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Dissertation

OPTIMAL SPATIAL LOCATION OF FOREST FUEL MANAGEMENT ACTIVITIES

Submitted by

José René Valdez-Lazalde

Department of Forest Sciences

In partial fulfillment of the requirements
for the degree of doctor of philosophy
Colorado State University
Fort Collins, Colorado
Summer, 2001

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WE HEREBY RECOMMEND THAT THE DISSERTATION PREPARED UNDER OUR SUPERVISION BY JOSE RENE VALDEZ-LAZALDE ENTITLED OPTIMAL SPATIAL LOCATION OF FOREST FUEL MANAGEMENT ACTIVITIES BE ACCEPTED AS FULFILLING IN PART REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY.

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ABSTRACT OF DISSERTATION

OPTIMAL SPATIAL LOCATION OF FOREST FUEL MANAGEMENT ACTIVITIES

Recent wildfire events in many parts of the world have galvanized public and private organizations to spend billions of dollars to reduce the risk of fires to natural and man-made structures. In the previous century, much of this effort was concentrated on developing the science and technology needed to suppress wildfires once they were ignited. However, man's ability to control burning wildfires is limited. Therefore, natural resource managers are now emphasizing fire-preventive (pre-suppression) strategies. Among the most common of these preventive strategies are efforts to reduce the amount of fuel present in the landscape. Unfortunately, no standard methodology exits to help managers optimizing the spatial location of preventive fuel treatment activities.

This dissertation describes the conception, definition, implementation, and validation of a heuristic model that spatially optimizes the placement of forest fuel management operations under budgetary constraints. It combines geographic information systems (GIS) based spread cost analysis operations and fire management concepts and techniques to locate the areas where fuel treatments should be applied. Its main purpose is to define near-optimal locations for fuel management practices that minimize the risk of having catastrophic wildfire events negatively affecting points or areas of value.

The model was implemented as a GIS-linked computer program and optimized to reduce the computing time required to obtain a solution. It was validated through a comparative study among fuel management prescriptions developed by fuel management experts and solutions generated by the computer model. Results from the validation indicated that the fuel treatment prescriptions defined by the model outperformed the fuel management plans defined by fuel experts. On average, experts' prescriptions were from 40 to 50% less efficient (in terms of the amount of time needed for a wildfire to impact a point of value) than the solutions generated by the computer model.

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I greatly appreciate the good disposition, advice and constructive comments received from the members of my graduate committee: Dr. David Betters, Dr. Melinda Laituri, and Dr. Charles Anderson.

Two women have enormously influenced the current status of the life I enjoy today: **Elsa and Leovy. To them I sincerely dedicate this work.**

Leovy, my mother, had the courage and great vision of leading me into the earliest stages of my academic formation despite of knowing the many difficulties and sacrifices that would be required on her part and on the whole family. Your always present willingness to sacrifice for others brought to life one of my dreams. Gracias Mamá.

Elsa, my wife, whom still struggles to polish the rough individual she found years ago, has also sacrificed too much so we can enjoy having a united family. Even though you might find it hard to believe, you have greatly and positively influenced my personal life and professional development during my graduate studies. Thank you for your support, time, sacrifice, and above all for your patience. I love you.

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INTRODUCTION

In recent decades an increasing number of people are choosing to live near or within forested areas, in the so-called wildland/urban interface (WUI) zones. Data from the Forest Service indicated that by 1997 about 129,000 homes have been built within high fire risk WUI zones in Arizona alone (USDA-FS 1997).

More people living and building valuable structures in these areas, which have experienced a continuous accumulation of natural fuels due to fire suppression practices in the past century, have raised concern regarding their protection. As shown by Martin and Sapsis (1995), who reported the most important wildfires that have occurred in WUI zones since the 1800's, wildfires that take place in these areas are potentially disastrous in terms of human, property, and natural resource losses.

These circumstances present an extremely challenging problem to natural resource managers due to the responsibility they share in protecting the lives and possessions of the people living in these areas. In addition, these managers retain their original role of protecting other natural and artificial resources (soils, visual quality, recreational use, natural reserves, archeological sites, etc.) from wildfires. Thus, WUI managers have need for defining management approaches that allow them to identify on an acre-by-acre basis, optimal, or at least near optimal, pre-suppression fuel management plans that result in a reduction of the probability that a WUI wildfire may negatively impact valuable areas or structures.

Managers are now beginning to emphasize preventive strategies designed to reduce the probability that ignited fires become catastrophic. Among the most common of these preventive strategies are efforts to reduce the amount of fuel present in the landscape. Unfortunately, there currently is no objective procedure or decision making tool to assist managers in optimizing the spatial location of preventive fuel treatment activities.

Contrary to the ideal situation, where increasing responsibilities would imply an increment in financial and technical support from public or private agencies, managers must try to accomplish their protection tasks under limited budgets (Botti 1995; USDA-FS 1997). This situation obligates natural resources managers to use all their experience and accumulated professional knowledge to define spatially and temporally (where and when), the application fuel treatments activities such as prescribed burn, mechanical treatments, silvicultural practices, chemical treatments; among other.

Without doubt, many experienced managers can develop outstanding fire preventive fuel treatment plans using current manual and subjective procedures, however, their decisions can be characterized by having unknown efficiency and no repeatability. Decisions made under these conditions impair analysis and learning of less experienced managers. Also, objective justification of monetary and human resources to implement fuel management plans might be difficult to achieve.

The purpose of this dissertation is to develop a method to spatially locate fuel management activities in an optimal fashion while accounting for budget constraints.

The foregoing provides justifies developing a methodology to optimally locate fuel management programs across space. Furthermore, the fact that it is cheaper and of less disastrous consequences to prevent severe forest fires, instead of fighting them once they occur provides another incentive to develop a methodology such as the one proposed here (Botti 1995; USDA-FS 1997).

Key concepts and techniques behind the method, such as anisotropic cost spreading (ACS) and fire spread models, come from the geographic information systems (GIS) arena and the fire and fuel management sciences, respectively. ACS is a technique used by geo-spatial analysts to model how a process progresses from some starting point to all other points in a landscape. The *burning time* criterion, a relative measure of fire risk defined as the amount of time needed for a fire to traverse from an ignition point to an area of value, is used to rank the best management alternatives.

The substance of the dissertation consists of three parts, which are presented here as separate but related manuscripts, in formats that are suitable for submission to referred journals.

Article 1, entitled "Reconstructing Anisotropic Spread Cost Surfaces After Minor Changes to Unit Cost Structures: Decreasing Execution Times for Models Performing Repeated Spread Cost Analysis", describes the basic concepts of anisotropic cost spreading upon which the fuel spatial location optimization model is based. Also, it reports on a new procedure developed as part of this study to improve the computer execution times of repeated cost spreading operations.

Article 2, entitled "Near-Optimal Spatial Location of Forest Fuel Management Practices Under Budget Constraints", details the conceptual fuel treatment optimization model, model assumptions, and its implementation and architecture as a computer program.

Article 3 focuses on analyzing and comparing data from 89 forest fuel management plans developed by fuel/fire management experts and plans produced by the computer model. This manuscript is entitled "Forest Fuel Management: an Efficiency Comparison Among Experts' Prescriptions and Computer Generated Solutions".
The final portion of this dissertation is a summary of the study. It contains the main findings and conclusions derived and reported in the three interrelated articles presented.

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USDA-FS. 1997. Arizona's wildland-urban interface: National forest fuels reduction treatment proposals. USDA, For. Serv., Southwestern Region. 9 p.

Article 1

RECONSTRUCTING ANISOTROPIC SPREAD COST SURFACES AFTER MINOR CHANGES TO UNIT COST STRUCTURES: DECREASING EXECUTION TIMES FOR MODELS PERFORMING REPEATED SPREAD COST ANALYSIS

Formatted for submission to the Geographic Analysis Journal

RECONSTRUCTING ANISOTROPIC SPREAD COST SURFACES AFTER MINOR CHANGES TO UNIT COST STRUCTURES: DECREASING EXECUTION TIMES FOR MODEL PERFORMING REPEATED SPREAD COST ANALYSIS

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ABSTRACT

Anisotropic cost spreading operations, a technique used by geospatial analysts to model how an anisotropic process progresses from some starting point to all other points in a landscape, are frequently used to find optimal routes across a landscape. These optimal routes often represent minimum cost paths for new roads, trails, or utility lines, but they can also be used to represent the paths followed by a growing wildfire, the routes followed by wildlife moving through an area, and so on. Recently, researchers and other geographic information (GIS) users have developed sophisticated analysis procedures that make use of repeated anisotropic cost spreading operations. Frequently, these multiple cost spreading operations only differ from one another in relatively minor ways.

Anisotropic cost spreading procedures are highly computer intensive and when applied to large databases, considerable amounts of time are needed to produce solutions. However, if a particular cost spreading problem is only a minor variation of a previously solved problem, it stands to reason that a solution to the new problem can be derived relatively easily by modifying the existing solution to the old problem. The purpose of this study is to develop a cost spreading solution algorithm that can be applied to problems that are slight modifications of previously solved problems, and test and evaluate this new procedure relative to standard anisotropic cost spreading procedures under a variety of circumstances.

Keywords: Anisotropic cost spreading, spatial optimization, spread cost analysis.

INTRODUCTION

Anisotropic cost spreading (ACS) operations, a technique used by geospatial analysts to model how an anisotropic process progresses from some starting point to all other points in a landscape, are used to find minimum cost paths across a landscape. Paths defined using this technique can be used to represent wildlife migration routes, least-cost road construction paths to connect two or more points of interest, wildfire spread paths, etc. (Douglas 1994; Dean 1997; Heimiller and Dean 1998; Cowen *et al.* 2000; Valdez-Lazalde and Dean In Review).

The idea of building a spread cost surface as part of a process intended to define least-cost paths is not new; Warntz (1965) introduced the relevant concepts over 35 years ago. However, the computer hardware and software available in the mid 1960s precluded practical implementation of cost spreading, so Warntz's ideas remained largely theoretic for more than three decades. Fortunately, the speed and capability of the current generation of computers makes it possible to develop, and in most cases implement, spread cost concepts. The principles and concepts of practical ACS are described by Huriot, *et al.* (1989) and Smith (1989).

Examples of applied ACS concepts and techniques are not uncommon in a wide range of fields. Feldman *et al.* (1996) used this technique to identify the least-cost path to build a pipeline. Dean (1997) used it to define minimum cost routes to link access points to forest harvest sites. Burrough and McDonnell (1998), p. 209-213, demonstrated how the technique can be applied to optimize the extraction of timber products as a function of forest accessing costs, location of valuable trees, among other factors. More recently, Cowen *et al.* (2000) used the ACS technique to identify the optimum route for a new railroad track. Valdez-Lazalde and Dean (In Review) used ACS concepts to develop a model to optimally define the location of forest fuel treatment activities. Other examples of applied ACS techniques are from the area of location management (Aronow *et al.*1998). They used ACS to locate minimum distance facilities given terrain characteristics. ACS has also been widely used in the areas of robotics and vehicle guidance to identify optimal paths that minimize a certain measure of risk or distance when traversing across space (Stefanakis and Kavouras 1995; Wu *et al.* 2000; Hallam, *et al.* 2000).

Some recent applications of ACS in natural resources management have been highly repetitive in nature. These applications require hundreds or thousands of cost spreading analyses to be conducted during the course of solving larger models designed to find optimal locations for wildfire mitigation activities, impacts of road developments on wildlife migration patterns, and so on (Pool and Dean 1996; Heimiller and Dean 1998; Valdez-Lazalde and Dean In Review). Unfortunately, current cost spreading algorithms are highly computer intensive and very time consuming, and fall into the NP-complete class of computer algorithms (non-polynomial completion time, e.g., the amount of time needed to complete a spread cost analysis increases exponentially as the size of the data sets used in the analysis increases in a linear fashion). As a result, repeated cost spreading operations involving large data sets quickly become prohibitively time consuming.

However, in certain situations it seems possible to efficiently solve multiple cost spreading operations. In particular, applications such as the one reported by Valdez-Lazalde and Dean (In Review) which require repeated construction of anisotropic spread cost surfaces that are only minor variations of surfaces constructed previously. It seems plausible to hypothesize that updating an existing spread cost surface to create a new surface that differs only slightly from the original should require only a fraction of the time needed to build the original spread cost surface from scratch.

The purpose of this study was to develop and test a cost spreading solution algorithm that can be used to construct new anisotropic cost spreading surfaces that are slight modifications of previously built surfaces. The algorithm was tested and evaluated by comparing its results to those produced by standard anisotropic cost spreading procedures.

Glossary

For the sake of clarity, before describing the new algorithm developed in this study, certain terms and background material will be presented. An anisotropic *unit cost map* is a raster spatial data layer where each raster cell contains a value representing the cost of traversing (moving) from the center of the cell in question to the center of a particular adjacent cell. Thus, a cell in an "up and left" unit cost map containing the value *X* implies that it will cost *X* units to move from the center of the current cell to the center of the cell above and to the left of the current cell. Note that the values in a unit cost map can represent any type of costs, whether they be economic, ecological, temporal, etc. The anisotropic cost spreading algorithm used in this study requires eight unit cost maps as inputs, one representing the cost of movement in each of the eight possible directions of movement from one cell center to an adjacent cell center (Figure 1).

A *source map* identifies a source cell or cells that will be used as the starting point(s) for the anisotropic cost spreading analysis. A source map and the eight unit costs maps mentioned previously represent the nine inputs required by the anisotropic cost spreading operation.

A *spread cost map* is the first of two outputs produced by the anisotropic cost spreading operation. The spread cost map records the total cost of traversing from each cell in the map back to the least-costly-to-reach source cell. Thus, a cell in a spread cost map containing the value *X* indicates that the total cost of traveling from the cell in question back to the least-costly-to-access source cell is *X* units.

Finally, a *backlink map* is the second (and last) output of the anisotropic cost spreading algorithm. Each cell in a backlink map contains a code value that identifies which of the cell's neighbors is on the minimum cost path running from the cell back to the least-costly-to-access source cell. By repeatedly tracing backward from cell to neighboring cell through the backlink map, it is possible to find the minimum cost route from any given cell back to the least-costly-to-access source cell.

The inputs and outputs of the anisotropic cost spreading procedure are shown in Figure 1.

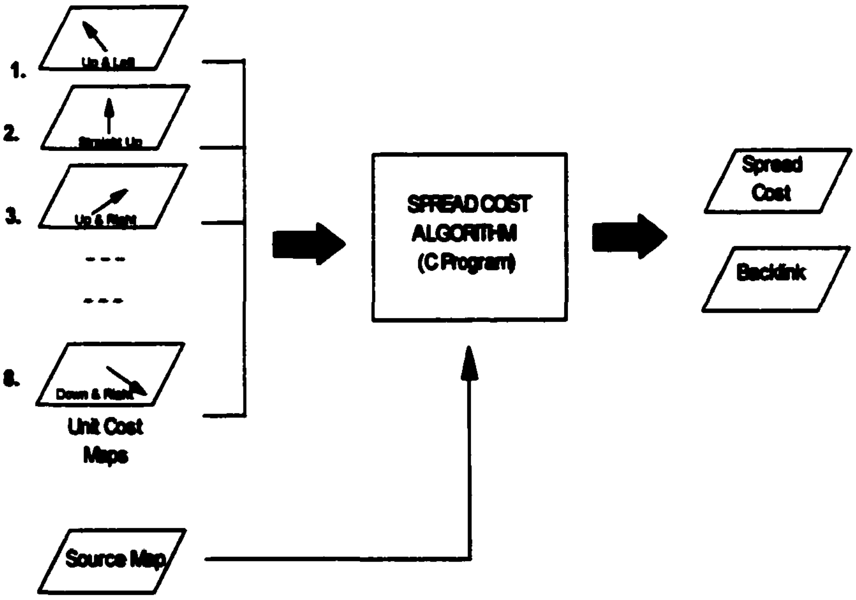

Figure 1. Anisotropic cost spreading flowchart process as defined by Dean (1996).

Standard anisotropic cost spreading

A variety of algorithms have been used to implement anisotropic cost spreading; the only real difference between these algorithms is how they deal with the direction-specific nature of anisotropic unit costs. Some algorithms use a single unit cost surface which gives each raster cell a base unit cost. This base cost is then modified via a user-specified mathematical function to reflect cost differences due to direction (e.g., unit cost = base cost × azimuth) (Eastman 1995; Arc/Info 1992). An alternative method for handling unit costs has been presented by Dean (1996). This method uses multiple direction-specific unit cost maps to reflect costs of movement in various directions. The first technique has the advantage of being able to consider movement in an infinite number of directions, but has the disadvantage of forcing the same cost modification function on all cells throughout the entire map. In contrast, Dean (1996)'s technique can only consider costs in a finite number of directions, but allows the cost modification function to vary infinitely across the map. Dean's method was used as the starting point for this study.

Regardless of how the directionality of unit costs is handled, all anisotropic cost spreading algorithms build their outputs by iteratively searching for least-costly routes from cells whose spread cost values are known to neighboring cells whose spread cost values are unknown (Dean 1996, 1997). In the first iteration of the algorithm, all source cells are assigned a spread cost of zero, and source cells in the backlink map are assigned a code value indicating that they mark the ending point of any minimum cost paths originating at non-source cells. The second and all subsequent iterations evaluate all cells that were either (i) assigned spread cost values in any previous iteration, or (ii) adjacent to cells that were assigned spread costs value in previous iterations. For any such cell A, this evaluation involves testing each cell that both neighbors A and already has a spread cost computed in a previous iteration. Call such a neighbor β. The cost of traveling from the center of β to the center of A can be obtained from the unit cost maps, and the total cost of reaching β from the least-costly-to-access spread source cell can be obtained from the growing spread cost map. Thus, the total cost of traveling from the least-costly-to-access spread source to cell A through cell β can be computed by simply adding β's spread cost to the appropriate unit cost value extracted from the input unit cost surfaces. The anisotropic spread cost algorithm functions by carrying out evaluations of this sort for all possible β's for each cell A, and then recording the lowest value discovered for each cell A as the new spread cost for A (and recording the direction of movement from A to β in the backlink map for cell A). This process stops only when an iteration occurs where no cells are assigned new spread cost values. Note that since this process continuously reevaluates spread costs computed in previous iterations, initial suboptimal solutions for individual cells are corrected in later iterations. This ensures that the final solution produced by this algorithm is truly optimal.

METHODS AND MATERIALS

A modified spread cost algorithm for use in special cases

Applications such as the one proposed by Heimiller and Dean (1998) and Valdez-Lazalde and Dean (In Review), which focus in defining optimal locations for forest fuel management activities, require repeated anisotropic cost spreading operations. In the case of Valdez-Lazalde and Dean (In Review), the spread cost problems are solved iteratively. In general, the only difference between the spread cost problem encountered in iteration *n+1* and the problem solved in iteration *n* is a change in the unit costs in one or a handful of raster cells. Additionally, the unit cost changes are unidirectional: All unit cost changes involve replacing lower unit cost from iteration *n* with higher unit cost in iteration *n+1*. This is true because fuel treatment activities reduce the amount of fuel present, condition that slow down the fire rate of spread, *i. e.*, increases the time needed by a fire to traverse a given distance.

A modified spread cost algorithm was developed to solve the type of spread cost problems encountered by Valdez-Lazalde and Dean (In Review). This modified algorithm is based on the knowledge that the only raster cells whose spread cost and backlink values can change from iteration *n* to iteration *n+1* will be those cells whose backlink paths pass through the cells whose unit costs changed between iterations *n* and *n+1*. This is a result of the fact that in Valdez-Lazalde and Dean (In Review)'s model, unit costs can only increase from one iteration to the next. Consider a cell from iteration *n+1*. If the minimum cost path from this cell to a spread source (i.e., the path recorded in the backlink map) does not pass through a cell whose unit cost value increased, the cell will not be impacted by the unit cost increase. Conversely, a cell from iteration *n+1* whose backlink path does pass through a cell whose unit costs have increased will likely suffer increased spread costs due to the unit cost increase. These increased spread costs may also cause the minimum cost path from the cell back to a spread source to shift, which will alter the cell's backlink characteristics. Note that it is possible that a cell whose backlink path passes through a cell whose unit cost have increased may suffer no increase in spread cost if an alternative route to a spread source is available at the same total cost as the original route. In this case, a cell's spread cost value will not change, but its backlink characteristics will.

The modified spread cost algorithm is shown in Figure 2. The algorithm's principles are simple, however, its implementation as a computer program can be tedious if the backlink map is not properly built. Fortunately, Dean's (1996) algorithm outputs a well structured backlink map, so implementing the new algorithm was fairly straightforward.

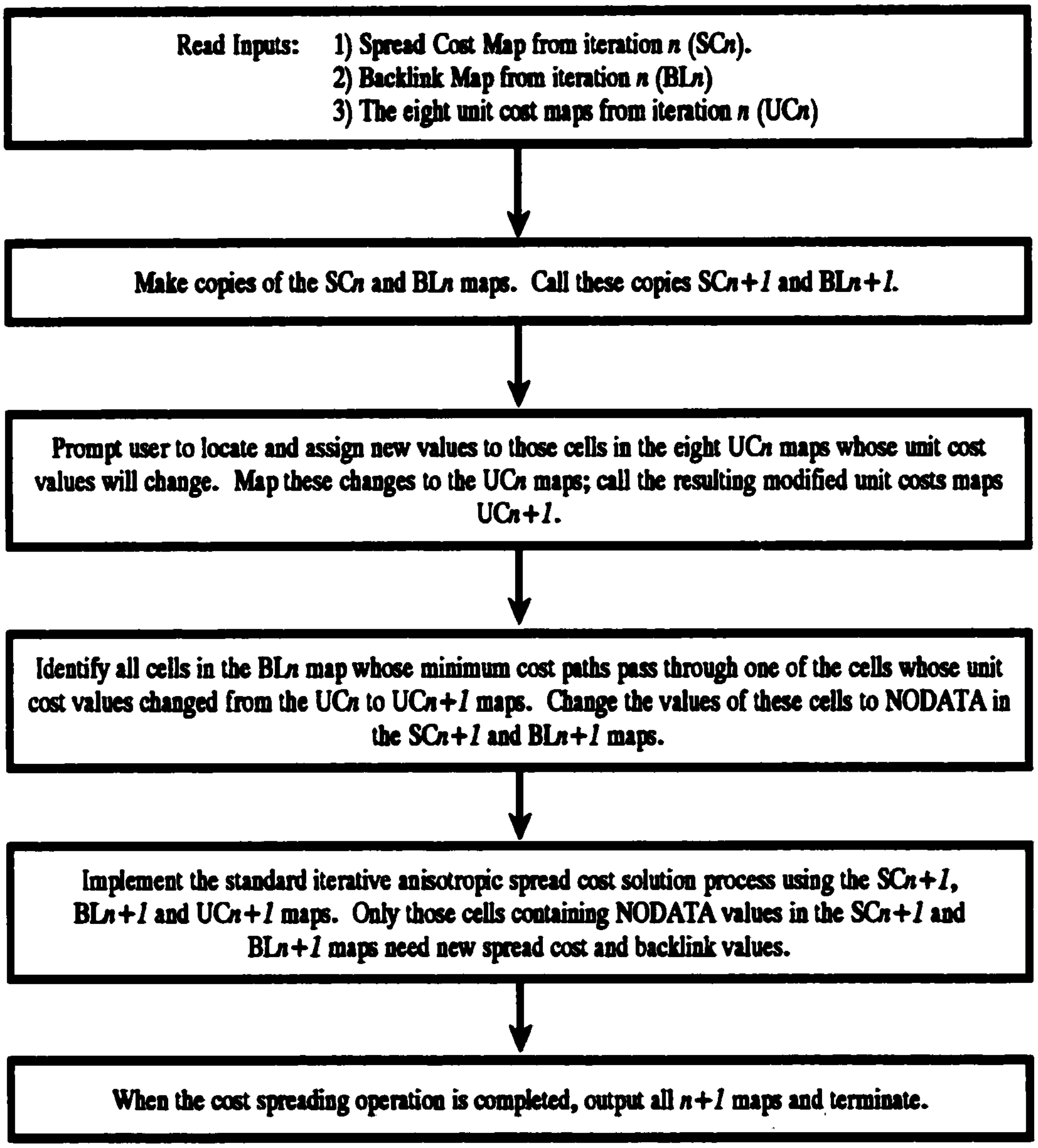

Figure 2. Flow chart showing the main steps to reconstruct an anisotropic spread cost map.

Algorithm implementation and evaluation

Both the standard anisotropic cost spreading operation as described by Dean (1997) and the modified spread cost algorithm just described were implemented using the C programming language. Unit cost maps were derived using an ARC/INFO AML (Arc Macro Language) program that implemented an arbitrary function that computed anisotropic unit costs as a function of gradient and wind direction. Unit cost maps of a variety of sizes (100 cells x 100 cells, 150x150, 200x200, 250x250, 300x300, and 450x300) were constructed. In addition to these unit cost maps, spread source maps of the same dimensions were created in ARC/INFO's GRID module by randomly locating a pre-defined number of source points within each source map. Source maps with one, two, three, four, five, or eight source points were evaluated.

Once the unit cost and source maps were built, they were used as inputs in the standard cost spreading algorithm. This produced what we termed the *original spread cost* and *original backlink* maps. Next, a single cell was selected from the unit cost maps; the costs in all eight units cost maps for this cell were arbitrarily changed to twice their original values. This resulted in a new set of unit cost maps that was used as input into both the standard anisotropic spread cost system (along with the original spread source map) and the modified system (along with both the original spread source, original backlink and original spread cost maps). The amount of time needed by both of these algorithms to produce final results and the percentage of total number of cells in the map required to be recalculated were recorded.

Not surprisingly, results from preliminary evaluations suggested that the time required to re-compute a spread cost map using the modified algorithm was directly related to the total number of cells needed to be recalculated. Thus, the number of cells requiring recalculation was used to stratify the results presented here. Ten-unit percentage ranges were used for this purpose. The usefulness of stratifying the results will become clear when the results are presented. Briefly, if re-computing a small percentage of the total cells in a spread cost map takes a small fraction of the time required to compute the same map from scratch, then substantial time gains are possible as long as the case of re-computing a small percentage of cells occurs sufficiently often. The opposite will also be true.

In order to investigate the influence of location and distribution of source point(s) on the performance of both the standard and modified algorithms, the evaluation process described was repeated 100 times for each combination of the map sizes 100x100, 150x150, and 200x200 and number of source points (one through eight). Only 15 repetitions were carried out for the map sizes 250x250, 300x300, and 450x300, due to the high computer time required to build or reconstruct anisotropic cost spreading operations on large maps. Besides, a similar trend was observed when comparing the results derived when using 100 and 15 repetitions (see Table 1). The 100 or 15 repetitions differentiated from one another only in their randomly elected source point locations. For each repetition, the modified ACS algorithm was run as many times as the number of cell in the map minus the number of source points; *i. e.*, about 10000 times for a map consisting of 100 rows and 100 columns. However, only a maximum of 10000 "rebuilt" cases were computed for any of the 10-unit percentage categories defined. Simulating a change in all the cells of the unit cost map was necessary to obtain, or at least to approach the 100 repetitions desired in all 10-unit percentage categories.

RESULTS AND DISCUSSION

Table 1 reports the number of evaluations conducted to obtain the average computer processing time required to build from scratch and to rebuild the ACS surfaces when a percentage of the total number of cells in the map had to be recalculated given a change in the unit costs of a single cell. The six main rows in column 1 of the table correspond to the six sizes of raster maps evaluated.

Table 1. Number of evaluations carried out to obtain average computer processing time required to build from scratch and to rebuild anisotropic spread cost surfaces.

Grid Size	Source Points	From Scratch	Rebuilt ACS Surface									
			Percentage of total number of cells requiring re-calculation									
			0-10%	10–20%	20-30%	30–40%	40-50%	50-60%	60–70%	70-80%	80-90%	90–100%
100x100	1	100	10000	7654	1249	829	608	652	265	178	156	43
	2	100	10000	6009	1051	484	235	195	114	66	12	1
	3	100	10000	4834	805	339	178	102	25	16	-[†]	-
	4	100	10000	3695	663	208	57	45	14	11	-	-
	5	100	10000	2910	399	119	59	22	4	1	-	-
	8	100	10000	1385	103	25	7	-	-	-	-	-
150x150	1	100	10000	9334	4515	2396	649	360	106	38	68	68
	2	100	9900	8283	2401	1052	319	52	4	-	2	-
	3	100	10000	7156	1563	745	192	22	43	2	-	-
	4	100	9900	5262	1058	202	55	3	-	-	-	-
	5	100	10000	4951	750	257	33	2	2	-	-	-
	8	100	10000	2144	239	26	-	-	-	-	-	-
200x200	1	100	10000	9798	6261	299	1392	430	387	242	199	88
	2	100	10000	9065	3334	956	470	148	24	42	9	-
	3	100	10000	8028	1886	410	64	20	18	33	16	-
	4	100	9900	6463	1031	135	62	7	-	-	-	-
	5	100	10000	5593	998	85	16	12	3	-	-	-
	8	100	9900	2807	177	21	-	-	-	-	-	-
250x250	1	100	1500	1499	1125	538	164	125	74	157	129	8
	2	100	1500	1500	965	252	113	41	17	1	-	2
	3	100	1500	1383	585	221	49	-	4	-	-	-
	4	100	1500	1191	220	58	2	5	-	-	-	-
	5	100	1500	1065	209	24	5	-	-	-	-	-
	8	100	1500	719	86	2	-	-	-	-	-	-
300x300	1	100	1500	1500	1277	779	318	203	61	242	23	200
	2	100	1500	1474	941	440	84	47	25	13	1	3
	3	100	1500	1458	727	175	102	78	1	-	8	2
	4	100	1500	1380	569	303	16	66	34	15	-	-
	5	100	1306	365	98	132	2	50	-	-	-	-
	8	100	1500	804	24	-	-	-	-	-	-	-
450x300	1	100	1500	1500	1290	690	505	242	324	331	136	150
	2	100	1500	1500	920	654	149	55	29	86	92	183
	3	100	1500	1472	752	539	142	144	73	4	-	5
	4	100	1500	1439	625	244	78	49	-	-	-	-
	5	100	1500	1311	582	325	88	102	-	2	-	-
	8	100	1500	1028	206	88	18	12	-	-	-	-

[†] No cases were present in this range for the grid analyzed.

The second column indicates the number of randomly defined source points used. Column three shows the number of repetitions conducted using the traditional spread cost algorithm as defined by Dean (1997). Columns four through thirteen record the number of repetitions of the modified algorithm falling into each of several categories of percentage of map cells requiring to be recalculated given a change in the unit costs of a single cell.

The number of evaluations reported in Table 1 are very uneven. This reflects the difficulty of finding cases where changing unit costs in a single cell caused changes to a high percentage of the cell in the map. Our goal was to find 100 cases for each map being evaluated. However, in many cases it was not possible to do this. Table 1 shows the number of cases actually found.

Showing all the repetitions conducted helps to exemplify the difficulty to obtain cases (repetitions) for the 80% and above range categories and the easy to obtain cases in the low categories. In order to simplify the analysis, a maximum of 10000 repetitions were allowed for each of the categories.

Table 2 reports the results of the execution time comparison between the standard algorithm (building ACS surfaces from scratch) and the modified algorithm (reconstructing ACS from already existing ones). Clearly, the time gains produced by the new algorithm are most dramatic when only a small percentage of the total number of cells require recomputing, but measurable gains can still be seen when up to 70-80%

Table 2. Computer time (sec) required to build from scratch and to rebuild a spread cost maps or surfaces. Time needed to identify cells that will be changed is included in the figures. Values are average of the repetitions as indicated in Table 1.

Grid Size	Source Points	From Scratch	Rebuilt ACS Surface										
			Percentage of total number of cells requiring re-calculation										Weighted Ave. (sec)
			0-10%	10–20%	20-30%	30–40%	40-50%	50-60%	60–70%	70-80%	80-90%	90–100%	
100x100	1	2.33	0.00[‡]	0.13	0.28	0.63	0.83	1.34	1.61	2.20	2.49	2.81[¶]	0.005[*]
	2	2.68	0.00	0.14	0.26	0.69	0.84	1.31	1.57	2.33	2.58	3.00	0.002
	3	2.70	0.00	0.12	0.32	0.75	1.06	1.44	1.80	2.56	-[§]	-	0.001
	4	2.36	0.00	0.12	0.31	0.59	0.71	1.17	1.71	2.36	-	-	0.002
	5	2.55	0.00	0.11	0.29	0.61	1.06	1.27	1.25	2.00	-	-	0.001
	6	2.49	0.00	0.09	0.23	0.40	0.28	-	-	-	-	-	0.000
150x150	1	7.96	0.00	0.36	0.88	1.53	2.38	2.81	3.33	6.55	8.17	8.85	0.008
	2	8.28	0.00	0.34	1.06	1.80	2.78	3.23	5.75	-	8.5	-	0.004
	3	8.38	0.00	0.34	1.10	1.82	3.09	4.04	5.55	7.50	-	-	0.003
	4	8.74	0.00	0.33	0.94	1.39	2.96	4.33	-	-	-	-	0.002
	5	8.90	0.00	0.32	1.07	1.82	3.00	5.5	6.00	-	-	-	0.001
	6	8.56	0.00	0.40	1.05	1.96	-	-	-	-	-	-	0.001
200x200	1	19.61	0.00	1.07	2.23	3.97	7.22	8.09	11.60	17.35	22.51	23.26	0.020
	2	20.38	0.00	0.96	2.16	4.09	6.42	8.64	15.00	19.23	18.66	-	0.008
	3	20.27	0.00	0.91	2.18	3.78	7.32	13.85	20.00	10.09	16.62	-	0.004
	4	20.28	0.00	0.92	2.65	4.69	6.16	12.71	-	-	-	-	0.003
	5	20.36	0.00	0.85	2.29	4.57	5.37	10.00	15.00	-	-	-	0.002
	6	20.21	0.00	0.72	2.03	3.47	-	-	-	-	-	-	0.001
250x250	1	40.68	0.00	2.60	5.25	9.82	12.90	19.40	19.72	45.47	44.73	38.87	0.042
	2	40.58	0.00	2.51	5.46	10.53	16.84	15.53	31.35	34.00	-	51.00	0.019
	3	41.85	0.00	1.91	4.41	8.46	7.81	-	27.75	-	-	-	0.011
	4	42.45	0.00	2.31	5.38	9.89	12.50	24.00	-	-	-	-	0.005
	5	41.61	0.00	1.89	5.97	10.62	19.40	-	-	-	-	-	0.004
	6	38.57	0.00	1.58	3.58	5.00	-	-	-	-	-	-	0.001
300x300	1	78.88	0.00	3.92	8.44	17.67	20.87	30.31	36.37	65.28	67.43	75.61	0.067
	2	76.97	0.00	3.70	7.79	16.74	27.40	48.21	39.64	74.07	77.00	75.66	0.024
	3	74.54	0.00	2.91	7.83	9.39	15.83	20.23	39.00	-	62.5	53.50	0.015
	4	74.97	0.00	3.13	7.83	15.90	23.68	22.19	36.73	39.00	-	-	0.015
	5	74.32	0.00	3.06	11.60	20.18	41.75	47.00	69.34	-	-	-	0.016
	6	73.13	0.00	4.55	10.37	-	-	-	-	-	-	-	0.003
400x300	1	133.95	0.00	4.50	14.01	21.74	32.65	52.70	61.95	87.53	102.64	128.02	0.099
	2	146.10	0.00	4.20	15.24	31.34	43.31	52.63	88.62	133.83	150.23	212.49	0.068
	3	153.15	0.00	5.18	14.93	24.58	42.12	97.43	105.84	133.00	-	127.40	0.039
	4	150.17	0.00	4.32	14.03	27.79	47.73	56.26	-	-	-	-	0.017
	5	148.55	0.00	6.14	18.54	20.57	46.84	47.63	-	23.00	-	-	0.022
	6	142.61	0.00	10.54	24.59	24.12	67.33	80.50	-	-	-	-	0.015

[‡] Zero values does not imply that the operation is instantaneous, but that the elapsed time was so short that the computer could not accurately register it.

[§] No cases were present in this range for the grid analyzed.

[¶] Higher values than the ones found for constructing an ACS surface from scratch (column 3) are possible because the time requires to identify the cells to be recomputed is included in the figures shown in the table. Before the cells had to be recalculated they must be first identified and changed to an initial value, which counts for the total time recorded.

[•] Weighted average for the times required to recompute the ACS. The weights are defined as the number of times a given percentage (within the ranges defined in the table above) of cells had to be recomputed when changing, in a cell by cell basis, all the cells in the unit cost maps. Actual weight values can be approximated with the percent values shown in Table 3. For instance, the weight for the time shown in the first entry of column 4 above can be calculated as the 96.77% (value from Table 3) of the total number of cell in the grid minus the number of source points defined (10000 -1).

of the map requires recomputing. According to this table, execution times can be reduced by more than 94% when reconstructing ACS surfaces that require to recompute from 0 to 20% of the cells in the map.

Table 3 shows the resulting frequency of recomputing certain percentage of the total number of cells in a map when the unit costs of a single cell are changed. For instance, the 98.77% value at the very top of column 3 (Table 3) indicates that if the unit cost values of any given cell in a 100x100 map are changed, there is a 98.77% chance that only from 0 to 10% of the cells in the map had to be recomputed to correctly rebuild a new spread cost map or ACS surface.

Table 3 also indicates that for all the map sizes tested, in over 99% of the cases (99% results from adding the values in columns three and four, for instance, 98.77 + 0.82 = 99.59), changing the unit costs in a single cell required recomputing 20% or less of the cells when re-building an ACS surface from an existing one.

A joint analysis of the results shown in Tables 2 and 3 indicates that the modified ACS algorithm produced enormous computer executing time savings. Two facts made this savings possible: (1) the high number of cases where only a small percentage of the total number of cells has to be recalculated (<20%) and (2), the low computer executing time required to rebuild ACS surfaces when <20% of the cells have to be recomputed.

Table 3. Percentage or probability that a predefined number of cells (range) has to be recalculated when a single cell is changed in the unit cost maps. Values are an average of the repetitions indicated in Table 1.

		Rebuilt ACS Surface									
	Source	Percentage of total number of cells requiring re-calculation									
Grid Size	Points	0-10%	10–20%	20-30%	30–40%	40-50%	50-60%	60–70%	70-80%	80-90%	90–100%
100x100	1	98.83	0.76	0.12	0.08	0.06	0.07	0.03	0.02	0.02	0.00
	2	99.15	0.61	0.11	0.05	0.02	0.02	0.01	0.01	0.00	0.00
	3	99.34	0.48	0.08	0.03	0.02	0.01	0.00	0.00	-[†]	-
	4	99.49	0.37	0.07	0.02	0.01	0.00	0.00	0.00	-	-
	5	99.59	0.29	0.04	0.01	0.01	0.00	0.00	0.00	-	-
	8	99.77	0.14	0.01	0.00	0.00	-	-	-	-	-
150x150	1	99.01	0.61	0.20	0.11	0.03	0.02	0.00	0.00	0.00	0.00
	2	99.36	0.46	0.11	0.05	0.01	0.00	0.00	-	0.00	-
	3	99.53	0.35	0.07	0.03	0.01	0.00	0.00	0.00	-	-
	4	99.68	0.24	0.05	0.01	0.00	0.00	-	-	-	-
	5	99.71	0.22	0.03	0.01	0.00	0.00	0.00	-	-	-
	8	99.86	0.10	0.01	0.00	-	-	-	-	-	-
200x200	1	99.18	0.50	0.18	0.08	0.03	0.01	0.01	0.01	0.00	0.00
	2	99.52	0.34	0.09	0.02	0.01	0.00	0.00	0.00	0.00	-
	3	99.67	0.26	0.05	0.01	0.00	0.00	0.00	0.00	0.00	-
	4	99.77	0.19	0.03	0.00	0.00	0.00	-	-	-	-
	5	99.81	0.15	0.02	0.00	0.00	0.00	0.00	-	-	-
	8	99.90	0.07	0.00	0.00	-	-	-	-	-	-
250x250	1	99.40	0.34	0.13	0.06	0.02	0.01	0.01	0.02	0.01	0.00
	2	99.57	0.27	0.11	0.03	0.01	0.00	0.00	0.00	-	0.00
	3	99.67	0.23	0.07	0.03	0.00	-	0.00	-	-	-
	4	99.82	0.14	0.02	0.01	0.00	0.00	-	-	-	-
	5	99.83	0.14	0.02	0.00	0.00	-	-	-	-	-
	8	99.90	0.08	0.01	0.00	-	-	-	-	-	-
300x300	1	99.49	0.26	0.10	0.06	0.02	0.02	0.00	0.02	0.00	0.02
	2	99.67	0.20	0.08	0.03	0.01	0.00	0.00	0.00	0.00	0.00
	3	99.71	0.19	0.07	0.01	0.01	0.01	0.00	-	0.00	0.00
	4	99.75	0.16	0.04	0.03	0.00	0.00	0.00	0.00	-	-
	5	99.83	0.12	0.03	0.01	0.01	0.00	0.00	-	-	-
	8	99.92	0.07	0.00	-	-	-	-	-	-	-
450x300	1	99.52	0.24	0.10	0.05	0.03	0.01	0.02	0.02	0.01	0.01
	2	99.67	0.19	0.07	0.04	0.01	0.00	0.00	0.00	0.00	0.01
	3	99.71	0.20	0.04	0.03	0.01	0.01	0.00	0.00	-	0.00
	4	99.80	0.14	0.03	0.01	0.00	0.00	-	-	-	-
	5	99.82	0.12	0.03	0.02	0.00	0.01	-	0.00	-	-
	8	99.91	0.07	0.01	0.00	0.00	0.00	-	-	-	-

[†] No cases were present in this range for the grid analyzed.

CONCLUSIONS

In the vast majority of cases, the modified spread cost algorithm developed here clearly produced results much more quickly than did the conventional algorithm. Only in a small percentage of the cases the modified algorithm produced results that were at least as fast or slightly slower than the standard procedure. Slower results are possible because the time recorded for reconstructing ACS surfaces includes the time required to identify the cells that ultimately will be recalculated.

Computer execution time gains were possible due to two well identified conditions. One, it was extremely difficult to find situations where a change in the unit cost maps of a single cell required re-computing for more than 80% of the cells of the map. Contrarily, it was very common (frequency greater than 98%) that only a small percentage of the cells (0-10%) had to be recalculated. Two, the modified ACS algorithm developed in this study is very efficient for re-computing ACS surfaces when a small percentage of the total number of cells in a map (<20%) has to be recalculated.

Valdez-Lazalde and Dean (In Review) used the modified ACS algorithm here presented to spatially define near-optimal location of forest fuel treatment activities. They found that enormous computer execution time savings can be obtained when solving practical problems if the modified algorithm is used. For instance, for a fuel management scenario represented by a map composed of 250 rows times 233 columns, these authors found a near-optimal solution to the problem posed in about 203 minutes when using the modified ACS algorithm. If they had used the standard algorithm it would had taken about 113 days (about 40.68 seconds per ACS operation times 240690 ACS operations that were needed to solve the problem) to come up to the same fuel management solution. Concluding, using the modified ACS algorithm makes the solution to real problems much more practical.

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Article 2

NEAR-OPTIMAL SPATIAL LOCATION OF FOREST FUEL MANAGEMENT PRACTICES UNDER BUDGET CONSTRAINTS

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NEAR-OPTIMAL SPATIAL LOCATION OF FOREST FUEL MANAGEMENT PRACTICES UNDER BUDGET CONSTRAINTS

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ABSTRACT

This paper describes a model that spatially optimizes the placement of forest fuel management operations. The model seeks to reduce the risk of catastrophic wildfire events effecting areas of value. Based on a heuristic algorithm, it combines geographic information systems (GIS)-based spread cost analysis operations and fire management concepts to locate the areas where fire-preventive (pre-suppression) fuel treatments should be applied when budgetary constraints are a concern. Preliminary results indicated that fuel treatment prescriptions defined by the model outperform fuel management plans defined by fuel management experts, despite having a different spatial distribution.

Keywords: Forest fuels management, spatial decision making, spatial optimization, GIS, Geographic Information Systems, anisotropic cost spreading.

INTRODUCTION

In recent decades many people have chosen to live within or near forested areas, in so-called wildland/urban interface (WUI) zones (USDA-FS, 1997). This raises the issue of protecting these individuals and their property from the risk of wildfires. It is certainly possible that a wildfire event taking place in a WUI area could cause massive damage to property, loss of human life, and/or damage to natural resources.

WUI wildfire management poses a challenging problem to natural resource managers. They need to identify optimal, or at least near-optimal, fuel management plans that reduce the probability that a wildfire will negatively impact valuable areas or structures. As a practical matter, these plans must always reflect the reality of limited budgets.

Unfortunately, there currently is no objective procedure or decision making tool to assist natural resource managers in developing such fuel management plans. Most managers struggle to manually define, both spatially and temporally, fuel treatment plans.

Without doubt, many experienced managers can develop outstanding, or at least adequate, fuel management strategies using manual and subjective procedures. However, these strategies have unknown efficiency and cannot be objectively recreated. Besides, objective justification of the monetary and human resources needed to implement these plans might be difficult to produce.

The purpose of this paper is to develop a practical and objective methodology for defining optimal locations for fuel management activities under limited budgets.

LITERATURE REVIEW

Fire spread modeling

Understanding forest fire behavior is essential to developing fuel management plans. Particularly, it is important to be able to predict surface fire rate of spread (FROS), which is one of the fundamental fire behavior measures (Rothermel 1972; Finney 1998). FROS is the speed at which a fire's flame front moves forward. Modeling FROS is a critical ingredient of the fuels management optimization procedures proposed in the present research.

Since the 1950's, more than a dozen mathematical models of varying characteristics and complexity have been proposed to predict or "explain" fire behavior parameters, among them FROS (Albini 1976; Coleman and Sullivan 1996; Finney 1998). By the 1980's, the Rothermel fire spread equation had been accepted as a good mathematical model of fire behavior. This equation forms the heart of the BEHAVE fire simulation computer model (Burgan and Rothermel 1984; Andrews 1986). More recently, Rothermel's surface FROS equation has been implemented as the "fire spread engine" of SiroFire (a PC-based fire spread prediction application developed by the Commonwealth and Industrial Research Organization, FARSITE (fire area simulator), and FIRE! systems (Campbell *et al.* 1996; Coleman and Sullivan 1996; Finney 1998).

According to Schoning *et al.* (1997), Rothermel's model is currently the most widely used method to estimate fire behavior. Given this level of acceptance, Rothermel's equation is the logical candidate for use in predicting the surface FROS needed to feed the fuels management optimization model being developed here. Readers interested in a step by step description of Rothermel's calculations are referred to Rothermel (1972, 1983) and Albini (1976). Briefly, the equation is summarized in Equation (1).

$$R = \frac{[I_R \times \chi \times (1 + F_W + F_S)]}{(r_b \times e \times Q_{ig})} \qquad (1)$$

where: R = Fire rate of spread (ft min^{-1})

I_R = Reaction intensity (Btu ft^{-2} min^{-1})

χ = Propagation flux ratio

F_W = Wind coefficient

F_S = Slope coefficient,

r_b = Oven-dry bulk density (lb ft^{-3})

e = Effective heating number

Q_{ig} = Heat of pre-ignition (Btu lb^{-1}).

Rothermel's equation calculates FROS in steady state when properly fed with parameters relevant to wind speed and direction, terrain, fuel moisture, and a detailed description of the fuel bed or fuel model through which the fire is burning.

Fuel Models

In simple terms, fuel models are a set of values that describe fuel characteristics or parameters in a way that is objectively measurable and repeatable. There are two main types of fuel: foliage and wood. The woody fraction is further subdivided according to its size class. Thus 1 hr, 10 hour, 100 hour and 1000 hour woody dead fuel types exist. The name corresponds to the time needed for the fuel size class to achieve 63% of its expected equilibrium moisture content. Anderson (1982) described 13 standard fuel models, each with all of the components needed as inputs for Rothermel's FROS equation.

The fact that Anderson (1982) defined only 13 standard fuel models does not limit the applicability of Rothermel's equation to only those conditions described by the standard models. Fuel managers can define custom fuel models so that the exact conditions of a site are properly reflected (Burgan and Rothermel 1984).

Earlier studies on forest fuel management strategies definition

Only a handful of studies have described methods to assist in locating fuel management activities (Chou 1992; Almeida 1994; Richardson *et al.* 1994; Blaird *et al.* 1994; Weatherspoon and Skinner 1996; Caprio *et al.* 1997; and Keifer *et al.* 1999). Unfortunately, all the proposed approaches incorporate the spatial component of fuel management indirectly in the modeling process, rather than making the spatial component an explicit part of the model. At most, common GIS operations such as reclassifications and overlays are used to prioritize areas to receive fuel treatment based on fire probability functions or fire danger indicators (Chou 1992; Caprio *et al.* 1997; Keifer *et al.* 1999).

Chou (1992) presented a method to compare predefined, spatially explicit, potential prescribed burning strategies. His method implies that managers define, before the analysis takes place, the potential areas to treat based on surface and or administrative characteristics. Chou's technique compares these proposed fuel treatment plans to identify the plan that results in the smallest value of district fire danger index (DFDI). The DFDI is a decision criterion that indicates the average, area-adjusted, probability of a fire occurring in a predefined district.

This sort of comparison and identification of a predefined alternative represents a type of activity analysis (Paredes and Brodie 1988). As argued by Dean (1996b), planning through activity analysis poses several disadvantages. It limits the selection of the best management option to a predefined set of potential strategies rather than defining the optimal solution from scratch within the process. Besides, creating an adequately diverse list of areas to treat can be very difficult and time consuming. Furthermore, Chou's method does not take into account the locations of potential ignition points and fire spread characteristics when computing the best management alternative.

Blaird *et al.* (1994) and Richardson *et al.* (1994) incorporated the spatial component of fuel management into their modeling efforts to develop a fuel treatment planning system, but in a very limited manner. Their systems link a GIS with a data base management software. The systems select areas to receive fuel treatment if they satisfy certain predefined non-spatial criteria or rules such as: (1) burn with low intensity fire areas of open forest in time class X, Y, or Z; (2) exclude low intensity burning from areas with vegetation types X or Y, etc. Twenty five of these sorts of rules were used by Blaird *et al.* (1994) to define areas that should be burned in a natural reserve. Finding sites which satisfy these rules was done entirely in the data base software; the GIS component of their system was only used to present the results of the assignation. Thus, the spatial component does not have any influence in the definition of the resulting fire management plans.

A work reported by Schoning *et al.* (1997) tries to overcome the disadvantages mentioned above. They implemented a spatially explicit model to calculate the probability of fire damage for certain areas while accounting for the position of ignition points and expected fire spread. Unfortunately, their work is still exploratory and no attempt has been made to use their system to optimally define the location of fuel management strategies.

It is worth re-emphasizing that except the system developed by Schoning *et al.* (1997), all the other systems do not consider the location of potential fire ignition points; nor explicitly consider the spread of potential fires in the definition of fuel management plans.

Anisotropic cost spreading (ACS)

Cost spreading is a technique used by geospatial analysts to model how a process progresses from some starting point(s) to all other points in a landscape.

Anisotropic cost spreading is a variant of standard cost spreading that considers anisotropic processes in its analysis. Those interested in the theory of ACS should refer to Huriot *et al.* (1989) and Smith (1989). Excellent descriptions of applied ACS are provided by Douglas (1994) and Dean (1996a, 1997).

The fire spread model developed in this study is based in part on this geospatial modeling technique --ACS. To understand ACS consider the situation shown in Figure 1. In this example, a fire has ignited at the indicated point on the terrain and is spreading out in all directions. Assuming that there is no wind to influence the fire and fuel conditions are uniform throughout the area, we would expect the fire to spread more rapidly in direction *A* than in direction *B*. This is true because wildfires are known to spread faster uphill than across a slope or downhill (Van Wagner 1988). This makes fire spreading an anisotropic process, meaning that it has "different physical properties or actions in different directions" (Burrough and McDonnell 1998, page 298).

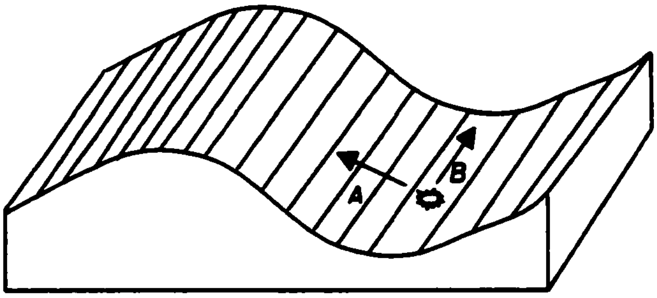

Figure 1. Fire spreads faster uphill (*A* direction) than perpendicular to the main slope (*B* direction).

In an ACS analysis, the landscape of interest is broken into small areas, typically raster cells (Figure 2). One or more of these raster cells represent the starting point for the process. In our case, the starting points represent the ignition points of a fire. They can be identified using techniques such as the ones proposed by Vega-Garcia *et al.* (1996) and Davis and Dean (2000).

In addition to the starting points, a cost spreading analysis requires as input one or more unit cost surfaces, which indicate the "cost" to the process being modeled of traversing each raster cell. In our example, "cost" could be measured by burning time. Thus, it would take a fire *X* minutes to burn from one side to the other (traverse) of a raster cell with a unit cost of *X*. If a single raster cell has only a single unit cost for all directions of traverse (*e. g.*, the unit cost of traversing the cell from left to right equal to the cost of traversing the cell from right to left), the cost spreading process is termed isotropic; if the cell has multiple traverse costs (*e. g.* the unit cost of traversing the cell from left to right does not equal the cost of traversing the cell from right to left), the cost spreading operation is anisotropic by definition (Burrough and McDonnell 1998; Workboys 1995).

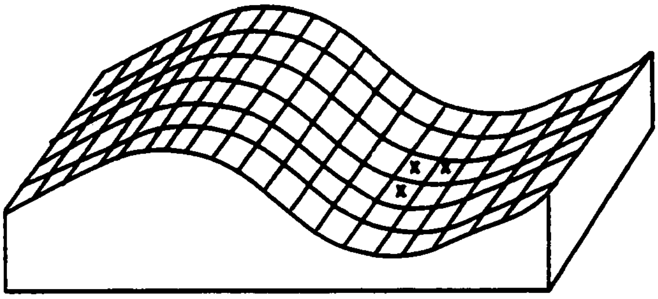

Figure 2. In a GIS raster environment the landscape is tessellated into cells of equal size. Individual cells or groups of them are used to represent any spatial phenomenon.

The output of the cost spreading process is a new surface termed a spread cost surface. Each raster cell in this surface indicates the minimum accumulated unit cost (spread cost) of traversing from a starting point to the cell in question. Thus, in our fire example, it would take a wildfire *Y* minutes to travel from an ignition point to a raster cell with a spread cost *Y*.

Dean (1996a) provides a detailed summary of the main algorithms available to develop spread cost surface including his own approach, which was applied to define optimal road networks to access forest harvest sites. An important difference among the algorithm defined by Dean (1996a) and other reported algorithms is that his method uses eight unit cost maps to build the spread cost surface, while the others use only one unit cost surface to accomplish the same objective. Using eight unitary cost maps allows to incorporate with more realism the influence of unit cost spreading spatial phenomena that behave anisotropically (slope for instance), instead of simply applying a correction factor to a base unitary cost depending on a compass direction as it is defined in other approaches (Eastman 1995; ARCINFO 1992).

Detailed examples of how this process is carried out using hypothetical maps can be found (in order of increasing complexity) in Christman (1997) and Dean (1997), respectively.

Once a spread cost surface has been built, a process known as pathway analysis can be used to define the least-cost path to connect any point in the surface with the origin point defined earlier --points or areas from where the spreading operation was initiated. Details behind the algorithm to implement the pathway analysis vary from one implementation to another (Douglas 1994; Eastman 1995; Dean 1997), however, all of them rely on an iterative process that defines a single cell along the least-cost path at each iteration.

As mentioned above, ACS uses raster spatial data layers to build the cost surfaces and to define the shortest path through a back propagation algorithm. In theory these procedures could be implemented using vector data bases and mathematical programming techniques. However, its definition and implementation would much more involved and probably also very computer intensive to solve. It is not intuitive how the

ACS procedure implemented for this model could be presented as a mathematical programming problem.

MODEL DEVELOPMENT AND IMPLEMENTATION

Decision criterion

In this work, *burning time* is used as the criterion to evaluate the effectiveness or benefit gained by applying fuel treatments to a particular area. Burning time is defined as the time needed for a fire to spread from an ignition point to a point or region of value that is to be protected from the effects of fire. The idea is that longer burning times are more desirable than shorter times, because the longer a wildfire takes to burn to a point or region of value, the higher are the probabilities of suppressing it before it consumes the point of value. The logic behind this criterion is better understood using an example as provided by Heimiller and Dean (1998).

Figure 3 shows a hypothetical landscape model as typically represented in a raster GIS. The dark cells represent a potential wildfire ignition point and a point of value. Figure 3 also shows the path (indicated by the arrows inside the cells) that a wildfire would follow while traversing from the ignition point to the point of value. As is indicated in the figure, it would take 60 minutes for the fire to complete this traverse.

A key assumption to this approach is that the fire path shown in Figure 3 represents the fastest route that the fire could follow to reach the point of value. Thus, any other path or route, no matter how slight or drastic difference, would require more than 60 minutes to reach the point of value. Due to this assumption, any fuel reduction activity applied to a cell along the fire spread path shown in the figure will delay the time needed for the fire to move from the ignition point to the point of value.

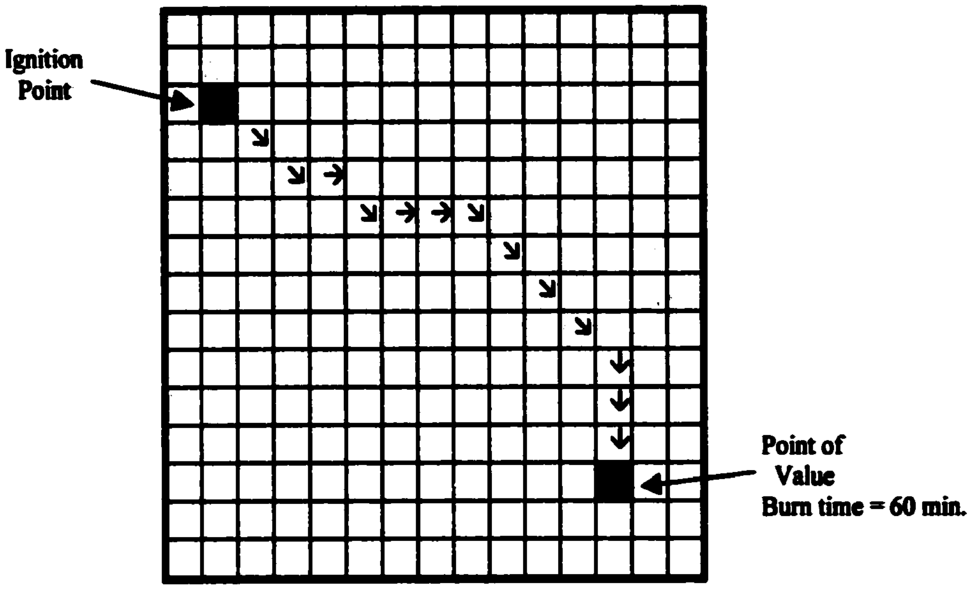

Figure 3. A predicted path and burn time for a wildfire to spread from an ignition point to a point of value.

Figure 4 graphically illustrates this idea. The new shaded cell (in gray) shows where a fuel treatment activity was carried out. After treatment it would take 90 minutes to the fire to reach the point of value. The difference between the before and after fuel treatment burning times (90 - 60 = 30 minutes) can be interpreted as a measure of the reduction in risk achieved by applying a fuel management activity in the cell shown in the figure. This idea is fundamental to the heuristic optimization model presented here.

It is worth emphasizing that the model developed uses this idea but in a wider context, *i. e.*, predicts shortest fire paths from more than one ignition point to more than one area or point of value. When simulating fuel treatment alternatives, the model looks for the management alternative that maximizes the burning time value that results from "connecting" all the ignition points to the least-costly to reach points or areas of value.

Using only one shortest path (the one resulting in the smallest burning time for a potential fire moving from any ignition point to a point of value) in the optimization procedure guarantees prescription of treatment to areas of value that are near to potential ignition points. However, such modification comes to a price. If the fuel treatments applied are not effective enough, *i. e.*, do not reduce the fuel to "sufficiently" low amounts, the optimization procedure might halt prematurely because it may find that re-treating an area is more effective than prescribing treatment to locations that would protect the area of value from ignition points located at a more distance location. The model proposed uses multiple shortest paths during the optimization procedure.

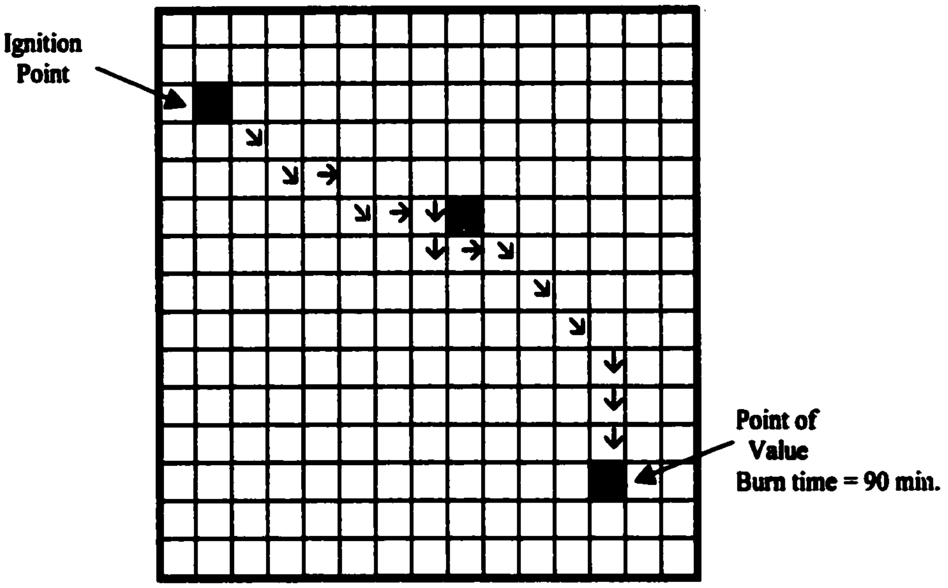

Figure 4. New predicted path and burn time required for a wildfire to spread from an ignition point to a point of value after fuel on one cell of the original path has been treated.

Fuel treatment cost

In practice, the application of fuel treatment activities are restricted by budget constraints. Consequently, it is important to properly account for the spatial variation in fuel treatment costs in a model such as the one being presented here. Studies on this matter have found that fuel treatment costs depend, among other factors, on the size of the area where they are applied (Gonzalez-Caban and McKetta 1986; Wood 1988; Rideout and Omi 1995). All these authors concluded that, on a per acre basis, treating large areas is cheaper than applying treatments to small ones. Wood (1988, page 118) mentioned that this type of cost advantage is "due to efficiencies in supervision and equipment requirements and geometric advantages in the fire line preparation."

In addition to the economies of scale noted by the previous authors, it is plausible that treatment costs will be influenced by site factors. Difficulty of access, roughness of the terrain, and size and amount of fuel all seem to likely influence fuel treatment costs.

To incorporate these findings, the model proposed is capable of using area and perimeter cost raster grids to calculate fuel treatment cost. This allows adjustment of the perimeter cost every time a new adjacent cell is defined to receive treatment. Furthermore, the model is general enough to allow for treatment cost variability of any desired level of complexity. For this particular study, an area constraint was used in the simulations instead of entering a budget constraint. This facilitated the definition of fuel treatment alternatives defined by experts.

Conceptual model: the heuristic

Figure 5 depicts the sequential flow of processes used by this study's fuel treatment optimization model. The model is iterative. Each iteration of the model's main loop (labeled the cell treatment loop in Figure 5) identifies the cell along the current fastest path whose treatment will produce the maximum increase in burn time from ignition points to points/regions of value. The inner loop (labeled the cell evaluation loop) evaluates each cell along the current faster burn path.

The inner cell evaluation loop terminates after each cell along the current fastest burn path has been evaluated. The outer cell treatment loop terminates when either no

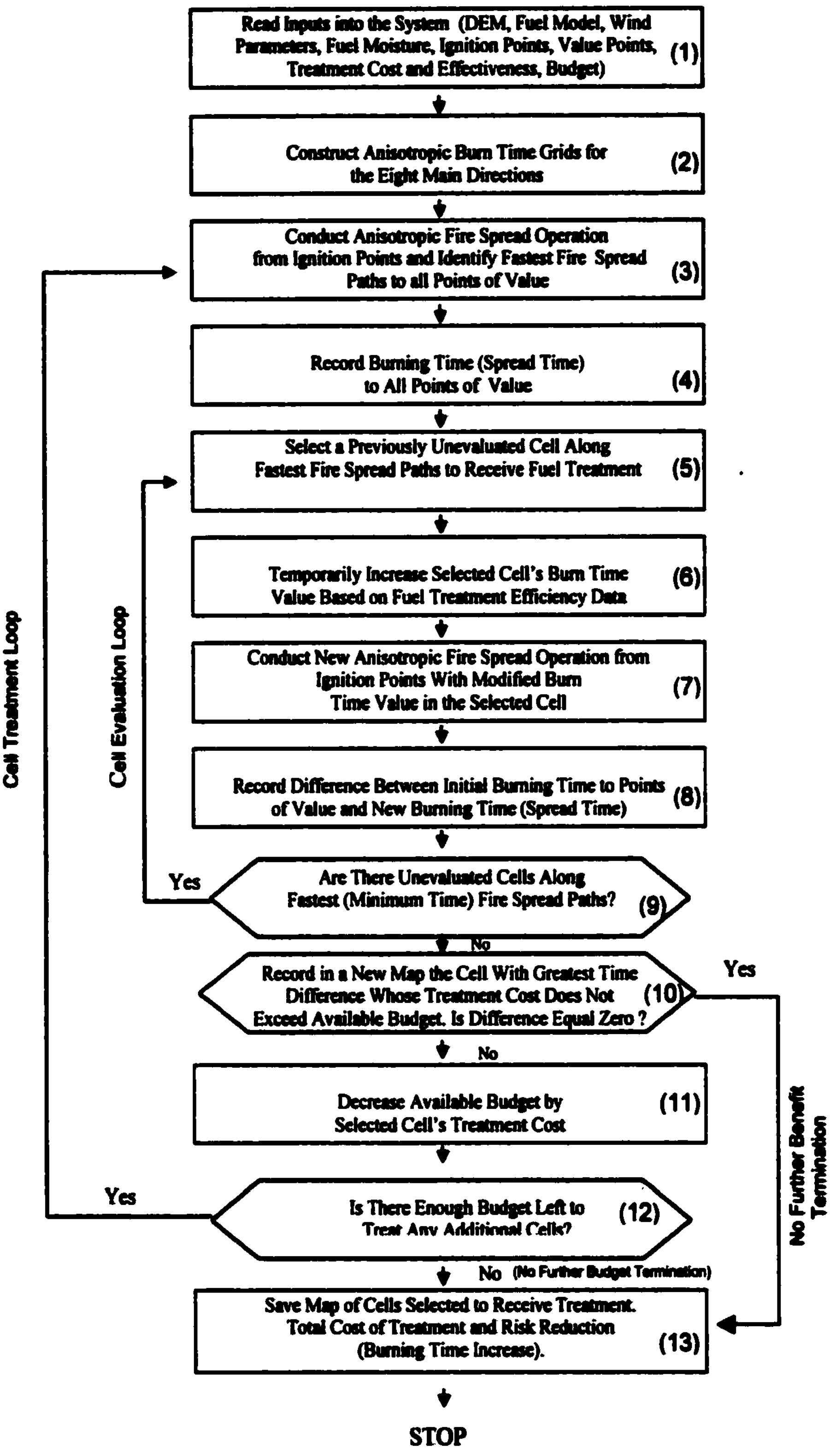

Figure 5. Flow chart showing the main steps to conduct the fuels treatment placement optimization algorithm (conceptual model).

additional benefit can be gained by treating additional cells, or when the budget for fuel treatment will no longer support any additional cell treatments.

It is important to note that the model relies heavily on the anisotropic spread cost principles and concepts introduced previously and reported in more detail by Dean (1996a, 1997). Within each iteration of the cell treatment loop, each cell along the current faster burn paths must be evaluated, and each of these evaluations requires an anisotropic analysis. When dealing with a grid of considerable size (more than 200 rows x 200 columns), the number of cost spreading operations easily builds up to unmanageable levels due that cost spreading operations are extremely computer intensive and time consuming. Fortunately, these spreading operations tend to be very similar to one another (they often differ from each other by only a single cell's unit costs), and modified cost spreading procedures can be used. These modified procedures are much faster than conventional cost spreading. This is true because they avoid re-computing values of cells that do not change from one iteration to another. The development and testing of these modified procedures are described in Valdez and Dean (2000) and Valdez-Lazalde and Dean (In Review(a)).

To better understand the optimization procedure depicted in Figure 5, the individual components of the model are discussed in the following section. Boxes in Figure 5 are numerated to facilitate their explanation in the coming paragraphs.

Inputs to the model (Box 1)

As indicated in box 1 of Figure 5, the data needed to start the heuristic consist of a series of raster data layers and scalar values. A brief description follows.

Digital elevation model (DEM). A DEM is a spatial data layer where each raster cell contains an elevation measure.

Fire behavior fuel models (FMs). FMs are entered into the model as a raster data layer where each raster cell contains an integer value representing one of the 13 fire behavior models as presented by Anderson (1982), or any other integer value representing an *ad hoc* fuel model.

Ignition points. These data is entered into the model as a raster data layer containing integer values on the cells representing ignition points and "background" values everywhere else.

Points or regions of value. Points or regions of value points are entered into the model as a raster data layer containing integers in the places representing points or regions of value and "background" values everywhere else.

Fuel moisture. The model requires up to four spatial data layers or scalar values to describe fuels moisture. One layer is required for each of the fuel classes into which fire behavior model are subdivided: One-hour, 10-hour, 100-hour, and live fuels (Anderson 1982). Each of these layers contain real numbers indicating the percent moisture in the various types of fuel. If scalars are used instead of raster maps, a constant moisture level is assumed for all raster cells.

Fuel treatment types and costs. As currently implemented, the model requires only an estimated fuel treatment cost for each raster cell. The system computes total treatment costs by simply adding these per-cell costs for each treated cell; no effort is made to account for economies of scale. In the future, we plan to modify the treatment cost system to include both an area-based cost and a perimeter component, which will thus require two cost inputs instead of the single input used here.

Fuel treatment effectiveness. This is a raster data layer describing the impact fuel treatment actions will have on the time required for a wildfire to burn through each cell. This raster map contains real values that indicate after treatment burn time.

Wind speed and direction. One spatial data layer is required to record wind speed [miles/hr] and another for wind direction [azimuth]. Wind speed and direction can be entered as scalar if it is assumed that they are spatially constant across the area being analyzed.

Anisotropic burn time sub-model (Box 2)

The first task in modeling the spread of a wildfire across a landscape is to estimate the time the fire needs to burn through each raster cell in the maps describing the landscape. This can be accomplished using the inputs described above and the Rothermel FROS equation. This process is diagramed in Figure 6.

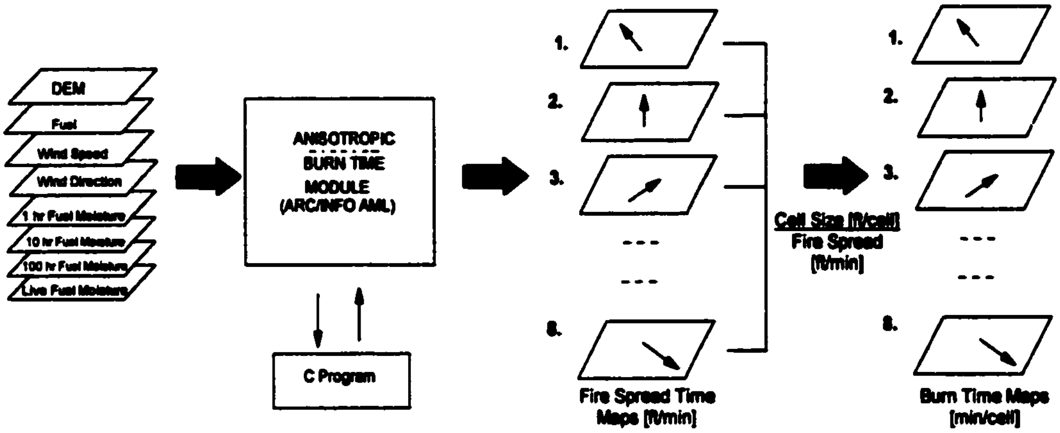

Figure 6. Burn time spatial data layers building process. This sub-model accomplishes action indicated in box 2 of Figure 5.

The inputs to the fire spread model are the eight maps shown on the left side of Figure 6 (the last six inputs can also be entered as scalar values; only the DEM and the fuel maps are required to be raster data layers). These inputs are used in Rothermel's FROS equation (Equation 1) to build maps that show the rate of spread (in ft/min)in each of the eight principle directions. This is accomplished using a combined ARC/INFO (AML) and a custom C program. Each of these rates of spread maps is divided by the size of the raster cells used in the analysis to produce the cell burn time maps used in the remainder of the model.

Fire spreading surface building sub-model (Boxes 3 and 7)

After the eight burn time maps are created, they are used as the inputs to construct a wildfire spread cost map using anisotropic cost spreading principles.

The model uses Dean's (1997) algorithm, which, unique among ACS algorithms, uses eight unit cost maps (burn time maps) and a spatial layer indicating potential wildfire ignitions points to build a fire spreading surface (Figure 7).

The outputs of the ACS analysis are a fire spread map and a backlink map. The spread map indicates the total time required for a wildfire to spread from the ignition points used in the ACS analysis to each raster cell, and the backlink map identifies the routes the wildfire will travel from the ignition points to each raster cell.

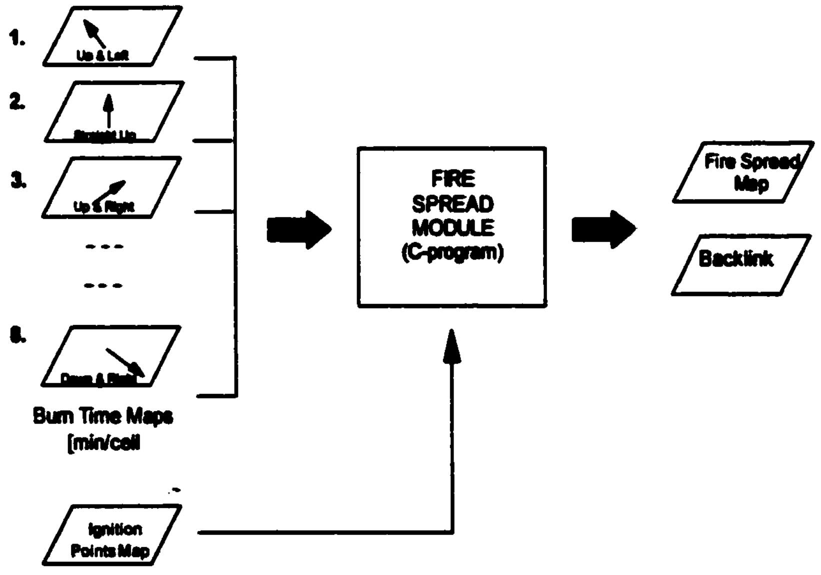

Figure 7. Anisotropic fire spread or fire propagation flow chart process.

Fuels treatment benefit sub-model (Boxes 3 through 12)

Fuel treatment benefit refers to the increase in burning time resulting from applying a fuel treatment to an area (Figure 8). A clear delineation of the sub-model used to compute this benefit is difficult because it incorporates portions of the fire spread sub-model just described and the fuels treatment delineation sub-model (described below).

This sub-model identifies the location of the raster cells that if treated would result in the maximum gain in burning time. Within a given iteration, once this sub-model identifies a given raster cell as the best candidate to receive treatment, it passes that cell's coordinates to the fuels treatment delineation model for permanent recording as a cell to be treated in a raster data layer. Additionally, information on the benefit obtained is reported.

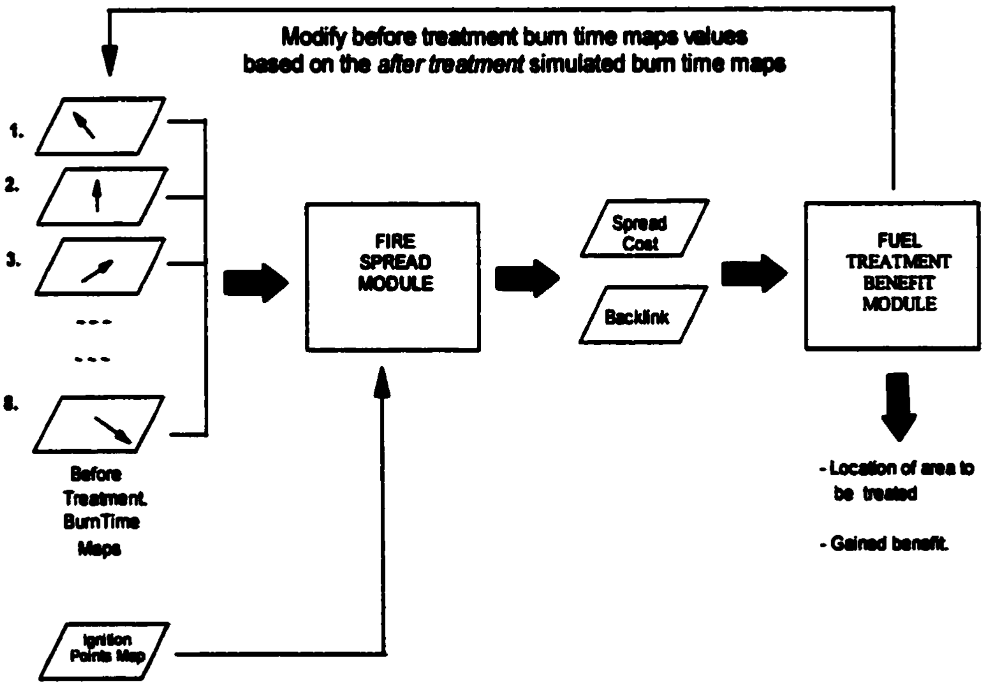

Figure 8. Fuels treatment benefit model process (flow chart).

The inner loop in Figure 5 explains in detail how this sub-model works and what it accomplishes. However, it is important to notice that the fuels treatment benefit process iterates until all cells representing the fastest fire spread path or paths are analyzed. This can be a time consuming process because each cell evaluation involves an ACS analysis, which itself can be time consuming. In an attempt to improve the performance of this sub-model, Valdez-Lazalde and Dean (In Review(a)) developed a modified ACS solution technique that takes advantage of the high degree of similarity between each ACS analysis conducted in the iterative modeling process. This modified ACS process decreases execution time by two to four orders of magnitude. However, even this performance enhancement may not be enough to produce acceptable overall model performance when dealing with very large datasets. In these cases, the process shown in Figure 5 can be modified to sample only a subset of cells along the minimum burn time path, rather then evaluating every cell. This obviously results in less optimal solutions, but can decrease execution time very dramatically.

Fuels treatment delineation and budget sub-models (Boxes 10 and 11)

As shown in Figure 9, these sub-models work cooperatively to accomplish the simple task of permanently recording the areas to receive fuel treatment. The candidate cell identified by the fuels treatment benefit sub-model is permanently assigned to receive treatment only if the costs of treating the cell do not exceed the available budget, and if its treatment results in a gain in burning time. As soon as one of the restricting conditions mentioned above is violated the process halts.

Once a raster cell is selected to receive fuel treatment it cannot be considered for further treatment in subsequent iterations. In fact, the model excludes those areas from further analysis so that the process becomes more efficient.

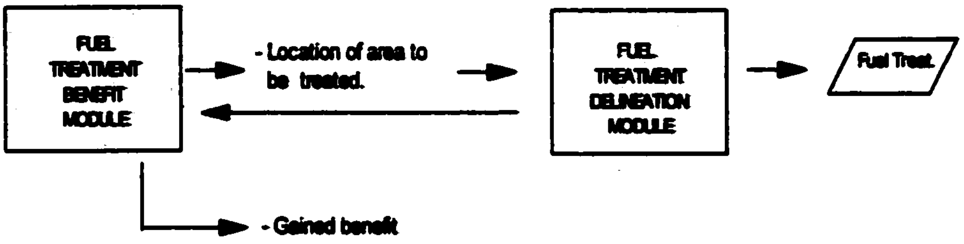

Figure 9. Fuels treatment delineation process (flow chart).

Figure 10 summarizes the interaction between each of the sub-models just described.

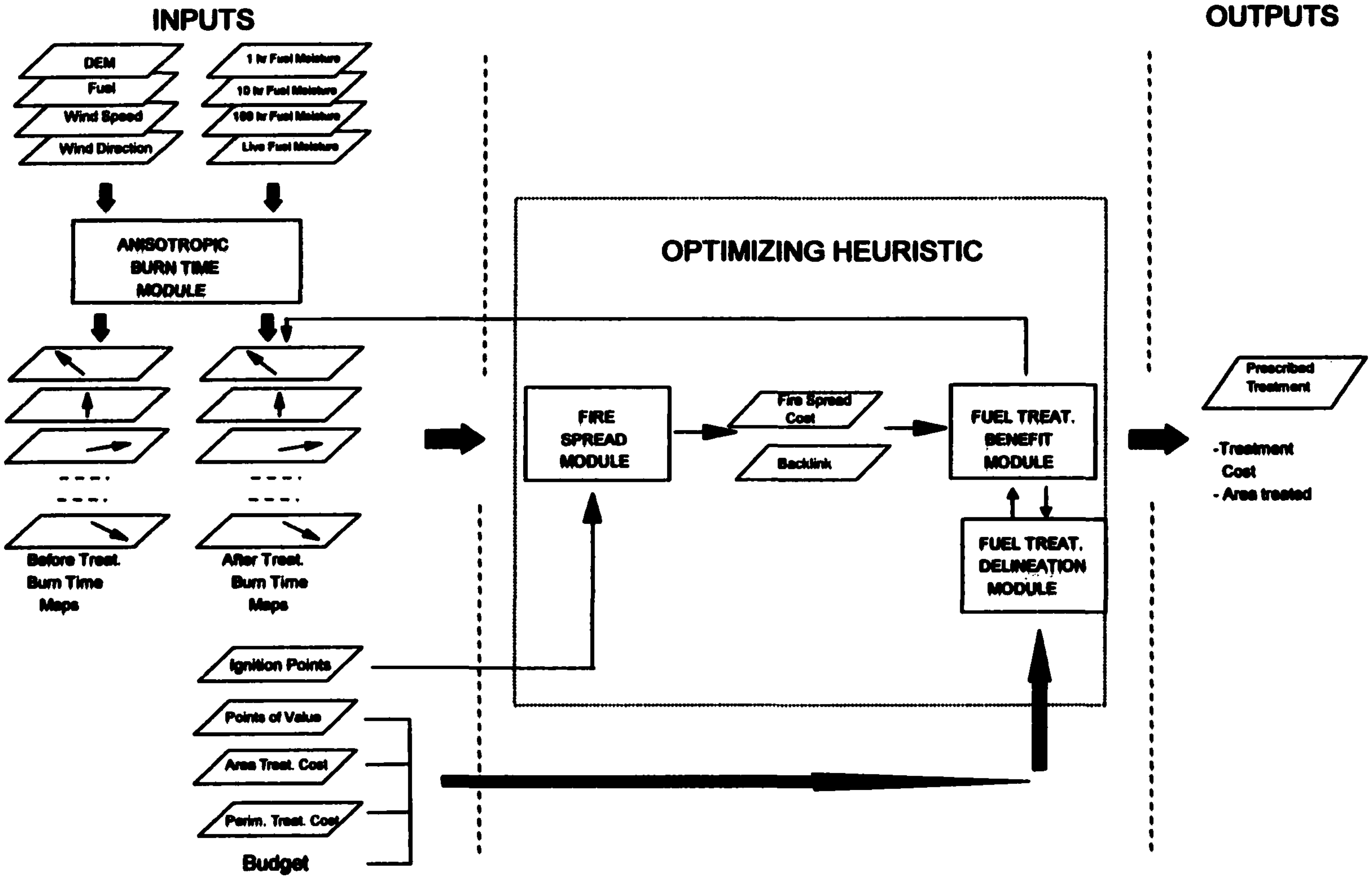

Figure 10. Fuels treatment management optimization model architecture.

MODEL EVALUATION AND STUDY CASE

A detailed comparative analysis of the model described is the focus of Valdez-Lazalde and Dean, In Review(b). Space limitations prohibit a full discussion of this validation effort. Instead, this section describes the efforts aimed to evaluate each of the sub-models described previously. The study case presented here involves comparing a fuel treatment recommendation produced by the model to a recommendation developed by a fuel/wildfire expert.

Anisotropic burn time sub-model –construction of burn time surfaces

As this sub-model is nothing but the implementation of the well established and tested Rothermel's fire spread equation (Rothermel 1972), all that was required to validate this sub-model was to make sure that the coded AML and C programs properly represented, within a spatial context, the Rothermel's equation. This was accomplished by computing burn time estimates by hand for a random sample of raster cells, and comparing these hand-produced estimates to those created by the sub-model. In all cases, the comparisons demonstrated that the sub-model was correctly implementing Rothermel's equation.

Anisotropic fire spreading sub-model –fire spread estimation

Initially, we attempted to validate this sub-model using real wildfire data from the 1994 South Canyon Forest Fire (Butler *et al.* 1997). The idea was to compare simulated fire perimeters (fire spread status) at given points in time after the fire was ignited against fire perimeters from a real wildfire event for the same elapsed time period after ignition. Thus, real wildfire event perimeters from the 1994 South Canyon Forest Fire (Butler *et al.*, 1997) were converted to digital format and compared to fire perimeters resulting from the fire spreading modeling process. Unfortunately, simulated rates of spread and consequently fire growth perimeters were consistently higher than the same parameters reported for the real wildfire event. Finney (1998) attributes such disparities to a possible "general conflict of scale between the frequency of data inputs to the simulation and the frequency of variation in real environmental conditions affecting the fire", page 31. Finney mentioned, for example, that wind data is usually input at discrete intervals (hourly) and are typically general measures that do not reflect conditions in micro sites. With these sorts of data inadequacies, it is not surprising that predicted and actual fire spread parameters differ.

Despite the unexpected outcome, the comparative results were consistent with estimations carried out by other authors in other areas.

Due to these problems, an alternative validation procedure was needed. Following Finney's advice (Finney 1999)[1], the sub-model was validated by testing it under simple known conditions where it was easy to predict the outcome. Thus, simulations of FROS and fire perimeter growth for varying wind directions and speeds, changes in fuel characteristics (depth, moisture, load, surface to volume ratio, etc.), and slope were carried out. In reality, this was a sensitivity analyses as opposed to having a validation. Inputs were varied while observing output changes and checking for consistency and logical behavior.

Table 1 shows the factors involved in this analysis. They represent a small sample of the input characteristics that cover the whole range of values given by fuel models, wind speed and directions, and topographic models. The total number of unique combinations of the factors and levels shown in Table 1 is 17,496 (3x3x3x3x9x3x8). Testing each of these combinations is impractical. Thus, only a sample of the most important factor combinations were tested.

Table 1. Fuel load, fuel moisture, wind, and topographic (DEM) factors used to develop de sensitivity analysis for the wildfire spread sub-model implementation.

Fuel					Wind	
Load (lb/ft2)	Depth (ft)	StoV♦ (1/ft)	Moisture (%)	Terrain Characteristics	Speed (mph)	Direction (Azimuth)
0.04	0.20	1500	1	Flat	0	22.5
0.17	3.20	2500	15	Slope Up and Left	10	67.5
0.30	6.20	3500	30	Slope Straight Up	20	112.5
				Slope Up and Right		157.5
				Slope Straight Left		202.5
				Slope Straight Right		247.5
				Slope Down and Left		292.5
				Slope Straight Down		337.5
				Slope Down and Right		

♦ Surface to volume ratio

The sub-model behaved as expected. Increasing the steepness of the terrain, wind speed, fuel loadings and dryness all increased fire spread rates, as would be expected. Fire spread direction responded to changes in topography and wind direction as expected. Some examples are shown in Figure 11.

Fuel treatment and fuel delineation sub-model – Optimizing heuristic

It is impractical to separate the fuel treatment sub-model from the fuel treatment delineation sub-model. Furthermore evaluating these two sub-models requires validating the complete fuel treatments optimization model developed. As mentioned before, a detailed comparative study ("validation") of the complete model is the focus of Valdez-Lazalde and Dean (In Review(b)). Due to space limitations, no details are here given on this matter.

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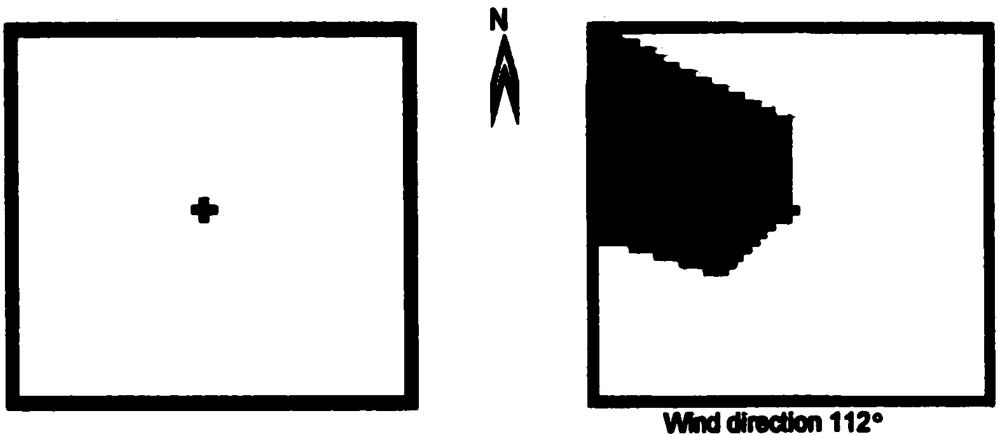
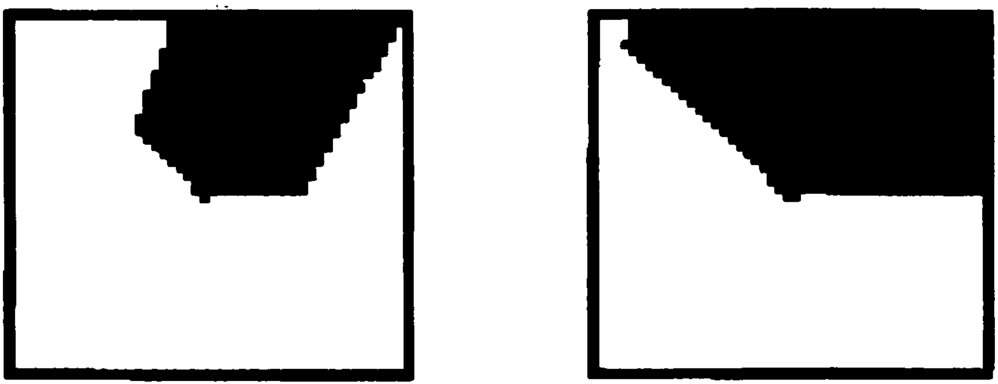
[1] Finney, M. 1999. Personal comunication



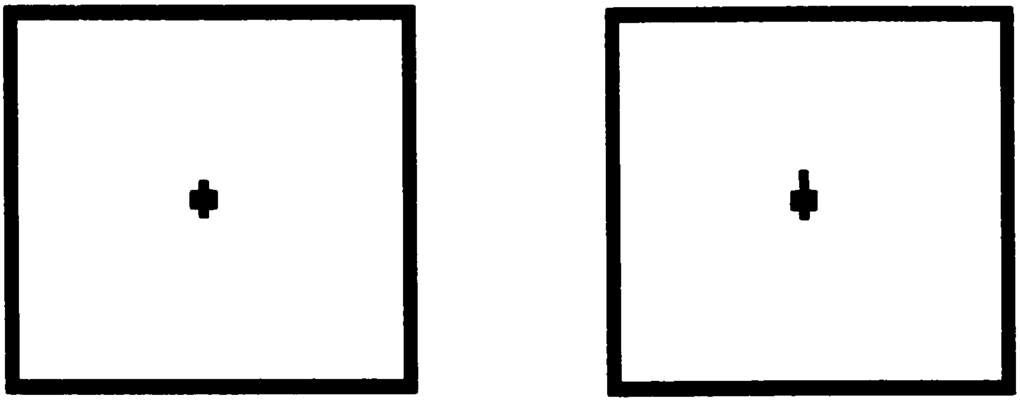
No wind, flat terrain

Wind direction 112°
Wind speed 10 mph
Flat terrain



Wind direction 222°
Wind speed 10 mph
Flat terrain

Wind direction 222°
Wind speed 20 mph
Flat terrain



No wind, South aspect
with increasing slope 20%

No wind, South aspect
with increasing slope 40%

Fire Perimeter After Ignition

■ 30 minutes
■ 20 minutes
■ 10 minutes

Figure 11. Examples of the effect of wind direction, wind speed and slope on fire

Example comparison of model and expert recommendations

The fuel, terrain and wind condition maps shown in Figures 12 and 13 were both sent to a fuel/fire manager expert with the U.S. Forest Service for evaluation and used as inputs into the fuel treatment model. Figure 14 shows the areas identified for fuel treatment by both the model and the expert.

As shown in Figure 14, 21.5% of the area treated is common to both the model and expert prescriptions. However, judging the validity of the model's solution by comparing how well it overlaps with the expert's counterpart is by no means sufficient. This is true because the expert's solution might be highly subjective and non repeatable *i. e.*, a different solution may result if a different expert is consulted for a solution. Thus, another criterion was needed to rank the solutions. We used the burning time criterion to accomplish that purpose.

An assumption made clear to both the expert and the model was that areas selected to receive treatment would reduce their fuel characteristics to half of the conditions existing before treatment. Thus, both solutions were used to update the fuel parameter values to 50% of its original amount. Afterwards, burning time values were computed for both prescriptions and compared. As the objective was to maximize burning time (minimize risk), the fuel treatment plan with the larger after treatment burning time was considered a better prescription. In relative terms, the solution generated by the model resulted in a burning time value that was 35% higher than the prescription defined by the expert, *i.e.*, the model's solution seemed to provide a more efficient use of the limited resources.

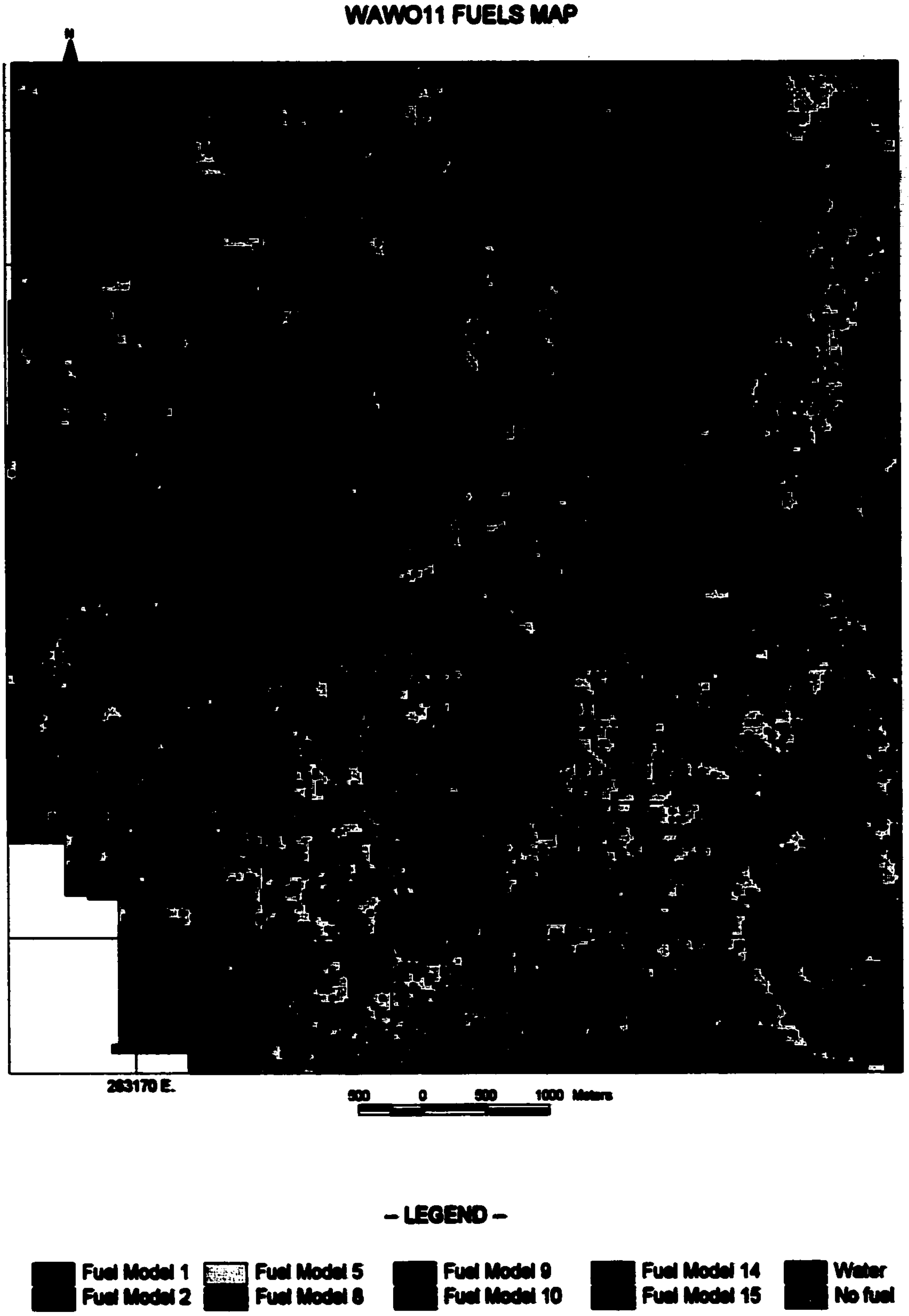
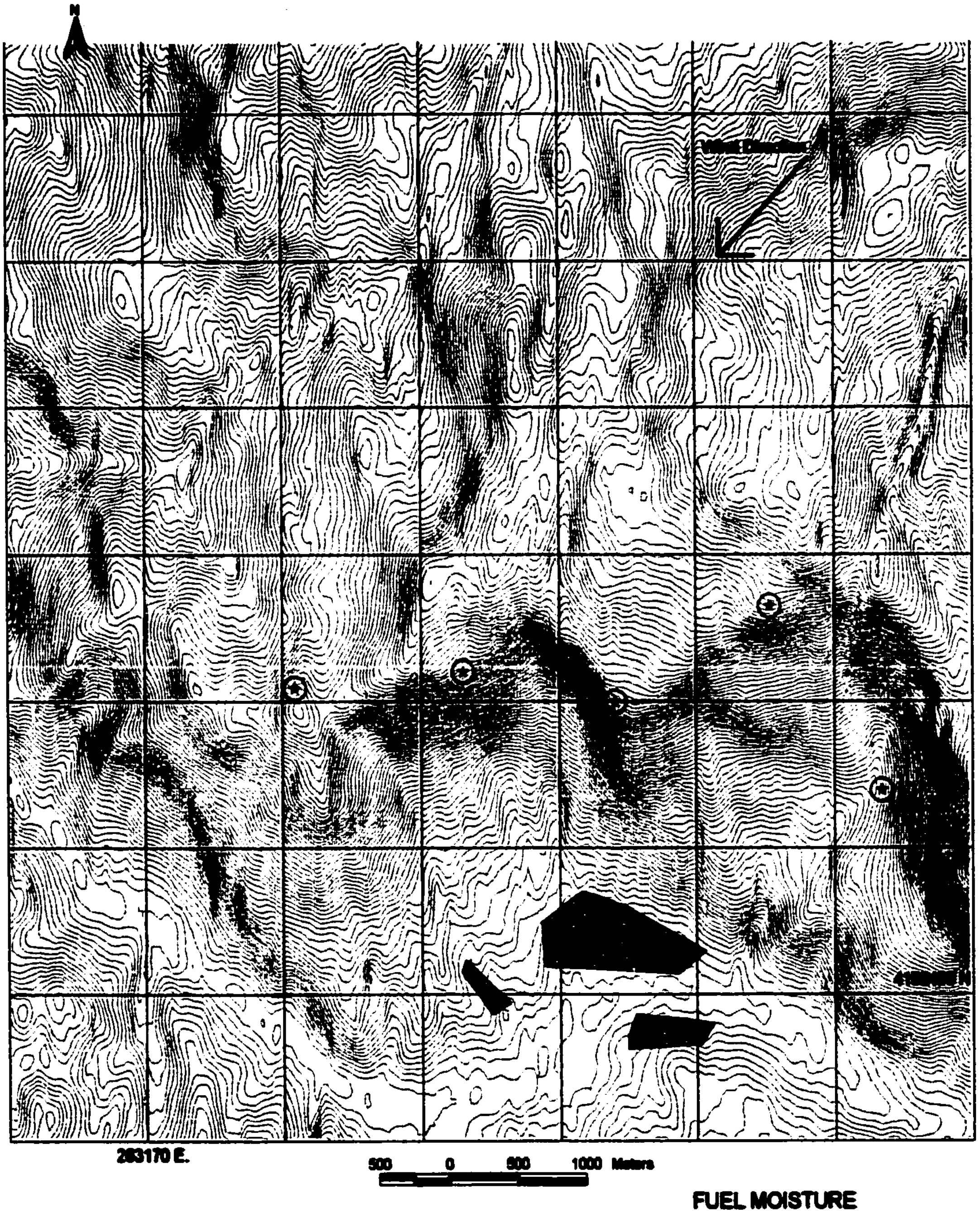


Figure 12. Reduced copy of a fuel map sent to fuel management experts.

WAWO11 TOPOGRAPHIC MAP



- LEGEND -

- ⊛ Fire ignition point
- ■ Area to protect
- /\/ UTM Grid
- /\/ Countour interval (40 ft)

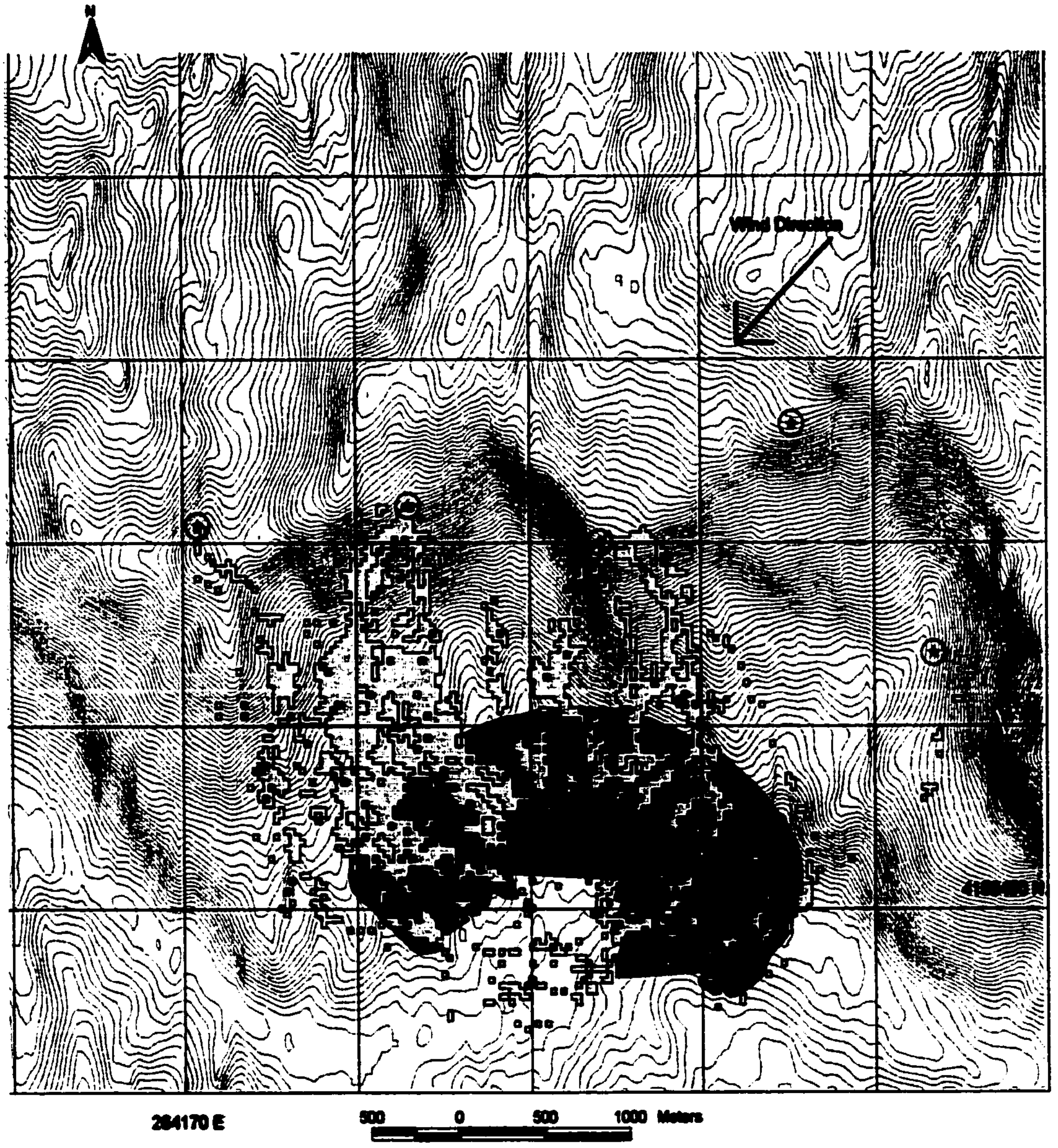
FUEL MOISTURE

1 hour	5%
10 hour	7%
100 hour	12%
Live	90%

WIND PARAMETERS
Effective speed 3 mph
Direction (azimut) 45 deg.

Figure 13. Reduced copy of a topographic map sent to fuel management experts.

WAWO11 TOPOGRAPHIC MAP AND FUEL TREATMENTS



– LEGEND –

⊛ Fire ignition point
■ Area to protect
UTM grid
▨ Computer model
■ Fuel manager
Countour interval (40 ft)

FUEL MOISTURE

1 hour	5%
10 hour	7%
100 hour	12%
Live	90%

WIND PARAMETERS
Effective speed 3 mph
Direction (azimut) 45 deg.

Figure 14. Location of fuel treatment activities defined by a fuel manager and by the computer model.

Another restriction that was required to consider while defining the fuel management prescription was that only a maximum of 200 ha could be treated due to budget constraints. The model solution defined that all the 200 ha allowed should receive fuel treatment to maximize the burning time. The expert's solution required that 203 ha were treated. Despite the minimal difference in area prescribed to receive treatment, as mentioned above, there was a substantial difference (41%) in burning time between the two prescriptions. The spatial distribution between the two prescriptions may be the cause of such difference. The only way to get a better understanding of the model solutions is through a more complete validation. An upcoming study by Valdez-Lazalde and Dean (In Review (b)) will focus on that matter.

Figure 15 shows a second, model-defined, strategy for the location of fuel treatments. In this case only one shortest fire path was considered at each iteration. The general location of both prescriptions (see also Figure 14) is similar. However, considering only one path at the time seems to emphasize treatments to protect areas of value that are easier to reach by the fire; which is desirable and also achieved to some degree by the first solution (Figure 14). Its disadvantage is that it defined much less area to be treated and left uncovered the areas of value that could be affected by fire starting at further located ignition points.

It is worth noting that because of the high iterative nature of the algorithm the model takes a considerable amount of computer time and resources to come up with a solution. However, as it currently stands we believe the model can be used to define fuel treatments for small areas or for large ones if a cell size of 60 or more meters is used to describe the data inputs.

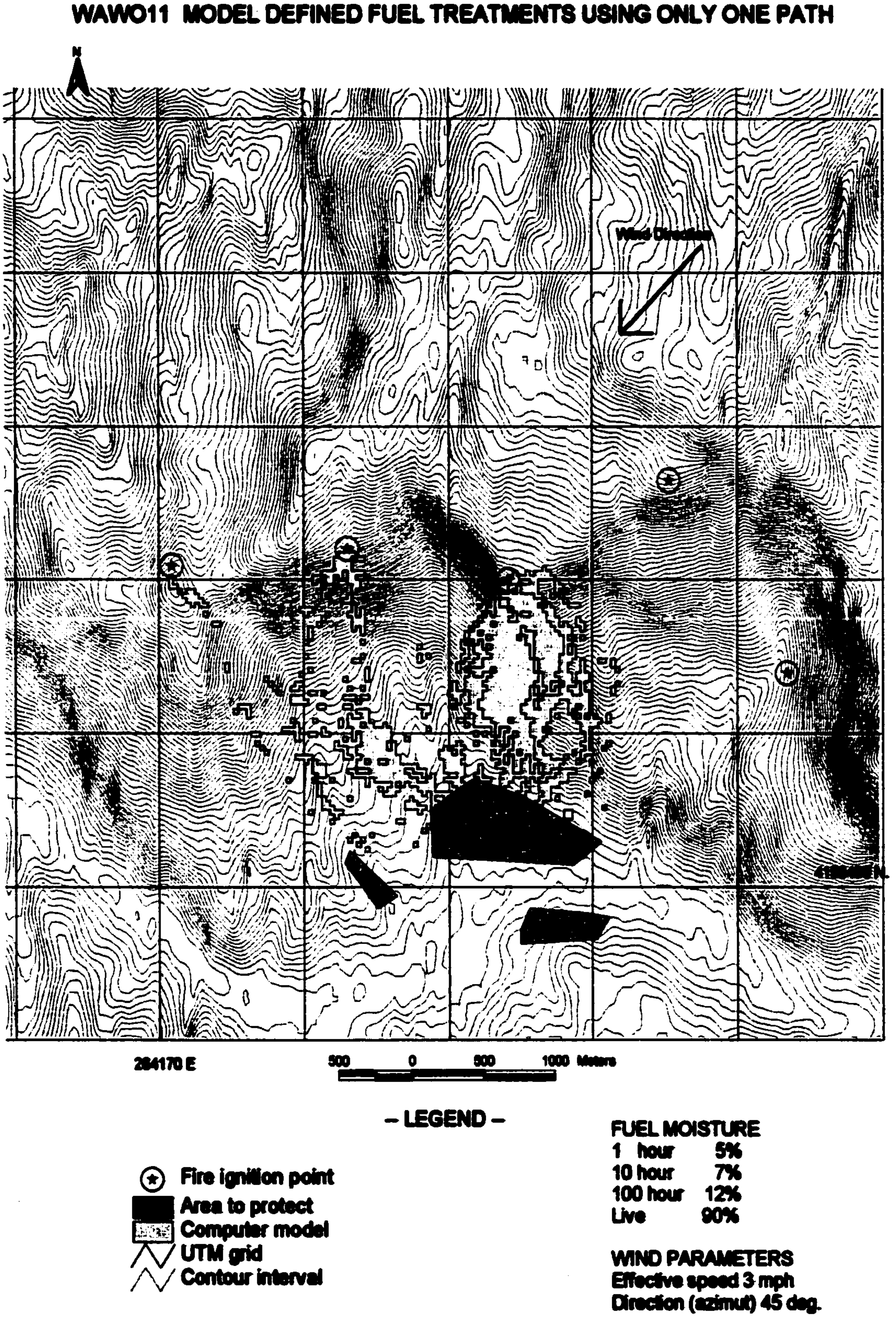


Figure 15. Location of fuel treatment activities defined by the computer model using one shortest path at each iteration.

CONCLUSIONS

The model reported represents a new approach for objectively locating the application of forest fuel management activities. It incorporates existing fire spread concepts and knowledge and spatially explicit fuel, topographic and weather related information to generate a near-optimal solution. The model objectively and repeatedly finds fuel treatment locations through a combination of heuristic optimization procedures, fire spread concepts, and GIS-based anisotropic cost spreading analysis. We believe this model is a substantial contribution to the solution of spatially explicit optimization problems within the field of forest management.

It is worth noting that the model requires spatial data as input. In practice, data of this sort may be unavailable, or if available, may contain errors or generalizations of questionable accuracy. How these errors impact the current model are unknown.

Finally, it must be emphasized that this model is intended as the basis for a decision *support* system to prescribe the placement of fuel management alternatives, and not as a system that provides absolute and definitive solutions to it At the end, experienced managers must use all their expertise, common sense, and knowledge of the phenomenon under scrutiny to decide if the solution provided by the model should be completely, partially, or not at all considered for practical implementation

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Article 3

FOREST FUEL MANAGEMENT: AN EFFICIENCY COMPARISON AMONG EXPERTS' PRESCRIPTIONS AND COMPUTER GENERATED SOLUTIONS

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FOREST FUEL MANAGEMENT: AN EFFECTIVENESS COMPARISON EVALUATION AMONG EXPERTS' PRESCRIPTIONS AND COMPUTER GENERATED SOLUTIONS

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ABSTRACT

This paper reports a comparative study among forest fuel treatment prescriptions defined by U.S. fuel managers and a computer optimization model. It also reports a detailed validation of the model developed by Valdez-Lazalde and Dean (In Review (b)). Twenty-three hypothetical fuel management scenarios were set up and used in the study. Fuel treatment prescriptions were compared for spatial agreement (overlap), relative effectiveness to protect areas of value, and compliance with a maximum area to receive treatment (budget constraint). Results from the study showed that the spatial location of fuel treatment activities prescribed by experts are very different from one expert to another. For most scenarios, the spatial overlap among experts' prescriptions was less than 20%; in many cases less than 10%. The overlap among the experts' prescriptions and the computer generated solution was even lower; less than 10% for most scenarios. In all cases, the computer generated prescriptions resulted to be more efficient than the ones defined by fuel managers. Most experts' prescriptions were from 30 to 50% less efficient than the solutions generated by the computer model. Regarding area used, on average, about half of the prescriptions defined by the experts used only 50% of the maximum area allowed, however, several exceeded the imposed area limit. The model, on the other hand, defined the areas to receive treatment over a wider range; from 10.5% and up to the maximum area allowed (100% = 200 ha); it never exceeded the specified area limit.

Key words: spatial optimization, spatial analysis, decision support systems, GIS.

INTRODUCTION

Public and private organizations spend billions of dollars worldwide to minimize the negative consequences of wildfires. Due to the difficulty in controlling wildfires once they ignite, managers currently focus their efforts on reducing wildfire risks before ignition. One way to accomplish this is through the use of forest fuel treatment activities (SNEP 1996; Baird *et al.* 1994). Recently, Valdez-Lazalde and Dean (In Review (b)), proposed a method to help managers optimize the location of preventive fuel treatment activities. The purpose of this paper is to assess Valdez-Lazalde and Dean's methodology relative to fuel management plans developed by experts.

Currently, fuel managers use tools such as BEHAVE (Burgan and Rothermel 1984; Andrews 1986), FARSITE (Finney 1998), or other existing systems along with their professional judgment, to develop fuel management plans. However, tools such as FARSITE and BEHAVE were not designed to prescribe fuel management activities, but to predict forest fire growth and behavior. Thus, they are mainly used to help in designing fire attack activities. Thus, these systems do not give fuel managers the ability to find optimal sites to conduct treatments; such optimization is entirely a consequence of the manager's individual skill.

Undoubtedly, many experts are capable of developing fuel management plans that substantially reduce wildfire risks while simultaneously making effective use of available budgets. However, plans developed in this fashion are highly subjective, *i. e.*, depend on the background, experience, and personal values of the individual. Consequently, they might be difficult to defend and justify before superior decision makers. Furthermore, its the development process is difficult and time consuming and less skilled managers may not be able to develop effective plans at all. These factors make the development of an objective procedure to locate fuel treatment activities highly desirable.

Valdez-Lazalde and Dean (In Review(b)) proposed such a procedure. Their system was based on GIS-based anisotropic cost spreading techniques, the Rothermel fire behavior equations (Rothermel 1972), and a simple heuristic optimization procedure. This earlier paper validated the model piecemeal, by validating each of its components individually. Here, we validate the model in its entirety by comparing its results to fuel management plans developed by experts.

Fuel management planning

Valdez-Lazalde and Dean (In Review (b)) used *burning time* as a criterion to measure the relative effectiveness of fuel treatment activities. They defined burning time as the time needed for a forest fire to traverse from an ignition point to a point or area of value. These authors proposed that, for a given area, fuel treatment plans that produced higher burning times were more desirable than plans producing lower burn times. The reasoning behind this proposal was that the longer it takes for a fire to reach an area of value (a place or structure we wish to protect), the better are the chances for the fire to be extinguished or controlled by natural causes or human intervention. Also, more time is available to prepare the point or area of value for the arrival of the fire.

In practice, the extent of fuel treatments a manager can conduct is limited by the cost of treatments and the available budget. These treatment costs vary across the landscape; *e. g.*, treatment costs are relatively low in areas with easy access and gentle terrain and relatively high in areas where access and terrain are difficult. This spatial variability in treatment costs, combined with spatial variability in treatment effectiveness (*i.e.*, fuel treatments conducted on one location might have no impact on the burning time of a wildfire moving from some ignition point to a point of value, while and identical fuel treatment activity conducted in a different location might have very profound impacts on this same burn time), makes fuel treatment optimization a fundamentally spatial process.

METHODS AND MATERIAL

This study compared the spatial location, relative effectiveness, and area of 89 hypothetical fuel treatment plans (representing 23 unique fuel treatment scenarios, each with three to five repetitions) manually defined by U.S. fuel management experts. These expert-developed plans were also compared to plans developed by the computer optimization model developed by Valdez-Lazalde and Dean (2000; In Review (b)).

Development of fuel management scenarios

Six different areas of approximately 5240 ha (12950 acres) were identified for use as study sites. All of these areas were located within Yosemite National Park (Figure 1). For each area, we obtained actual information on fuel types and topography from Jan van Wagtendonk (Research Scientist, Yosemite National Park, El Portal, CA) and the USGS (edcwww.cr.usgs.gov/webglis). We then created four (three for one of the areas) hypothetical scenarios for each site by creating artificial wind speed and direction, fuel moisture contents, fire ignition points, and areas of value. In total, 23 fuels management scenarios were created. Table 1 lists some of the primary characteristics of each scenario. Each scenario was presented using a fuel type map (Figure 2, for example) and a topographic map that also showed wind speed and direction, ignition points, points of value, and fuel moisture levels (Figure 3, for example).

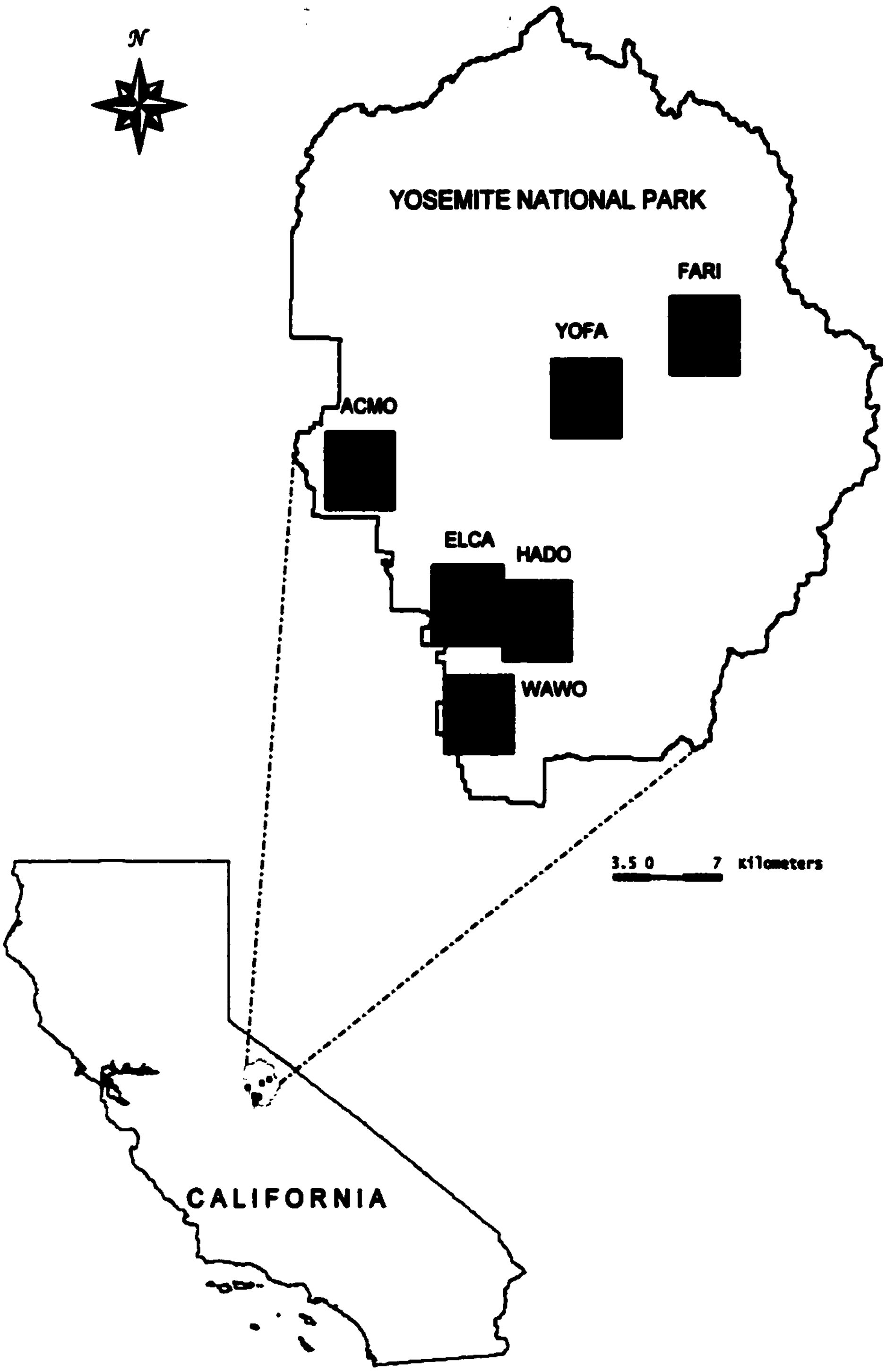


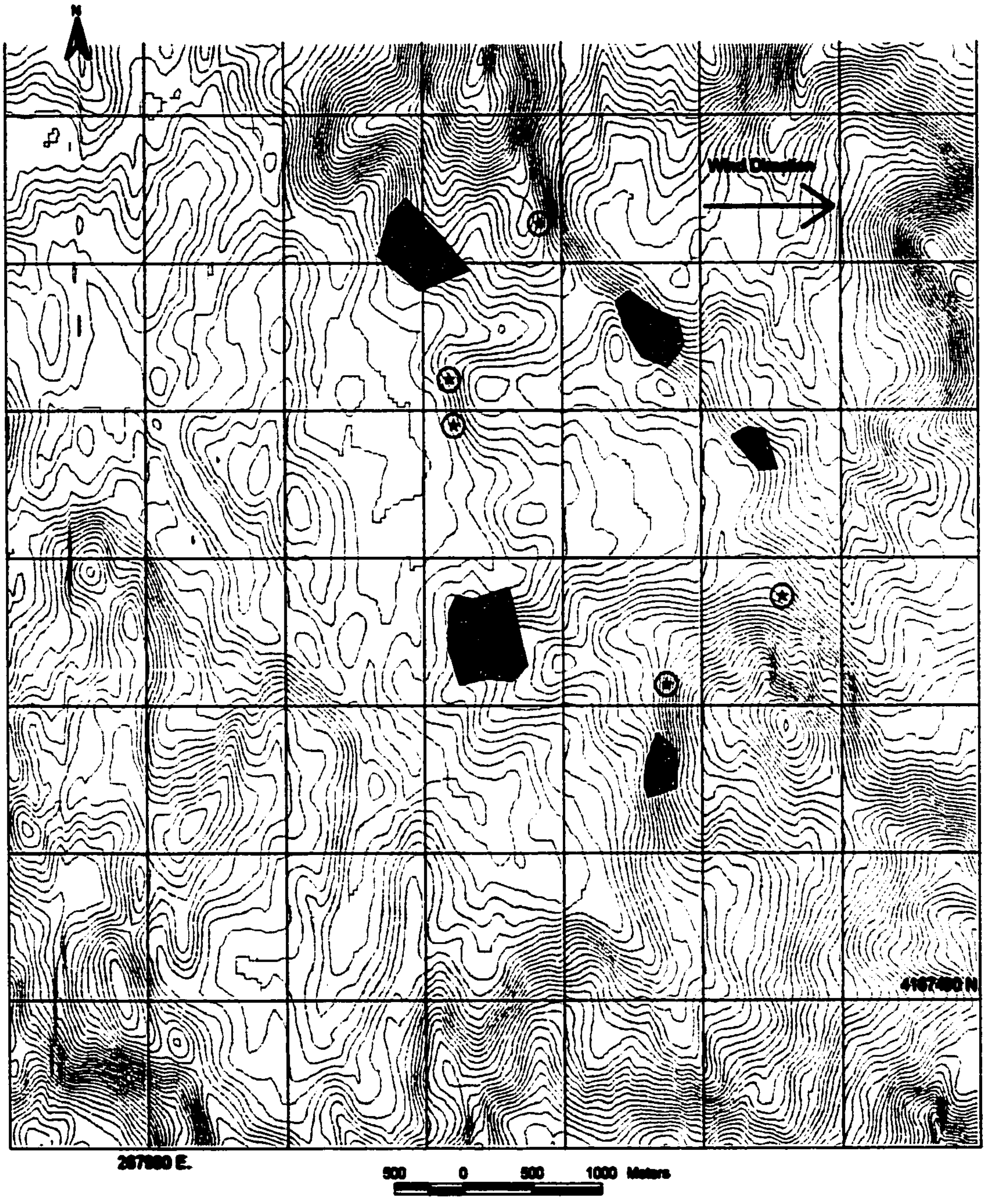
Figure 1. Location of the fuel management scenarios used in the study.

Table 1. Scenarios used to carry out the comparison study and the validation of the fuels treatment optimization model.

SCENARIO	UTM MAP COORDINATES		WIND PARAMETERS		FUEL MOISTURE (%)			
	SW CORNER (EASTING/NORTHING)	NE CORNER (EASTING/NORTHING)	SPEED ($m\ hr^{-1}$)	DIRECTION (°)	1 hr	10 hr	100 hr	Live
ACMO11	249990/4181010	256990/4188510	5	360	3	5	7	90
ACMO22	" "	" "	8	270	10	15	17	130
ACMO33	" "	" "	8	135	5	7	12	105
ACMO44	" "	" "	3	45	5	7	12	105
ELCA11	261000/4167990	267900/4175490	5	90	3	5	7	90
ELCA22	" "	" "	8	270	10	15	17	130
ELCA33	" "	" "	5	360	3	5	7	90
ELCA44	" "	" "	8	135	5	7	12	105
FARI11	285000/4194000	292000/4201500	5	180	3	5	7	90
FARI22	" "	" "	8	135	5	7	12	105
FARI33	" "	" "	5	90	3	5	7	90
FARI44	" "	" "	10	315	2	4	7	90
HADO11	267990/4166490	274990/4173990	5	180	3	5	7	90
HADO22	" "	" "	8	270	10	15	27	135
HADO33	" "	" "	10	90	3	5	5	90
HADO44	" "	" "	10	225	4	8	12	125
YOFA22	273000/4188000	280000/4195500	10	360	3	3	5	90
YOFA33	" "	" "	10	90	3	5	5	90
YOFA44	" "	" "	10	225	4	8	12	125
WAWO11	262170/4157490	269170/4164990	3	45	5	7	12	105
WAWO22	" "	" "	10	315	2	4	7	90
WAWO33	" "	" "	5	360	3	5	7	90
WAWO44	" "	" "	10	315	2	4	7	90

Figure 2. Reduced copy of a fuel map sent to fuel management experts.

HADO22 TOPOGRAPHIC MAP



– LEGEND –

- ⊛ Fire ignition point
- ■ Area to protect
- UTM Grid
- Countour interval (40 ft)

FUEL MOISTURE

1 hour	10%
10 hour	15%
100 hour	27%
Live	135%

WIND PARAMETERS
Effective speed 8 mph
Direction (azimut) 270 deg.

Figure 3. Reduced copy of a topographic map sent to fuel management experts.

Survey of fuel/fire managers

Forty-one fuel management experts from the U. S. Forest Service, National Park Service and Bureau of land Management expressed willingness to participate in the fuel planning exercise. Four fuel management scenarios (composed by maps similar to the ones shown in Figures 2 and 3), along with instructions (Appendix 1) were sent to each one of the experts. We requested the experts to delineate on the topographic map the best location of fuel treatment activities. To incorporate budget constraints, we restricted to 200 hectares the maximum area to receive treatment.

A total of 23 experts returned 89 usable fuel treatment plans, representing 23 unique scenarios, to the researchers for the analysis. These plans were digitized into a computerized GIS software package for further analysis.

Model generated fuel treatment prescriptions

The 23 hypothetical scenarios defined were entered into the computer optimization model developed by Valdez-Lazalde and Dean (In Review (b)) to define near-optimal location of fuel treatment. As was the case with the expert's evaluations, the computer model was constrained to treat at the most 200 hectares. The model's outputs, which were in a form of raster GIS data layers, were converted to vector data layers in order to be compatible with the vector data layers generated by the experts.

Comparative analysis

Once fuel treatment prescriptions for a given scenario were obtained from both the experts and the computer model, their spatial overlap, burning time (effectiveness), and total area treated were compared. Details of each comparison are described below.

Spatial overlap

A GIS overlay operation was used to determine the degree of agreement between any two generated fuel treatment prescriptions (Figure 4.) This process combined multiple fuel treatment prescriptions maps into a single combined map, which allowed computation of overlapping areas to two or more prescriptions. These common areas were converted into percentages to eliminate any incompatibility problems between fuel treatment scenarios.

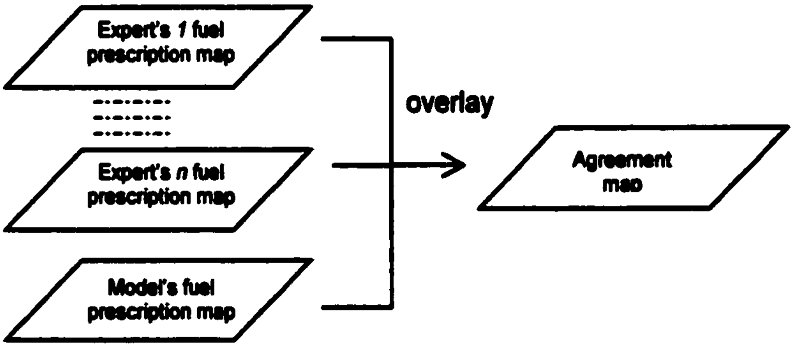


Figure 4. Simplified flow chart process followed to compare the fuel treatment location activities provided by experts and the model.

Effectiveness

The burning time criterion defined by Valdez-Lazalde and Dean (In Review (b)) was used to calculate the relative effectiveness of the fuel treatment prescriptions obtained from the fuel management experts and the computer model.

First, before-treatment burning times were computed for the fuel management scenarios using the anisotropic cost spreading algorithm defined by Dean (1996, 1997) and explained in detail in Valdez-Lazalde and Dean (In Review (a)). Then, the fuel depth and load parameters were reduced to half of their original before-treatment value in all areas where fuel treatment operations were prescribed. After-treatment burning time values were then computed using the same algorithm used for computing the before-treatment burning times. This 50% fuel reduction assumption was made clear to all of the experts in the instructions letter provided to them.

For each scenario, the before-treatment burning time was assigned a value of 100% and all other burning times were ranked against this benchmark. Again, this was done to eliminate incommensurability problems.

Area treated

The final criteria used to compare the various fuel treatment prescriptions was area treated. Recall that a 200 ha limit was placed on the area treated; all prescriptions' treated areas were computed as a percentage of this amount. Thus, a prescription that called for treating 100 ha would have treated 50% of the available treatment area, and a prescription calling for treatment of 300 ha would treat 150% of the available area.

RESULTS AND DISCUSSION

Spatial overlap

Table 2 shows the percentage of overlap among the different fuel treatment prescriptions defined by fuel management experts and the model. Ideally, each scenario was to be evaluated by five experts as well as the computer model. Unfortunately, this was not entirely possible because not all of the scenarios sent to experts were returned.

There was surprisingly little overlap between the areas recommended for treatment by experts. Overlap between individual pairs of experts ranged from 0% to 57.5%, and averaged only 15.4%. Examining the prescriptions developed by the experts, it was clear that the experts employed different strategies in developing their prescriptions (see Figures 5 and 6 for examples). More than half of the experts attempted to protect the points of value by surrounding them with fuel treatments. Roughly one third used treatments in critical places between ignition points and areas of value. The remaining experts treated areas around the likely fire ignition points.

Figures 5 and 6 show two examples of the spatial location of fuel management prescriptions defined by both fuel experts and the model for two of the fuel management scenarios used in the study.

It is important to notice that for several scenarios (ACMO11, ACMO22, ELCA44, FARI44, WAWO11, and YOFA22) the percent of spatial overlap between some experts was above 30% (Table 2). However, many pairs of experts produced prescriptions with 0% overlap. Almost half as many pairs of experts produced prescriptions with no overlap (15) as did pairs of experts who produced prescriptions with greater then 30% overlap (34).

Table 2. Percent (%) of spatial overlay among fuel treatment prescriptions defined by fuel management experts and by the model.

		SCENARIO											
EXPERT		ACMO11	ACMO22	ACMO33	ACMO44	ELCA11	ELCA22	ELCA33	ELCA44	FARI11	FAR122	FARI33	FARI44
	Overlap w/E2	47.4	33.5	18.7	0.2	10.0	0.2	0.0	26.6	23.0	0.0	3.0	57.5
	Overlap w/E3	24.6	12.5	18.3	37.3	7.0	6.6	1.2	11.5	5.9	11.8	0.0	21.3
E1	Overlap w/E4	0.0	11.2	-	2.3	-	0.9	-	-	6.8	-	16.7	5.5
	Overlap w/E5	30.1	0.1	-	-	-	-	-	-	-	-	-	21.0
	Average % Overlap w/other experts	25.5	14.3	18.5	13.3	8.5	3.9	0.6	19.1	11.9	5.9	6.6	26.3
	Overlap w/Model	6.5	1.9	2.6	7.3	1.0	0.5	2.1	3.5	1.9	4.2	5.7	10.6
	Overlap w/E1	47.4	33.5	18.7	0.2	10.0	0.0	0.0	26.6	23.0	0.0	3.0	57.5
	Overlap w/E3	28.3	15.4	19.1	0.0	18.0	12.3	15.6	38.3	20.0	0.0	4.6	22.9
E2	Overlap w/E4	0.0	16.4	-	7.1	-	9.6	-	-	21.0	-	1.0	7.4
	Overlap w/E5	20.6	2.3	-	-	-	-	-	-	-	-	-	25.9
	Average % Overlap w/other experts	24.1	16.9	18.9	2.4	14.0	7.3	7.8	32.5	21.3	0.0	2.9	28.4
	Overlap w/Model	5.6	3.9	4.7	1.0	4.0	1.6	1.2	5.3	6.9	6.2	15.5	9.7
	Overlap w/E1	24.6	12.5	18.3	37.3	7.0	6.6	1.2	11.5	5.9	11.8	0.0	21.3
	Overlap w/E2	28.3	15.4	19.1	0.0	18.0	12.3	15.6	38.3	20.0	0.0	4.6	22.9
E3	Overlap w/E4	0.0	14.8	-	0.8	-	22.3	-	-	40.8	-	4.1	26.6
	Overlap w/E5	12.7	1.2	-	-	-	-	-	-	-	-	-	30.7
	Average % Overlap w/other experts	10.3	11.0	18.7	12.7	12.5	13.7	8.4	24.9	22.2	5.9	2.9	25.4
	Overlap w/Model	8.2	1.8	4.4	6.7	2.0	4.3	2.4	6.6	20.0	7.6	11.6	16.6
	Overlap w/E1	0.0	11.2	-	2.3	-	0.9	-	-	6.8	-	16.7	5.5
E4	Overlap w/E2	0.0	16.4	-	7.1	-	9.6	-	-	21.0	-	1.0	7.4
	Overlap w/E3	0.0	14.8	-	0.8	-	22.3	-	-	40.8	-	4.1	26.6
	Overlap w/E5	6.0	2.4	-	-	-		-	-	-	-	-	17.8
	Average % Overlap w/other experts	1.5	11.2	-	3.4	-	10.9	-	-	22.9	-	7.3	14.3
	Overlap w/Model	1.7	5.2	-	6.8	-	3.9	-	-	8.0	-	1.5	9.1
	Overall Average % Overlap Among Experts	15.3	13.4	18.7	10.6	11.7	11.9	5.6	25.5	19.6	3.9	4.9	23.6
	Model's Average % Overlap w/Experts	5.5	3.2	3.9	5.5	2.3	2.6	1.9	5.1	9.2	6.0	8.6	11.5

(Continued on next page)

Table 2. Continued from former page.

EXPERT		SCENARIO										
		HADO11	HADO22	HADO33	HADO44	WAWO11	WAWO22	WAWO33	WAWO44	YOFA22	YOFA33	YOFA44
E1	Overlap w/E2	9.5	6.0	6.6	0.0	0.0	12.3	5.4	22.3	27.0	12.3	6.2
	Overlap w/E3	7.3	5.0	6.3	47.0	19.0	5.0	1.0	1.0	32.0	32.0	16.9
	Overlap w/E4	-	11.1	-	-	31.0	18.7	20.0	8.0	39.0	-	-
	Overlap w/E5	-	-	-	-	17.0	-	21.5	15.7	32.1	-	-
	Average % Overlap w/other experts	8.4	7.4	6.5	23.5	16.8	12.0	12.0	6.2	32.5	22.2	11.6
	Overlap w/Model	8.1	5.3	1.0	4.9	8.6	7.8	1.0	2.5	9.2	9.7	0.0
E2	Overlap w/E1	9.5	6.0	6.6	0.0	0.0	12.3	5.4	22.3	27.0	12.3	6.2
	Overlap w/E3	22.0	21.0	45.8	0.0	0.0	25.0	26.0	2.0	27.0	15.9	16.4
	Overlap w/E4	-	8.8	-	-	0.0	37.5	1.0	3.0	11.0	-	-
	Overlap w/E5	-	-	-	-	0.0	-	1.0	12.1	12.5	-	-
	Average % Overlap w/other experts	15.8	11.9	26.2	0.0	0.0	24.9	8.4	9.9	19.4	14.1	11.3
	Overlap w/Model	6.1	7.8	1.8	2.1	1.0	19.1	6.1	1.0	4.3	8.1	1.7
E3	Overlap w/E1	7.3	5.0	6.3	47.0	19.0	5.0	1.0	1.0	32.0	32.0	16.9
	Overlap w/E2	22.0	21.0	45.8	0.0	0.0	25.0	26.0	2.0	27.0	15.9	16.4
	Overlap w/E4	-	7.2	-	-	26.2	53.7	0.0	14.0	22.0	-	-
	Overlap w/E5	-	-	-	-	33.0	-	0.0	4.8	31.6	-	-
	Average % Overlap w/other experts	14.7	11.1	26.1	23.5	19.6	27.9	6.8	5.5	28.2	24.0	16.7
	Overlap w/Model	4.1	1.8	1.7	4.1	21.5	14.3	3.8	0.7	9.1	12.0	0.1
E4	Overlap w/E1	-	11.1	-	-	31.0	18.7	20.0	8.0	39.0	-	-
	Overlap w/E2	-	8.8	-	-	0.0	37.5	1.0	3.0	11.0	-	-
	Overlap w/E3	-	7.2	-	-	26.2	53.7	0.0	14.0	22.0	-	-
	Overlap w/E5	-	-	-	-	38.6	-	26.9	11.1	53.6	-	-
	Average % Overlap w/other experts	-	9.0	-	-	24.0	36.6	12.0	9.0	31.4	-	-
	Overlap w/Model	-	7.2	-	-	8.5	13.5	1.6	0.5	12.2	-	-
	Overall Average % Overlap Among Experts	12.9	13.1	19.6	15.7	15.1	33.8	9.8	7.6	27.9	20.1	13.2
	Model's Average % Overlap w/Experts	6.1	5.5	1.5	3.7	10.4	18.2	3.1	1.2	8.7	9.9	0.6

WAWO44 TOPOGRAPHIC MAP AND FUEL TREATMENTS

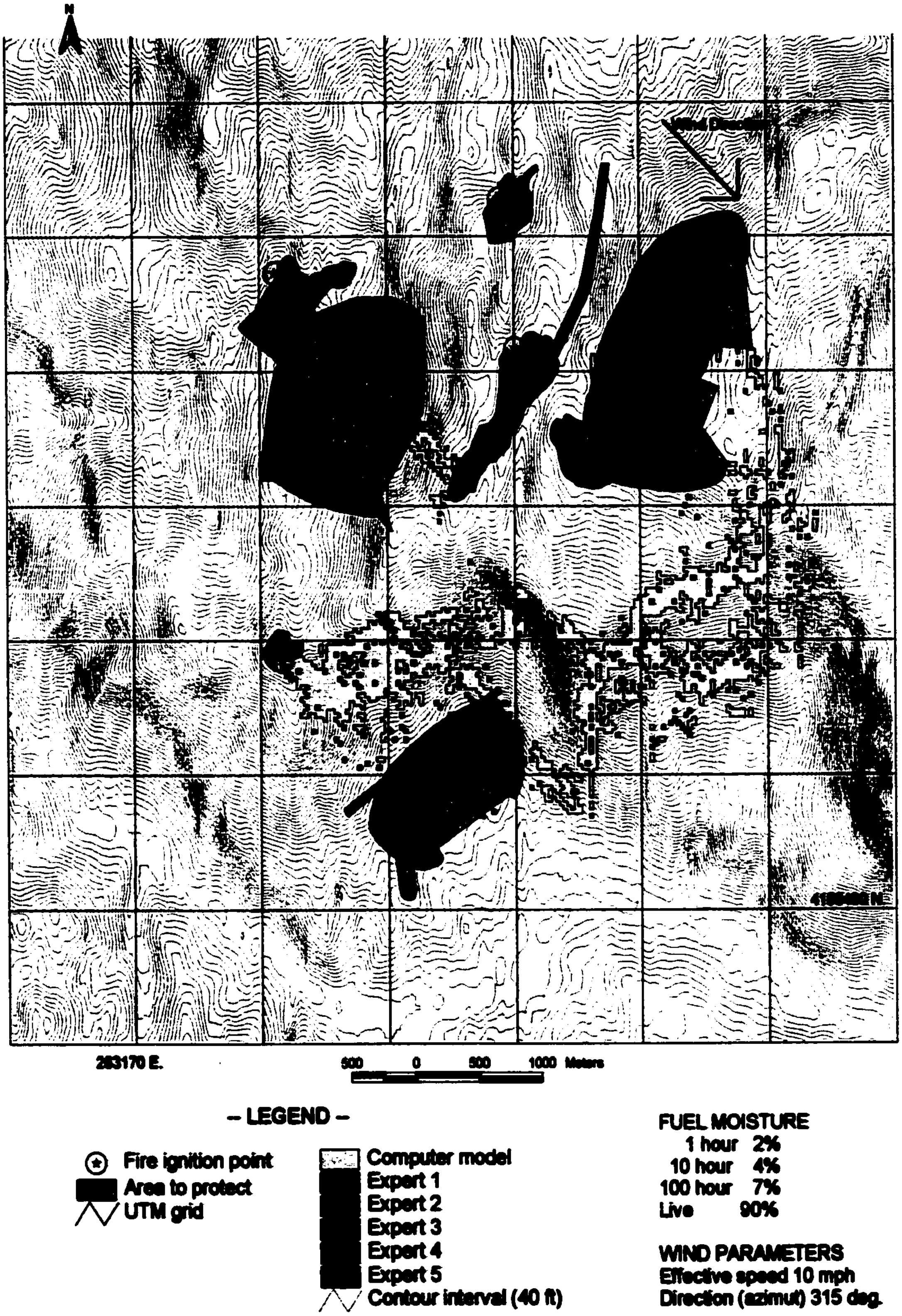


Figure 5. Location of fuel treatment activities defined by fuel managers and the computer model.

Figure 6. Location of fuel treatment activities defined by fuel managers and the computer model.

Overlap between the experts and the model were even lower, ranging from 0% to 20%, and averaging only 5.8%. The model clearly favored the approach of treating areas between the ignition points and the points/areas of value, and visually more dispersed, than the relatively compact areas identified by the experts (Figure 5)

It is worth noting that the solutions generated by the model generally located treatments in areas having fuel types with a potentially high fire spread rate –usually models 5, 14. By treating areas with potentially high rates of fire spread the model generally reduces the risk (increase burning time) by more than if treatment is applied to areas with slower fire spread rates. In general, human experts did not adopt this strategy.

It is also important to note that for a few scenarios the areas defined by the model to receive treatment were highly fragmented, which could prevent practical implementation of the generated solution. This problem could be prevented by modifying the algorithm in a way than a penalty is imposed on prescribing treatment in isolated areas; *i.e.* encourage to model to prescribe fuel treatment in areas adjacent to areas selected formerly to receive treatment. This is an area that requires further investigation.

A standard two-way analysis of variance was carried out to investigate any relationship between the model's and experts' prescriptions overlap, the dependent variable, and two independent variables; the scenario being evaluated and the expert evaluating the scenario. Table 3 shows the results.

Table 3. Analysis of variance on dependent variable percent (%) Overlap

Source	df	MS	*F*-value	*p*-value
Fuel scenario	22	50.53	4.93	<0.0001
Expert	23	17.18	1.68	0.0745

There is a highly significant relationship between the model's and experts' prescriptions overlap and the scenario evaluated (*p*-value less than 0.0001). This finding was expected due that some scenarios are relative easy to prescribe fuel treatments, while other may require much more careful planning to come up with a solution more similar to the one generated by the model. The expert evaluating the scenario had "marginal" significance at the 0.05 level. This also makes sense as more skilled experts might be able to produce more adequate solutions than less skilled managers.

Effectiveness Analysis

Table 4 presents standardized percentage values of burning time (relative fire damage risk reduction) resulting from the fuel prescriptions defined by both experts and the computer model. We defined a benchmark risk reduction percentage equal to 100 for the before treatment burning time value; *i. e.* risk without treatment. All fuel treatment prescriptions were compared against this benchmark condition.

Prescriptions produced by the experts always resulted in lesser burn times than the prescriptions produced by the model. Sometimes these differences were quite dramatic. Some of the experts' prescriptions, especially those for the YOFA22 and YOFA44 scenarios, resulted in burning time values that were 50% or less compared with the model's solution. Only 34% of the fuel management prescriptions defined by experts resulted in effectiveness values 10% or higher relative to benchmark condition (no treatment). The remaining sixty-six percent (66%) of the experts' prescriptions resulted in effectiveness values that were only between zero and 10 percent points above the benchmark values. Only two (2) prescriptions, out of 89 scenarios evaluated (2.2%), experts prescribed a fuel treatment that resulted in an effectiveness value 25% or higher than the benchmark solution (WAWO11, expert 3 and WAWO22, expert 2).

Table 4. Percent of fire risk reduction (burning time) resulting from fuel prescriptions defined by experts and the computer model. The benchmark (100% risk reduction) was defined as the prescription that maximized the after treatment burning time value.

	SCENARIO											
	ACMO11	ACMO22	ACMO33	ACMO44	ELCA11	ELCA22	ELCA33	ELCA44	FARI11	FARI22	FARI33	FARI44
EXPERT 1	104.7	107.1	101.8	102.8	108.8	118.2	100.7	103.0	100.7	102.5	104.1	115.2
EXPERT 2	103.7	103.9	104.8	100.0	121.2	120.0	104.4	107.3	105.0	112.7	112.6	116.0
EXPERT 3	105.1	102.1	106.9	103.8	117.3	124.5	122.4	111.4	111.8	111.3	108.4	115.7
EXPERT 4	107.3	100.1		101.8					109.7		102.2	112.3
EXPERT 5	101.8	100.7										122.5
EXPERTS' AVERAGE	104.5	102.8	104.5	102.1	115.8	120.9	109.2	107.2	106.8	108.8	106.8	116.3
MODEL	155.4	115.9	156.7	168.0	165.4	195.7	135.9	171.1	175.3	161.1	151.9	183.9

	HADO11	HADO22	HADO33	HADO44	WAWO11	WAWO22	WAWO33	WAWO44	YOFA22	YOFA33	YOFA44
EXPERT 1	110.1	111.0	102.3	114.1	122.9	101.3	100.1	106.3	109.5	100.0	100.3
EXPERT 2	102.4	119.1	107.3	102.1	104.9	135.7	112.5	101.3	101.8	104.0	100.0
EXPERT 3	105.8	109.1	100.6	103.6	127.1	113.4	105.2	101.2	118.5	106.6	104.4
EXPERT 4		119.0			107.6	112.8	100.5	100.0	119.2	112.8	
EXPERT 5					111.1		104.6	102.6	121.8		
EXPERTS' AVERAGE	106.1	114.6	103.4	106.6	114.7	124.4	104.6	102.3	114.1	106.3	101.3
MODEL	157.7	150.6	121.8	171.3	168.2	168.5	144.1	162.7	180.8	156.1	170.3

The prescriptions defined by the model produced burn time percentage gains higher than 50% in all but two prescriptions when compared to the benchmark value (100%). Thus, the model's prescriptions reduced the relative measure of fire risk values (burning time) by about 50%. Clearly, the model was consistently able to produce prescriptions resulting in higher burn times than were the experts. This was no doubt due to the spatial management of the model's prescribed fuel treatments.

As with percent overlay, a two-way analysis of variance was carried out to detect any relationship between the effectiveness of the prescription (dependent variable), and fuel scenario and expert as the independent variables. Table 5 below shows the results of the analysis.

Table 5. Analysis of variance on dependent variable Effectiveness of treatment.

Source	df	MS	*F*-value	*p*-value
Fuel scenario	22	193.32	22.52	<0.0001
Expert	23	23.67	2.76	0.0024

Both independent variables, the fuel management scenario considered and the expert making the prescription, were highly significant (*p*-value less than 0.0001) and significant (*p*-value equal to 0.0024), respectively, to predict the effectiveness of the prescription. Again, the results conform with what was expected. The reasoning is that some scenarios are easier to evaluate than scenarios representing complex combinations of areas to protect, ignition points, fuel models, etc.; thus, it is possible to generate highly effective prescriptions when the scenarios are straightforward, but difficult to achieve when the scenarios are convoluted. The same logic applies to the expert variable. More skilled experts produce more effective prescriptions than less skilled experts.

Area Analysis

In nine (9) out of 89 cases evaluated (10.1%), experts prescriptions exceeded the 200 ha maximum area allowed to receive treatment (Table 6). Despite that, as shown in Table 4, these prescriptions proved to be less effective at reducing burning times than the model's prescriptions, which adhered to the 200 ha limit. The model's prescriptions were more effective than the almost 90% of expert prescriptions that failed to treat the 200 ha allowed.

Table 6 shows the percent of area prescribed to receive treatment relative the maximum allowed area. A detailed analysis of its data reveals that more than half (55%) of the experts' evaluations prescribed fuel management plans using only 50% or less of the maximum area allowed. On the other hand, only 29% of the model prescriptions used less than 50% of the area allowed.

Table 7 shows the results of a standard two-way analysis of variance conducted to observe whether a relationship exists between the area used when prescribing a treatment and the scenario being evaluated and/or the expert producing the prescription.

As indicated by the *p*-values, both the fuel scenario and the expert variables were significant at the 0.5 level. This indicates that there is a relationship between these variables and the area used. It is interesting to note that area used variable is very related to the experts prescribing the fuel management plan, and not that much to the fuel scenario evaluated.

Table 6. Percent of area selected to receive fuel treatment in reference to the maximum area allowed to be treated (200 ha).

	SCENARIO											
	ACMO11	ACMO22	ACMO33	ACMO44	ELCA11	ELCA22	ELCA33	ELCA44	FARI11	FARI22	FARI33	FARI44
EXPERT 1	39.0	62.5	35.5	58.5	19.0	16.5	19.0	10.5	10.0	13.0	29.5	58.0
EXPERT 2	37.0	71.0	50.0	17.5	72.0	13.5	17.5	36.0	42.0	55.0	31.5	56.0
EXPERT 3	59.5	60.0	53.0	49.0	118.5	101.5	108.5	90.5	87.5	65.0	43.0	46.0
EXPERT 4	44.0	48.0		93.5		93.5			47.0		22.5	69.5
EXPERT 5	52.0	30.5										52.5
EXPERTS' AVERAGE	46.3	54.4	46.2	54.6	69.8	56.3	48.3	45.7	46.6	44.3	31.6	56.4
MODEL	88.5	97.5	100.0	100	44.0	100.0	15.5	72.5	100	31.0	46.5	37.0

	HADO11	HADO22	HADO33	HADO44	WAWO11	WAWO22	WAWO33	WAWO44	YOFA22	YOFA33	YOFA44
EXPERT 1	111.5	69.0	88.0	63.5	71.5	55.5	38.5	165.5	44.5	0.0	8.0
EXPERT 2	48.5	56.0	63.0	94.0	92.0	157.5	138.5	42.0	12.0	31.0	13.5
EXPERT 3	61.5	42.5	37.5	37.5	101.5	80.0	44.5	37.0	40.0	43.5	80.5
EXPERT 4		60.0			32.5	104.0	65.5	34.0	71.5	83.0	
EXPERT 5					35.5		37.5	46.5	80.0		
EXPERTS' AVERAGE	73.8	56.9	62.8	65.0	66.6	99.3	64.9	65.0	49.6	39.4	34.0
MODEL	100.0	23.0	10.5	81.0	100.0	87.5	100.0	100.0	34.5	35.0	72.0

Table 7. Analysis of variance on dependent variable Area Used.

Source	Df	MS	*F*-value	*p*-value
Fuel scenario	22	923.43	2.01	0.0270
Expert	23	2298.55	5.00	<0.0001

Model execution times

For the scenarios tested, the model required a minimum of 3 hours and up to more than 48 hours to produce a solution. Execution times are influenced by the number of ignition points and points/areas of value, but what most impacted the execution time was the size of the grid (number of columns and rows) used to represent the area of management. Valdez-Lazalde and Dean (In review (a)) describe how the model was optimized to improve performance (using a new variation of anisotropic cost spreading analysis), but the times reported here already include these improvements. It is worth noting that without these improvements the model would be completely impractical – months would be required to produce solutions.

The use of bigger size cell sizes greatly speeds up the optimization model. In an exploratory analysis, cell sizes used for the analysis were increased from 30 to 60 (reducing the number of cells by a factor of four) meters and it was found that the executing time was reduced approximately two orders of magnitude.

CONCLUSIONS

There is little agreement among experts, and even less agreement between experts and the optimization model presented here, regarding optimal prescriptions for wildfire fuel treatment. However, using the objective burn time criterion, there is reason to believe that the prescriptions developed by the optimization model are at least as effective, and may be more so, than the prescriptions developed by experts.

Spatial location of fuel treatment activities varies highly from one expert to another. For most scenarios evaluated the spatial overlap among experts' prescriptions was less than 30%, and in many cases less than 10%. The overlap between experts' prescriptions and the model was even lower; for most of the scenarios the overlap was less than 10%. Despite their spatially different location, most fuel prescriptions defined by experts were on average between 40 and 50% less effective in reducing burn times than the prescription generated by the model. Only in a few cases the effectiveness of managers prescription exceeded by more than 20% the benchmark effectiveness value.

In general, the model appears to provide adequate solutions to the problem of locating fuel treatment activities. However, the issue of fragmented prescriptions needs to be addressed, and practical testing in the field is needed. It is worth noting that, as in many of the models used to plan natural resource management activities, this model as currently stands, was not designed to fully substitute the decision making process carried out by fuel managers, but to serve as an aid to facilitate it.

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SUMMARY AND CONCLUSIONS

The model proposed represents one of the first and innovative spatially explicit approaches to optimally locate forest fuel management activities under budgetary constraints. It incorporates existing fire spreading concepts and tools; spatially explicit information on forest fuel types, topography, and weather-related information to generate a near-optimal solution to the problem posed. The model finds a solution through a highly iterative heuristic algorithm based on the GIS-based principles of anisotropic cost spreading.

One of the first problems encountered when implementing the model was that it required long periods of time to find a near-optimal solution due to its highly iterative nature when building the fire spread surfaces. Fortunately, we realized that once an initial fire spread surface was built, many of the subsequent iterations required only minor modifications of it. Thus, we were able to modify and existing algorithm to take advantage of this situation and improve the execution time of the optimization model.

Results from a comparative study to observe the efficiency of the modified algorithm indicated that for most cases analyzed, the modified spread cost algorithm produced results much more quickly than did the conventional algorithm. Only in a small percentage of the cases the modified algorithm produced results that were at least as fast or slightly slower than the standard procedure. This was possible because the time needed for reconstructing the cost spreading surfaces included the time required to identify the cells that ultimately will be recalculated.

The model was implemented as a series of computer programs written in the C programming language and the ARCINFO AML scripting language. We validated the model by comparing the spatial distribution, efficiency, and size of the model generated fuel treatment solutions with solutions defined by fuel managers working in the field.

Surprisingly, the spatial location of fuel treatment activities highly varied from one expert to another and with respect to the model generated solutions. For most scenarios evaluated, the spatial overlap among experts prescriptions was less than 30% and in many cases less than 10%. The overlap between experts' prescriptions and the model was even lower; most of the times, less than 10%. Most fuel prescriptions defined by experts resulted 50% or less effictive than the prescription generated by the model. Only in a few cases the effectiveness of managers prescriptions exceeded by 20% or more the effectiveness value of the benchmark condition *e. i.* the before-treatment burning time value. For all the scenarios evaluated, the computer model generated the most efficient solutions by maximizing the burning time criterion.

Regarding area used, 55% of the experts' prescriptions used approximately 50% of the maximum area allowed. However, in a few cases they exceeded a 200 ha limit. The model's prescriptions ranged from only 10.5% of the maximum area allowed and up to 100% in eight out of 23 different scenarios evaluated.

Experts' solutions can be grouped in three different types according to the general location of the fuel treatment activities with reference to the fire ignition points and areas of value. Some experts tended to treat areas close or in areas with a high potential for fire ignition, *i.e.*, close to the fire ignition points. A second group prescribed fuel activities somewhere in the middle between the ignition points and the areas to protect. A last group located most of the treatments around the areas to protect.

Readers must be aware that the model uses a great deal of spatial data layers and scalar information to characterize fuel type, fuel moisture; topography and wind related conditions, which invariably contain errors. Consequently, there is an error propagation throughout the modeling procedure.

Finally, we must emphasize that the proposed model is intended as the basis for a decision *support* system to prescribe the placement of fuel management alternatives, and not as a system that provides absolute and definitive solutions to it. As most systems, the one proposed here greatly borrows from other scientific fields to provide the best possible solution to a practical problem. In the measure that these related fields advance and provide with more accurate inputs and faster computer processors become available, the model will provide much better and faster solutions.

Experienced managers must use all their expertise, common sense, and knowledge of the phenomenon under scrutiny to decide if the solution provided by the model should be completely, partially, or not at all considered for practical implementation. Building a model is a continuous task that leaves margin for changes as long as better or new knowledge is obtained on any of the factors influencing the system being modeled.

The following areas are open for further research to refine the model. (1) Temporal and spatial wind information. As it stands, the model takes inputs on wind speed and direction that remain constant during the optimization procedure. A more realistic condition would allow these inputs to vary, temporally and spatially, during the optimization. (2) Incorporation of access facilities into the landscape representation. Roads and rivers are important to consider because they act as barriers to control fire. However, using 30-meter-wide cells to represent a road may be an exaggeration of real conditions. Not including roads within the model provides conservative prescriptions of the fuel treatments. Only further research will show the effect and feasibility of including these type of features as part of the models inputs to obtain better fuel treatment prescriptions.

APPENDIX 1.

INSTRUCTIONS FOR DEFINING AREAS TO TREAT

Thank you very much for participating in the Colorado State University/Joint Fire Science Program wildfire fuel treatment model validation study! Without your help, we could not develop this model.

The wildfire fuel treatment model (WFTM) is intended to help managers decide where are the best places to conduct fuel treatment operations (like controlled burning, mechanical thinning, and so on), subject to a limited budget. The central assumption of the model is that given fuel loading, topographic relief, and average weather conditions we can predict the approximate path and rate of spread of a wildfire from an ignition point to any other point on a map. The model uses this assumption to predict the path and the time required for a wildfire to spread from an ignition point to one or more *points of value* - places that we'd like to protect from wildfire (a place of value could be a housing development, a sensitive environmental area, an archeological site, and so on). The model uses this predicted path and spread time to find where fuel treatment operations can be placed to maximize the amount of time it takes for a wildfire to spread from the ignition point to the point of value.

Included in this mailing are a set of maps that define four (4) different fuel treatment scenarios. Each scenario is described on two maps – a colorful "Fuels Map" and a less colorful "Topographic Map." You should have exactly four Topographic Maps (one for each scenario), but you may have less than four Fuels Maps (you might have less than four Fuels Maps because one Fuels Map may apply to two or more of the topographic maps). You'll know which Fuels Maps go with which Topographic Map by comparing the titles shown at the top of each map. Each title begins with a four-letter code that identifies which Fuels Map goes with each Topographic Map. There are six possible codes – ELCA, ACMO, WAWO, HADO, YOFA and FARI. Thus, a Fuels Map with the code ELCA in its title can be matched up with any Topographic Map whose title includes the ELCA code. Note that in addition to the four letter codes, the titles shown on the Topographic Maps also include a two-digit identifier; you can simply ignore these identifiers. Thus, the Fuels Map with ELCA in its title can be paired up with a Topographic Map with ELCA11 in its title to describe one scenario. The same Fuels Map can be paired up with a second topographic map with ELCA22 in its title to describe a second scenario, and so on.

For each scenario, the Fuels Map shows the NFFL fuel models for the existing fuels throughout the region covered by the map. These fuels models are described in the attached table. The Topographic Map shows the terrain, the assumed wildfire ignition points, the points of value to be protected from wildfire, the typical wind speed and direction throughout the region, and fuel moisture levels. Please assume equal moisture levels (as indicated on the legend of each topographic map) for all fuel models shown on the Fuels Map. For instance, if the Topographic Map indicates that the moisture level for the 1 hour fuel type is 3%, assume that the 1 hour fuels of *all* of the fuel models shown on the Fuels Map have moisture levels of 3%. If a given fuel model does not have a 1 hour fuel component (*e.g.* model 1), ignore the 1 hour moisture level for that fuel model.

What we would like you to do is for each of the four scenarios included in this mailing, mark on the Topographic Map where you would conduct fuel treatment operations designed to protect the points of value from wildfire igniting at the indicated ignition points, given the fuels, topography, wind conditions and moisture levels shown on the maps. Assume that your fuel treatment operations remove 50% of the fuel present on a site. Furthermore, your budget only allows you to treat a maximum of 494 acres of land (494 acres is 5.5 square inches on these maps, or the area of two of the large grid cells shown on the Topographic Maps). Note that while you are limited to a maximum of 494 total acres, you can distribute these acres any way you'd like – you can treat a few acres in one spot, a lot of acres in another spot, and additional acres in a third spot. However, the total area of *all* of the treatments you conduct for any given scenario cannot exceed 494 acres. Furthermore, you do not *have* to treat 494 acres – you can treat less if you feel doing so is justified.

Mark on each of the topographic maps where you would conduct your fuel treatment operations. Once you have completed marking the Topographic Maps, replace them in the mailing tube. Place the enclosed return mailing label on the tube (covering up the current label with your name and address on it) and place it in the mail. The tube will be returned to us for analysis, and Colorado State University will cover all mailing costs.

We cannot thank you enough for your time and effort, and we sincerely hope that you do not find this review too burdensome. If you would like a copy of the results of this project, we will be happy to send you one as soon as we complete our analysis. To receive a copy of the results, please fill out and include in your return mailing the enclosed "Send me a copy of the results" card. Thank you once again, and if we can answer any questions you might have, please do not hesitate to contact us.

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Table 1. Description of NFFL and custom fuel models used in fire behavior (Rothermel, 1983 with minor modifications)[1].

Fuel Model (Shown in Fuels Map)	Typical Fuel Complex	Fuel Loading				Fuel Bed Depth	Moisture of Extinction Dead Fuels
		1 hr	10 hr	100 hr	Live		
	Grass and Grass-Dominated	*Tons/acre*				*Feet*	*Percent*
1	Short grass (1 ft)	0.74				1.0	12
2	Timber (grass and understory)	2.0	1.0	0.50	0.50	1.0	15
3	Tall grass (2.5 ft)	3.0				2.5	25
	Chaparral and Shrub Fields						
4	Chaparral (6 ft)	5.0	4.0	2.0	5.0	6.0	20
5	Brush (2 ft)	1.0	0.50		2.0	2.0	20
6	Dormant brush, hardwood slash	1.5	2.5	2.0		2.5	25
7	Southern rough	1.1	1.9	1.5	0.37	2.5	40
	Timber Litter						
8	Closed timber litter	1.5	1.0	2.5		0.2	30
9	Hardwood litter	2.9	0.41	0.15		0.2	25
10	Timber (litter and understory)	3.0	2.0	5.0	2.0	1.0	25
	Slash						
11	Light logging slash	1.5	4.5	5.5		1.0	15
12	Medium logging slash	4.0	14.0	16.5		2.3	20
13	Heavy logging slash	7.0	23.0	28.0		3.0	25
	Custom fuel models						
14	Model 5 modified	3.0				0.5	50
15	Model 9 modified	3.0	0.4	0.15		0.5	25
99	No fuel (rocks, bare soil, etc).						

[1] Rothermel, R. C. 1983. How to predict the spread and intensity of forest and range fires. USDA, For. Serv. GTR-INT-143.

APPENDIX 2.

MODEL ASSUMPTIONS

1. Rothermel's model limitations (Rothermel 1972).

2. Fire spread directions. Only eight potential fire propagation directions are considered when simulating fire spread. Obviously real fire events are not restricted to eight spread directions, however, incorporating more spread options will considerably slow down the computing performance of the model without much gain in modeling realism. Theoretically, there is no reason why this assumption could not be relaxed to consider more spread directions.

3. Fuel models. Fuel models distribution are considered to be continuous and invariable within pixels -- only between pixel variations are allowed. This is an over simplification of real conditions because small variations in topography and vegetation influence changes in the fuels distribution and consequently in fire spreading. The same limitation applies for all other raster maps or spatial data bases handled by the model (DEM, fuel moisture, etc.). These limitations can be relaxed by changing the resolution (pixel size) of the raster maps containing fuel. However, it would be an extremely expensive and time consuming task to accomplish. Besides, it would require that all other spatial data layers entered into the model had the same resolution. The use of very large scale raster maps (for instance 5m x 5m or 1m x 1m grids) would further limit the model in two ways: 1) by increasing the amount of data to be handled by the model, and 2) by dramatically slowing down the processing operations required to implement the optimization model. As better spatial resolution data layers are built, and fastest computing processors become available this limitation will be overcome if it proves to enhance the model's representability.

4. Wind speed and direction temporal and spatial continuity. Wind speed and direction are considered to be temporarily and spatially constant (within a pixel) during the whole model simulation process. This is perhaps the most restricting limitation of the model. To overcome it, careful thinking and additional computer code will be needed. Fortunately, because the model simulates fire spread rates under extreme or severe wind conditions, it is expected that it will provide with reliable estimations. Without doubt, this limitation will is an open area of research for future improvements to the model.

5. Ignition points definition. Potential wildfire ignition points are defined by forest managers with certain degree of accuracy. As was the case for all other inputs to the model, the accuracy involved in ignition points predictions will largely influence the applicability of the solutions derived from the model's optimization process.

6. Fuel treatment effectiveness. It is assumed that the effectiveness (reduction in fire spread rate) and cost of applying a given fuel treatment to an area are known and accurate.

7. All points of value are equally important.