solution - lower tree density
	: within 80 - 85 % of most preferred solution - lower tree density
	: within 85 - 90 % of most preferred solution - lower tree density
	: within 90 - 95 % of most preferred solution - lower tree density
	: above 95 % of most preferred solution lower tree density
	: most preferred solution
	: above 95 % of most preferred solution - higher tree density
	: within 90 - 95 % of most preferred solution - higher tree density
	: within 85 - 90 % of most preferred solution - higher tree density
	: within 80 - 85 % of most preferred solution - higher tree density
	: below 80 % of most preferred solution - higher tree density

Figure 6. *The columns represent the varying decision variable values, whereas each row represents CP results under different weighting scheme and p-values. The most preferred solutions for a given weighting scheme are colored in a dark green. "V" indicates varying weights assigned to the different management objectives and "Eq." indicates weighting all objective categories equally.*

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Table 3. *The most preferred tree basal area with respect to its performance in achieving all 20 management objectives simultaneously under the three different weighting schemes and three values of p.*

	P Parameter "*p*"		
	1	2	∞
Weighting scheme	Most preferred basal area in m^2/ha	Most preferred basal area in m^2/ha	Most preferred basal area in m^2/ha
Equal	27	25	6, 25, 38, 45
Varying	26	18	6
Extreme	36	38	38

Table 4. *Values for each one of the 20 forest management objectives corresponding to the most preferred vegetation management alternative under p = 1, 2 and ∞. The best and worst values for each objective are also shown in the last two columns, respectively. Because there are multiple preferred management levels of 6, 25, 38 and 45 m^2/ha for p = ∞, only the values for 6 and 45 as well as 25 (same as p = 2) are shown.*

		p = 1	p = 2	p = ∞		Best	Worst
Criteria	Criterion scale	27 m^2/ha	25 m^2/ha	6 m^2/ha	45 m^2/ha	Value	Value
Scenic Beauty Index	Ordinal (1-3)	2.48	2.39	1.34	1.71	2.39	1.34
Willingness to pay[1]	US $/ha	66.67	67.62	0.00	0.00	67.45	0.00
Willingness to pay[2]	US $/ha	17.66	17.87	0.00	0.00	17.87	0.00
Beetle attacked trees	% of BA killed	1.62	1.54	0.72	2.19	0.72	2.19
Bark beetle rating	Ordinal (1-12)	6.89	6.45	2.31	10.81	2.31	10.81
Dwarf mistletoe rating	10-yr infection rate	1.05	1.02	0.77	1.28	0.77	1.28
Individual exotic plants	plants/ha	8.95	9.63	25.79	3.96	3.96	25.79
Amount of herbage	kg/ha	139.22	164.63	1,298.64	59.65	1,298.64	59.65
Timber yield	m^3/ha	107.77	102.03	29.38	143.40	143.40	29.58
Cost of tree removal	US $/ha	594.54	660.60	1,288.17	1.35	1.35	1,288.17
Crown fuel load	t/ha	8.81	8.13	1.67	14.93	1.67	14.93
Heat intensity	kJ/m^2	99.51	91.38	40.39	309.11	40.40	309.11
Crown fire	% crown burned	41.73	37.00	8.58	98.38	8.57	98.38
Sediment yield	t/ha/yr	5.64	6.32	12.78	0.00	0.00	12.78
Streamflow	m^3/sec	8.79	9.27	17.44	6.76	17.44	6.76
Peak flow	m^3/km^2	48.19	50.27	70.03	29.47	29.47	70.03
Abert squirrel habitat	Ordinal (1-5)	1.81	1.72	1.3	2.69	2.69	1.03
Mexican spotted owl habitat	Ordinal (1-5)	1.27	1.08	0.00	2.79	2.79	0.00
Mule deer habitat	Ordinal (1-5)	3.69	3.87	3.41	3.02	4.32	2.85
Northern goshawk habitat	Ordinal (1-5)	3.00	2.59	0.00	1.78	3.87	0.00

[1]Willingness to pay for forest conditions based on forests as cultural resource.

[2]Willingness to pay for forest conditions based on forests as a recreational resource.

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function values for the 20 management objectives under the most preferred tree basal area treatment. The last two columns of the table also show the best and worst objective function values used in the CP analysis.

A target basal area of 27 m^2/ha was chosen with a thinning-from-below prescription for the FVS simulation. Sample results of the modeling effort for each individual stand in the project area through time are displayed spatially in Figure 7. Treatment was simulated in 2007. Figure 7a shows the achievement level the individual stands in the project area belong prior to the simulated treatment. Figure 7b illustrates the same immediately following the simulated treatment. Since trees continue to grow, stand densities are generally expected to increase. As time progresses the performances of most individual stands change adversely with increases in their tree density (Figure 7 c-f). Only forest stands which had a stand density below the most preferred solution, obtained by CP, eventually grew into the most preferred solution and at times may continue to grow beyond it. Table 5 indicates that the simulated treatment for 2007 reduces the forest stand areas classified as too dense (less than 90% of the achievement level) by about half. Areas with a stand density below the target basal area remained untreated and grew through the most preferred tree density level with time.

CONCLUSION

The modeling effort presented in this paper uses CP in a temporal and spatial framework. Twenty objective response functions related to one specific stand density decision variable, tree basal area, are constructed to represent various ecosystem components. The 20 response functions are then evaluated using CP to: (1) determine the most preferred decision variable value, and (2) to assign a level of closeness to an ideal solution for stand densities that did not represent the most preferred solution. FVS was employed as the temporal component, to project the values of the decision variable in the study into the future under a variety of other variables that influence the future development of the particular decision variable used in this study. ArcGIS was used next to assign an achievement level to polygons representing forest stands, based on the decision variable. This was done in a series of time steps and the results were displayed spatially as they changed through time.

Even though only 20 objective response functions are presented here, it does not mean that they are the only objectives to use. Other objective response functions can be added or replace existing ones to make the analysis more holistic as new information becomes available. In the modeling effort presented here, the 20 response functions were assigned equal, varying and extreme weights, and evaluated using p-metric parameter values of 1, 2 and ∞ to determine the sensitivity of the CP technique to changing weights and p-values. The results indicate that though CP is fairly robust, it is sensitive to both the decision makers' weights and the *p*-metric values.

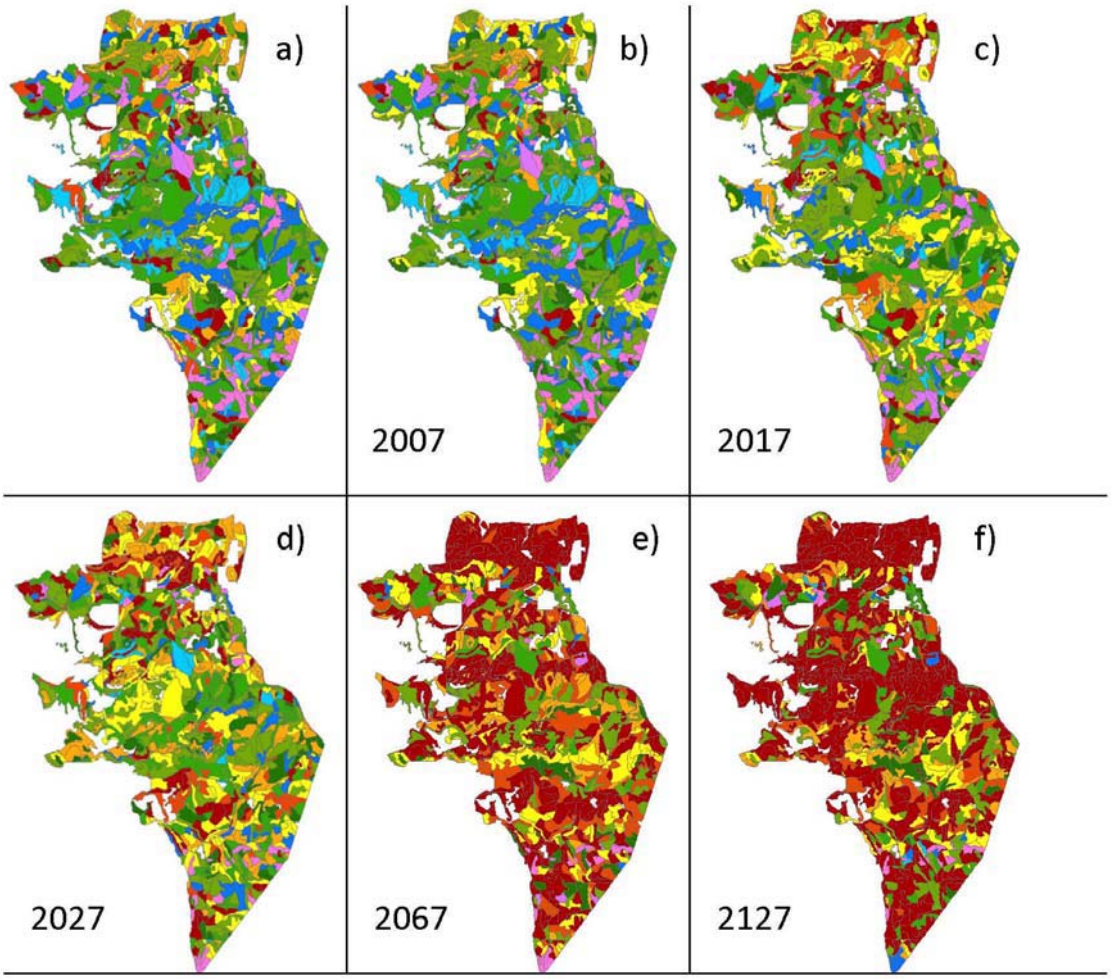
The output from CP indicates that the most preferred tree basal area when all objectives have equal weights and under a p-value of 1 is 27 m^2/ha. When the individual management alternatives (expressed in tree basal area) are evaluated in terms of their level of closeness to the most preferred alternative (Figs. 3-6), the differences between the preference structures becomes more apparent. However, the technique is easy to use. Also CP uses a straightforward computation, which makes is easy to handle using a spreadsheet.

The use of FVS as the temporal module in the modeling process has several advantages. Generally the software is widely used by land managing agencies, such as the US Forest Service and is easily understood and trusted by decision makers and stakeholders (Dixon 2002). The interactive nature of the modeling effort presented in this paper allows analysts to plug in FVS simulations results to receive a spatiotemporal MODM output with very little extra effort.

The advantage of this model, compared to other growth and yield models described in the literature (Miner et al. 1988, Edminster el al. 1991, Dixon 2002) is its ability to visually display how well numerous forest ecosystem management objectives are met simultaneously on a forest-stand basis, across an entire project over a landscape. It allows decision makers and land managers to see into the future, which stands may require additional treatment and which stands do not. However, one short coming of this modeling effort is the absence of interaction at the ArcGIS stage among the spatially distributed results. While FVS takes interactions between different forest stands into account, ArcGIS does not. The displayed analysis results are purely based on the basal area calculated in CP and then simulated in FVS. This issue should be explored in future modeling efforts.

Today's computing power allows us to realize possible management scenarios that in previous decades had been only considered as concepts. ArcGIS Modelbuilder, for example, allows the user to combine the outputs of the CP analysis with those of the dynamic forest vegetation growth simulator FVS and display them on a stand by stand basis across an entire landscape. In other words, it allows us to model forest ecosystem management in a spatiotemporal multi-objective decision making

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	: below 80 % of most preferred solution - higher tree density

Figure 7. *Different levels at which individual forest stands in the project area meet all management objectives simultaneously under equal weights and the p-value of 1. a) Prior to treatment b) At the time of treatment in 2007; and c) through f) represent the simulated performance at the indicated time steps. White areas are either indicative of non-Forest Service lands or non-ponderosa pine dominated stands.*

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Table 5. *Summary of number of hectares of the project area falling into the various achievement levels (for equal weights and a p-value of 1).*

	Prior to Tx	2007	2067	2127
Achievement level	land in ha	land in ha	land in ha	land in ha
Below 80% of most preferred solution – lower tree density	1,024	1,025	507	286
Within 80-85% of most preferred solution – lower tree density	607	607	77	82
Within 85-90% of most preferred solution – lower tree density	1,485	1,485	267	38
Within 90-95% of most preferred solution – lower tree density	2,030	2,030	767	307
Above 95% of most preferred solution – lower tree density	3,091	2,091	2,455	774
Most preferred solution	1,380	1,494	1,431	685
Above 95% of most preferred solution – higher tree density	3,960	4,852	3,189	1,383
Within 90-95% of most preferred solution – higher tree density	1,432	1,716	3,292	1,626
Within 85-90% of most preferred solution – higher tree density	1,339	721	2,400	1,397
Within 80-85% of most preferred solution – higher tree density	364	188	1,752	1,282
Below 80% of most preferred solution – higher tree density	1,180	583	1,754	10,063

framework that addresses the needs of multiple interests through time.

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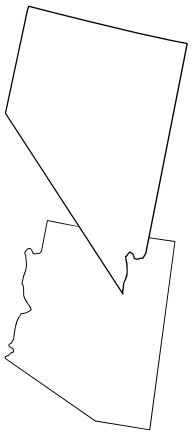
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