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BROAD AREA FOREST FUELS AND TOPOGRAPHY MAPPING USING DIGITAL LANDSAT AND TERRAIN DATA

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I. ABSTRACT

A spatially registered digital data base of fuels and terrain information was generated for a test site on the Lolo National Forest in Montana. The data base was developed specifically for providing spatially relevant data to a mathematical fire behavior model developed by the Forest Service which integrates this information along with current weather data to produce realistic estimates of probable fire behavior.

Methodologies for the processing and analysis of Landsat MSS and digital terrain data for the mapping of U.S. Forest Service fuel types were developed and demonstrated. Key elements in the mapping process were the development of a fuels-terrain distribution model which provided a statistical description of the topographic distribution patterns of fuels within spectral classes, and secondly, the application of a layered classifier which incorporated the spectral and terrain data in a two-stage maximum likelihood classification framework for the mapping of fuels.

I. INTRODUCTION

Recent legislation, and advances in fire management technology, have altered policies governing forest and rangeland fire management strategies. New policies direct fire managers to develop alternative fire management plans for both planned and unplanned ignitions. Consequently, U.S. Forest Service fire managers require an accurate and consistent method to predict the behavior of forest and rangeland fires. Typical applications range from broad scale planning for National Forests, to real-time site-specific estimates of probable fire behavior. The parameters relevant to this task can be grouped into the broad categories of fuel types, weather, and topography. A mathematical fire model has been developed which integrates this diverse information and provides realistic fire behavior estimates for the myriad of fuels, weather and topographic situations that occur throughout the United States.[12,1]

At present, fuels and topographic data for fire behavior predictions are available on most National Forests at either very low or very high resolution levels. For example, in most fire planning applications the minimum mapping unit for fuels information is on the order of 4,000 hectares or more, and a single slope value is generally selected to represent the topographic relief of the entire planning unit. However, for site-specific situations, a fire manager often makes fuel assessments for areas of 4 to 40 hectares, and he estimates slope to within a few percent. Little mapping capability currently exists between these two extremes due to a lack of site specific information.

The process developed in this study, in which Landsat and terrain data have been merged for the generation of fuel model maps and a digital topographic data base provides a potential tool for bridging this information gap. The resulting fuel and topographic data base offers considerable flexibility in fire planning efforts from the regional level, which may cover several states, to ranger districts which are about the size of counties. For example, Forest Service fire policy currently makes no attempt to suppress fires resulting from lightning or accidental man-caused fires if a fire management plan has been established for the area and if conditions at the time of fire satisfy rigid pre-set specifications. The fire manager's capacity to monitor such fires and make decisions concerning suppression requirements could be aided significantly if he could simulate the expected fire behavior. The output from such simulations could include estimates of fire growth and summaries of probable spread rates and intensities.

The project described in this paper was carried out as a cooperative demonstration project between the U.S. Forest Service's Northern Forest Fire Laboratory (NFFL) in Missoula, Montana, and U.S. Geological Survey's EROS Data Center in Sioux Falls, South Dakota. The principal objective was to develop vegetation mapping techniques utilizing Landsat data to better define the location and extent of fuel types, over the broad areas of terrain addressed by fire danger rating and planning. This paper discusses how Landsat multispectral scanner data and U.S. Geological Survey digital elevation model (DEM) topographic data were utilized to produce a digital data base containing spatially registered forest fuels and terrain information, and suggests how the data base could be combined with the mathematical fire model to analyze wildland fire potential at various levels of resolution.

II. STUDY SITE AND DATA DESCRIPTION

A. STUDY SITE DESCRIPTION

The Lolo Creek study area (1,180-km^2), located in the Lolo National Forest in Western Montana, was a site for which the digital fuels and terrain data base was developed. This area, in the Northern Rocky Mountains, was selected because of the diversity of vegetation types, mountainous terrain, and the availability of high resolution digital terrain data.

The Bitteroot mountains are the dominant physical landscape feature with elevation ranging from 910 meters (3,000 feet) along Lolo Creek in the center of the study area to over 2,800 meters (9,200 feet) at Lolo Point on the southern boundary. The Idaho and Boulder Batholiths are the principle geologic formations which make up the range; their composition is predominantly granitic with inclusions of gneiss and schist. Forest soils of the area are quite rocky, reflective of the mountainous setting, with Cryaborolls, Cryandepts and Cryochrepts being the major great groups represented.

The climate may be generally characterized as a relatively mild inland type, strongly influenced by moisture-laden air masses which move in from the North Pacific. Mild cloudy weather characteristically prevails with 50-66 centimeters of precipitation evenly distributed throughout the year with the exception of July and August which are relatively dry months. Within this generalized weather pattern, however, strong modifications occur locally due to the mountainous terrain. As elevation increases, the mean annual air temperature decreases and precipitation increases. North and south exposures experience differing levels of solar insolation, snow accumulation and soil development. These macro- and microclimatic influences of the terrain are quite strongly reflected in the distribution of the different plant communities found within the region.

The vegetation of the study area is characterized by an abundance of the intermountain forest species. Principle tree species represented include ponderosa pine (Pinus ponderosa), Douglas fir (Psuedotsuga menziesii), western larch (Larix occidentalis), subalpine fir (Abies lasiocarpa), lodgepole pine (Pinus contorta), grand fir (Abies grandis), and englemann spruce (Picea engelmanii). Figure 1 provides a generalized description of the distribution of the species over an altitudinal gradient. In the valleys moisture becomes a limiting factor for the coniferous communities and grasslands typically comprised of Agropyron spicatum, Festuca idahoensis and Festuca scabrella associations occur.

B. FOREST FIRE FUEL CLASSES

The classification system (mapping framework) which was utilized in this study, is based on a fire manager's need for information which describes wildland fuels in a meaningful way. The classes mapped in this study were intended to be representative of stylized fuel models. These fuel models, or classes, provide a quantitative description of a general vegetation type (fuel quantity, particle size, and fuel bed depth) which can be used in the mathematical fire model to calculate how that vegetation type will burn under various environmental conditions. The fuel classes are stylized in the sense that a limited number have been developed to describe the average fuel characteristics of major vegetation types throughout the United States.

Stylized fuel classes represent a compromise to the detailed and expensive "on the ground" inventory work necessary to fully determine the fuel characteristics at a specific location. The six fuel classes mapped in this project (Table 1) were taken from the set of 20 stylized fuel classes developed for the 1978 National Fire Danger Rating System (NFDRS).[4] Figure 2 illustrates some of the fire behavior characteristics for the stylized fuel classes used in this study.

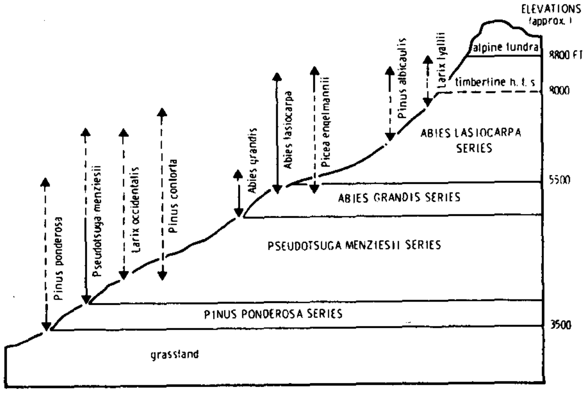

Figure 1. Distribtion of tree species in west-central Montana. Arrows show the relative elevational range of each species; solid portion of the arrow indicates where a species is the potential climax and dashed portion shows where it is seral.[10]

Table 1. Forest fuel classes identified in the Montana fuel mapping project and other mapped classes.[4]

Class (Model) L - Western grasslands dominated by perennial grasses.

Class (Model) T - Sagebrush-grass types of the Intermountain West.

Class (Model) C - Open stands of pine, principally Ponderosa.

Class (Model) H - Healthy stands of short needle conifers (moderate amounts of dead and down material).

Class (Model) G - Decadent stands of short needle conifers (heavy amounts of dead and down material).

Class (Model) J - Clearcuts and thinned conifer stands.

Barren - Non-vegetated sites such as rock outcroppings and snow fields.

Agriculture - Crop land and irrigated pasture.

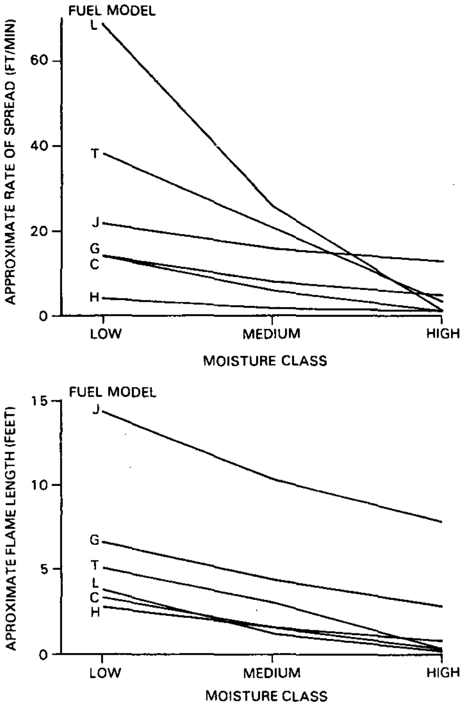

Figure 2. Fire behavior characteristics of the stylized fuel model classes mapped, at three general levels of fuel moisture.

C. LANDSAT, TOPOGRAPHIC AND SUPPORT DATA

The digital image analysis, processing, and interpretation work performed in this project was done on the Interactive Digital Image Manipulation System (IDIMS) at the EROS Data Center (EDC). IDIMS is a multiple user system which supports both interactive and batch processing of a wide variety of image data. Statistical analysis of field data and the generation of map output products was performed on a Burroughs/6700 mainframe system.

The Landsat MSS data used in this project came from portions of two scenes (Frame No. 1720-17493 and Frame No. 1720-17495, both obtained on July 13, 1974). Geometric correction of the Landsat data to a 60 meter universal transverse mercator (UTM) grid projection resulted from selecting and digitizing control points, calculating a geometric transformation equation, and applying the equation to the Landsat data. Following registration of a mosaicked subscene, data covering the project area was extracted and mosaicked together to produce one data set, 512 by 512 pixels (1,180-km) in size.

Two forms of digital elevation data were used in the project to provide coverage for the entire 512 by 512 project area. Digital elevation model (DEM) data and Defense Mapping Agency (DMA) digital terrain data was acquired from the National Cartographic Information Center in Reston, Virginia. DEM terrain data is a byproduct of the USGS orthophoto mapping program which transforms photo coordinates into model coordinates through automatic correlation by the Gestalt Photo Mapper II. The coordinate values stored on magnetic tapes, are digital representations of terrain elevations. Each file consists of a sampled array of elevations located at 30-meter intervals within a standard 7.5 minute quadrangle. For this study, thirteen 7.5 minute quadrangles were obtained and mosaicked together using coordinate information provided on the tapes. This mosaic, which provided coverage for approximately eighty-five percent of the study area, was registered and resampled to fit the same 60-meter UTM projection established as the reference plane for the Landsat MSS data.

The DMA terrain data, which was used to fill in a small portion in the northwestern corner of the project area for which DEM data was not available, results from manually digitizing contour lines of 1:250,000 scale U.S.G.S. maps having contour intervals of 61 meters. The resulting digital elevation tape which comes in a grid cell format, has a cell size of 63.5 meters square. These data were registered and resampled to fit the 60 meter UTM projection. The block of data necessary to fill in the corner was extracted and then mosaicked with the registered DEM terrain files.

From the registered digital DEM-DMA elevation data, slope and aspect information were calculated on a pixel by pixel basis for use in the fire fuels classification and also to serve as input to the fire simulation model. Slope is output as percent slope and aspect is output in two degree increments from 0 to 180 where 0 and 180 are due north and 90 is due south. The elevation, slope and aspect data were then merged with the four Landsat channels to produce a seven band data file.

The support data used in this project consisted of 7.5 minute U.S.G.S. topographic maps, color aerial photography (1:15,840 scale), color infrared aerial photography (1:120,000 scale) and ground acquired field data for eighteen sample blocks (30x30 pixels). Topographic maps were used to select control points for registration of Landsat and terrain data. The color aerial photography was used for the delineation of vegetation units within eighteen (30x30 pixel) sample blocks and the subsequent estimation of parameters relating to vegetative cover for those units. NASA high altitude color infrared aerial photography was used to select sample blocks for the development of spectral classes and for orientation during the gathering of field data and in the accuracy assessment. Field data for the sample blocks was acquired in August, 1979 to provide on the ground forest fire fuels information and to verify the photointerpreted data.

The field and photo data gathered for each of the sample blocks was added to the existing Landsat-terrain data base. Thus, for every pixel in each 30 by 30 block, information was available pertaining to percent cover, species composition and fuel type as well as the seven bands of spectral and terrain data. Table 2 presents the 23 variable file which existed for each of the 16,200 cases comprising the 18 sample blocks. This information was used to examine the relationship between spectral classes and fuel classes, and to develop the fuels-terrain distribution models used in the classification process.

Table 2. 27 variable file used in labeling spectral classes and developing the vegetation-terrain distribution model (16,200 cases).

Variable Number	Variable Description
1	Stand number
2	Cover class
3	Dominant tree species
4	Fuel model
5	% Ponderosa pine
6	% Western larch
7	% Subalpine fir
8	% Lodgepole pine
9	% Engelmann spruce
10	% Subalpine fir
11	% Other
12	% Barren
13	% Grass
14	% Shrub
15	% Forest
16	MSS Band 4
17	MSS Band 5
18	MSS Band 6
19	MSS Band 7
20	Elevation
21	Slope
22	Aspect
23	Sun angle

III. METHODOLOGY

A. OVERVIEW

The digital analysis techniques used to map the fuel classes utilized both Landsat multispectral data and digital terrain data in a two-layered maximum likelihood classification framework. A generalized flowchart of the classification process is displayed in Figure 3. The first level of the layered classifier involved classification of the four bands of Landsat MSS data into 48 spectral classes using controlled clustering techniques.[11,6] Within spectral classes identified as representing more than one fuel model, based on analysis of the field data, a second classification was performed on a four variable terrain image. At this level, each spectral class was handled as an individual data set where terrain data was used to assign individual pixels to fuel classes. The development of a fuel class - terrain distribution model, for each spectral class, in which the topographic distributions of the individual fuel classes were quantitatively defined was the key to incorporating the terrain information as an ancillary data source.

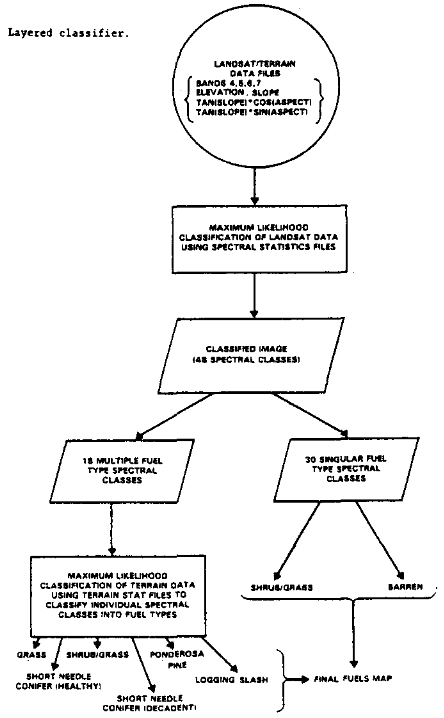

Figure 3. Layered classifier.

The layered spectral terrain classification procedure developed for mapping fuel models, outlined above, consisted of four principle steps:

1) controlled clustering of the 18 sample blocks (30 by 30 pixels) to derive spectral classes and associated statistics (mean and covariance matrices).

2) statistical analysis of spectral classes to determine their relationship to the fuel models.

3) identification and modeling of fuel model - terrain relationships for spectral classes through stepwise discriminant analysis.

4) the maximum likelihood layered classification of the Landsat and terrain data channels into fuel models.

B. DETAILED DESCRIPTION OF METHODOLOGY

1. Controlled Clustering of Landsat MSS Data. The approach used to derive spectral training classes from the Landsat data is a procedure well documented in recent literature and is commonly referred to as controlled or modified clustering. From a visual examination of the Landsat data, and small scale color infrared photography, 18 sample blocks (30 pixels by 30 pixels square) were selected. The blocks were chosen to incorporate the full range of variation in spectral reflectance values and vegetation types present in the study area as well as the variation in the physical terrain. The four bands of Landsat data for each of the 18 blocks were then extracted and mosaicked into a single data set and a clustering algorithm applied for the purpose of grouping pixels into relatively homogeneous spectral classes.

From the iterative clustering process 48 spectral classes were identified. The results of clustering provided the spectral training statistics in the form of mean and covariance matrices for classification of the spectral data for the entire project area.

2. Spectral Class - Fuel Model Relationships. Relationships between spectral classes and fuel model classes for the pixels in the sample block data set were examined using a contingency table shown in table 3. It was apparent that a number of the spectral classes were representing more than one fuel class, and that individual fuel classes were occurring in several spectral classes. This was particularly true for the larger spectral classes.

Based on the contingency table analysis, the decision was made to assign 30 of the spectral classes directly to either a single fuel model (model-T, grass/shrub) or to the barren class developed to account for rock outcroppings, snow and other non-vegetated cover types. All of the 30 spectral classes were relatively small and accounted for only 15 percent of the pixels in the sample block data set. For the remaining 18 multiple fuel class spectral classes terrain was utilized in combination with the spectral classification results an attempt to more accurately identify and map fuel classes.

Table 3. Fuel Model - Spectral Class Contingency Table for the 18 Cluster Blocks. (Field Data Only)

Spectral Class	L	T	C	H	G	J	Non-fuel Model Type	Total
1	0	0	0	0	0	0	54	54
2	9	30	112	65	5	0	0	221
3	1	14	0	0	0	0	16	31
4	0	16	26	637	43	0	0	722
5	0	0	0	0	0	0	42	42
6	38	76	187	122	34	77	0	534
7	4	13	5	5	5	9	0	41
8	5	4	11	700	125	3	0	848
9	0	0	0	0	0	0	40	40
10	16	44	230	219	14	0	0	523
11	6	48	13	31	12	9	0	119
12	11	55	89	460	30	5	0	650
13	33	72	104	80	7	22	0	318
14	0	5	14	701	81	1	0	802
15	0	0	0	0	0	0	44	44
16	2	37	4	3	7	0	0	53
17	0	0	0	0	0	1	42	43
18	43	67	160	216	57	62	0	605
19	7	8	6	0	6	11	58	96
20	0	0	0	0	0	0	36	36
21	13	47	26	19	2	0	0	107
22	0	0	0	0	0	0	34	34
23	1	2	0	0	3	1	37	44
24	0	1	0	0	0	0	60	61
25	54	28	56	50	18	35	0	241
26	6	32	28	20	13	100	0	199
27	0	0	0	0	0	0	40	40
28	0	7	8	425	73	0	0	513
29	6	39	3	8	0	0	0	56
30	26	34	83	37	29	140	0	349
31	0	4	0	0	0	0	34	39
32	0	1	0	0	0	0	31	32
33	0	20	5	4	5	0	44	78
34	0	0	0	0	0	0	31	31
35	6	4	10	5	4	9	42	80
36	0	26	0	1	1	0	0	28
37	0	0	0	2	0	0	55	57
38	4	0	0	0	0	0	41	45
39	1	0	1	0	0	0	44	47
40	16	28	101	302	77	46	0	570
41	0	0	0	0	0	0	44	45
42	1	0	4	0	2	0	50	57
43	0	0	2	149	56	0	0	207
44	5	4	31	199	36	5	0	280
45	0	0	0	0	0	3	62	65
46	4	33	0	7	0	0	0	44
47	0	5	1	1	2	0	53	65
48	0	0	0	0	0	0	34	34

3. Statistically Defining Fuel Model - Terrain Relationships. The objective of this phase was to identify a means for quantifying relationships between variables of terrain and fuel classes in such a way that this information could be incorporated into the classification process. The concept of incorporating terrain data into the Landsat classification process as a means for improving classification results has been previously documented.[6,14,15] Fleming in Colorado, and Straehler in California, demonstrated the use of regression analysis, discriminant analysis and logistic response functions as means for quantitatively characterizing the topographic distribution of vegetation types. Much of their work was predicted by ecological studies which have proven that topographic position in mountainous environments directly and indirectly influences the distribution of plant species and plant communities. The mosaic of vegetation patterns which are found are determined largely by factors of macroclimate, microclimate, soil fertility and soil drainage for which the variability within an area such as this study site is largely a function

of topographic position.[3] While zonation patterns have been examined and defined for species and habitat types in the Intermountain region, little or no research has been done on the distribution patterns of U.S.F.S. National Fire Danger Rating System fuel classes. Thus two points were addressed by this phase of the project. First, was to determine whether or not the spatial distribution patterns displayed by the fuel classes could be related to variables of terrain. Secondly, was to develop statistical descriptions of these relationships so that the probability for a given fuel model occurring at any given elevation, slope or aspect, could be determined. These descriptions were provided in a form that could be incorporated into the classification process as training statistics for the maximum likelihood classifier.

The objective of this phase was to statistically distinguish between fuel types on the basis of terrain variables for the purpose of classifying pixels in an optimal manner. Stepwise discriminant analysis was employed to accomplish this objective. In general, discriminant analysis was used to determine how separable groups were based on observations made in the field for the sample block pixels. More specifically the objective was to identify discriminating terrain variables, which when weighted and combined in an optimal manner, forced the fuel classes to be as statistically separable as possible. From the discriminant analysis classification results for pixels for whom the fuel class assignment was known, estimates of the probability of a correct classification for unknown cases were obtained. The fuel type-terrain relationships discriminant analysis thus provided:

1) the means for identifying terrain variables which would aid in the discrimination between fuel types within spectral classes.

2) classification results which estimated the potential classification accuracies to be anticipated from a maximum likelihood classification of the terrain data set for the entire project area.

The specific discriminant analysis routine employed is a component of in the Statistical Package[9] for the Social Sciences (SPSS) software. Options available in the SPSS discriminant analysis procedure which were utilized included the stepwise selection and entry of variables from a list of potential variables based on user supplied criterion and the use of individual group covariance matrices for the classification portion of the analysis.

From numerous iterations of the discriminant procedure performed on each of the 18 multiple fuel class spectral classes involving different transformations and combinations of terrain variables, four variables were identified as being consistently useful for distinguishing between fuel types. They were elevation, slope (percent), tangent of the slope times the sine of the aspect, and tangent of the slope times the cosine of the aspect. The two latter variables have been documented as being effective expressions of the influence of aspect and slope on site productivity in the intermountain region.[13] The multivariate F ratios from the first step and the last step of the stepwise entry procedure for each of the four variables for the complex spectral classes are presented in Table 4. This table also presents the discriminant analysis classification results for each of the spectral classes in column five.

In examining this table, it is apparent that elevation was consistently high in significance, dominating in all but three of the spectral classes. The other variables do, however, contribute significantly to the discrimination between fuel models within spectral classes and serve to improve the classification results achieved with the discriminant functions constructed from these variables. Based on the overall classification accuracy of 74.5 percent for all 18 clusters, an acceptable statistical characterization of the fuel classes relative to the terrain data had been obtained. The estimated multivariate normal distributions (mean and covariance matrices) provided by the discriminate analysis were constructed as statistics files for later use in the classification process.

Table 4. Multivariate F - Ratios from stepwise discriminant analysis of fuel models within spectral classes. F's to enter from step 0 are the upper values, F's to remove from the last step are the lower values within each cell of the table.

	Variables				
Spectral Class (Fuel Classes)	Elevation	Slope	TAN (Slope) *COS(Aspect)	TAN (Slope) *SIN(Aspect)	Percent Correctly Classified Within Discriminant Analysis
2-(T,C,H)	39.92 21.99	.52 18.62	32.30 41.32	9.72 19.54	74.24
4-(H,G)	83.89 30.96	39.37 40.17	19.98 4.12	93.94 56.94	87.7
6-(L,T,C,H,G,J)	73.06 72.77	22.64 7.49	22.24 15.59	23.35 6.77	60.1
8-(H,G)	352.81 325.03	50.43 43.77	18.95 8.13	31.43 --	84.9
10-(T,C,H)	43.44 35.12	.95 5.52	69.84 49.82	20.59 21.19	72.3
11-(T,H)	30.28 29.50	.97 9.70	2.08 13.43	12.47 30.50	84.8
12-(T,C,H,G)	54.13 48.81	17.20 11.24	26.44 12.46	33.65 5.48	66.1
13-(L,T,C,H)	12.42 --	2.28 5.57	17.19 19.38	27.88 33.70	59.9
14-(H,G)	127.88 137.78	3.44 12.03	6.91 --	.30 --	78.5
18-(L,T,C,H,G)	151.53 139.15	31.72 5.24	31.33 --	7.23 14.35	50.63
21-(T,C)	24.72 24.59	8.85 8.40	12.04 --	17.12 5.15	83.6
25-(L,C,H,J)	239.50 246.13	25.13 12.53	27.71 16.49	8.26 --	72.3
26-(T,C,J)	80.63 22.76	43.49 12.30	37.01 5.01	3.85 7.70	80.5
28-(H,G)	150.3 158.17	8.81 --	.017 6.18	10.08 --	79.12

Spectral Class (Fuel Classes)	Elevation	Slope	TAN (Slope) *COS(Aspect)	TAN (Slope) *SIN(Aspect)	Percent Correctly Classified Within Discriminant Analysis
	383.63	88.56	69.96	19.79	79.86
30-(C,H,G,J)	266.57	26.50	10.87	7.10	
	201.38	10.31	28.95	31.16	65.4
40-(C,H,G)	198.44	--	21.92	11.16	
	457.23	.05	.22	.80	94.2
43-(H,G)	474.59	--	5.68	--	
	849.23	.89	5.41	7.15	97.3
44-(H,G)	886.61	10.64	4.40	--	
OVERALL					74.5

4. Layered Classifier. The approach used for incorporating terrain data into the classification process has been the development of a fuels terrain distribution model. The terrain model is a quantitative characterization of the topographic distribution of individual forest fuel classes within spectral classes in the form of estimated mean and covariance matrices. The layered classifier provides the mechanism for incorporating this information along with the spectral class statistics directly into the classification process for mapping fuel classes.

The first level of the layered classifier involved the application of a maximum likelihood classification algorithm to the four bands of Landsat data covering the project area. As previously described, the statistics files for this stage were derived from clustering the 18 training blocks which had produced 48 spectral classes. The resulting 48 class image was stratified into two images, one comprised of the 30 simple spectral classes and the other comprised of the 18 complex classes. Each of the thirty simple classes, and their associated pixels (8.7 percent of the area) were assigned to one of the two appropriate mapping classes, fuel class-T (shrub/grass) or barren. The 18 complex classes and their associated pixels (91.3 percent of the area) entered into the second level of the classifier.

Within the second level, each spectral class was handled as an individual data set. The pixels corresponding to one spectral class and their associated terrain values for each of the four bands (VAR1, VAR2, VAR3, VAR4) were extracted and classified into fuel classes independent of the other spectral classes utilizing the terrain model developed specifically for each spectral class. This procedure was repeated for each of the 18 classes and resulting images were merged together with the classified image from the 30 simple spectral classes into one classified image.

The resulting image contained the six fuel classes as well as the barren class representing snow and rock outcroppings. Two small portions of the project area which were known to be agricultural lands (irrigated pasture) were digitized from a base map and entered in as an eighth class in the image. This image was then smoothed by an algorithm which passes a 3 by 3 pixel window through the data and replaces the value of the window's centermost pixel with the value or class most frequently occurring within that window. The objective of this procedure was to remove excessive detail from the final image by approximating a 10-acre minimum mapping unit. To enhance the interpretability of the final fuels map and also add another valuable piece of information to the fire planning process, the principle road network was digitized, registered and merged into the final fuels classification.

III. RESULTS

A. PRODUCTS

The final classification map of fuel classes, barren and agricultural land and roads was merged with the elevation, slope, and aspect data to provide the digital data base necessary for driving the mathematical fire model. In addition to the computer tape upon which this data base resides, numerous film and CALCOMP map products and tabular summaries were generated. These products demonstrated the utility and versatility of the digital data set when linked with some fundamental geoprocessing and graphic display capabilities. Additional output products included a synthetic stereo image pair made by introducing parallax into the eight class image.[2] This proved to be a very useful tool for displaying the impact of terrain on the location and distribution of fuel classes in the final product.

B. ACCURACY ASSESSMENT

To determine the accuracy of the final classification, two assessments of classification accuracy were made. The first entailed comparing the classification results with the field data for the 18 study blocks from which the terrain classification training statistics were derived. The results of this analysis are presented in table 5 where within class and overall accuracies are presented along with a contingency table to identify where confusion was occurring. As shown in the table, the final fuel model images showed agreement 73.2 percent of the time between the field data and the fuel model classification.

Table 5. Contingency table for accuracy assessment of the final classified image versus the field data for the 18 study blocks on a pixel by pixel basis.

	Field Data Fuel Class Assignments								
	L	T	C	H	G	J	Barren	Ag	TOTAL	Percent Correct
L	149	29	56	36	0	0	0	0	270	55.19
T	72	568	99	254	79	77	14	0	1164	48.84
C	12	17	868	179	12	21	10	0	1119	77.57
H	61	131	275	3652	157	164	29	0	4469	81.72
G	7	20	0	348	481	37	1	0	894	53.80
J	0	27	9	9	12	258	0	0	315	81.90
Barren	11	12	8	2	4	12	1021	0	1070	95.42
Ag	6	0	0	0	0	0	0	169	175	96.57
TOTAL	318	804	1315	4480	745	569	1075	169	9476	
OVERALL ACCURACY										73.25 ± 1.21 (t=1.96)

In order to obtain an independent assessment of the accuracy of the total fuel model map, barren and agricultural lands included, a stratified random sample of pixels (205) were allocated among the eight map classes. Individual pixels were randomly selected and plotted with the CALCOMP directly onto 7.5 minute quad mylar overlays. The plotted pixels were then manually transferred to orthophotos covering the project area. The points were then located in the field with a helicopter from which a call was made by a U.S. Forest Service representative without prior knowledge of the predicted class for the point being examined. Overall accuracy from this point by point assessment was estimated to be 68.24 percent with a standard error of 3.63 percent (t = 1.96). No attempt was made to isolate classification errors from potential registration errors. Overall classification accuracy estimates from the two assessments do not appear to differ significantly.

In order to assess the impact of incorporating the terrain data as an ancillary data source for mapping fuel models an estimate of classification accuracy for a classified image generated without terrain data was obtained. The six fuel models and the barren and agricultural classes were assigned to spectral classes based on plurality from contingency table analysis of the field data. The 187 points of data obtained in the helicopter assessment of classification accuracy were used to estimate the accuracy of this map product. Overall accuracy was estimated to be 52.25 percent with a standard error of 5.3 (t = 1.96). Improvements in classification accuracy achieved through the layered classification process was an increase of 16 percent.

IV. THE USE OF DIGITAL TOPOGRAPHY AND FUEL INFORMATION IN MODELING FIRE POTENTIAL

Successful linkage of terrain and fuels data, with the mathematical fire model, will provide a simulation tool for broadscale fire planning, monitoring of active wildland fires, assessing damage potential of incipient fires, and a variety of other fire management activities. By entering this data into the mathematical fire model to simulate wildland fires, and varying other input variables such as meterological data from other sources, a wide range of fire behavior patterns and planning regimes can be generated and evaluated. Figure 4 illustrates that flow of the data base information in the fire modeling process.

The role of topographic data in the fire modeling process serves two other functions in addition to its use in mapping fuel classes. The first is in extrapolating fuel moistures over large areas. Fuel moistures are an extremely important parameter in fire modeling as weather measurements are available only from widely scattered locations, typically near towns, forest ranger headquarters, or remote automatic weather stations. Moisture content estimates for live and dead vegetation are a function of antecedent weather; therefore quality moisture calculations can be produced only for weather station locations. Slope, elevation, and aspect are three important variables used in an algorithm for extrapolating fuel moistures from one location to another. Topography, in the form of slope steepness, also enters directly into calculation of flame lengths and forward rate of fire spread. The magnitude of the effect of slope depends on fuel type and moisture content.

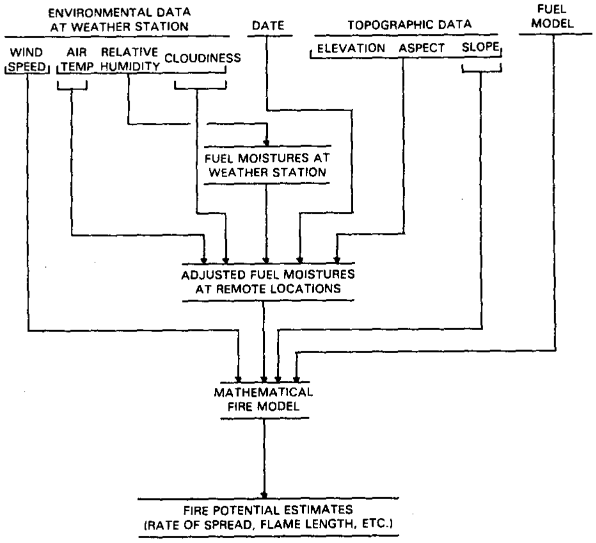

Figure 4. Information flow in mathematical modeling of fire potential.

In addition to contributions to fire management and planning, a spatially defined digital data base of fuels and topographic data shows great potential for enhancing the capability of a lightning detection system adapted by the Bureau of Land Management (BLM), and now being tested by the BLM and the U.S. Forest Service. This lightning detection system can identify and locate cloud to ground lightning discharges. To assess the probability that a fire was actually started, and its potential behavior, however, requires information about the fuel type, moisture context, and terrain characteristics. By interfacing the detection system with the fuels and topographic data base, such point specific estimates could be provided.

V. SUMMARY

A methodology for incorporating Landsat MSS and digital terrain data for the mapping of fuels in the Rocky Mountains of Montana was developed and demonstrated. Key elements in the mapping process were the development of a fuels terrain distribution model which provided a statistical description of the topographic distribution patterns of fuel models within spectral classes for a four band terrain image, and secondly, the application of a layered classifier which incorporates the spectral and terrain data in a two-stage maximum likelihood classification framework for the mapping of fuel classes. By combining the spatially registered digital data base of fuels and topographic information with the mathematical fire simulation model, the digital data can be transformed into management and planning level information.

The USGS DEM terrain data used in this project provided relatively accurate estimates of elevation from which acceptable estimates of slope and aspect could be derived. The data, therefore, has value in both the fuel model mapping work as well as in the fire behavior model. Research is currently underway to use DMA data to reclassify the project area to determine whether or not it significantly impacts classification results. Further research will also be needed to assess the impact of the lower resolution DMA data on the predictive abilities of the fire behavior model.

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