DR. CRAIG H. TOM Science Applications, Inc. Golden, CO 80401 DR. LEE D. MILLER Texas A & M University College Station, TX 77843

Forest Site Index Mapping and Modeling

Employing Landsat MSS imagery and a unified, multivariate data base, 97 percent accuracy was achieved in a test site in the coniferous forests of Northcentral Colorado.

INTRODUCTION

FOREST SITE PRODUCTIVITY expresses the combined influence of the biotic, climatic, and edaphic conditions on the timber-growing capacity of wildlands (Davis, 1954). Site productivity in even-aged American forests is commonly designated by a site index number which relates tree species height to age. That is, site productivity is most practical, consistent, and generally useful indicator of forest site quality (Davis, 1954).

PRESENT SITE EVALUATION APPROACHES

On-the-ground site index evaluations are derived through field measurements of volume per tree in relation to age, soil factors, and lesser vegetation, and tree height in relation to age. How-

ABSTRACT: Forest site productivity refers to the timber-growing capacity of wildlands, and is commonly designated by a site index number which relates tree species height to age. Landscape modeling was used to merge a single summer Landsat scene of four MSS bands and six MSS band ratios with nine ancillary map variables, including topographic elevation, slope, aspect, solar radiation, four MSS insolation band ratios, and photointerpreted vegetation type, to predict and map forest site productivity with a supervised nonparametric classifier. The stepwise linear discriminant classification of 37 randomly selected field incentory plots into nine site index classes yielded a training set accuracy of 43 percent using only the four basic MSS bands and 68 percent using only the five basic ancillary map variables, but achieved 97 percent accuracy using all 19 image and map variables. Total direct mapping cost was \$19 per square mile, or \$1,060 for the entire 71/2-minute quadrangle. Flexibility of data input and analysis with landscape modeling indicated that further site classification accuracy gains and/or cost reductions were possible. However, the real value of such a unified, multivariate data base lies not in just a singlepurpose function, but in its applicability to a wide range of resource management, planning, and research areas.

defined as the average height of sample canopy trees in pure, even-aged stands at selected index ages, usually 50 or 100 years (Alexander, 1966; Jones, 1969). For example, site index 125 on a 100-year base means that the dominant and codominant trees averaged 125 feet (38.1 m) in height at 100 years of age (Tom and Miller, 1979). Tree height in relation to age has been found to be the ever, measurements of volume and growth on an area are time-consuming and expensive jobs, particularly if done only to measure site (Davis, 1954).

The most successful methods for site classification from aerial photographs have involved the recognition of topographic classes (ridge top, upper slope, lower slope, and bottom land) and generalized soil textural classes (sands and

PHOTOGRAMMETRIC ENGINEERING AND REMOTE SENSING, Vol. 46, No. 12, December 1980, pp. 1585-1596. gravels, loams, silts, and clays). Forest site quality is generally well correlated with a combination of these two factors. Site can be classified on aerial photographs, therefore, but not always in the same terms or on the same schemes as are used on the ground (Spurr, 1960).

More recent alternatives to direct field or airphoto measurement currently include vegetation classification and ordination, plus a number of environmental approaches including soil-site equations, forest soil classification and mapping as done in the United States and Germany, and the ordination of vegetation and physical environments into moisture, nutrient, and temperature regimes (Jones, 1969). All vegetation and environmental approaches, like direct measurement, require site productivity parameters for which there are no inexpensive, readily available surrogates.

BACKGROUND

Foresters traditionally have been concerned with the spatial distribution of site productivity over large land holdings. A major need for many federal, state, and private forest managers has been for a regional site productivity map. Site productivity has a profound effect on the volume, value, and timber species that can be best grown on an area. While foresters can manipulate timber density, species composition, quality, and stem size distribution through cutting, the *potential* productivity is controlled by the site (Davis, 1954).

LANDSCAPE MODELING

Landscape modeling is the name given to the long-overdue merger of geographic information systems and remote sensing. This synergistic combination of two closely related but hitherto separate technologies organizes and overlays data from existing maps, airphotos, Landsat imagery, and numerical tables into a single computer framework (Figure 1). The resulting data assemblage provides a multivariate, multitemporal mathematical model that represents the landscape much as a three-dimensional model of the physical terrain is represented by a topographic map.

This analytical framework not only facilitated site index modeling, but also the identification of influential variables, expected levels of classification accuracy, and recommended computational techniques. It was hypothesized that readily available image/map data could serve as cost-effective data surrogates for direct site and airphoto measurement and alternative quantitative inputs. Additionally, it was felt that combining available remote sensing imagery with map data in such a digital landscape model could substantially improve both mapping and modeling activities.

SELECTION AND DESCRIPTION OF TEST AREA

The Eaton Reservoir 7¹/₂-minute U.S. Geological Survey (USGS) topographic map quadrangle was



FIG. 1. Simple schematic representation of the landscape modeling concept. Spatially referenced data from a variety of sources is overlaid in the landscape model. Point- and/or area-format data from continuous forest inventory plots, for example, can be readily input also. The result is a unified data base for improved mapping and modeling activities.

designated as the study area for this site productivity mapping effort. This test area was imaged on the 15 August 1973 Landsat-1 scene designated as path 36, row 32. A considerable amount of work was already completed in compiling topographic elevation (Figure 2), slope, aspect, and vegetation cover data for previous wildfire hazard mapping studies (Tom and Getter, 1975). The quadrangle is located in the Colorado Front Range approximately 94 statute air miles (151 km) northwest of Denver, Colorado, and 51 air miles (82 km) southwest of Cheyenne, Wyoming (Figure 3). The area is rectangular in shape, with dimensions of 6.5 miles (10.5 km) east-west and 8.6 miles (13.8 km) north-south, and an area of approximately 56.2 miles2 (145.6 km2). Diverse landscapes with a va-



FIG. 2. Three-dimensional perspective view of the Eaton Reservoir quadrangle looking from the southeast. Incorporation of terrain data into the digital landscape model allowed the computation of ancillary slope, aspect, and image insolation data planes, as well as Landsat band transformation ratios.

1586



FIG. 3. Location of Eaton Reservoir quadrangle test area. This quadrangle was used to study forest site productivity mapping with digital Landsat image and ancillary map data inputs to a landscape modeling process.

riety of landforms and vegetation types occur within the test site. The elevation ranges from 7,680 feet (2,341 m) to 9,840 feet (2,999 m) above mean sea level. The climate is characteristic of the Colorado Rockies, with abundant sunshine, mild summers with frequent showers, heavy winter snows, and wide fluctuations of temperature. Annual precipitation ranges from 10 to 22 inches (25 to 56 cm), with over half of this precipitation falling during the snowy winter months. Major forest cover types include lodgepole pine (*Pinus contorta* Dougl.), ponderosa pine (*P. ponderosa* Laws.), limber pine (*P. flexilis* James.), Douglas-fir (*Pseudotsuga menziesii* (Mirb.) Franco), and quaking aspen (*Populus tremuloides* Michx.).

GROUND CONTROL EMPLOYED

Ground control efforts consisted of initial field inventory and subsequent image/map registration efforts. Field crews visited 14 forest stands selected at random within the study area, and sampled 37 temporary inventory plots. Statistics were compiled for timber type, stand size class, stocking class, stand area, and site index. The latter sample site indices ranged from 25 through 65 on a 100-year base, and constituted the training set data employed in subsequent pattern recognition analyses.

LANDSAT IMAGE PREPROCESSING

The 15 August 1973 Landsat-1 scene was geometrically corrected and resampled to yield 137 lines and 102 columns of 2½-acre (1.01-ha) squares for all four Mss bands to cover the quadrangle (Figure 4). A nearest-neighbor algorithm correcting for Earth rotation, scanline skew, and nonlinear mirror velocity was used to generate the image data set. Other features included scene rotation and pixel resampling without ground control points. Eaton Reservoir was the only readily identifiable feature in the scene, and the boundaries of the image subscene were adjusted to the uscs map sheet with the use of an MSS band 7 gravmap.

Six additional Mss band ratios were formed from the four original Mss bands (Mss-4, Mss-5, Mss-6, and Mss-7) as Mss-5/Mss-4, Mss-6/Mss-4, Mss-7/Mss-6, Mss-5/Mss-6, Mss-7/Mss-5, and Mss-7/Mss-6, and interspliced back into the multichannel image file. Ratioing is simply the division of the digital radiance value of one Mss band by that of another on a pixel-to-pixel basis, and has been proposed as a means of effectively reducing random fluctuation of reflectance values caused by source variations and changing atmospheric conditions (Maxwell, 1976; Sung and Miller, 1977).

ANCILLARY LANDSCAPE DATA REGISTRATION

The preceding geometric rectification allowed the spatial registration of Landsat spectral data with ancillary topographic elevation, slope, aspect, and photointerpreted vegetation type data. A fifth landscape variable, solar radiation, was calculated for the incident insolation on the Eaton Reservoir terrain model at the time of the Landsat-1 overflight (Figure 5).

Ancillary landscape data consisted primarily of existing maps and map transformations, but can also include point- and area-format numerical data, tables, or narratives. The utilization of comprehensive, in-place mapping efforts and available data bases offers significant potential to improve machine classification efforts as pseudospectral channels. Conversely, the use of timely remote sensing inputs offers considerable reciprocal advantages to land-cover mapping and modeling efforts (Tom, Miller, and Christenson, 1978). The most efficient approach is one in which remote sensing, geomapping systems, and ground techniques are properly balanced. All data inputs have their place and all must be used if accurate mapping/modeling is to be obtained in a minimum time and at a minimum cost.

Four MSS/insolation band ratios were created as the last four ancillary variables. This normalization is proposed as another preprocessing technique specifically to remove terrain effects, and is simply the division of the digital MSS radiance by the computed image insolation on a pixel-to-pixel basis. Thus, the four original MSS bands and six MSS band ratios were registered with nine ancillary landscape variables and overlayed as 2½-acre (1.01-ha) cells (Table 1).

MACHINE ALGORITHM APPLIED

Stepwise linear discriminant analysis was the nonparametric statistical technique used for site index classification. The original set of image and ancillary landscape variables is transformed into a single classification parameter through a discri-



(c) Rectified solar IR1 Image (MSS band $6 = 0.7-0.8 \mu$ m)

(d) Rectified solar IR2 Image (MSS band 7 = $0.8-1.1 \mu m$)

FIG. 4. Display of Eaton Reservoir quadrangle rectified/resampled multispectral Landsat-1 imagery emphasizing lowest band spectroreflectance (in black). The original picture elements were 192-foot (58.5-m) by 259-foot (78.9-m) inclined rectangles which were rectified and resampled to 330-foot (100.6-m) north-south squares to overlay ancillary map data. Note the lack of spatial and tonal variation in these four spectral bands due to the dominance of terrain-induced radiance variation. These multispectral images are displayed from computer-compatible tapes as electrostatic plotter graymaps with a cellular resolution of 2½ acres (1.01 ha) per picture element. Image taken 15 August 1973. Rectified scale nominally 1:215,000.

minant function. The initial multivariate problem collapses down into a univariate situation, then, and discriminant analysis is seen to be closely related to linear regression analysis (Duda and Hart, 1973). Mathematically, a linear discriminant function is derived such that

$$\mathbf{Y}_i = a_1 \mathbf{x}_1 + a_2 \mathbf{x}_2 + \dots a_n \mathbf{x}_n$$

where x_1, x_2, \ldots, x_n are the n = 19 independent Landsat/ancillary landscape variables associated with each of the 37 field site index measurements, and a_1, a_2, \ldots, a_n are calculated to yield a value for Y_i , the linear compound, which minimizes the misclassification probability of the *i*th field plot into the nine site index classes.

Not all of the variables included in the discriminant function are equally useful in distinguishing one site productivity class from another. The вмD07м biomedical computer program used in this study operates in a stepwise fashion, iteratively entering another nonincluded variable which produces the greatest improvement in the discriminating power of the linear function at each step (Dixon, 1967). The program allows for variable deletion or forcing, as well as program termination, if the unentered variables are poor discriminators. The final discriminant function consequently contains only useful variables, and the expression is commonly checked by seeing how well it classifies unknown cases for each group or category of interest.

MACHINE CLASSIFICATION OBJECTIVES

Stepwise linear discriminant analyses were performed on various combinations of the 19 Landsat and ancillary variables to see how well they could replicate their own basic training or calibration data set of 37 site index plots. The various analyses were evaluated by a figure-of-merit, an average classificational accuracy expressing the total number of site indices which were correctly classified over the total number evaluated.

The objectives of these machine classification tests were fourfold as follows:

- To structure a multivariate model for site index productivity with readily available Landsat/ ancillary data surrogates for hard-to-obtain field measurement variables;
- To test each Landsat and/or ancillary variable for both significance and contribution to site index mapping;
- To explore cost-effective or 'best' model subsets of the total 19 variables, where cost-effectiveness is evaluated by classificational time/accuracy considerations; and
- To classify and map the full Eaton Reservoir quadrangle for site index productivity with supporting summary tables.

Five training set classification tests were conducted with stepwise linear discriminant analysis for site productivity mapping as follows:

- Four basic Mss channels only;
- Four MSS channels and six MSS band ratios;
- Five basic ancillary landscape variables only;
- Five landscape and four ancillary MSS/insolation ratios; and
- All 19 Landsat and ancillary landscape variables.

MACHINE CLASSIFICATION RESULTS

The initial or baseline classification used only the original four MSS channels and no other variables to correctly reclassify 43.2 percent of the 37 training set points back into their correct site index class (Table 2). This correct percentage, or figureof-merit, will hereafter be referred to as the training set accuracy.

A second classification used the four original Mss bands plus the six transformed image channels consisting of the ratios of the basic bands to yield an improvement of 16.3 percentage points for a training set accuracy of 59.5 percent. This result indicated that the six ratios of the basic four bands were useful for site index mapping (Table 3).

Next, the five basic ancillary landscape variables, exclusive of any image-related variables, were tested separately. The end training set accuracy for these ancillary data variables was 67.6 percent (Table 4).

The four ancillary MSS-normalized variables, created as the ratio of each MSS band divided by the terrain model-derived Landsat image insolation, were next added to the five initial ancillary landscape variables for testing. Again, these variables were tested separately of any pure image data, and showed a training set accuracy of 94.6 percent (Table 5). This indicated that the insolation ratios of the basic four spectral bands contributed measurably to the site index mapping classification.

All 19 Mss, Mss ratios, physiographic, vegetation, and Mss/insolation ratio variables were then jointly tested, resulting in a training set accuracy of 97.3 percent for the nine site index classes (Table 6). This meant that 97.3 percent of the 37 field site plots could be correctly assigned to their known site productivity class. Simple random assignment of these points to the nine site index categories would yield 1/n = nine classes times 100 percent = 11.1 percent expected accuracy. This represented, therefore, a significant increase in the accuracy of machine-classified Landsat imagery with the synergistic inclusion of spatially overlaid ancillary landscape data. Neither the basic four Landsat channels alone nor the basic five landscape variables alone were effective discriminants; however, the joint utility of Landsat and ancillary landscape data was clearly evident for site productivity mapping (Figure 6).

The linear discriminant analysis algorithm automatically added each non-included Landsat/ landscape variable in the order in which it contributed the most to the site index mapping accu1590









(c) Topographic aspect, degrees



(d) Landsat-1 image (15 August 1973) Insolation, centilangleys minute⁻¹

(e) Photointerpreted Vegetation cover

FIG. 5. Display of Eaton Reservoir quadrangle ancillary landscape data emphasizing lowest elevation, slope, northeast aspect, insolation, and limber pine cover (in black). Topographic elevation data were manually coded from the 1:24,000-scale uses quadrangle map. Slope and aspect were computed from the digital terrain model, and insolation was also computed for the time of the 15 August 1973 Landsat-1 overflight. Vegetation cover type was photointerpreted from NASA aircraft photography. These ancillary landscape data planes are displayed from computercompatible tapes as electrostatic plotter graymaps with a spatial resolution of 2½ acres (1.01 ha) per cell. Display scale nominally 1:215,000.

racy at that step. Clearly, many of the less useful mapping variables did not meaningfully contribute to the final training set accuracy, and, in fact, decreased the cost-effectiveness of the full 19variable model and increased the total computational cost. Machine cost-effectiveness considerations, then, dictated the examination of various subsets of the full 19-variable model prior to automated classification of the Eaton Reservoir quadrangle. Fortunately, this task was greatly simplified by the stepwise nature of the discriminant algorithm.

FOREST SITE INDEX MAPPING AND MODELING

Symbol	Variable	Unit of Measurement
X ₁	Landsat-1 MSS-4 (visible green)	Watts cm ⁻² μ^{-1} sr ⁻¹
X ₂	Landsat-1 Mss-5 (visible red)	Watts cm ⁻² μ^{-1} sr ⁻¹
X ₃	Landsat-1 MSS-6 (solar IR1)	Watts $\mathrm{cm}^{-2} \mu^{-1} \mathrm{sr}^{-1}$
X4	Landsat-1 MSS-7 (solar IR2)	Watts cm ⁻² μ^{-1} sr ⁻¹
X5	Topographic elevation	Feet above mean sea level
X ₆	Topographic slope	Slope, percent
X ₇	Topographic aspect	Azimuth, degrees
X8	Landsat-1 image insolation	Centilangleys minute ⁻¹
X9	Vegetation cover type	Code number
X10	MSS-5/MSS-4 band ratio	Dimensionless
x11	MSS-6/MSS-4 band ratio	Dimensionless
X12	MSS-7/MSS-4 band ratio	Dimensionless
X13	MSS-5/MSS-6 band ratio	Dimensionless
X14	MSS-7/MSS-5 band ratio	Dimensionless
X15	MSS-7/MSS-6 band ratio	Dimensionless
X16	MSS-4/image insolation ratio	Watts-Minute cm ⁻² μ^{-1} sr ⁻¹ Centilangleys ⁻¹
X17	MSS-5/image insolation ratio	Watts-Minute cm ⁻² μ^{-1} sr ⁻¹ Centilangleys ⁻¹
X18	MSS-6/image insolation ratio	Watts-Minute cm ⁻² μ^{-1} sr ⁻¹ Centilangleys ⁻¹
X19	MSS-7/image insolation ratio	Watts-Minute cm ⁻² μ^{-1} sr ⁻¹ Centilangleys ⁻¹

 Table 1. List of Landsat Spectral and Ancillary Landscape Variables Used for Forest Site

 Productivity Mapping. Various Linear Combinations of these Variables Were Examined

 through Stepwise Linear Discriminant Analyses, and the Statistical Contribution

 of each Variable to Mapping Accuracy Was Quantified.

TABLE 2. FOUR ORIGINAL LANDSAT-1 MSS BAND TRAINING SET ACCURACY. SIXTEEN 2½-ACRE (1.01-ha) TRAINING SET POINTS WERE CORRECTLY RECLASSIFIED INTO NINE SITE INDEX CLASSES FOR A 43.2 PERCENT FIGURE-OF-MERIT. THE LANDSAT-1 IMAGE VARIABLES WERE ADDED IN A FREE STEPWISE FASHION AND CLASSIFIED USING LINEAR DISCRIMINANT ANALYSIS. IMAGE TAKEN 15 AUGUST 1973. C-P = CENTRAL-PROCESSOR.

		Train Classi	ing Set fication	Step	Step	Average	
Step Number	Variable Entered	Total Right	Percent Right	Time, Seconds	Pts Per C-P Sec	Pts Per C-P Sec	F-Value To Enter
1	MSS-5 (visible red)	11	29.7	0.08	137.5	137.5	4.44
2	MSS-6 (solar IR1)	12	32.4	0.08	150.0	143.8	1.46
3	MSS-4 (visible green)	13	35.1	0.09	144.4	144.0	1.26
4	MSS-7 (solar IR2)	16	43.2	0.68	23.5	55.9	0.92

TABLE 3. FOUR ORIGINAL LANDSAT-1 MSS AND SIX BAND RATIO TRAINING SET ACCURACY. TWENTY-TWO 21/2-ACRE
(1.01-ha) Training Set Points Were Correctly Reclassified into Nine Site Index Classes for a 59.5 Percent
FIGURE-OF-MERIT. THE LANDSAT-1 IMAGE VARIABLES WERE ADDED IN A FREE STEPWISE FASHION AND CLASSIFIED
Using Discriminant Analysis. Image Taken 15 August 1973. C-P = Central-Processor.

Step Number Variable Entered		Training Set Classification		Step	Step	Average	
		Total Right	Percent Right	Time, Seconds	Pts Per C-P Sec	Pts Per C-P Sec	F-Value To Enter
1	MSS-5 (visible red)	11	29.7	0.21	52.4	52.4	4.44
2	MSS-5/MSS-4 band ratio	13	35.1	0.21	61.9	57.1	2.20
3	MSS-4 (visible green)	14	37.8	0.21	66.7	60.3	1.46
4	MSS-6 (solar IR1)	13	35.1	0.24	54.2	58.6	1.12
5	MSS-6/MSS-4 band ratio	14	37.8	0.23	60.9	60.2	1.04
6	MSS-7/MSS-4 band ratio	17	46.0	0.23	73.9	63.0	0.68
7	MSS-7/MSS-5 band ratio	21	56.8	0.24	87.5	67.5	1.09
8	MSS-7 (solar IR2)	19	51.4	0.25	76.0	67.0	1.08
9	MSS-5/MSS-6 band ratio	20	54.1	0.25	80.0	68.6	0.55
10	MSS-7/MSS-6 band ratio	22	59.5	1.12	19.6	51.4	1.24

Step Number Variable Entered	Training set Classification		Step	Step	Average		
	Total Right	Percent Right	Time, Seconds	Pts Per C-P Sec	Pts Per C-P Sec	F-Value To Enter	
1	Topographic elevation	16	43.2	0.09	177.8	177.8	7.68
2	Vegetation cover type	19	51.4	0.09	211.1	194.4	3.94
3	Topographic slope	22	59.5	0.09	244.4	211.1	3.58
4	Topographic aspect	24	64.9	0.10	240.0	218.9	1.93
5	Landsat image insolation	25	67.6	0.69	36.2	100.0	1.65

TABLE 4. FIVE BASIC ANCILLARY LANDSCAPE VARIABLE TRAINING SET ACCURACY. TWENTY-FIVE 2½-ACRE (1.01-ha) TRAINING SET POINTS WERE CORRECTLY RECLASSIFIED INTO NINE SITE INDEX CLASSES FOR A 67.6 PERCENT FIGURE-OF-MERIT. THE ANCILLARY LANDSCAPE VARIABLES WERE ADDED IN A FREE STEPWISE FASHION AND CLASSIFIED USING LINEAR DISCRIMINANT ANALYSIS. C-P = CENTRAL-PROCESSOR.

Each mapping variable is added to the discriminating set according to greatest F-value to enter, and can be considered as statistically 'optimal' for each iteration. Consequently, the first variable selected is the 'best' single variable, the second variable selected when combined with the first variable selected is the 'best' pair of channels, and the *k*th variable selected when combined with the previously selected variables is the 'best' *k* linear combination of *n* variables, where $k \leq n$.

The best 11-variable combination, consisting of two original MSS bands, three MSS band ratios, five ancillary landscape variables, and one ancillary MSS/insolation ratio, preserved all of the 19variable training set accuracy, but took only 46 percent of the total execution time. The mean and covariance statistics derived from the 11-variable training set were then applied to classify the entire Eaton Reservoir quadrangle into nine site index classes.

SITE INDEX MAP GENERATION

The machine classification of the study area utilized five Landsat-1 spectral bands and six ancillary variables in the mapping of nine site index classes. The result is displayed as a classification map showing the nine site index classes in different shades of gray (Figure 7), and as a tabular summary (Table 7).

Further testing, or verification, is commonly done to determine how accurately the training set procedures extended to the mapping of the entire study area. However, the random selection of the input forest stands ensured a statistically representative sample of the full quadrangle and, consequently, eliminated the need for verification on another test set of unknown site index plots. The training set classifications, therefore, directly represented mapping or verification accuracy in lieu of the training set accuracy usually achieved by this type of activity (Miller, *et al.*, Tom, *et al.*, 1978; Tom and Miller, 1980).

Caution should be exercised in interpreting the many examples of both training and test site accuracy in the technical literature, particularly when test fields are selected in much the same way as the initial training set, and are also statistically unrepresentative. Iudicious selection of training sets

TABLE 5. NINE ANCILLARY LANDSCAPE VARIABLE TRAINING SET ACCURACY. THIRTY-FIVE 2½-ACRE (1.01-ha) TRAINING SET POINTS WERE CORRECTLY RECLASSIFIED INTO NINE SITE INDEX CLASSES FOR A 94.6 PERCENT FIGURE-OF-MERIT. THE ANCILLARY LANDSCAPE VARIABLES WERE ADDED IN A FREE STEPWISE FASHION AND CLASSIFIED USING LINEAR DISCRIMINANT ANALYSIS. IMAGE TAKEN 15 AUGUST 1973. C-P = CENTRAL-PROCESSOR.

Step Number		Training Set Classification		Step	Step	Average	
		Total Right	Percent Right	Time, Seconds	Pts Per C-P Sec	Pts Per C-P Sec	F-Value To Enter
1	Topographic elevation	16	43.2	0.22	72.7	72.7	7.68
2	MSS-7/insolation ratio	19	51.4	0.23	82.6	77.8	4.42
3	Vegetation cover type	22	59.5	0.22	100.0	85.1	3.38
4	Topographic slope	26	70.3	0.24	108.3	91.2	3.16
5	Topographic aspect	28	75.7	0.24	116.7	96.5	2.65
6	MSS-4/insolation ratio	30	81.1	0.26	115.4	100.0	1.83
7	Landsat image insolation	31	83.8	0.25	124.0	103.6	1.46
8	MSS-6/insolation ratio	34	91.9	0.25	136.0	109.8	1.51
9	MSS-5/insolation ratio	35	94.6	1.09	32.1	83.3	0.98

1592

FOREST SITE INDEX MAPPING AND MODELING

TABLE 6. IMPROVEMENT IN THE TRAINING SET ACCURACY OF LANDSAT IMAGE DATA BY THE ADDITION OF ANCILLARY PHYSIOGRAPHIC, VEGETATION, INSOLATION, AND INSOLATION RATIO DATA. THIRTY-SIX 2½-ACRE (1.01-ba) TRAINING SET POINTS WERE CORRECTLY RECLASSIFIED INTO NINE SITE INDEX CLASSES FOR A 97.3 PERCENT FIGURE-OF-MERIT. THE LANDSAT-1 IMAGE VARIABLES AND ANCILLARY LANDSCAPE DATA WERE ADDED IN A FREE STEPWISE FASHION AND CLASSIFIED USING LINEAR DISCRIMINANT ANALYSIS. IMAGE TAKEN 15 AUGUST 1973. C-P = CENTRAL-PROCESSOR.

		Training Set Classification		Step	Step	Average	
Step Number	Variable Entered	Total Right	Percent Right	Time, Seconds	Pts Per C-P Sec	Pts Per C-P Sec	F-Value To Enter
1	Topographic elevation	16	43.2	0.25	64.0	64.0	7.68
2	MSS-6 (solar IR1)	20	54.1	0.25	80.0	72.0	7.16
3	Topographic slope	26	70.3	0.27	96.3	80.5	4.20
4	MSS-4 (visible green)	29	78.4	0.27	107.4	87.5	3.52
5	MSS-6/MSS-4 band ratio	29	78.4	0.28	103.6	90.9	5.53
6	Vegetation cover type	33	89.2	0.29	113.8	95.0	2.79
7	Landsat image insolation	35	94.6	0.28	125.0	99.5	2.58
8	Topographic aspect	33	89.2	0.28	117.9	101.8	1.56
9	MSS-7/MSS-4 band ratio	34	91.9	0.29	117.2	103.7	1.29
10	MSS-7/MSS-6 band ratio	35	94.6	0.29	120.7	105.5	3.81
11	MSS-4/insolation ratio	36	97.3	0.31	116.1	106.5	1.19
12	MSS-7 (solar IR2)	36	97.3	0.31	116.1	107.4	1.64
13	MSS-5/insolation ratio	36	97.3	0.32	112.5	107.9	2.29
14	MSS-5 (visible red)	35	94.6	0.32	109.4	108.0	1.07
15	MSS-5/MSS-4 band ratio	35	94.6	0.33	106.1	107.8	1.04
16	MSS-7/MSS-5 band ratio	36	97.3	0.33	106.1	107.9	0.54
17	MSS-5/MSS-6 band ratio	36	97.3	0.35	102.9	107.6	0.83
18	MSS-6/insolation ratio	36	97.3	0.35	102.9	107.3	0.86
19	MSS-7/insolation ratio	36	97.3	1.35	26.7	91.1	1.79



FIG. 6. Training set accuracy of site index classification with-and-without Landsat imagery. The vertical axis represents the percentage of 37 training points correctly reclassified into their one of nine site index classes. The lower and intermediate curves represent the stepwise training set accuracies achieved when the classification is restricted to the four Landsat image variables and five ancillary map variables, respectively. The upper curve represents the improved stepwise training set accuracy obtained when all 19 Landsat image and ancillary landscape variables are synergistically combined. Specific spectral/ancillary variables are cross-referenced to the list of variables (Table 1) by the enclosed numbers; i.e. [].

can be used to manipulate the final training set accuracy to be anywhere from very poor to very good, depending on the desired results.

SITE PRODUCTIVITY MAPPING COST ANALYSIS

Lastly, an analysis was performed to assess the various direct computer, labor, and material costs and times involved in site mapping the Eaton Reservoir quadrangle. These figures were based on the Control Data Corporation *Cyber 172* computer used at Colorado State University at the basic campus research rate of \$290 per machine-hour and an hourly work rate of \$5 per man-hour. Quoted figures represent only direct computer, labor, and material costs/times.

Field inventory costs alone represented \$720 of the total \$1,060.35, or almost 68 percent of the total direct cost Only \$340.35, or about 32 percent, was expended on direct computer costs. The equivalent average cost per unit area for the final 11variable site index mapping was calculated as either 3.04 cents per acre, 7.50 cents per hectare, \$19.43 per mile², or \$1,060.35 per 7½-minute usos quadrangle (Table 8).

Cost/time savings could be realized immediately if accurate, digitized topographic elevation data were readily available. Additionally, these direct costs also potentially represented development, assembly, and testing costs for a large-scale geographic data base, so that these costs could also



FIG. 7. Display of Eaton Reservoir quadrangle site quality emphasizing highest productivity (in black). An 11-variable linear discriminant function was used to classify the test area into nine site index classes. This classification is displayed from computer-compatible tapes as an electrostatic plotter graymap with a spatial resolution of 2½ acres (1.01 ha) per cell. Display scale nominally 1:214,830.

be shared by other functions such as land-use planning, for example, and reduced accordingly for this single-function application of site index mapping.

FUTURE RESEARCH AND NEW OPPORTUNITIES

The experience and preliminary results derived from this unsponsored internal study have pointed

out additional research areas to pursue. These are summarized as follows:

- Topographic elevation data digitization. Elevation, together with its derivative slope, aspect, and insolation data, is an essential element of site index mapping. Alternative elevation data sources need to be developed to replace the tedious hand cellularizing used in this study and the low-resolution, 1:250,000-scale Defense Mapping Agency digital terrain tapes. The proposed *Stereosat*, with a 17-m pixel, appears promising for terrain relief, slope, strike, and dip studies (Doyle, 1978; Henderson and Ondrejka, 1978).
- Multidate/multitemporal Landsat data analysis. Point geometric congruence through image rectification allows multiple areas and/or scenes to be overlaid. The cost-effectiveness of exploiting the temporal dimension for improved machine classification accuracy needs to be more fully addressed;
- Additional ancillary data inputs. The most obvious landscape variables have been examined, but other possibilities exist as well. For example, soil survey maps would be highly useful *where* available, and would tend to improve the site index mapping effort; and
- Further geoinformation systems development. The synergistic combination of Landsat image and ancillary landscape data demonstrated here strongly suggests additional spatial information systems development to provide complete, objective, and consistent data and analyses. The versatility of a unified, multivariate data base can be used to address a wide spectrum of management, planning, and research problems.

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TABLE 7. SUMMARY TABLE OF EATON RESERVOIR SITE QUALITY. AN 11-VARIABLE LINEAR DISCRIMINANT FUNCTION WAS USED TO CLASSIFY EACH 2½-ACRE (1.01-ha) CELL IN THE TEST AREA INTO ONE OF NINE SITE INDEX CLASSES.

Site Index Class	Total Cells	T Area, Acro	Total Area, Acres (Hectares)		
25	3,257	8,142.5	(3,289.6)	23.2	
30	1,139	2,847.5	(1, 150.4)	8.2	
35	1,479	3,697.5	(1, 493.8)	10.6	
40	1,135	2,837.5	(1, 146.4)	8.1	
45	2,067	5,167.5	(2,087.7)	14.7	
50	779	1,947.5	(786.8)	5.6	
55	519	1,297.5	(524.2)	3.7	
60	1,229	3,072.5	(1.241.3)	8.8	
65	2,370	5,925.5	(2.393.7)	17.0	
GRAND TOTALS	13,974	34,935.0	(14, 113.7)	100.0	

	Task Description		Cost		
1.0	ANCILLARY LANDSCAPE DATA INPUT:				
1.1	Topographic elevation coding	11.4	man-hrs	\$	57.08
1.2	Topographic slope/aspect mapping	288.0	C-P sec		23.20
1.3	Landsat image insolation modeling	60.0	C-P sec		4.83
1.4	Vegetation photointerpretation	4.2	man-hrs		21.00
1.5	Vegetation map digitization	4.0	man-hrs		20.00
		1.0	subtotal	\$	126.11
2.0	LANDSAT IMAGE PREPROCESSING:				
2.1	CCT data reformatting	394.0	C-P sec	\$	31.74
2.2	Image rectification/rotation	259.0	C-P sec		20.86
2.3	Image channel ratioing	514.0	C-P sec		49.46
2.4	Landsat/landscape file merging	195.0	C-P sec		15.71
		2.0	subtotal	\$	117.77
3.0	STATISTICAL FEATURE EXTRACTION:				
3.1	Classification file creation	39.0	C-P sec	\$	3.16
3.2	Multivariate classification	534.0	C-P sec		43.02
3.3	Field inventory sampling	139.8	man-hrs		699.00
		3.0	subtotal	\$	745.18
4.0	OUADRANGLE CLASSIFICATION:				
4.1	Classification file creation	477.0	C-P sec	\$	38.43
4.2	Multivariate classification	131.0	C-P sec		10.55
4.3	Graphics generation	277.0	C-P sec		22.31
		4.0	subtotal	\$	71.29
	7 ¹ / ₂ -MINUTE USGS QUADRANGLE GRA	ND TOTAL		\$1	,060.35

TABLE 8. SITE PRODUCTIVITY MAPPING ANALYSIS. QUOTED FIGURES REPRESENT ONLY DIRECT COMPUTER, LABOR, AND MATERIAL COSTS/TIMES. THE AVERAGE DIRECT COST WAS 3.04 CENTS PER ACRE (7.50 CENTS PER HECTARE). SOME 68 PERCENT OF THE TOTAL DIRECT COST WAS IN FIELD SAMPLING, SO THERE ARE SIGNIFICANT OPPORTUNITIES FOR FURTHER COST/TIME SAVINGS. C-P = CENTRAL-PROCESSOR.

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REFERENCES

- Alexander, R. R., 1966. Site Indexes for Lodgepole Pine, with Correction for Stand Density: Instructions for Field Use. U.S. Forest Service Research Paper RM-24. Rocky Mtn. Forest and Range Exp. Sta., Fort Collins, Colo. 7 p., illus.
- Davis, K. P., 1954. American Forest Management. McGraw-Hill Book Co., New York. 482 p., illus.
- Dixon, W. J., 1967. BMD Biomedical Computer Programs. Univ. of Calif. Publications in Automatic Computation 2, Univ. of Calif. Press, Berkeley, pp. 214a-214s.
- Doyle, F. J., 1978. The Next Decade of Satellite Remote Sensing. Photogram. Eng. and Remote Sensing 44(2): 155-164.
- Duda, R. O., and P. E. Hart, 1973. Pattern Classification

and Scene Analysis. John Wiley and Sons, New York. 482 p., illus.

- Henderson, F. B., and R. J. Ondrejka, 1978. GEOSAT: Geological Industry Recommendations on Remote Sensing from Space. *Photogram. Eng. and Remote* Sensing 44(2): 165-169.
- Jones, J. R., 1969. Review and Comparison of Site Evaluation Methods. U.S. Forest Service Research Paper RM-51. Rocky Mtn. Forest and Range Exp. Sta., Fort Collins, Colo. 27 p., illus.
- Maxwell, E. L., 1976. Multivariate Systems Analysis of Multispectral Imagery. Photogram. Eng. and Remote Sensing 42(9): 1173-1186.
- Miller, L. D., K. Nualchawee, and C. H. Tom, 1978. Analysis of the Dynamics of Shifting Cultivation in the Tropical Forests of Northern Thailand Using Landscape Modeling and Classification of Landsat Imagery. In Proceedings of the Twelfth International Symposium on Remote Sensing of Environment, The Univ. of Michigan, Ann Arbor, April 20-26, pp. 1167-1186. (Preprinted as NASA Technical Memorandum 79545, Goddard Space Flight Center, Greenbelt, Md. 19 p., illus.).
- Spurr, S. H., 1960. Photogrammetry and Photo-Interpretation, Second ed. Ronald Press Co., New York. 472 p., illus.
- Sung, Q. C., and L. D. Miller, 1977. Land Use/Land Cover Mapping (1:25,000) of Taiwan, Republic of China by Automated Multispectral Interpretations

of LANDSAT Imagery. NASA preprint X-923-77-201, Goddard Space Flight Center, Greenbelt, Md. 168 p., illus.

- Tom, C. H., and J. R. Getter, 1975. Computer Mapping of Wildfire Hazard Areas: A User-Oriented Case Study. Resources Division, Colorado State Forest Service, Fort Collins, Colo. 44 p., illus.
- Tom, C. H., L. D. Miller, and J. R. Christenson, 1978. Spatial Land-Use Inventory, Modeling, and Projection/Denver Metropolitan Area, with Inputs from Existing Maps, Airphotos, and Landsat Imagery. NASA Technical Memorandum 79710, Goddard Space Flight Center, Greenbelt, Md. 225 p., illus.

Tom, C. H., and L. D. Miller, 1979. "Forest Site Produc-

tivity Mapping in the Coniferous Forests of Colorado with Landsat Imagery and Landscape Variables." In Proceedings of the Thirteenth International Symposium on Remote Sensing of Environment, The Univ. of Michigan, Ann Arbor, April 23-27, pp. 675-692.

—, 1980. Spatial Land-Use Inventory/Denver Metropolitan Area with Inputs from Existing Maps, Airphotos, and Landsat Imagery. In Proceedings of the Fourteenth International Symposium on Remote Sensing of Environment, The Univ. of Michigan, Ann Arbor, April 23-30. 10 p., illus.

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- 2. Ordinarily *two* copies of the manuscript and two sets of illustrations should be submitted where the second set of illustrations need not be prime quality; EXCEPT that *five* copies of papers on Remote Sensing and Photointerpretation are needed, all with prime quality illustrations to facilitate the review process.
- 3. Each article should include an abstract, which

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1596