DIGITAL CLASSIFICATION OF LANDSAT THEMATIC MAPPER IMAGERY FOR RECOGNITION OF WILDLIFE HABITAT CHARACTERISTICS

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ABSTRACT

We present a variation of the supervised approach to image classification in which specific forest stand attributes are recognized as the label for a training area. We have developed condition specific spectral classes that have lower variances than classes developed by traditional methods. We find these classes to be consistently correlated to various forest types and less likely to represent commission errors than the more variable classes developed by traditional methods. The large number of classes (150-200) thus produced would be difficult to handle if they were not aggregated into a polygon map. We also describe a variation on the use of unsupervised training, for classifying those regions not classified by supervised methods.

INTRODUCTION

A recently passed California State Assembly Bill, AB 1580, directs the California State Resources Agency to convene a Timberlands Task Force to improve the protection of wildlife resources, and resolve issues concerning their management. One of the directives within the task force workplan is to develop a coordinated base of scientific information regarding the location, extent, and species composition of timberland ecosystems in California. Lack of a comprehensive habitat database of the detail and extent necessary to model wildlife habitats required that new timberlands information be developed. The Task Force responded by initiating a pilot study, managed by the California Department of Forestry and Fire Protection (CDF), Forest and Rangelands Resources Assessment Program (FRRAP), that would utilize Landsat satellite imagery and automated data processing techniques to identify and map habitat types on two study areas within the Klamath Province in northern California.

CDF-FRRAP initiated a contract in 1990 with Geographic Resource Solutions (GRS), an image processing and GIS consulting firm, to map Wildlife Habitat Relationships (WHR) cover types (Mayer and Loudenslayer, 1988) over a six million acre study area in northwest and north-central California. GRS is using Landsat, Thematic Mapper, digital imagery to create this vegetation layer, throughout the project area. CDF-FRRAP, the Mapping and Wildlife Advisory Committees, the California Interagency Wildlife Task Group, and GRS participated in the development of rules that would identify the WHR types and provide a systematic approach to the classification and determination of WHR habitat types and classes (Table 1).

Table 1: Classification Scheme for WHR Types

WHR Vegetation Classes:

Subalpine Conifer	Jeffrey Pine
Red Fir	Ponderosa Pine
White Fir	Eastside Pine
Douglas-fir	Pinyon-Juniper
Redwood	Juniper
Closed-Cone Pine/Cypress	Mixed Conifer
Montane Hardwood/Conifer	Hardwood
Lodgepole Pine	Shrub
Herbaceous/Forb	Barren
Water	

WHR Tree Canopy Closure Classes:

Class	Canopy Closure
0	Non-vegetation types
1	10 - 24% (SPARSE)
2	25 - 39% (OPEN)
3	40 - 59% (MODERATE)
4	>= 60% (DENSE)

WHR Size Classes:

Class	Average Tree Size (QMD)
0	Non-tree types
1	0.0 - 5.9"
2	6.0 - 10.9"
3	11.0 - 23.9"
4	24.0 - 35.9"
5	>= 36.0"

WHR Canopy Closure Classes for non-tree vegetation:

Class	Canopy Closure
2	10 - 39%
3	>= 40%

WHR Structure Classes:

Class	Structure
UNDF	Non-tree type
E	Even
U	Multi-layered(Uneven)

Objectives

The primary goal of the pilot study has been to provide information about the feasibility of developing GIS databases and mapping timberlands using Landsat Thematic Mapper imagery.

Our specific objectives are to:

1. Define a methodology for developing a WHR habitat, polygon database, based upon Landsat image classification methods and raster to vector conversion routines, that is feasible, repeatable, and cost-effective so that it could be consistently applied to the entire state and enable automated map updates.

2. Compare the WHR habitat database, created for a 200,000 acre subset of the project area, using a 5-acre minimum size mapping unit with a data base of the same region, using a 40-acre minimum size mapping unit.

3. Perform an assessment of the accuracy of each WHR characteristic estimated using this methodology.

Our purpose in this paper is to discuss the methodology used for Landsat image classification (the first part of objective 1). A companion paper, also in this session, by K. Stumpf and J. Koltun (1992) will address the comparison of minimum mapping units (objective 2) and the general issue of converting raster classifications to polygon maps (the last part of objective 1). The accuracy assessment (objective 3) is currently underway and will be reported at a later date.

<u>Project Area</u>
Two regions within the Klamath Ecological Province were selected for the Mapping Pilot Study, Project Area (Figure 1).

The coastal area contains approximately 5.2 million acres and comprises Del Norte, Humboldt, and Mendocino counties. The inland region is a 1 million acre rectangle centered about Mt. Shasta. These areas were chosen to encompass a wide variety of vegetation types, including the old growth redwood and Douglas-fir habitats of the northern California coast. Within the coastal region, a smaller area was evaluated to compare the effects of changing the minimum mapping unit from forty, to five acres (Stumpf and Koltun, 1992).

DIGITAL IMAGE PROCESSING

We used Intergraph software and hardware and custom programed utilities to integrate image processing techniques, grid modeling, and GIS analysis. This methodology incorporated a combination of supervised and unsupervised techniques to classify the TM imagery.

<u>Satellite Imagery</u>
Five TM scenes provided the basis for the classification of the project area. The imagery was geo-corrected for terrain and satellite-orientation distortions and resampled to a pixel size of 25 meters by Hughes STX Corporation. Due

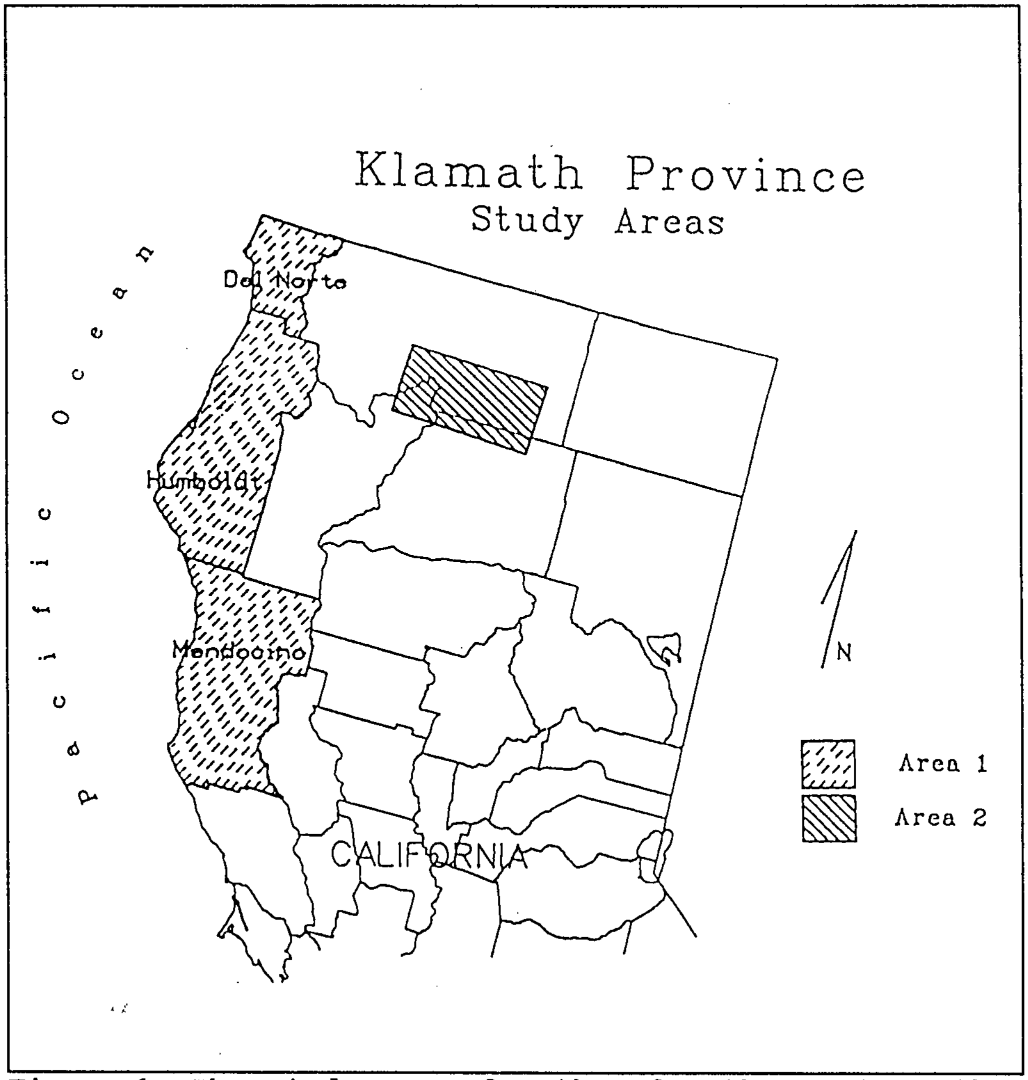

Figure 1. The study area for the Klamath mapping pilot project.

to unfavorable weather conditions and the poor data quality of one scene, the five scenes used for this project were acquired on two different dates. Three of the scenes were acquired on June 27, 1990 and two, on May 1, 1990. We did not consider these to be optimum dates. Coincident dates in the early summer (near the summer solstice) would have been preferable to minimize terrain shadowing and capture maximum spectral diversity between forest types.

Collateral Data

Thematic data of different formats and from multiple sources have been translated and incorporated into the project databases. These data have assisted in the organization, planning, and review of the classification processes. Themes used in this effort include: transportation, hydrology, vegetation type, elevation, ownership, political boundaries, latitude-longitude projection grids, and regeneration/stocking status data.

Collateral information was not incorporated into the WHR classification but rather we relied on spectral signature alone to identify WHR types. We felt strongly that since this was a pilot project investigating the application of image processing methods that the results should reflect the potential of these processes and not be enhanced or altered by including data, not based on image processing. Therefore, elevation data were not included to differentiate between the location of red fir and white fir stands and soil information was not used to identify areas that probably supported Jeffrey pine stands rather than ponderosa pine stands. This information may be incorporated later in the process, following the determination of the accuracy of the image processing techniques, if this information corrects problems identified during the accuracy assessment phase of the project.

Image Classification Techniques

The compilation of spectral data for the WHR habitat delineation required the development of image training data that was linked to quantitative ground data. We used both supervised and unsupervised training methods since both training methods offer advantages and limitations (Fox, et al, 1983). The supervised method is based on homogeneous training areas selected to develop spectral classes that represent the vegetation classes, required for the mapping project. The unsupervised method is based on mathematical clustering procedures that define spectral classes that may or may not coincide with the vegetation classes required for the mapping project. The supervised method alone would have limited the final classified map to a narrow set of possible classes, leaving a portion of the image unclassified. The unsupervised method alone would have been based on spectral information only, without regard to the vegetation class characteristics (Lillesand and Kiefer, 1987). Once spectral signatures were defined, a maximum likelihood algorithm was used to classify the pixel image (Figure 2).

Our workflow deviates from the standard techniques outlined in many textbooks (eg, Lillesand and Kiefer, 1987) in that we did not aggregate our spectral training areas into WHR categories in order to develop spectral signatures representing a particular WHR type. Instead, we kept each of our training areas separate and developed spectral signatures for each training area. The training areas were selected with the goal of encompassing spectral diversity visible in the imagery so that blatantly redundant training areas were not defined. This meant that we could not label a training area as canopy closure class 3, 40-59 percent cover, for example, since that spectral signature came from one training area with one specific canopy closure, 52.3 percent. We decided that a specific percentage of canopy closure, developed from the ground transects taken in that training area, was a better estimate of the actual canopy closure of the spectral class than the WHR closure class. Similarly, we labeled each of the supervised spectral classes with specific data on species composition, tree size, and percentage canopy closure. We therefore developed spectral class labels that precisely represented the attributes of the pixels in the training area.

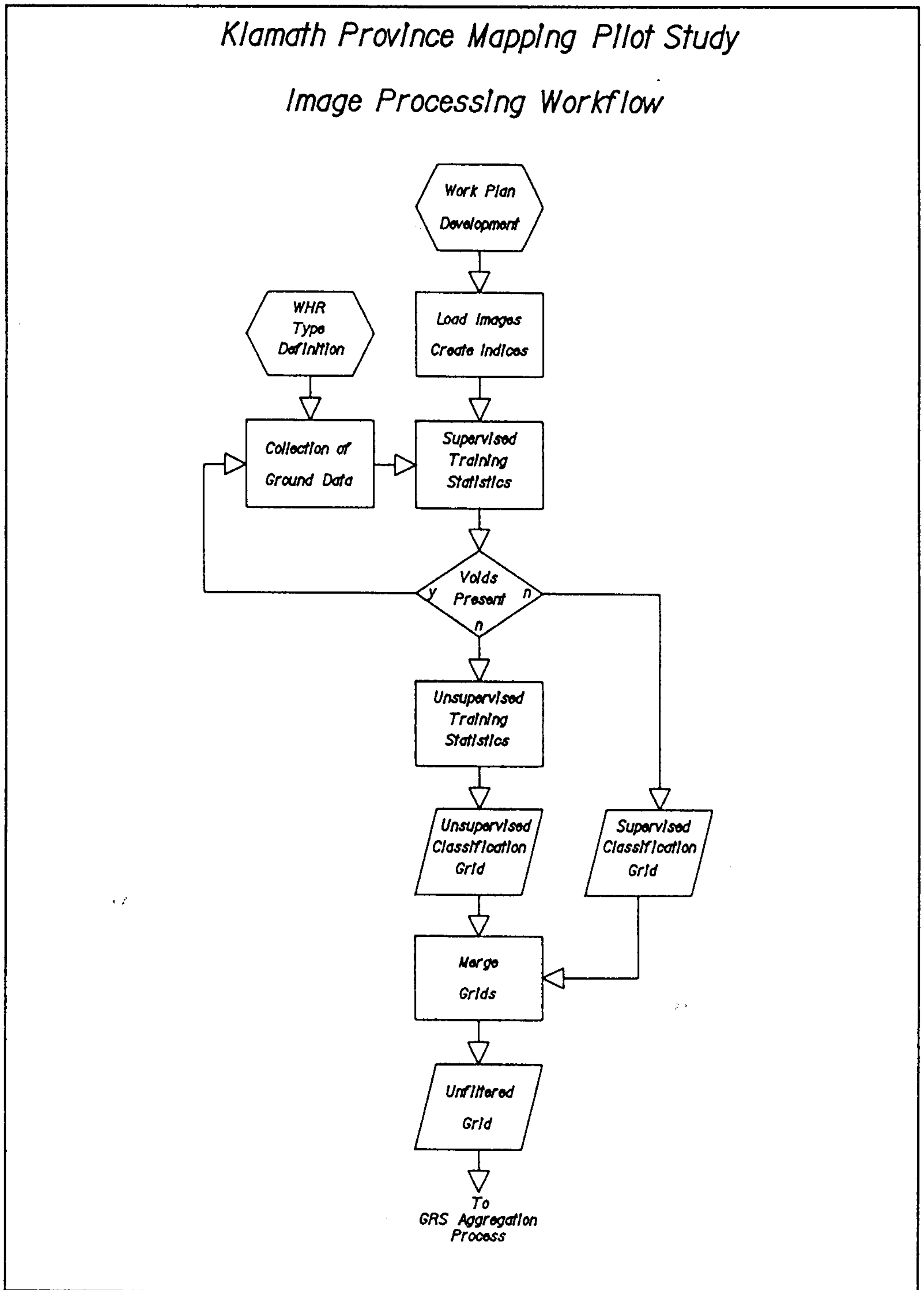

Figure 2. Schematic work flow for developing spectral signatures and classifying Landsat Thematic Mapper Data.

A disadvantage of this approach is that we created a large number of supervised spectral classes (approximately 150 to 200, depending on the region). This precluded the ability to simply "color the classification" and display a thematic map, since using 150 colors produces a very confusing map display. We did not feel this disadvantage to be a major problem since we were aggregating the pixel map into polygon map in order to produce the final vegetation classification and we could always aggregate the color scheme by WHR type in order to produce an understandable display of the vegetation classification.

Supervised Training. Training sets were developed for multiple TM scenes if they shared the same image acquisition date and the same bio-region. Training was based on data collected from representative ground samples (stands) that were homogeneous in terms of species, size, canopy closure and structure. A matrix of WHR types was developed to ensure representation of all WHR attributes present in the study area. Ground sample transects were then located on computer screen displays of digital imagery and digitized into a GIS. Spectral statistics were then developed for spectrally homogeneous regions surrounding the sample transects.

The selection of training areas for ground sampling was based on the vegetative characteristics to be mapped during the project and the spectral separability of the pixels in a particular training area. Prior to the ground data collection, foresters from the different regions were contacted and interviewed about the vegetation conditions encompassed by their geographic area of responsibility or ownership. These interviews proved useful in finding large homogeneous areas of desired stand characteristics. Potential training plots were delineated on USGS, 7.5 minute quad maps, orthophoto products, and the most recent aerial photography available from the various property owners. These potential training areas were reviewed for spectral homogeneity before data were collected.

Ground data were collected for the development of quantitative information on species composition, percent canopy cover, tree size in terms of quadratic mean diameter (QMD), and canopy structure from transects located within each training area. The ground "training" data were measured and collected using a pin-point transect method. The sampling transect was broken into three, 396-foot sections, that were laid out in the form of a triangle to insure that each of these triangles was located within perceived boundaries of homogeneous stands and away from stand edges. Canopy closure was calculated from a set of 100 transect points. The field observer viewed vertically upwards at each point using a custom designed periscope and recorded "crown intersection" or "no crown intersection".

After ground sampling, the training area locations were transferred into a GIS layer using a computer display of color composite imagery, DLG data layers, and field survey data. A stand boundary was digitized around the training plots and placed as a GIS theme to represent a training area on the imagery. We included only those pixels that were immediately surrounding the location of a field data collection area. Spectral variation was minimized within the training area by excluding those pixels exhibiting clear color differences as they were displayed in the color image. A TM band 5,4,3 (RGB) false-color composite was used to represent the three major parts of the TM spectrum in the color display: middle infrared, near infrared and visible. Six of the seven bands of TM data were selected from the training area for each spectral class. The thermal infrared band (TM6) was excluded due to high variances evident in this band. These classes were homogeneous spectrally, having maximum single band standard deviations of 15 digital numbers or less.

The supervised training areas were then evaluated for spectral separability using Euclidean and J-M distance statistics. For the portions of the study area completed thus far, 98 percent of the supervised classes were judged to be separable from each other spectrally. The inseparable classes were of early succession plantations representing the same WHR type so that spectral discrimination was not expected or necessary.

Supervised Classification. All TM bands (except band 6) and several transformed bands (NDVI, TM4-TM3/TM4+TM3; TVI, square root of NDVI; ARCTAN, arc tangent of TM4/TM3; PC1, the first principal component of TM1, TM2, and TM3) were considered for use in the final classification. In order to evaluate classification performance, all possible band combinations including transformed bands were used to produce multiple classifications of only the pixels in the training areas. Error analysis reports from these classifications were reviewed and bands were selected to maximize correct classification thus minimize band to band correlation. This selection method yielded different band combinations for different geographical areas. For example, two spectral bands, TM bands 4 and 5, and two transformed bands, the transformed vegetation index (TVI) and the first principal component of TM bands 1, 2 and 3, where selected for classification of all habitat components (species, size, canopy closure, structure) in a portion of the coastal study area. A maximum likelihood classifier was then used to perform the classification.

Unsupervised Training. Approximately 15 percent of a TM data set remained unclassified after classification with a two-standard deviation threshold placed on the supervised classifier. In order to classify the remainder of the image, an unsupervised clustering algorithm was used to generate unsupervised statistics for about 85 unsupervised spectral classes. The same TM bands were used in the development of these statistics as were used to classify the supervised training areas. The number of unsupervised classes developed was dependent on the standard deviation and the Euclidean distances of the classes after two iterations. If the variance within a class or any number of classes was above a desired level of 15 digital numbers or if the Euclidean distances between classes was considered too close (less than 8 digital numbers) to be considered unique, then changes were made in the parameters for the clustering algorithm to merge or divide the classes. This process was continued until the training statistics met the desired criteria and migration of data between classes stopped.

Unsupervised Classification. The unsupervised class statistics were used to drive a maximum likelihood classification with the same bands used in the supervised approach. This process classified approximately 90 percent of the image. This process was used to classify the entire image, not just the pixels left unclassified by the supervised methods.

Labeling Unsupervised Classes. Some of the unsupervised classes developed represented non-forest types and were easily identified in homogeneous regions on the image, spatially correlated with aerial photographs, and field notes, and labeled accordingly. However, some of these classes were associated with forest types, heterogeneous in their spatial arrangement and exceedingly difficult to label.

A spatial, GIS overlay between the supervised and the unsupervised classifications was used to produce a report listing all the unsupervised classes that were needed to complete the final classification. That is, an unclassified area in the supervised classification was "filled in" by one or several classes from the unsupervised classification. A second overlay was then performed between the two classifications to generate a list of all the unsupervised classes and their corresponding supervised classes (that is, the class values that share the same pixel location). A summary table showing the number of supervised classes represented by each of the unsupervised classes was generated using grid analysis software. An example is presented in Table 2.

Table 2: Distribution of supervised classes within one unsupervised class

Unsupervised Class	Supervised Class	Number of Pixels
15	0	15040
15	1	8204
15	16	5744
15	28	10
15	29	3221
15	50	2626
15	52	1146
15	54	9803
15	55	140

This summary table was then referenced as a class description by the aggregation software that we developed to generate labels for the unsupervised classes, that were used to fill unclassified areas in the supervised classification. The labeling program assigns labels for the unsupervised spectral classes based on the frequency distribution of supervised classes that correspond to each unsupervised class. Of course there is always the possibility that an unsupervised spectral class might be completely unclassified with respect to the supervised classification. This would indicate that more training data were needed to characterize this unsupervised class.

FINAL THOUGHTS

Preliminary accuracy assessments indicate the spectral classes represented by these methods are more specific to one particular vegetation condition and site, than spectral classes generated using more conventional techniques. The main difference with our approach is that many more classes are generated, and class variance is much lower than classes developed from conventional techniques. Defining precise spectral signatures is desireable yet dealing with 200 spectral classes is undesirable. We were able to work with large numbers of spectral classes since we used the pixel classification only as an intermediate product. The final polygon map was aggregated from the pixel data.

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