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# Integrating Supervised and Unsupervised Classification Methods to Develop a More Accurate Land Cover Classification

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**Abstract**

The classification and mapping of land cover provides fundamental information about the characteristics, activities, and status of specific areas on the earth's surface. The quality of the final classification is critical in providing accurate information for ecologists and resource managers in decision-making and for developing a landscape-level understanding of an ecosystem. A land cover classification was developed for 5 research watersheds in Garland and Saline counties in Arkansas using 2002 LANDSAT 7 Enhanced Thematic Mapper Plus (ETM+) satellite imagery. The supervised classification was based upon 146 training areas identified from reference data and then applied to the imagery using the maximum likelihood classification algorithm. The unsupervised classification used an Iterative Self-Organizing Data Analysis Techniques (ISODATA) algorithm to classify the imagery into 300 spectral classes which then were identified from reference data. Data from 171 field locations were used to assess the accuracy of the final classifications using an error matrix. The supervised classification had an overall accuracy of 74.85% compared to 40.94% for the unsupervised classification. However, the dense canopy pine plantation class, which comprises 10.69% of the total area of the watersheds (1,216.69 ha), was more accurately classified in the unsupervised classification (64.29%) than the supervised classification (43.86%). The unsupervised classification of dense canopy pine plantation was incorporated into the supervised classification to produce a final integrated classification with an improved overall accuracy of 76.61%. We found that, where greater accuracy is desired, both classification methods should be used and the results integrated to utilize each method's strengths.

## Introduction

Land cover is a distinct concept applied to the classification of the earth's land surface (Estes et al., 1982). Estes et al. (1982) define land cover as æthe vegetational and artificial constructions covering the land surface". The classification of land cover is the assignment of geographic areas to certain classes based upon similar characteristics of land cover. There are numerous uses and purposes for the classification of land cover. Ustin et al. (1999) stated that land cover can provide insight into the underlying soils and geologic conditions of an area. Land use/land cover maps also have the potential for use in preserving prime agricultural farmland, in guiding land development decisions in metropolitan areas, or in developing large scale inventories of resources at the county, state, or federal level (Anderson, 1982). Land cover data, particularly when used in conjunction with other data such as terrain maps available from Digital Elevation Models (DEMs), can be useful in identifying areas more or less suited to specific land management practices and thereby aid in the assessment of appropriate practices for use in a specific area to attain certain goals (Bonner et al., 1982). Development of land cover maps can also be critical in monitoring the changes in land cover for a given area of study or management (Estes et al., 1982). Often an understanding of changes that have occur and the extent of such changes is critical for making appropriate land management decisions (Estes et al., 1982). Land cover classification of a region can help clarify the status of an ecosystem at a specific time. The accuracy of a land cover classification is therefore critical to its utility and value in providing accurate information for ecologists and resource managers.

Supervised and unsupervised are 2 primary methods of image classification, such as a land cover classification. Supervised classification involves the classification of pixels of unknown identity by means of a classification algorithm using the spectral characteristics of pixels of known informational class (referred to as training areas) identified by the analyst (Campbell, 2002). There are several advantages to using this approach to classification. First, the analyst has full control of the informational categories, or classes, to be assigned in the final classification. This allows for easier comparison with other classifications by using identical classes for both. Second, through the process of selecting training areas, the resulting classification is tied to specific areas on the image of known identity. Third, the analyst does not face the problem of matching spectral classes to informational classes, because this is addressed during the selection of training areas. Finally, the training data can be compared with the final classification as one means of detecting serious errors or problems in the classification process (Campbell, 2002). There are also disadvantages and limitations to the use of supervised classification. First, the analyst is "imposing a classification structure upon the data" (Campbell, 2002) by the selection of training areas and of specific information classes, which may not necessarily be present in the data. Second, spectral properties are generally not the primary characteristics used in identifying training areas, which can lead to overlap and ambiguity during the classification process. Third, the selection of training areas requires of the analyst an extensive knowledge of the area and an investment of time and resources that is not required for unsupervised classification. Finally, unique classes present in the image may be overlooked by the analyst during the selection of classes and training areas.

Unsupervised classification involves the separation of image pixels into natural groupings based upon similar spectral characteristics by means of a classification algorithm and the resultant assignment of those groupings to informational classes by the analyst. There are three primary advantages to using this approach to classification. First, extensive knowledge of the area being classified is not required for the initial separation of image pixels. Second, there is less opportunity for human error as the analyst is not required to make as many decisions during the classification process. Third, unique classes in the data will be recognized by unsupervised classification, where as they may be overlooked in a supervised classification. There are also disadvantages and limitations to the use of unsupervised classification. First, the natural groupings identified by the classification process are spectrally homogeneous, which may not necessarily correspond with the informational classes of interest. Second, the analyst has limited control over the classes chosen by the classification process, and the relationships between the natural groupings of spectral classes and that of the desired informational classes are not always directly correlated.

When evaluating an image classification, there are two forms of accuracy that can be considered. The first is non-site-specific accuracy, which looks at the overall agreement between the classified image and the reference data without examination of the agreement between them at specific locations. For example, non-site-specific accuracy involves the examination of the percent Mature Pine Forest in the classified image and the comparison of it to the percent Mature Pine Forest in the reference data. Relying solely on non-site-specific accuracy to evaluate a classification can hide errors resulting from disagreement in the placement of classes between the classified image and the reference data.

The second form of accuracy is site-specific accuracy, which examines the agreement between classes at specific locations on the classified image and in the reference data. This examination is done by means of an error matrix (also known as a confusion matrix or contingency table) to compare, for specific locations, what an area is in the reference data versus how that area has been classified. The error matrix helps to identify instances of classification error for specific classes. There are 2 main types of these classification errors: errors of omission and errors of commission. Errors of omission are instances in which site has been excluded from a class to which it actually belongs. Errors of commission are instances in which a site is included in an incorrect class. Campbell (2002) noted that these errors tend to balance each other, as an error of omission for one class will also be tabulated in the error matrix as an error of commission in another class. Given the characteristics of these errors, it is best to examine them on a class-by-class basis before assuming the errors in one class reflect the errors found in all classes.

For site-specific accuracy assessment using the error matrix, there are three primary measures of classification accuracy: overall classification accuracy, producer's accuracy, and user's accuracy. Overall classification accuracy is the measure of how much area was correctly classified out of the entire area classified. From the error matrix, overall classification accuracy is the sum of the diagonals divided by the total. Producer's accuracy is calculated for each class and gives an indication of how well a particular class has been classified by the producer of that classification. This accuracy is most often used by the producer as a means to assess how well the classification was performed. From the error matrix, the producer's accuracy for each class is the result of dividing the correctly classified pixels by the number of reference data pixels in that class (as determined by the column total). User's accuracy is also calculated for each class and gives an indication of how often the areas assigned to a given class on the image classification actually belong to that class "on the ground". This accuracy is of greater importance to the users of the classification because this indicates how true the classified image is to the actual situation on the ground. From the error matrix, the user's accuracy for each class is the result of dividing correctly classified pixels in a given class by the total number of pixels in that class on the classified image (as determined by the row total).

This paper describes the development of a land cover classification using 2 separate methods (supervised and unsupervised) that were then compared and integrated to improve the overall accuracy of the final classification as determined by means of an accuracy assessment. The land cover classification was derived from LANDSAT 7 Enhanced Thematic Mapper Plus (ETM+) imagery for five watersheds in the Ouachita Mountains in Garland and Saline counties north of Hot Springs, Arkansas.

## Materials and Methods

***Study Area***.–A land cover classification was developed for five research watersheds included in the Ouachita Mountains Ecosystem Management Research Project (OMEMRP) shown in Fig. 1. These watersheds are located in the Ouachita Mountains in Garland and Saline counties north of Hot Springs, Arkansas. The watersheds are as follows: Little Glazypeau – 2,275 ha predominantly under Weyerhaeuser Company ownership; North Alum Creek – 3,961 ha with approximately equal mixtures of Weyerhaeuser Company and USDA Forest Service ownership; Bread Creek – 1,535 ha predominantly under USDA Forest Service ownership; South Alum Creek – 1,499 ha predominantly under USDA Forest Service ownership; and Validation Watershed – 2,110 ha with mixture of USDA Forest Service and Weyerhaeuser Company ownership.

***Data Preparation***.–The base images used in the classification were LANDSAT 7 Enhanced Thematic Mapper Plus (ETM+) satellite images taken January 15th, March 4th, and September 12, 2002. The raw LANDSAT 7 ETM+ satellite images were preprocessed prior to inclusion in classification. These images were orthorectified by the Spatial Analysis Laboratory (SAL) with ERDAS Imagine® software using National Elevation Dataset (NED) Digital Elevation Models (DEMs) for vertical ground control and Digital Orthophoto Quadrangles (DOQ) data for horizontal ground control. Orthorectification is the process of tying image coordinates to ground coordinates by means of ground control for the purpose of creating a planimetrically and geometrically correct image. This process removes or minimizes errors produced by scale variation, sensor attitude/orientation, and internal sensor errors and provides the image with a real coordinate system that can be tied to the ground. Once the satellite images were orthorectified, 3 bands, the 2 thermal bands and the panchromatic band, were removed from each image and not included in the classification. The images were then subset to a bounding rectangle where the outer edges of the watersheds were at least 1.6 km (1 mile) from the bounding rectangle. The remaining bands from all 3 images (January, March, and September) were then merged for use in classification.

***Reference Data***.–Three primary sources were utilized for reference during the classification process: a prior land cover classification of the area, color infrared (CIR) digital orthophoto quadrangle (DOQ) images, and field-collected data. The prior land cover classification was created from 1995 LANDSAT 5 Thematic Mapper (TM) satellite images for OMEMRP that included 4 of the research watersheds and was reported and used by Tappe et al. (2004). The color infrared (CIR) digital orthophoto quadrangle (DOQ) images used as reference during the classification process were acquired between April 2000 and March 2001, with most of the images acquired in late January and February 2001. The DOQ images had a pixel resolution of 1m. These images were obtained from the Natural State Digital Database (http://sal.uamont.edu) which is maintained by the Spatial Analysis Laboratory, University of Arkansas at Monticello.

The field-collected data were obtained during several trips between late January and early March in early 2004 to the study area with two objectives in mind. The first objective was to become more familiar with the area and to collect land cover data from selected locations throughout the watersheds to assist in performing the classification. This first objective was accomplished during the first trip of January 28-30 during which land cover data were recorded for 64 locations throughout the study area. Spatial locations were determined by a Trimble Global Positioning System (GPS) receiver and visual estimates and measurements were made for land cover, forest composition, canopy cover, tree height, forest status (natural vs. plantation), and age. These data were then incorporated into the classification process to assist in identifying spectral classes generated during unsupervised classification and in developing training areas for the supervised classification in order to improve the accuracy of the classification.

The second and final objective was to collect land cover data to be used in developing an accuracy assessment for the classification. This final objective was completed when data collected for use in the accuracy assessment were recorded for 171 additional locations during two trips in early 2004. Spatial location was determined using a Trimble GPS receiver for spatial location, a photograph was taken of the plots in each of the 4 cardinal directions, and measured and visual estimates were taken for land cover, forest composition, canopy cover, tree height, forest status (natural vs. plantation), and age.

***Supervised Classification***.–The combined satellite images were classified by means of supervised classification with ERDAS Imagine® software. Information from the field data, CIR DOQs, and a prior 1995 land cover classification were utilized to identify 146 training areas representing the land cover classes described in Table 1. The Signature Editor in ERDAS Imagine® is an important tool for creating a supervised classification from training areas. Once each training area is identified on the image, the spectral characteristics across all bands and all dates for each pixel in the training area are then input into the Signature Editor where the signature for that training area can be labeled, evaluated, edited, and then incorporated into the supervised classification. The Signature Editor is a means of managing all of the spectral signatures from the training areas for the image(s) being classified. Using the Signature Editor, the spectral signature across all image bands for each training area was obtained and then labeled by land cover class for use in the classification process. The supervised classification, using the maximum likelihood classification method, utilized all 146 individual signatures from the training data. The classification was then passed through both a 3 by 3 pixel majority filter and a 3 by 3 pixel class variety filter using ArcGIS software to allow for possible location inaccuracies during the classification's accuracy assessment.

***Unsupervised Classification***.–The combined satellite images were classified by means of unsupervised classification using an Iterative Self-Organizing Data Analysis Techniques (ISODATA) algorithm with ERDAS Imagine® software. ISODATA is a clustering algorithm that uses an iterative process to separate image pixels into spectrally similar clusters based upon their position in nth dimensional spectral space. The algorithm begins with an initial clustering of the data and the calculation of cluster means in nth dimensional space. Each iteration compares the spectral distance of each pixel to the cluster means and assigns them to the cluster whose mean is closest. Once all pixels are assigned, the cluster means are recalculated, and the pixels are again compared and clustered based on spectral distance to cluster means in nth dimensional space. This process is repeated until specified criteria, such as a convergence threshold, are met or the maximum number of iterations is reached. This process is highly successful at finding inherent clusters in the data and is not biased by initial clustering because of the iterative nature of this algorithm. The parameters for the unsupervised classification were set to 300 initial classes with maximum iterations of 350 and a convergence threshold of 0.990. Information from the field data, CIR DOQs, and a prior 1995 land cover classification were utilized to assign the resulting 300 spectral classes to the land cover classes described in Table 1. The classification was then passed through both a 3 by 3 pixel majority filter and a 3 by 3 pixel class variety filter using ArcGIS software to allow for possible location inaccuracies during the classification's accuracy assessment.

***Integrated Approach***.–As previously discussed, the supervised and unsupervised classification methods each have advantages and disadvantages. An integrated approach that incorporates both methods was explored. The resulting classifications from both methods were compared visually and by using the results of the accuracy assessment to assess the strengths and weaknesses of each with the goal of combining the results for a more accurate and useful final classification. The preliminary results found that the supervised classification was most accurate overall (see Table 3). One land cover class, dense canopy pine, was more correctly classified by the unsupervised method than the supervised method. Using the Spatial Analyst extension in ArcGIS®, the dense canopy pine pixels in the unsupervised classification were incorporated into the supervised classification by means of a CON statement, (If–then–else statement), which determined if a given pixel was a dense canopy pine pixel in the unsupervised classification. If it was, it would be assigned that value in the final classification, but if not, then the value for that pixel was based upon its value in the supervised classification. The integrated classification was also passed through both a 3 by 3 pixel majority filter and a 3 by 3 pixel class variety filter using ArcGIS® software to allow for possible location inaccuracies during the classification's accuracy assessment.

## Results and Discussion

Based upon the final classification, there are four primary land cover classes found within the five watersheds in the Ouachita Mountains Ecosystem Management Research Project: Mixed Forest at 18.88% (2,148.19 hectares); Sparse Pine at 16.73% (1,903.98 hectares); Hardwood/Pine Forest at 11.60% (1,319.82 hectares); and Dense Canopy Pine Plantation at 10.69% (1,216.69 hectares) (see Table 2). There are four other land cover classes with at least 5.00% coverage within the five watersheds: Thinned Pine Plantation at 7.97% (907.25 hectares), Mature Pine Forest at 7.90% (898.42 hectares), Mature Hardwood Forest at 7.00% (796.84 hectares), and Sparse Hardwood Forest at 5.60% (636.98 hectares). The remaining six land cover classes with less than 5.00% coverage within the five watersheds are: Young Pine Plantation at 4.69% (533.65 hectares), Pine/Hardwood Forest at 3.46% (394.12 hectares), Clear-cut at 3.21% (365.68 hectares), Urban/Roads/Bare Ground at 1.82% (206.91 hectares), Field/Grass at 0.43% (48.68 hectares), and Water at 0.02% (2.23 hectares).

***Accuracy Assessment***.–The unsupervised classifi-cation had an overall accuracy of 40.94% (see Table 3), which was the lowest of the three classifications considered. Furthermore, only four classes in the unsupervised classification had either the producer's or user's accuracy greater than 60%: Urban/Roads–user's accuracy 100.00%; Clear-cut–producer's accuracy 71.43%; Dense Canopy Pine Plantation–producer's accuracy 64.29%; and Pine/Hardwood Forest–user's accuracy 66.67%.

The supervised classification had an overall accuracy of 74.85% (see Table 3). Unlike the unsupervised classification, only four classes in the supervised classification had either producer's or user's accuracy below 60.00%, with most over 75.00%: Field–producer's accuracy 25.00%; Dense Canopy

Pine Plantation – producer's accuracy 42.86%; Thinned Pine Plantation – user's accuracy 48.15%; and Mature Pine Forest – producer's accuracy 57.14%.

As classification of Dense Canopy Pine Plantation was more accurate using the unsupervised classification (producer's accuracy of 64.29%) than the supervised classification (42.86%), it was decided to incorporate the unsupervised classification of Dense Canopy Pine Plantation into the supervised classification to improve its accuracy in a combined classification. The Field class was left as is due to the low incidence of this class in the watersheds. Also the Water class was not included in the accuracy assessments for 2 reasons: first, water is spectrally distinct from all other classes and therefore easy to separate from them during classification; second, water constituted only 0.02% of the total area of all watersheds and was not available for ground truthing (precluding involvement in the accuracy assessment).

The integrated classification, which incorporated the Dense Canopy Pine Plantation from the unsupervised classification into the supervised classification, had an overall accuracy of 76.61% (see Table 3). The result was accuracies for all but two classes being over 60.00% with most being 75.00% or greater. The Field class continued to have a producer's accuracy of 25.00%, and the Mature Pine Forest class had a producer's accuracy of 52.38%. Given the overall performance of the integrated classification in the accuracy assessment, the integrated classification was selected as the final classification for use in the Ouachita Mountains Ecosystem Management Research Project.

Given the performance of both supervised and unsupervised methods for the current classification of these 5 watersheds in the Ouachita Mountains, the question arises as to why the unsupervised method produced poorer results overall when compared to the supervised method. One answer appears to be that many of the classes shared similar spectral properties across the 3 image dates, leading to potential confusion in the natural groupings that were based solely on spectral properties by the unsupervised classification algorithm. During the assignment of these groupings to land cover classes, it was a fairly common experience to find a single grouping having several possible land cover classifications as judged from the reference data. This experience suggests that, although it would increase the amount of time required to complete the classification, setting the parameter for the number of initial class groupings higher than the 300 used in this research might have reduced the number of confused classes during the assignment process of unsupervised classification.

Another answer may lie in the use of a predetermined set of land cover classes for this classification. As the analyst has little control over the groupings determined in unsupervised classification, assigning those groupings to preset classes can be more difficult and complicated than assigning them to a more open set of land cover classes. This is 1 of the inherent disadvantages of the unsupervised method of classification. It should be noted, however, that in other situations where the final set of land cover classes is more open to adjustment this disadvantage may not be an issue in the classification.

Likewise, the supervised method produced better results for the current classification than the unsupervised method for similar reasons. The inherent disadvantages of the unsupervised method are advantages of the supervised method, and vice versa. Thus, the use of training areas that are determined by the analyst based on the predetermined set of land cover classes allowed for greater control and accuracy using the supervised method of classification.

The question then arises as to why not just use the supervised classification since it was more accurate than the unsupervised classification for most land cover classes. Comparison of the accuracy assessment results between the integrated classification and the supervised classification offers some reasons for using the integrated classification. First, even though it was small, there was an increase in the overall accuracy of the integrated classification (76.61%) versus the supervised classification (74.85%). Second, two of three accuracy results that were below 50% (Grass/Field Producer's – 25.00%; Dense Canopy Pine Producer's – 42.86%; Thinned Pine User's – 48.15%) for the supervised classification were improved to over 70% in the integrated classification (Dense Canopy Pine Producer's – 78.57% and Thinned Pine User's – 70.59%). Third, although a few accuracies were higher in the supervised classification (Dense Canopy Pine User's 100.00%; Thinned Pine Producer's – 81.25%; Mature Pine Producer's – 57.14%; Mature Pine User's – 85.71%; and Pine/Hardwood Forest User's – 80.00%) versus the integrated classification (Dense Canopy Pine User's 61.11%; Thinned Pine Producer's – 75.00%; Mature Pine Producer's – 52.38%; Mature Pine User's – 84.62%; and Pine/Hardwood Forest User's – 66.67%), only one of these was below 60% in the integrated classification (Mature Pine Producer's – 52.38%), and it should also be noted as below 60% in the supervised classification (Mature Pine Producer's – 57.14%). Thus, overall the integrated classification was an improvement over the supervised classification.

The final question is when the integrated approach should be used to produce a land cover classification. In circumstances where there are only enough resources to use one classification method, considerations should be made as to whether a particular method is best suited for the task when applied. For example, for the classification developed in this study and, by extension, classifications of a similar nature, the supervised method resulted in a more accurate classification than the unsupervised method for reasons already discussed. If the situation were reversed, it is likely that a classification developed using the unsupervised method could result in a more accurate classification. The main consideration then is whether the classification itself will maximize the effect of a particular method's advantages while minimizing the impact of its disadvantages. For circumstances where resources allow the use of both methods, the findings of the current study suggest that using both classification methods followed by integrating the results can produce an improved and more accurate classification, making use of the advantages found in both supervised and unsupervised classification methods.

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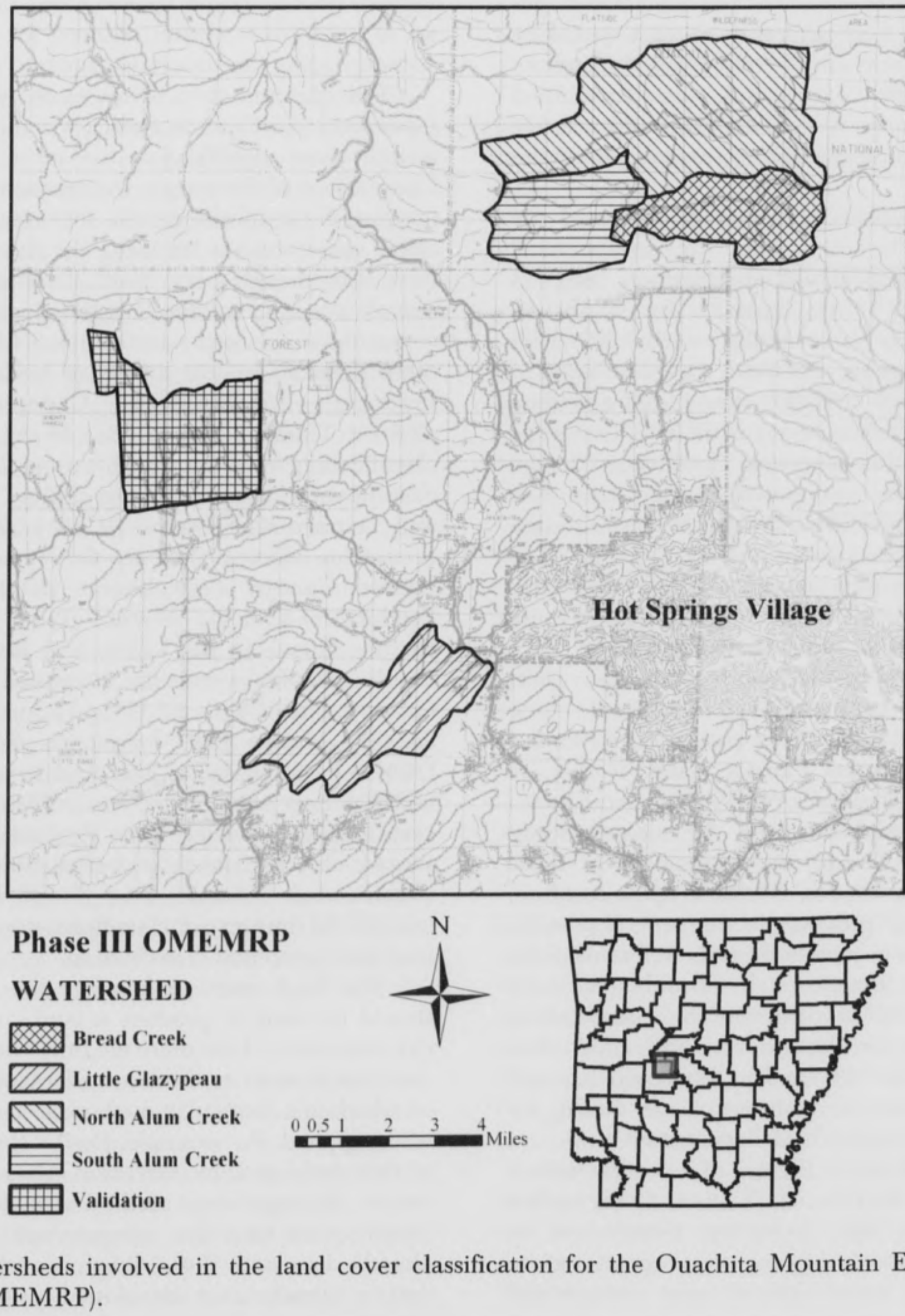


Fig. 1. The five watersheds involved in the land cover classification for the Ouachita Mountain Ecosystem Management Research Project (OMEMRP).

Table 1. Land cover classes and descriptions used in the classification of 5 watersheds in the Ouachita Mountains Ecosystem Management Research Project (OMEMRP).

| Class Number | Land Cover Description (2002) |
|---|---|
| 1 | Water |
| 2 | Urban Area/Roads/Bare Ground/Rocks |
| 3 | Grass/Field |
| 4 | Clear-cut |
| 5 | Young Pine Plantation |
| 6 | Dense Canopy Pine Plantation |
| 7 | Thinned Pine Plantation |
| 8 | Mature, Pine Dominant (>75%) Forest |
| 9 | Sparse Pine |
| 10 | Mature Pine/Hardwood (60-75% Pine) Forest |
| 11 | Mature Mixed Forest |
| 12 | Mature Hardwood/Pine (60-75% Hardwood) Forest |
| 13 | Sparse Hardwood |
| 14 | Mature Hardwood Dominant (>75%) Forest |

Table 2. Percent land cover and acreage for each land cover class for all 5 watersheds of the Ouachita Mountains Ecosystem Management Research Project (OMEMRP).

| Class Number | Description | % Land Cover | Area | |
|---|---|---|---|---|
| | | | acres | hectares |
| 1 | Water | 0.02% | 5.52 | 2.23 |
| 2 | Urban/Roads/Rocks/Ground | 1.82% | 510.88 | 206.91 |
| 3 | Grass/Field | 0.43% | 120.21 | 48.68 |
| 4 | Clear-cut | 3.21% | 902.91 | 365.68 |

Table 2. Continued.

| Class Number | Description | % Land Cover | Acreage | |
|---|---|---|---|---|
| | | | acres | hectares |
| 5 | Young Pine Plantation | 4.69% | 1,317.66 | 533.65 |
| 6 | Dense Canopy Pine Plantation | 10.69% | 3,004.17 | 1,216.69 |
| 7 | Thinned Pine Plantation | 7.97% | 2,240.13 | 907.25 |
| 8 | Mature Pine Forest | 7.90% | 2,218.34 | 898.42 |
| 9 | Sparse Pine | 16.73% | 4,701.19 | 1,903.98 |
| 10 | Pine/Hardwood Forest | 3.46% | 973.14 | 394.12 |
| 11 | Mixed Forest | 18.88% | 5,304.18 | 2,148.19 |
| 12 | Hardwood/Pine Forest | 11.60% | 3,258.82 | 1,319.82 |
| 13 | Sparse Hardwood Forest | 5.60% | 1,572.79 | 636.98 |
| 14 | Mature Hardwood Forest | 7.00% | 1,967.52 | 796.84 |
| | Total | 100.00% | 28,097.46 | 11,379.45 |

Table 3. Comparison of accuracy assessment results for final integrated classification, supervised classification, and unsupervised classification of five watersheds in the Ouachita Mountains Ecosystem Management Research Project (OMEMRP). Class Number 1 (Water) is not included in the accuracy assessment results for 2 reasons: first, water is spectrally distinct from all other classes and therefore easy to separate from them during classification; second, water constituted only 0.02% of the total area of all watersheds and was not available for ground truthing (precluding involvement in the accuracy assessment).

Table 3. Continued.

| Class Number | Description | Integrated Classification (Final) Producer's Accuracy | Integrated Classification (Final) User's Accuracy | Supervised Classification Producer's Accuracy | Supervised Classification User's Accuracy | Unsupervised Classification Producer's Accuracy | Unsupervised Classification User's Accuracy |
|---|---|---|---|---|---|---|---|
| 1 | Water | | | | | | |
| 2 | Urban/Roads/Rocks/Ground | 100.00% | 71.43% | 100.00% | 71.43% | 40.00% | 100.00% |
| 3 | Grass/Field | 25.00% | 100.00% | 25.00% | 100.00% | 0.00% | 0.00% |
| 4 | Clear-cut | 85.71% | 85.71% | 85.71% | 85.71% | 71.43% | 55.56% |
| 5 | Young Pine Plantation | 75.00% | 85.71% | 75.00% | 75.00% | 0.00% | 0.00% |
| 6 | Dense Canopy Pine Plantation | 78.57% | 61.11% | 42.86% | 100.00% | 64.29% | 56.25% |
| 7 | Thinned Pine Plantation | 75.00% | 70.59% | 81.25% | 48.15% | 50.00% | 34.78% |
| 8 | Mature Pine Forest | 52.38% | 84.62% | 57.14% | 85.71% | 52.38% | 44.00% |
| 9 | Sparse Pine | 76.19% | 72.73% | 76.19% | 72.73% | 52.38% | 37.93% |
| 10 | Pine/Hardwood Forest | 66.67% | 66.67% | 66.67% | 80.00% | 33.33% | 66.67% |
| 11 | Mixed Forest | 75.00% | 62.50% | 75.00% | 60.00% | 35.00% | 33.33% |
| 12 | Hardwood/Pine Forest | 90.91% | 83.33% | 90.91% | 83.33% | 31.82% | 41.18% |
| 13 | Sparse Hardwood Forest | 100.00% | 92.31% | 100.00% | 92.31% | 0.00% | 0.00% |
| 14 | Mature Hardwood Forest | 80.00% | 100.00% | 80.00% | 100.00% | 53.33% | 42.11% |
| | **Overall Accuracy** | **76.61%** | | **74.85%** | | **40.94%** | |

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