Using Guided Clustering Techniques to Analyze Landsat Data for Mapping Forest Land Cover in Northern California

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I. ABSTRACT

Three approaches to computer assisted Landsat multispectral classifications are described. The supervised classification technique enables the analyst to focus on land cover categories of interest. The unsupervised approach uses the statistical properties of the image to identify spectrally pure classes. Guided clustering combines the characteristics of both approaches to develop the maximum number of low variance classes for each land cover category defined.

The application of guided clustering to forest land classification is explained. EDITOR software was used to merge and edit spectral statistics to produce the maximum number of low variance, statistically separable classes. Color-infrared aerial photography was used to assign meaningful forest cover labels to spectral classes of unknown vegetative composition. Classification accuracies were high (91.6% omission, 91.4% commission).

III. ANALYSIS TECHNIQUES

Supervised and unsupervised classification techniques are the two commonly recognized approaches to Landsat multispectral classifications. The supervised approach allows the analyst the ability to identify training areas on the ground which represent specific land cover/land use categories. Training areas are used to develop sets of multivariate statistics which contain means, variances, and covariances. Statistics generated from these areas are then used to classify areas of unknown vegetative composition. A Gaussian maximum likelihood classifier.
is a common algorithm used in this process.

Errors often arise in supervised classifications when variances are high (15-30 digital numbers squared) within a training area. Given a constant Euclidean distance, statistical distances between classes are reduced when variances are high. This results in fewer unique spectral classes being defined and increased spectral confusion. High variances are especially common when supervised classifications are performed on areas of natural vegetation since areas that appear to be single cover types on aerial photographs may actually consist of several spectral classes. The analyst is often forced to accept high variances when using supervised techniques to classify a heterogeneous cover type.

The unsupervised technique uses the statistical properties of the image as the basis for classification. The analyst estimates a reasonable number of spectral classes that will be representative of the study area. Multivariate clustering algorithms are used to assign pixels to the selected spectral classes. The separability or divergence statistics for these classes are evaluated to determine their spectral proximity. If classes are inseparable, clustering will be performed again with fewer classes. This will assure that the maximum number of low variance classes will be defined.

Problems with this technique occur because the analyst must "estimate" a reasonable number of spectral classes. If too few classes are chosen initially, there will be a loss of spectral integrity within the classification. The classes defined may actually represent two or more spectral classes. It is difficult to determine from the class statistics (means, variances, and separabilities) whether enough spectral classes have been chosen, as variances are often not high enough to cause alarm (3-8 digital numbers squared). Another problem that occurs with the unsupervised technique is that the analyst may have little concept of the land cover categories represented by the spectral classes isolated. Since no training areas are defined, it becomes difficult to assign meaningful land cover labels to individual, or groups of spectral classes.

From our investigation, we found that the number of spectral classes defined was more than twice the number of land cover categories required for the inventory. To alleviate the above problems we employed both supervised and unsupervised techniques.

In this study the classification was approached using a supervised strategy and clustering within training areas, referred to as guided clustering. Training fields were defined for each vegetation category within the study area. Histograms were constructed from pixel digital counts in each channel for the training areas defined. A visual inspection of these histograms indicated the probable number of spectral classes present. These training areas contained between 3 and 6 spectral classes each. A minimum distance clustering algorithm was used to create several classes (spectral statistics). Swain-Fu distance was used as the separability statistic to insure spectral separation. 5 A separability of 0.0 to 0.45 for any two classes required that clustering be repeated with fewer classes. Statistical modeling suggested 0.45 as the minimum separability needed to classify with an approximate 0.95 probability of correct classification. 6 Clustering was also repeated when class variances were high (<10 digital numbers squared). This provided the opportunity to split high variance classes in order to reduce variances and increase classification accuracy. This technique was successful, resulting in the identification of the maximum number of separable classes for each land cover category. It is important to note that high light reflectance categories such as snow, always exhibited a high class variance. If a spectral class had a high variance and was significantly different from the other classes, it was saved and included in thestatistics file.

Approximately 10 to 15 training areas containing 50-100 pixels, were selected for each land cover category. Clustering within these areas was performed independently creating a series of statistics files, some of which contained similar spectral statistics. These statistics files for the vegetation cover categories were merged and edited to remove spectral confusion. Separability statistics were analyzed at each step, and separable classes (<.45) were retained in the merged file. A class was always deleted when it conflicted with two or more other classes. When a class conflicted with only one class, they were pooled together creating a new spectral class containing the combined spectral properties of the pooled classes (Table 1). If the pooled class was separable from the other classes in the statistics file, it was retained. This process continued until all of the vegetation cover categories had been included.
Table 1. Separability Matrix - Swain-Fu Distance.

Class 1 should be pooled with class 2 creating a new class 1. Class 3 should be deleted as it conflicts with class 4 and 5.

<table>
<thead>
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<th>CLASS</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>0.14#</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td></td>
<td>0.58</td>
<td>0.85</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3</td>
<td></td>
<td></td>
<td>1.76</td>
<td>1.82</td>
<td>0.21#</td>
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<tr>
<td>5</td>
<td></td>
<td></td>
<td>2.54</td>
<td>2.04</td>
<td>0.34#</td>
</tr>
</tbody>
</table>

Upon completion of guided clustering, an unsupervised classification was completed on the same Landsat scene. The spectral statistics from the unsupervised classification were merged with the final statistics created from guided clustering. The merged file was edited to remove spectral confusion. This insured the inclusion of any spectral classes not present in the training areas. Using this technique, it was possible to define a maximum number of low variance spectral classes for the entire study area. The class statistics were used to drive a Maximum Likelihood classification for all of the training areas and the classification was printed out in an alphanumeric code at approximately 1:24,000 scale. The shape and location of each training area was preserved on this printout.

U-2, 1:32,500, color-infrared photography was interpreted to determine the exact vegetation cover category at various points within each training area. This detailed photo interpretation enabled us to assign meaningful vegetation cover labels to the spectral classes defined within the training areas (Figure 1). However, spectral classes still existed without vegetation cover labels, as some classes did not appear in the training areas. A large window (100,000 pixels) was selected from the Landsat scene that was representative of the study area and classified with the final statistics. The remaining un-named spectral classes were identified and labeled through further detailed photo-interpretation.

*# indicates values below 0.45.*

**Figure 1. Detailed Photo-Interpretation.**

Maximum Likelihood classification results for a typical training area (A). Numbers 1-4 represent Landsat pixels. Vegetation mapping by photo-interpretation for the same training area (B). The analyst would conclude that class "1" represents dense conifer forest, classes "2" and "3" represent a reduction in conifer density, and class "4" is still unknown.

The accuracy of the final classification was evaluated using the previously mentioned U-2 photography. A black line grid produced on clear mylar that represented Landsat pixels, was locally fit to the photograph. Sampling clusters were chosen at random and sampled without replacement. Binomial approximation theory was used to develop error statements. Overall accuracy was 91.6% considering omission errors and 91.4% relative to errors of commission.

**IV. CONCLUSION**

Guided clustering has provided the means to produce a classification which contained a maximum number of low variance spectral classes. This meant that each spectral class normally represented one or at most very few similar types of vegetative cover. Usually a single category of cover was represented by several spectral classes. Since variances were low and classes were relatively pure, very little spectral confusion was present in the final classification. Guided clustering seemed especially beneficial when classifying complex ecological communities of heterogenous composition.

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VI. REFERENCES


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