Rule-Based Classification Models: Flexible Integration of Satellite Imagery and Thematic Spatial Data

Paul V. Bolstad
School of Forestry and Wildlife Resources, Virginia Polytechnic Institute and State University, Blacksburg, VA 24061
T. M. Lillesand
Environmental Remote Sensing Center, University of Wisconsin, Madison, WI 53706

ABSTRACT: A framework for automated land-cover classification based on a concept of a classification model was developed and tested. The framework employs a user-specified rule base to describe a classification model, defined as the series of spatial data operations and decisions used in landcover classification. Both evidential and hierarchical inference are supported utilizing a set of spatial data operators.

The concept was tested through the development and application of a set of computer programs which support classification models. A rule base, thematic spatial data, and satellite image data were then used to define a classification model for conditions in northeastern Wisconsin. The test model incorporated Landsat Thematic Mapper data, soil texture data, and topographic position data. Classification accuracies and efficiencies using the developed system were then compared to those for supervised maximum-likelihood classifications. The classification model approach resulted in statistically significant, 15 percent improvements in classification accuracy when averaged across different analysts, geographic areas, and years.

INTRODUCTION

SUPERVISED, PER-PIXEL, MAXIMUM-LIKELIHOOD SPECTRAL classifiers are the most commonly applied automated land-cover classification techniques due in part to a well developed theoretical base, ease in automation, and proven track record (Swain and Davis, 1978; Richards, 1986; Lillesand and Kiefer, 1987). Unfortunately, when used with satellite image data, these technologies often yield unacceptable accuracies for many applications. For example forest management agencies often require landcover classification at the Anderson *et al.*, (1976) level II/III with at least 95 percent accuracy, while automated classification of satellite data generally result in accuracies well below this level (e.g., Nelson *et al.*, 1984; Moore and Bauer, 1990).

Spatial data in a GIS have been shown to improve classification accuracy and aid in the extraction of information from remotely sensed imagery (Strahler *et al.*, 1978; Likens and Maw, 1981; Marble and Peuquet, 1983). Methods include incorporation before, during, or after a maximum-likelihood classification (Hutchinson, 1982; Richards *et al.*, 1982). However, current technologies do not allow easy *automated* integration of non-image spatial data (such as digital thematic maps and associated attributes) in image classification. In most instances spatial data are used in *manual* pre- or post-classification manipulations (Gaydos and Newland, 1978; Hutchinson, 1982). The integration of non-image data during classification often involves relatively inflexible hard-coded classifiers (Fleming and Hoffer, 1979; Hoffer *et al.*, 1978), or "logical channels" (Strahler *et al.*, 1978; Strahler *et al.*, 1980) which violate distributional conditions.

Artificial Intelligence (AI) and expert systems techniques have been investigated to improve land-cover classification (Ferrante *et al.*, 1984; Wharton, 1987; Argialas and Harlow, 1990), and show promise in the integration of non- image spatial data (Mason *et al.*, 1988), because of their flexibility, generality, and intuitive appeal. Both evidential and hierarchical approaches have been investigated. Evidential approaches rely on obtaining measures of the relative "mass" of evidence in support of alternative hypotheses (Duda *et al.*, 1979; Goldberg *et al.*, 1985; Lee *et al.*, 1987), and select the hypothesis (land-cover class assignment) with the greatest evidence mass. Hierarchical approaches, such as the "decision tree" techniques described by Swain and Hauska, (1977), eliminate competing hypotheses from consideration during inference until only one hypothesis remains. Conceptually, land-cover classes are considered leaves of bi- or multinary trees, with decision criteria applied at each node to eliminate or select the decision path (Swain *et al.*, 1977; Duda *et al.*, 1978; Ferrante *et al.*, 1984).

Strictly hierarchical approaches are computationally more efficient, but do not recover from decision errors; conversely, methods which strictly accumulate evidence incur high computational loads. Thus, there is a tradeoff between flexibility and run-time efficiency. Systems may be inflexible in that landcover classification can be difficult with satellite systems (e.g., SPOT versus Thematic Mapper), feature types, or areas different from those on which the systems were developed (Ferrante *et al.*, 1984; Wang and Newkirk, 1984; Goldberg *et al.*, 1985). Although principles apply, changed conditions entail significant recoding. Those systems that do incorporate easily modifiable rule-based strategies result in classification times an order of magnitude or more slower than the "standard" maximum-likelihood approach (Wharton, 1987; Mason *et al.*, 1988; Civco, 1989). This efficiency/flexibility trade-off results from the applicative approach adopted by rule-based systems (Mehldau and Schowengerdt, 1990) in that software for system development is designed for quick construction and prototyping, but provides unacceptable performance with large data volumes (Jackson, 1985). Thus, a combination of hierarchical and evidential approaches is often adopted (Shortliffe, 1976; McDermott, 1982; Jackson, 1986). This paper describes a land- cover classification approach controlling RS/GIS integration through an easily modifiable rule base, and which also provides rapid throughout.

DESIGN PHILOSOPHY

The adopted approach is based on a concept of a classification model. Classification models are defined as an automated sequence of operations applied to image and non-image spatial data which results in a land-cover classification. Classification models may be considered analogous to cartographic models defined for geographic information systems (Tomlin and Berry,

0099-1112/92/5807-965$03.00/0

1979; Burroughs, 1986). These models may use various decision criteria and operations to assign distinct land-cover classes. Although a broad-sense interpretation of the definition includes a "standard" supervised maximum-likelihood classifier, classification models will generally have several "levels", and use several different data types and spatial data operators. For example, in a classification model, image and non-image data may be automatically integrated to classify a geographic area into four land-cover classes: urban, forest, cropland, and water (Figure 1). Digital population density data may be used to identify urban classes, digital thematic maps to assign water, and a spectral-based maximum-likelihood classifier used to assign the crop and forest classes. Thus, in a classification model a set of spatial data analysis primitives are used to classify land cover, e.g., maximum-likelihood calculations and direct assignment based on thematic data values.

Classification models should support both evidential and hierarchical inference. As noted above, both types of inference have been successfully applied to land-cover classification, and the combination is desirable both to facilitate increases in classification accuracy and enhance run-time efficiency.

The inference strategy should be specified at a high level of abstraction, i.e., one which allows non-programmers to understand and develop classification models, and it should also be flexible and easy to modify. A higher level of abstraction is a common paradigm of much AI programming, and it allows a wider application of this approach (Jackson, 1986). Flexibility also entails an easily modifiable system which may be applied to a wide range of land-cover and data types. Classification may use only spectral data, only thematic data, continuous non-thematic and non-image spatial data, or a combination of these data types.

Classification modeling requires a defined set of spatial data operators which may be considered image classification primitives. These primitives are analogous to map algebra primitives (Tomlin and Berry, 1979), except that they are expanded to include operators specifically designed for land-cover classification. These primitives will then be called to operate on co-registered data during the inference process defined by the classification model. For example, spectral class likelihood calculation, the boolean combination of thematic spatial data, shape determination, or local texture computation may all be useful as classification primitives. The classification model is defined by the sequence and combination of these primitives.

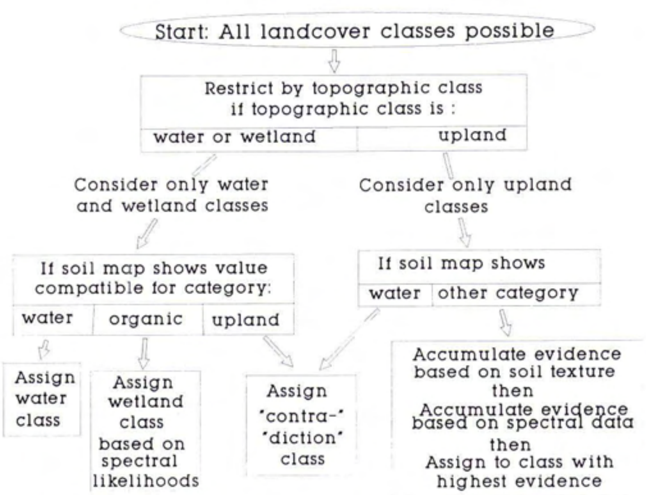

FIG. 1. An example classification model used in feature class assignment. Note that the timing and application of restriction and evidence accumulation operations may be based on the thematic and image data values.

CLASSIFICATION MODELER: PROTOTYPE

A system of programs was produced which supports the development of classification models. This system, herein called CLASMOD (classification modeler), allows the integration of thematic data, satellite imagery, and a rule-based, forward-chaining inference strategy in land-cover classification. The adopted approach uses a set of rules to define a classification model. Both evidential and hierarchical inferences are supported. Rules are used to describe feature types, data themes, the relationships among themes and feature types, and to define the inference path. Although CLASMOD is sufficient to test the concept of a classification modeler, it is an early prototype and as such is limited in many respects.

CLASMOD consists of three parts: a rule parser, "foundation code," and a compiler (Figure 2). These three are used with a rule base to define a classification model. First, the rule parser is applied to a rule base, generating computer code. For example the rule "if soil_text is sand and topo_position is upland then restrict_by topo_position" might be converted to the C code fragment "if (theme_var[i] = = theme_tab[a][b] || theme_var[j] = = theme_tab[c][d]) {restrict(theme_var[j]}".

The generated code is then compiled and linked with the foundation code to produce an executable classifier based on the classification model. The executable code then operates on the base and spatial data to classify land cover for a geographic area (Figure 2).

The rule parser recognizes a number of keywords in rules which are contained in the rule base (Table 1). The parser converts the rule base into C code and data tables which are used in the classification model. Rules are used to identify the set of

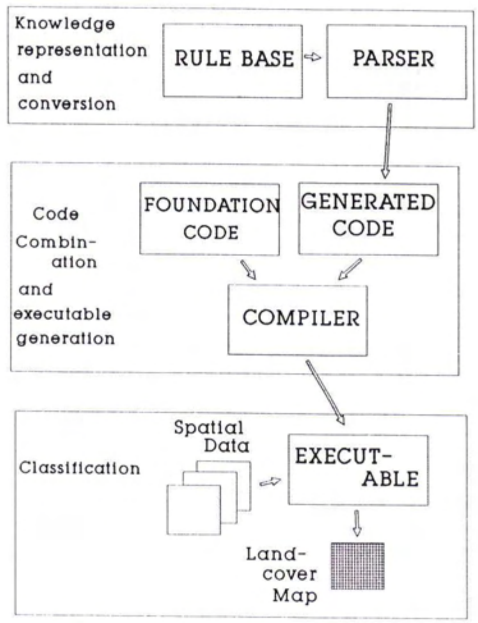

FIG. 2. System components and combination for land-cover classification. The rule base is converted to C code, which is then compiled with foundation code to produce an executable module. This executable module would then be combined with spatial data, possibly including both image and non-image data, to produce a land-cover classification.

TABLE 1. RULE TYPES, EXAMPLES, AND KEYWORDS RECOGNIZED BY THE RULE-PARSER. RULES ARE USED TO BUILD A CLASSIFICATION MODEL BY DEFINING FEATURE TYPE, THEMATIC DATA LAYERS, THEME CLASSES, EVIDENCE VALUES, AND THE TIMING AND TYPE OF DECISIONS USED IN CLASSIFICATION. KEYWORDS RECOGNIZED BY THE PARSER ARE ITALICIZED.

Rule Type	Example
Define land-cover classes and identify numeric coding	red_pine *isa feature_type with numeric id* 1
Define thematic data types	soil_text *isa evidence_theme*
Define theme classes and numeric coding	sand *isa* soil_text *with numeric_id* 7
Fix evidence values	*if* soil_text *is* sand *then evidence_for* jack pine *is* 90
Describe restrictions	*if* topo_position *is* wetland *then* black spruce *is_among plausible feature types*
Guide flow of control	*level 1 if* soil_text *is* sand *and* topo_position *is* upland *then restrict_by* topo position *level 1 if* topo_position *is* upland *and* soil_text *is* organic *then flag_contradiction* *level 2 accumulate_evidence_by* soil_texture

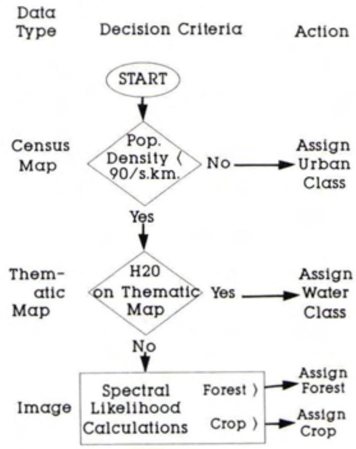

FIG. 3. The classification model used for system tests. This model applies restriction and evidence accumulation operators to classify land-cover in northern Wisconsin.

land-cover classes (feature types), thematic spatial data (e.g., income category, soil texture), the theme classes (e.g., sand, silt, or clay soil). The rule base is also used to specify how inference is to proceed during land-cover classification. English-like rules are used to describe the legal feature types (e.g., forests, road), spatial data themes (e.g., imagery, soil texture, terrain), thematic types for each theme (e.g., soil texture as sandy, aspect as northerly). Rules are also used to describe the relationships between themes and features (e.g., if soil texture is sandy, then evidence for jack pine is 0.5). Spatial data are identified by the name of the theme, e.g., "soil-texture," thematic class names, e.g., "coarse-sand, organic, silt-loam," and numeric identifiers. Identifiers are specified to provide the connection between the numeric data contained in the raster spatial data and the thematic variable. For example, "coarse-sand" might have an identifier of 1, and all cells with a value of 1 in the soil-texture data layer represent an area of coarse-textured soils.

Rules are also used to define the hierarchy or sequence of operator application. Timing is specified by "levels" (Table 1), and operations at lower levels are applied before operations at higher levels (i.e., level 1 operations are applied before level 2). Ordering of rules with the same level, e.g., two level 4 classification operations, follows their order in the rule base.

The foundation code is the shell of computer code into which code from the rule parser is embedded. This code defines general "housekeeping" constructs such as procedure, function, and data structures; data file opening routines; and error handling. Finally, the compiler is used to compile the computer code into an executable file. The C programming language was used in this work. An ANSI-compatible C compiler (Borland, International) was used on a DOS, Intel 80386 platform.

The system allows the incorporation of three types of data/information in addition to the "data" in the rule base: (1) thematic spatial data, (2) image data, and (3) spectral training data. These data are used with the executable code for land-cover classification (Figure 3). The adopted approach assumes all feature types are initially possible for any portion of the image. Feature types can be eliminated from consideration, and evidence for or against the remaining plausible feature types can be accumulated. Feature type elimination or evidence accumulation can be based on either the thematic or image data. Classification must be restricted to those regions for which the classification model is valid. However, the system is sufficiently flexible to allow the generation of different classification models for different regions or conditions.

A small set of classification primitives is currently supported: thematic restriction, thematic evidence accumulation, spectral evidence accumulation, and classification quality. While these constitute only a limited subset of potential operators, they allow the flexible incorporation of spectral and non-spectral data in image classification techniques.

Restriction operations are used when the occurrence of a thematic class reduces the set of plausible feature types. For example, we may be certain that only lowland vegetation types (e.g., black spruce and bog sedge) are found in areas which have been mapped as having organic surface soils. Thus, if we have a soil map, every time we encounter an organic surface soil we can eliminate all but the lowland types from consideration. Thematic evidence accumulation occurs when thematic data support or contradict feature type occurrence with less than complete certainty. For example, areas with sandy soils may be more likely to support jack and red pine, while loamy soils are more likely to support sugar maple. Note that the same thematic data layer can be used for both evidence accumulation and restriction. Finally, spectral evidence accumulation adds supporting evidence based on imagery which is proportional to spectral class likelihoods. The remotely sensed data are viewed as one of many spatial data sources from which information about land-cover may be extracted.

The spectral evidence accumulation primitive is based on likelihood calculations with image data. When this primitive is invoked, the likelihoods for all plausible spectral classes are calculated and ranked. Likelihoods are scaled using a Chi-square distribution. Spectral data coincident with training set mean values yield Chi-squares of zero and correspond to the highest possible likelihood for the training set. A zero Chi-square is set to correspond to 100 "evidence points," and values above a 95 percent Chi-square threshold are assigned 0 points. Spectral evidence is linearly scaled over this range.

Finally, operations can be included which gauge the quality of the spectral evidence. Evidence provided by the imagery may be deficient in several respects. For example, the highest calculated spectral likelihood may be below an acceptable level. Alternatively, two feature types may both contribute high spectral evidence. In either case, feature-type assignment may be based solely on the other non-image data layers. While this may be desirable in some instances, in others it may not. Rules can be included to flag low spectral evidence or contradictory classification results.

SYSTEM APPLICATION AND TESTING

An image classification model using CLASMOD was developed and tested for forested Lake States conditions of northeastern Wisconsin (Figure 4). Classification model development included generating both the spatial and "rule- base" data. Forested Lake States conditions are defined as the major land-cover types found in the forested regions of northern Minnesota, Wisconsin, and Michigan, and in the southern portion of Ontario. Maples, birch, pines, and aspen dominate the forest overstory in the study area, as is characteristic of northeastern hardwoods, although species diversity is somewhat reduced compared to other forests of this type, due to the recency of glaciation (Curtis, 1959). Two study sites were selected (Figure 4), one in central Vilas County (hereafter referred to as the western study site) and one in eastern Vilas County (hereafter referred to as the eastern study site). Each site encompassed a majority of the range of soils and vegetation types found in much of northern Wisconsin.

The tested system employed visible (band 3), near infra-red (band 4), and a mid-infrared (band 5) image data from the Landsat Thematic Mapper (TM), as well as soil and landform thematic and tabular data. Soils data were used for evidential information. Landscape position data (upland, wetland, and water), also referred to as topographic position, were used as a restrictive layer, and TM data were used for both restrictive and evidential information. Source documents were collected and converted to digital forms as necessary and co-registered for the study areas used in this investigation. All data were registered to a Universal Transverse Mercator (UTM) projection. Information acquired from interviews of domain experts was a point of departure for the rule-base. System operation and output were tested for a number of users, areas, and image acquisition dates.

Original mylar soil boundary maps were obtained for the USDA Soil Conservation Service. These maps originated from field data collection and manual photointerpretation of 1:20,000-scale black-and-white aerial photography. Contact print positives of original scribe coats were photographically reproduced on stable-base mylar. Tie points were manually drafted onto the mylar prints and then manually digitized.

Topographic position data were derived from 12 USGS 7.5-minute quadrangles. Topographic positions were categorized into four nominal categories: wetland, upland, water, and road. These four categories were chosen because they were related to vegetation distribution and were well represented on available USGS 7.5-minute quadrangles. Permanent water, road, and lowland areas were digitized directly from the quadrangles. All remaining areas were assigned to the upland topographic position class.

FIG. 4. Study site locations.

Landsat TM data were collected on 9 June 1988 and 23 September 1989. Radiometric quality of the 1988 scene appears good in all non-thermal bands. Degradation due to clouds and haze ranges from slight to significant over the entire TM scene, although haze and cloud effects are minimal over the study areas. The 1989 scene was also of high radiometric quality, and is nearly cloud free.

Field notes, Wisconsin Department of Natural Resources (DNR) vegetation maps, United States Forest Service (USFS) vegetation maps, and National High Altitude Aerial Photography (NHAP) color aerial photographs were assembled in support of the described research. These data were used to aid in training set development and for testing the CLASMOD. Thirteen feature types were defined in the set of rules (Table 2). These feature classes correspond approximately to the categorical detail of levels II and III of the Anderson classification system (Anderson *et al.*, 1976). Categories were defined according to a number of considerations, including previous work on type categories for northern boreal and eastern deciduous forests using current technologies (Nelson *et al.*, 1984; Buchheim *et al.*, 1985; Horler and Ahern, 1986; Vogelman and Rock, 1986; Hopkins *et al.*, 1988).

The developed rule base contained over 200 rules. Rules defined the land-cover classes, the thematic spatial data layers, thematic classes for each theme, and the sequence of spatial data operations used during classification. Examples of defined rules are included in Table 1.

The performance of the classification model was compared to traditional supervised maximum-likelihood classification methods for both study areas. This statistical comparison involved a stratified random sampling of predicted and true feature types for a number of points in both the human and rule-based classifications. Classification error rates were then calculated and compared for the two classification methods. Comparisons were made for two separate analysts on two image dates. Both the eastern and western study sites were classified.

First, the rule-based classifier was developed using the June 1988 sub-scene for the western study area. System refinement over each iteration included classification, evaluation, evidence value modification, and rule-base modification. Accuracy of the final classification was determined by comparison of the true and classified feature type for a number of points in the study

TABLE 2. FEATURE TYPES AND THEME TYPES AND CLASSES USED IN CLASSIFICATION.

Feature Types:	
Northern Hardwoods	Lowland Brush
Red and White Pine	Lowland Vegetation
Jack Pine	Sphagnum
Pine / Hardwood	Crop / Pasture
Upland Brush	Soil / Urban
Lowland Conifer	Aquatic Vegetation
Water	Unclassified
Theme Types:	
Soil Texture Map Theme Classes:	
Sand	Loam
Sandy Loam	Wet Sand
Fine Sandy Loam	Organic
Loamy Fine Sand	Water
Silt Loam	No Data
Topographic Position Theme Class:	
Upland	Water
Wetland	Urban
No Data	

area. The accuracy of a traditional maximum-likelihood classification of the same area was also determined, and a statistical comparison performed of the traditional versus rule-based classification. The traditional and rule-based classifiers were then applied to the eastern study area using the training data from the western study area. This work was performed by "Analyst 1." A second analyst (Analyst 2) classified the western study site using the traditional and rule-based methods. No rules or evidence weightings were changed, the only difference being spectral training data developed by the second analyst. The classification involved training on the western study site, and applying the spectral training data to the western and eastern sites.

A series of classifications was performed to gauge the sensitivity of classification results to the relative weights placed on the different evidence and restriction layers. Thematic evidence values were based on long-term observations of field experts, and spectral evidence could be considered well founded, assuming representative training. However, appropriate relative weightings of spectral and thematic evidence were not clearly defined. Spectral and thematic data provide different information, and there is no *a priori* reason to provide greater strength to one or the other. The current system weighted them equally under the assumption that the classification model is robust with respect to relative weightings. The appropriateness of this equal weighting was tested employing a series of classifications of the eastern study site using the 1988 imagery. Before accumulation, evidence values derived from the soil theme and satellite imagery were pre-multiplied by fractional coefficients W and $1-W$, respectively, where $0 \leq W \leq 1$. The coefficients summed to 1; thus, if the soil evidence was multiplied by 0.2, spectral evidence for that classification was multiplied by 0.8. Values of W applied were 0, 0.2, 0.4, 0.6, 0.8, and 1.0. These sensitivity classifications were performed both with and without the topographic restriction layer.

Approximately 20 to 40 features were ground-identified or photointerpreted for most feature types. Actual sample size per category was determined after preliminary visual classification revealed approximate class distribution (Williams, 1978). Between 360 and 410 sample points were identified in each of the eastern and western study areas. These land-cover points were used as "ground truth," that is, the true feature type for the ground point sampled. Because of land-cover changes from 1988 to 1989, the same sets of points were not used for both years, although there was a high degree of overlap among sets. The ground truth data were used to calculate Cohen's Kappa coefficients of agreement and conditional Kappa (Cohen, 1960). Pairwise significance tests between the new and traditional approaches were performed using large sample Kappa and conditional Kappa formulas developed by Fleiss *et al.* (1969).

RESULTS

Quantitative system assessment was based on two criteria: accuracy and efficiency. Classification accuracy comparisons are summarized below. Results from these comparisons are organized by study site, year of image acquisition, and operator. Next, the results from the sensitivity tests are provided. Finally, efficiency observations are reported.

Classification accuracy comparisons are summarized in Table 3. Improvements in classification accuracy were observed for five of the six operator, study area, and imagery combinations. Differences in Cohen's Kappa between the new and traditional methods, based on one-tailed z-tests, were statistically significant in five cases at the 10 percent level. Overall, pooled classification accuracies ranged from a low of 54 percent to a high of 90 percent. Using the CLASMOD and the defined classification model, classification accuracies averaged 83 percent, while accuracies for the traditional method averaged 69 percent. In general, the CLASMOD method provided more consistent, accurate classifications for the different combinations of study site and analysts.

TABLE 3. SUMMARY STATISTICS FOR IMAGE CLASSIFICATIONS. CLASSIFICATION ACCURACY, COHEN'S KAPPA (KHAT), VARIANCE OF KHAT, AND SIGNIFICANCE OF ACCURACY DIFFERENCES BETWEEN RULE-BASED (CLASMOD) AND TRADITIONAL (SUPERVISED MAXIMUM LIKELIHOOD). SIGNIFICANCE IS THE PROBABILITY OF SPURIOUS REJECTION IN A TWO-TAILED Z-TEST.

Method	%Correct	KHAT	Significance
Western Study Site, '88 Imagery, Operator 1			
Traditional	83	0.824	<0.05
Rule-based	94	0.931	
Western Study Site, '88 Imagery, Operator 2			
Traditional	83	0.815	<0.01
Rule-based	90	0.887	
Western Study Site, '89 Imagery, Operator 1			
Traditional	61	0.568	<0.01
Rule-based	69	0.663	
Eastern Study Site, '88 Imagery, Operator 1			
Traditional	70	0.664	<0.01
Rule-based	89	0.872	
Eastern Study Site, '88 Imagery, Operator 2			
Traditional	61	0.572	
Rule-based	82	0.804	<0.01
Eastern Study Site, '89 Imagery, Operator 1			
Traditional	54	0.492	<0.20
Rule-based	58	0.537	

Classification improvements associated with the CLASMOD were observed for both analysts in both study sites with the 1988 and 1989 imagery. The classification model was on average approximately 15 percent more accurate than the "traditional" approach for the 1988 data. The CLASMOD approach averaged 89 percent, while the supervised maximum-likelihood approach averaged 74 percent. For the 1989 data accuracies averaged 57 percent for the traditional method and 70 percent for the rule-based method. The same general patterns of misclassification were observed for both classification methods.

Accuracies were lower for the 1989 imagery than corresponding classifications for the 1988 imagery. At least two factors may have contributed to this reduction. First, spectral training area locations were defined on 1988 imagery. Training set coordinates were then transformed to the 1989 imagery and used to extract training samples. These samples were not tailored to the spectral characteristics of the 1989 imagery.

Second, class accuracies could be lower because of the spectral characteristics of the 1989 imagery. This imagery was collected during late September of a low rainfall year. Although data from earlier in the growing season were preferred, attempts at collecting imagery for the months of June, July, and August were unsuccessful due to cloud cover. Leaf senescence initiated early for some species and this may have resulted in both greater spectral variability within feature types and greater similarity among some feature types. This spectral variability was not present in the 1988 data.

Training times are equal for the new approach when compared to a traditional maximum-likelihood classification (Table 4). Training times for analyst 2 using the non-traditional approach are probably over-estimates, because they include some time dedicated to familiarization with the new approach. Prior to this work, analyst 2 was not familiar with the particular programs described herein. Classification run times for the two methods are comparable, running approximately 18 percent longer for the new approach. The slight increase associated with the rule-based approach can be attributed to additional overhead such as increased file I/O and to additional operations,

TABLE 4. TOTAL TIME REQUIREMENTS FOR BOTH TRAINING AND CLASSIFICATION USING TRADITIONAL AND NON-TRADITIONAL APPROACHES. ALL TIMES ARE IN MINUTES.

Analyst No.	Traditional Method Time (min.)	Rule-Based Method Time (min.)
1	363	432
2	402	492

such as restriction and evidence accumulation. For this specific classification model, the topographic restriction and soil evidence accumulation operators incur additional overhead relative to the traditional maximum-likelihood approach. However, they also reduced the time spent on computationally expensive likelihood calculations, in part offsetting the additional computational burden.

While these results provide a rough estimate of the relative times required for the new and traditional approaches, they do not reflect peak performance possible in a desktop environment for either approach. Although reasonable attempts were made to ensure computational efficiency for both the traditional and new approaches, neither was developed specifically to optimize speed of operation. Significant time savings could be realized in both instances through a number of techniques, including optimized I/O buffering (Knuth, 1973), table look-up classification techniques (Bolstad and Lillesand, 1990), faster clock speeds, or array processors (Westman, 1989).

Finally, results from the sensitivity tests indicate that the overall accuracies are robust relative to the relative weightings of the thematic and satellite image data during classification, at least with the adopted classification model (Figure 5). Classifications, both with and without the use of topography-based restrictions, remained high over a relative evidence weights of 0.2 to 0.8. In all cases, classification with the topographic restriction was improved over classifications using thematic soil and image data.

CONCLUSIONS

The adopted image classification approach has several advantages in comparison to standard approaches:

- The domain of discourse and control information is provided in an easily modified and understandable set of rules.
- Specific feature type, thematic variable, and image classification information can be persistent across different classifications of the same area, and can be modified for use in other regions or with different feature types.
- Computationally expensive operations can be avoided using restriction operators, without resorting to manual image recoding, masking, and image recombination.
- The modular rule-based approach allows the integration of evidential and deterministic discrimination techniques, and the incremental addition of new spatial data operators, thematic data, or knowledge, which aid land-cover classification.

The described rule-based approach illustrates a straightforward, flexible, unified means of improving classification accuracy while incorporating remote sensing, GIS, and AI techniques. Accuracy was improved in a statistically significant manner for different study areas, analysts, and image acquisition dates. This work demonstrates the potential for using AI and GIS techniques to integrate these accuracy improvements directly into the classification phase. Further, both strategic and descriptive information are explicitly represented and can be easily changed, supporting the persistence of knowledge and facilitating incremental improvement in the classifier, flexibility in the incorporation of new image processing techniques, and application of the method to new areas or feature types.

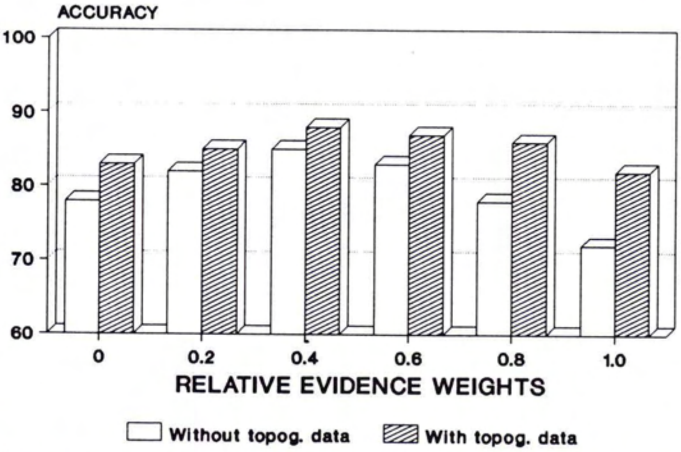

FIG. 5. Results of the sensitivity test classifications in which the relative weights of the image and thematic spatial data varied from 0 to 1. Classifications were based on a combination of TM and soils data (without topographic data) and a combination of TM, soils, and topographic position data (with topographic data). Overall classification accuracies are for 13 Anderson level II/III classes, based on 382 sample points.

LIMITATIONS AND PROSPECTS

Conclusions for the current work are limited to the conditions of the study. Although a range of conditions was tested, comparisons of new to traditional approaches for a broader range of themes, analysts, feature types, and image types are necessary to establish broad-scale generality of the new approach. However, the success of the RS/GIS/AI approach under a broader range of conditions is probable, particularly when a broader range of spatial data primitives is supported.

ACKNOWLEDGMENTS

This work was supported by the U. W. Institute for Environmental Studies, the U. W. College of Agriculture and Life Science, School of Natural Resources, and Sigma Xi.

REFERENCES

Anderson, J. R., E. E. Hardy, J. T. Roach, and R. E. Witmer, 1976. *A Land Use and Land Cover Classification System for Use with Remote Sensor Data*, Professional Paper 964, USGS, Washington D.C.

Argialis, D. P., and C. A. Harlow, 1990. Computational Image Interpretation Models: An Overview and a Perspective, *Photogrammetric Engineering & Remote Sensing*, 56(6):871-886.

Bolstad, P. V., and T. M. Lillesand, 1990. Rapid Maximum Likelihood Classification, *Photogrammetric Engineering & Remote Sensing*, 57(1):67-76.

Buchheim, M. P., 1988. *Non-Traditional Approaches to Classification of High Resolution Satellite Imagery in a Microcomputer Environment*. Unpublished Ph.D. thesis, University of Wisconsin-Madison, 236 p.

Buchheim, M. P., A. L. Maclean, and T. M. Lillesand, 1985. Forest Cover Type Mapping and Spruce Budworm Defoliation Detection Using Simulated SPOT Imagery, *Photogrammetric Engineering & Remote Sensing*, 51(8):1115-1122.

Burroughs, P. A., 1986. *Principles of Geographical Information Systems for Land Resource Assessment*. Clarendon Press, Oxford, 194 p.

Civco, D. L., 1989. Knowledge-based Land Use and Land Cover Mapping, *Technical Papers, ASPRS/ACSM Annual Convention*, pp. 276-291.

Cohen, J., 1960. A Coefficient of Agreement of Nominal Scales, *Educational and Psychological Measurement*, 20(1):37-46.

Curtis, J. T., 1959. *The Vegetation of Wisconsin*. University of Wisconsin Press, 657 p.

Duda, R. O., P. E. Hart, J. Gaschig, K. Konolige, R. Reboh, and J.

Slocum, 1978. *Development of the Prospector System for Mineral Exploration*, Final Report, SRI Projects 5821 and 6415, SRI International, Menlo Park, California.

Ferrante, R. D., M. H. Carlutto, H. Pomaraede, and P. W. Baim, 1984. Multi-spectral Image Analysis System, *Proc. 1st Conf. Artificial Intelligence Applications*, pp. 357-363.

Fleiss, J. L., J. Cohen, and B. S. Everitt, 1969. Large Sample Standard Errors of Kappa and Weighted Kappa, *Psychological Bulletin*, 72:613-619.

Fleming, M. D., and R. M. Hoffer, 1979. Machine Processing of Landsat MSS Data and DMA Topographic Data for Forest Cover Type Mapping, *Proc. Machine Processing of Remotely Sensed Data*, Purdue University, pp. 377-390.

Gaydos, L., and W. L. Newland, 1978. Inventory of Land Use and Land Cover of the Puget Sound Region Using Landsat Digital Data, *Jrnl. of Research*, U.S. Geological Survey, 6:807-814.

Goldberg, M., D. G. Goodenough, M. Alvo, and G. M. Karma, 1985. A Hierarchical Expert System for Updating Forestry Maps with Landsat Data, *Proc. IEEE*, 73:1054-1063.

Hoffer, R. M., S. C. Noyer, and R. P. Mroczynski, 1978. A Comparison of Landsat and Forest Survey Estimates of Forest Cover, *Proc. Fall Technical Meeting*, American Society of Photogrammetry, pp. 221-231.

Hopkins, P. J., A. L. Maclean, and T. M. Lillesand, 1988. Assessment of Thematic Mapper Imagery for Forestry Applications Under Lakes States Conditions, *Photogrammetric Engineering & Remote Sensing*, 54(1):61-70.

Horler, D. N. H., and F. J. Ahern, 1986. Forestry Information Content of Thematic Mapper Data, *Intl. Jrnl. of Remote Sensing*, 7(3):405-428.

Hutchinson, C. F., 1982. Techniques for Combining Landsat and Ancillary Data for Digital Classification Improvement, *Photogrammetric Engineering & Remote Sensing*, 48(1):123-130.

Jackson, P., 1986. *Introduction to Expert Systems*, Addison-Wesley Co., 204 p.

Knuth, D. E., 1973. *The Art of Computer Programming, Vol. 3: Sorting and Searching*. Addison-Wesley Co., 723 p.

Latty, R. S., 1984. Scene Segmentation Through Region Growing, *Proc. 7th Symp. on Machine Processing of Remotely Sensed Data*, pp. 305-314.

Latty, R. S., and R. M. Hoffer, 1981. *Waveband Evaluation of the Proposed Thematic Mapper in Forest Cover Classification*, LARS Technical Report 041581, LARS, Purdue University, W. Lafayette, Indiana, 12 p.

Lee, T., J. A. Richards, and P. H. Swain, 1987. Probabilistic and Evidential Approaches for Multisource Data Analysis, *IEEE Trans. on Geoscience and Remote Sensing*, GE-25(3):283-292.

Likens, W., and K. D. Maw, 1981. Hierarchical Modeling for Image Classification, *Proc. Pecora VII Symp.*, Sioux Falls, S.D., pp. 290-300.

Lillesand, T. M., and R. W. Kiefer, 1987. *Remote Sensing and Image Interpretation*, 2nd Ed., John Wiley and Sons, New York, 721 p.

Marble, D. F., and D. J.Pequet, 1983. Geographic Information Systems, *Manual of Remote Sensing*, Vol. 1, pp. 923-958.

Mason, D. C., D. G. Corr, A. Cross, D. C. Hogg, D. H. Lawrence, M. Petrou, and A. M. Tailor, 1988. The Use of Digital Map Data in the Segmentation and Classification of Remotely-sensed Images, *Int. Jrnl. of Geographical Information Systems*, 2(3):195-215.

McDermott, J., 1982. R1: A Rule-Based Configurer of Computers, *Artificial Intelligence*, 19:39-88.

Mehldau, G., and R. A. Schowengerdt, 1990. A C-extension for Rule-based Image Classification Systems, *Photogrammetric Engineering & Remote Sensing*, 56(6):887-892.

Moore, M. M. and M. E. Bauer, 1990. Classification of Forest Vegetation in North-Central Minnesota Using Landsat Multispectral Scanner and Thematic Mapper Data, *For. Sci.*, 36:330-342.

Nelson, R. F., R. S. Latty, and G. Mott, 1984. Classifying Northern Forests With Thematic Mapper Simulator Data, *Photogrammetric Engineering & Remote Sensing*, 50(5):607-617.

Richards, J. A., 1986. *Remote Sensing Digital Image Analysis*, Springer-Verlag, 292 p.

Richards, J. A., D. A. Landgrebe, and P. H. Swain, 1982. A Means for Utilizing Ancillary Information in Multispectral Classification, *Remote Sensing of Environment*, 12:463-477.

Shortliffe, E. H., 1976. *Computer-based Medical Consultations: MYCIN*, Elsevier, 622 p.

Strahler, A. H., T. L. Logan, and N. A. Bryant, 1978. Improving Forest Cover Classification Accuracy from Landsat by Incorporating Topographic Information, *Proc. 12th Int. Symp. on Remote Sensing of the Environment*, Philippines.

Strahler, A. H., J. E. Estes, F. C. Mertz, and D. A. Stow, 1980. Incorporating Collateral Data in Landsat Classification and Modeling Procedures, *Proc. 14th Internat. Symp. of Remote Sensing of Environment*, Environmental Research Institute of Michigan, pp. 1009-1026.

Swain, P. H., and S. Davis., 1978. *Remote Sensing: A Quantitative Approach*, McGraw-Hill Book Co., 396 p.

Swain, P. H., and H. Hauska, 1977. The Decision Tree Classifier: Design and Potential, *IEEE Trans. On Geoscience Electronics*, GE-15(3):142-147.

Tomlin, C. D. and B. J. L. Berry, 1979. A Mathematical Structure for Cartographic Modeling in Environmental Analysis, *Proc. 39th Amer. Cong. Surveying and Mapp. Ann. Mtg.*, Washington, D.C., pp. 269-283.

Vogelman, J. E., and B. N. Rock, 1986. Assessing Forest Decline in Coniferous Forests of Vermont Using NS-001 Thematic Mapper Data, *Intl. Jrnl. of Remote Sensing*, 7(10):1303-1321.

Wang, F., and R. Newkirk, 1987. Design and Implementation of a Knowledge Based System for Remotely Sensed Change Detection, *Jrnl. of Imaging Technology*, 13(4):116-122.

Westman, J., 1989. *Applications of a Cray X-MP Supercomputer to Digital Image Classification*. Unpublished Master of Science thesis, University of Wisconsin-Madison, 262 p.

Wharton, S. W., 1987. A Spectral-knowledge-based Approach for Urban Land-cover Discrimination, *IEEE Trans. on Geoscience and Remote Sensing*, GE-25(3):272-282.

Williams, B., 1978. *A Sampler on Sampling*, John Wiley and Sons, New York, 254 p.

(Received 11 February 1991; revised and accepted 29 October 1991)