NASA

Technical Memorandum 81993

Evaluating Landsat Wildland Classification Accuracies

David L. Toll

(NASA-TM-81993) EVALUATING LANDSAT WILDLAND CLASSIFICATION ACCURACIES (NASA) 35 p HC A03/MF A01 CSCL 08B

N81-24497

Unclas

G3/43 25765

AUGUST 1980

National Aeronautics and Space Administration

Goddard Space Flight Center
Greenbelt, Maryland 20771

TM 81993

EVALUATING LANDSAT WILDLAND CLASSIFICATION ACCURACIES

David L. Toll

August 1980

GODDARD SPACE FLIGHT CENTER
Greenbelt, Maryland 20771

CONTENTS

LIST OF TABLES

PRECEDING PAGE BLANK NOT FILMED

Table		Page

LIST OF FIGURES

Figure		Page

EVALUATING LANDSAT WILDLAND CLASSIFICATION ACCURACIES

David L. Toll

ABSTRACT

Procedures for evaluating the accuracy of Landsat derived wildland cover classifications are described and associated problems discussed. The evaluation procedures include: 1) implementing a stratified random sample for obtaining unbiased verification data; 2) performing area by area comparisons between verification and Landsat data for both heterogeneous and homogeneous fields; 3) providing overall and individual classification accuracies with confidence limits; 4) displaying results within contingency tables for analysis of confusion between classes; and 5) quantifying the amount of information (bits/square kilometer) conveyed in the Landsat classification.

Overall low classification accuracies for a test site in northwestern Colorado were determined for the entire sampled population at 37.3 percent (range 35.8 to 38.7 percent) and for the homogeneous areas at 61.3 percent (range 57.1 to 65.2 percent). A further evaluation was undertaken to evaluate possible errors not associated with Landsat classifications. Significant biases in classification accuracy were attributed to defining class characteristics for verification pixels which were not represented within the Landsat classifications. Analysis of sampled verification designations showed that 90 percent of the pixels which were misdesignated for verification were misclassified for Landsat data. Other problems were found with misregistration between verification and Landsat fields, photointerpretation errors for verification field designations, and separate class definitions used for the Landsat classifications and verification fields. An underlying factor contributing to the errors is attributed to ground cover class heterogeneity.

INTRODUCTION

When assessing Landsat land cover classification, there are often many problems which result in inaccurate reporting of classification accuracies. Unfortunately, there are not just one or two problems but usually several which may in effect either decrease or increase the calculated accuracy.

Special attention must be given to six primary areas, when addressing classification accuracy of Landsat maps.

1. The sample from which verification data are selected must have sufficient unbiased observations for providing specified confidence limits for the classification accuracies.
2. The verification data must approach 100 percent accuracy.
3. The class definitions used for the verification designations and Landsat classifications must be similar.
4. The verification data and Landsat classifications must represent the same location prior to area by area comparisons.
5. The results must be reported which provide omission (Type 1) and commission (Type 2) errors, along with sources of confusion between classes.
6. The evaluation of the performance of the Landsat classification requires an evaluation of homogeneous class pixels and not mixed class pixels which cannot be processed by most classifiers. Heterogeneous class pixels should also be analyzed for assessing the actual accuracy of classification maps.

The purpose of this paper is to describe some of the most likely problems associated with evaluating Landsat land cover classifications. In addition, procedures are described for use in an accuracy evaluation of Landsat land cover classifications.

LITERATURE REVIEW

Methods Used in Collecting Verification Data

Many workers have referenced the necessity of using a proper sampling design for evaluating the classification of processed multispectral data (Kelly, 1970; Berry and Baker, 1968; Hajic and Simonett, 1976; and Genderen and Lock, 1976). The sample design yields an unbiased selection of evaluation fields and adequately samples all classes.

Randomly selected coordinates are often used for locating unbiased evaluation fields. Stratification procedures may be used to subdivide large areas into units (strata), having similar features (e.g., soils, geology, topography, and climate) for more informative and useful evaluation. Stratification procedures also enable one to increase the sample size for strata which are heterogeneous in class composition, thus encouraging a better representation of rare classes. Zonneveld (1974), and Rudd (1971), achieved an adequate sample size for all categories by stratifying the study area by class cover and randomly sampling within groups of classes until the rare classes were adequately represented.

Given predetermined confidence limits and expected percent accuracies, Hord and Brooner (1976) and Genderen and Lock (1978) list tables to estimate the number of samples required. Ginevan (1979) provides procedures for providing confidence limits when the verification data are less than 100% accurate. A mathematical basis for selecting the number of sample points is fully described in these papers. Zonneveld (1974) selected the number of sample points based on the amount of time and money available. Hay (1979) reports a minimum sample size of 50 is sufficient for most applications.

Krebs (1976) evaluated different methods of obtaining verification data. She concluded that it is more efficient to use photointerpretation of aerial photography, when available, than actual field work. This approach reduces the time involved in collecting data and allows for the sampling of inaccessible areas. Genderen and Lock (1976) report field checks are necessary for areas which are difficult to photointerpret correctly.

Smedes (1975) reports on many of the problems associated with obtaining 100 percent accurate verification data. One problem in particular is the ground cover heterogeneity problem which causes: 1) compounded problems when there is spatial misregistration between verification and Landsat data; 2) frequent misphotointerpretation of verification fields; and 3) difficulty providing adequate class definitions patterning the Landsat classifications.

Methods of Analysis

In almost all quantitative studies, the processed data is compared with the verification data to obtain the percentage of correct or incorrect occurrences (Rudd, 1971; Biehl and Silva, 1975). The percentage agreement is supplied for each class and the total sampled population. Hord and Brooner (1976) give a formula for obtaining confidence limits for the accuracies.

A class confusion table was used by Genderen and Lock (1976) and Tom (1977) to obtain the frequency with which one class may be attributed to another, along with two types of error. Type I errors occur when the correct class is rejected by the Landsat classifications, while Type II errors occur when the Landsat classifications are incorrectly classified. The errors are referred to as omission and commission errors, respectively. A two-way decision table (Table 1) depicts the four possible outcomes for the results in a class confusion table.

Hord and Brooner (1976) recommend giving classification accuracies for various levels of classification. For example, a third level of classification separates aspen, cottonwood, ponderosa pine, and lodgepole pine. At level two, aspen is combined with cottonwood to form deciduous forest, and ponderosa pine with lodgepole pine to form coniferous forest. The lowest level of classification (level one) then combines deciduous with coniferous for a general forest class. At each level of classification, a classification accuracy should be established. This approach allows the evaluator to analyze the Landsat classifications for different groupings of ground cover communities. Anderson, et al. (1976) provide a hierarchical classification system based on remote sensing capabilities.

LANDSAT DERIVED CLASSIFICATION MAPS

The example of a Landsat derived classification used for this evaluation was a wildland classification of a 7,500 square kilometer area near Piceance Creek Basin in northwestern Colorado that was prepared under contract to the Fish and Wildlife Service (FWS) by Bendix Corporation (see Bendix Aerospace Systems Division, 1978). The classification scheme used (Table 2) was developed taking into consideration inputs of FWS wildlife biologists on wildlife habitat requirements. Training fields were selected from 1:30,000 color infrared photography and selectively ground checked. Several spectral signatures were developed for each land cover class to take into account the spectral variability introduced into each class by variations in topography, climate, soils, etc. A standard maximum liklihood supervised classification was used.

EVALUATION PROCEDURES

Statistical Sampling Scheme

The schemes used to obtain random and unbiased verification samples were designed for large areas of 2,500 square kilometers or more. The procedures provide for selection of a stratified sample to cover large areas which differ in spatial and spectral characteristics. This stratification encourages a proper sample size from areas differing in size and complexity.

Once the total area was stratified based on geology, climate, topography, and ground cover information, there was a systematic selection of 7½' quadrangles within each strata. Quadrangle size areas were used because quadrangle maps (U.S.G.S. 7½' topographic quadrangles) were readily available and were of a size convenient for the first level of sampling. The number of 7½' quadrangles selected within each strata was dependent on the class heterogeneity of the strata. We selected more 7½' quadrangles from heterogeneous strata in order to increase the sample size for rare classes.

From each 7½' quadrangle we evaluated a set of randomly located pixels. Since there would likely be spatial misregistration problems when working with isolated pixels, we decided to group a set of 9 pixels into a cell size of 10 acres for use in all evaluation procedures. Approximately 50 10-acre cells were selected for each 7½' quadrangle. We originally selected 25 quadrangles to ensure a good representation of cover for evaluation. This was thought to be within the budget constraints of the project. However, the original number was optimistic. We, therefore, had to reduce the number of 7½' quadrangles for evaluation from 25 to 13. The final distribution of the 7½' quadrangles is plotted in Figure 1.

Verification Data Collection

Photointerpretation and field visits were used to generate verification data. The 50 10-acre cells (see Figure 2 for example) were photointerpreted by personnel from Ecology Consultants, Inc. who had experience with western land cover. A Zoom Transfer Scope was used to plot the randomly selected 10-acre cells (as overlayed on 7½' quadrangles) onto color infrared photographs.

Genderen and Lock (1978) note that a form supplied to the personnel obtaining verification data will improve the efficiency and consistency of work. All of the information completed by ECI was placed on verification forms (see Figure 3). The information contains ground cover class identity for each pixel, ground cover class boundaries, percent pixel coverage, and overall cell relief, all of which are defined on the form.

The photointerpreters' decisions for the class designations of the pixels for the verification data were to be patterned after the training fields (as they appeared on color infrared photographs) used in the classification of Landsat. The purpose was to maximize the correspondence between the spectral and spatial characteristics used in the verification data class designations. This is necessary to evaluate the accuracy of the classification of Landsat data. Unfortunately, this was not completely achieved and is described in the section on Lack of Correspondence Between Signature and Verification Data Sets.

Evaluation Algorithms

We completed a pixel by pixel comparison between the verification data and Landsat classifications for four levels of classification. The results of the comparisons are displayed in class confusion tables. An important aspect of the tables are the classification accuracies.

Confidence limits were assigned to the accuracies by evaluating the approximation for ν:

$$\Pr\left(-b < \frac{\overline{X}-\nu}{\sigma\sqrt{N}} < b\right) = 1-\alpha \qquad (1)$$

where

- $100\,(1-\alpha)$ is the confidence level of the limit,
- ν is the probability that any pixel of a given class is correctly classified,
- x is the estimate of ν or the class accuracies,
- σ^2 is the variance of the binomial distribution of x_i,
- b is obtained from the normal distribution tables,
- α is the probability that any pixel of a given class may occur beyond the range of the confidence limits.

A more detailed description for assigning confidence limits is described by Hord and Brooner (1976). The logic for the proof of the approximation is given by Brunk (1965).

Information conveyed from Landsat in bits/square kilometer was computed for all levels of classification. This is accomplished by computing joint probabilities from the class confusion table obtained during evaluation. That is,

$$P(x,y) = P(x\,|\,y)\;P(y) = P(y\,|\,x)\;P(x) \qquad (2)$$

where x is defined as the verification data and y is the output from Landsat. These values are used to compute joint uncertainty:

$$H(x,y) = H(x|y) + H(y) = H(y|x) + H(x) \tag{3}$$

From these values we obtain contingent uncertainty, which was equated to information transmitted as:

$$H_T = H(x:y) = H_{max}(x,y) - H(x,y) \tag{4}$$

where $H_{max}(x,y)$ is the maximum uncertainty which exists when there is no correlation between x and y. The information transmitted is valid only if the verification data is 100% accurate. If not, the computed values should be used to compare performance between class levels and/or areas. For a more detailed explanation of procedures, see Maxwell (1975) and Garner (1962).

There are several problems associated with classification decisions when there is more than one ground cover class occurring within a pixel. Present classification algorithms, including the one used in this study, are not designed to classify mixed class pixels. Therefore, to fully test the capabilities of the classification of Landsat data, it is important to separately evaluate those cells which are homogeneous. In this study we separated the homogeneous areas within the sampled area and performed an additional evaluation only in those areas.

Another procedure implemented for reducing mixed class pixel problems was to aggregate nine-pixel cells for the verification data and Landsat classifications and select a single class designation based upon a majority of the classes present. Results from these comparisons also reduce sources of error attributed to minor differences in spatial registration between verification and Landsat classifications.

EVALUATION RESULTS

Registration Analysis

A necessary prerequisite for a pixel by pixel comparison between verification data and Landsat classifications are that they represent the same location (i.e., the Landsat pixel and the verification data are all precisely registered). As a check for possible misregistration of the Landsat classifications, we shifted the 3 x 3 pixel verification cells, simultaneously within each quad, by one pixel in all directions. The 3 x 3 verification cell has nine possible positions for comparison within an extracted 5 x 5 Landsat classified area.

For each 7½' quadrangle, we computed the overall classification accuracy between the verification and Landsat classifications of the nine possible positions. The overall classification accuracy for each location was weighted by the class acreages for the classification results, and the position with the highest value was assumed the best registered. This position was selected for all subsequent analyses. The weightings were added to ensure classes containing majority acreage cover have a stronger affect over the selection of the position with the best registration.

For another study area (see Bendix Aerospace Systems Division, 1978) there was a consistent tendency for best registration by shifting verification cells one pixel down and one pixel to the left. Since this position consistently gave best results, it was assumed the Landsat classifications were properly registered in this position and no further analysis was undertaken.

For this evaluation, there was no consistent best position based on classification with cell shift analyses. For this reason, the following additional effort was undertaken.

To check the spatial registration of the Landsat classifications, features on the 7½' quadrangle maps were manually positioned to register with appropriate classes representing the same features. Useful features included reservoirs, tree lines, and cliffs, with reservoirs being the most reliable.

We determined the Landsat classification maps to be spatially misregistered from zero to four pixels. The provision for shifting the verification data by one pixel in all directions could not correct for these errors. We therefore had to manually correct the misregistration.

We changed the x,y coordinates of the Landsat pixel areas to correct for the errors observed. This was accomplished for each quadrangle on an individual basis since the misregistrations were not the same for each quadrangle. However, the misregistration was consistent within a quadrangle.

To test the procedures for correction, we calculated the overall classification before and after registration correction. In all instances, except for the Jessup Gulch quadrangle, the overall percentages increased for the positionally corrected maps (see Table 7) and we proceeded with the analyses (all results given in previous tables are from positionally corrected maps).

The accurate location of verification cell boundaries on color infrared photographs referenced to 7½' USGS topographic quadrangles was necessary for the spatial registration of the verification data. The analysis of the accuracy of this registration was accomplished by comparing two people's work for identical cells.

The results for 12 cells showed a range in error from 0.01 cm to 0.10 cm with an average error of 0.05 cm. The pixel dimensions at 1:30,000 scale are approximately 0.18 cm in width and 0.25 cm in length. Thus the average error was about ¼ pixel which was deemed acceptable. This is by no means conclusive since a sample of 12 cells out of approximately 450 is not adequate, but spot checks later indicated reasonable accuracy was being maintained.

Typical Results

Evaluation of Landsat classifications for the four levels of classification, yielded overall low results. Results for the total sampled area at the 12 class level, for an example, are summarized in Table 3. Inspection of Table 3 yields information on confusion between classes, omission and commission errors, overall classification accuracy, confidence limits, and information quantity assessment. The data are a compilation of results from all quads. Other analyses were completed with individual quads and for quads grouped into strata (see Toll, 1978).

The data in Table 4 result from assigning 10-acre cells a single class designation, prior to comparisons between verification data and Landsat classifications to reduce adverse effects from mixed class pixels and possible spatial misregistration. A comparison between Table 3 and 4 at the 12 class level show an overall increase in accuracy from 37.6 percent to 44.2 percent.

We stated earlier, since we were interested in evaluating the performance of the Landsat classification, we felt a further evaluation should occur only for homogeneous cells. We therefore discarded all cells which were heterogeneous in land cover and evaluated only the homogeneous cells. Results (see Tables 5 and 6) at the 12 class level show an improved overall classification accuracy to 61.3 percent for the pixel by pixel comparisons and 73.9 percent when designating the 10-acre cells single classes prior to analysis. Clearly, the increases may be attributed to removing mixed class pixels from evaluation, which the classifier was not designed to categorize, and converting 10-acre cells (i.e., 9 class designations) into single class representations, thereby reducing the need for an accurate spatial registration.

Even though the additional analyses showed higher classification accuracies, we thought an evaluation was necessary to further examine errors which are not attributed to the Landsat data and/or the classifier used for the Landsat classifications. Results from these analyses are provided in subsequent sections.

Lack of Correspondence Between Signature and Verification Data Sets

Because of known deficiences in the training data and in photointerpreting the verification cells, the possibility of poor correspondence between the training fields and the verification fields was considered. In other words, it became evident that the ground cover conditions for the training fields classified low density sagebrush might not always be the same ground cover conditions which the photointerpreter identified as low density sagebrush. If this supposition were true, then there would be no basis for seeking agreement between the two sets of data (Landsat and verification). The following effort was undertaken to analyze the correspondence between the ground cover characteristics for the verification pixels seen on the color infrared photographs and the ground cover characteristics for the training fields as seen on the same photographs.

A sample of pixels from all the verification pixels was examined in detail for its correspondence to the training field descriptions. The sample was obtained from the quadrangles for which we had color infrared photography coverage (eight quadrangles overall). From each quadrangle we selected every other nine pixel cell and from those cells we analyzed three randomly selected pixels.

We examined the appearance of the sampled verification pixels in the color infrared photography for their ground cover type(s), color texture, and vigor as was done for the training fields. Once the spectral and spatial characteristics of the verification pixels were obtained, they were compared with the spectral and spatial characteristics of the training fields, to determine the frequency with which they had good correspondence. The criterion for good correspondence was that if the pixel had more than 75% spectral and spatial ground cover characteristics which were also included in the training field descriptions, then the pixel was said to be in good correspondence with the training fields. Of the ground cover characteristics, type and color characteristics were examined the closest. Although the texture and vigor information were useful in some borderline cases and in instances where there may have been reproductive differences in processing between photographs, we thought the ground cover type and color information were more important. We defined that if the pixel contained more than 25% of spectral and spatial characteristics not in the training data, then the pixel was said to be heterogeneous.

Once the criterion for correspondence was established we could examine the significance of **correspondence** (i.e., class definitions) to **agreement** (i.e., classification accuracy) between Landsat and verification data. If the verification pixels which were in **correspondence** with the training fields showed the same bias toward **disagreement** with the classification of Landsat as the verification pixels which **were not** in correspondence with the training fields, then we would conclude the poor correspondence for the verification pixels did not affect or contribute to the confusion between the verification and Landsat data. To evaluate the above statement, we set up the null hypothesis that the verification pixels which were not in correspondence to the training fields, did not show bias toward disagreement with the Landsat classifications. If the null hypothesis may be rejected at a low confidence level, then we may conclude most of the confusion between verification and Landsat data may be attributed to the ground cover characteristics of the verification pixels not corresponding to the ground cover characteristics of the training fields.

The results from the above analysis may be placed in a two-way contingency table (see Table 8). Along the rows are the verification data which either were or were not in **agreement** with the **Landsat classifications** and along the columns are the **verification** pixels which were or were not in good **correspondence** with the training fields.

For each of the classes, at two classification levels, we used the format in Table 8 to evaluate the null hypothesis. Fisher's exact probability test (from Till, 1974) was used to test the null hypothesis, by solving for P:

$$P = \frac{(a+b)!\ (c+d)!\ (a+c)!\ (b+d)!}{n!\ a!\ b!\ c!\ d!} \tag{5}$$

Where P, is the probability of partitioning the four possible frequencies (a, b, c, and d in the two-way contingency table) arising by chance. The value of P is the level at which the null hypothesis is rejected.

Information given in Table 9 provides confidence levels for two classification levels at which we may reject the null hypothesis. Overall, we conclude that poor correspondence between verification pixels and training fields was a factor for the low Landsat classification accuracies. There are three deficiencies contributing to the poor correspondence: 1) the training areas were not diverse enough to take into account most of the ground cover variation; 2) there were errors in photointerpretation where a verification cell was designated the wrong class; and 3) for many classes there were different class definitions used when designating the verification fields than were defined by interpreting the training fields. The underlying factor contributing to these errors were from the heterogeneous ground cover in the study area.

For the fir class, as an example, Table 10 shows that 5 out of the 21 pixels analyzed were in poor correspondence with the training field descriptions at the 24 class level. The five pixels with poor correspondence usually contained a shrub type in addition to fir.

An example of poor correspondence is given in Figure 4. For pixels 3 and 5 it may be seen that there exists over a 50% ground cover type other than fir. Within these pixels designated fir for the verification data there are both mixed shrub and sagebrush/grassland ground cover types, which would explain why pixel 3 was designated as a mixed shrub-sagebrush class and pixel 5 as a mixed shrub class for the Landsat classifications. Pixel 1 contains close to 100% fir and was designated as fir for the Landsat classifications. The situation seen in Figure 4 clearly explains the cause of confusion between the fir and shrub-sagebrush classes and is representative of the situation observed for these classes.

We tested the null hypothesis that the fir pixel designations for the verification pixels, which were not in correspondence with the training fields, did not show any bias toward disagreement with Landsat data. Using Fisher's test for the data in Table 10 the null hypothesis may be rejected at the 0.01 confidence level for the 24 class level and at the 0.02 confidence level for the 9 class level. Hence, much of the confusion may be attributed to the ground cover characteristics of the verification pixels not corresponding to the ground cover characteristics of the training fields.

Another obvious example in which poor correspondence between the verification data and training fields caused misclassification is with the mixed shrub-sagebrush class. The data in Table 11 shows that 45 out of the 63 pixels analyzed were in poor correspondence with the training field data at the 24 class level.

Again Fisher's test was used to evaluate the null hypothesis for the data in Table 11. For the 24 class level and 12 class level the null hypothesis may be rejected at the 0.01 confidence level. Much of the poor correspondence was the result of mixed class pixel problems and differences of shrub types between the verification pixels and training fields.

Figure 5 illustrates reasons for the poor correspondence between the verification pixels and Landsat classifications. Verification pixels 1 and 2 both contain approximately 50% or more of a barren-grassland combination not occurring in the training fields, along with approximately 20% pinyon-juniper. Furthermore, the shrub type which does occur in the verification pixels does not resemble the shrub types in the mixed shrub-sagebrush training fields as is represented in Figure 6.

Photointerpretation Errors

To obtain high classification accuracies the verification data must approach 100 percent accuracy. For this study photointerpretation along with spot field checks were used to classify the verification data. Since this was crucial to the evaluation of classification accuracy, we reevaluated the photointerpretation work.

The previous section on Lack of Correspondence Between Signature and Verification Data Sets shows the photointerpreters designating a pixel not in correspondence with class descriptions. This occurred for 63% of the sampled verification pixels. The photointerpreter should have designated those pixels as uncategorized. Additionally, there were many instances when the verification pixels should have been designated as another class.

The high occurrence for the misdesignation of the verification pixels (i.e., 63%) affected the reported classification accuracies. An examination of the misdesignated verification pixels showed 90% of them were in disagreement with the Landsat classifications. This clearly demonstrates that much of the disagreement between the Landsat classifications and the verification pixels was a result of photointerpreter error and not from misclassified Landsat data. However, the inability of the photointerpreters to satisfactorily designate verification pixels classes patterning the training fields, stems from the fact that the training fields used in the Landsat classifications did not adequately represent the study area ground cover.

Figure 7 provides a typical example of the need for the photointerpreters to have designated verification pixels uncategorized or as another class. Verification pixel 2 is an example of a barren class designated as low density sagebrush. In the training fields for low density sagebrush there are no barren area components. Furthermore the lowest density sagebrush training field contains around 70 percent sagebrush. Pixel 2 has only 10 percent sagebrush with the remaining land cover closely patterning the tone and texture in the barren training fields. Verification pixel 5 has a combination of barren, grassland, and sagebrush land cover. This pixel does not correspond with any of the training fields and should have been designated as uncategorized.

Changing Class Definitions

After obtaining overall poor results, we evaluated the possibility of having different class definitions for the signature and verification data sets. One inadequacy in particular was with the high density pinyon-juniper class. There were almost three times as many pixels designated high density pinyon-juniper in the Landsat classifications as there were in the verification data. This was a result of one of the training fields used in the Landsat classifications (see Figure 8) containing equal proportions of pinyon-juniper, grassland, sagebrush, and other types of shrub, causing areas of these mixtures to be designated as high density pinyon-juniper. The photointerpreters assumed there were no mixtures of these cover types and did not use such information in their interpretations; therefore contributing to the lower properties of pinyon-juniper designated for the verification data and the confusion with shrubs and grass classes (see Tables 3 through 6).

Several other deficiencies were noticed. First, the ground cover densities for low density and high density sagebrush classes as defined by training fields, both contained 70% sagebrush. However, photointerpretation of low density sagebrush stands even when occurring in mixtures of other ground cover stands were usually designated as low density sagebrush. In Landsat classifications these areas were mixed class pixels, resulting in the frequent designation of a non-sagebrush class. Second, a training field for the mixed shrub class more closely patterned the mixed shrub-sagebrush class, which likely contributed to the confusion between these classes. Third, the mixed shrub types found in the training fields only represented a minority portion of the shrub types occurring through the study area. Whereas in the photointerpretation most all shrub types were designated as mixed shrub even though there was no representation in the training fields. Finally, a training field for the dry agriculture class contained some irrigated agriculture areas. Most of these problems were eliminated when evaluating lower classification levels. Classes which had homogeneous cover and a representative selection of training fields, such as aspen, showed higher classification accuracies.

SUMMARY AND CONCLUSIONS

Evaluating classification accuracy requires much more than a simple sample design and analysis of results. Procedures must be developed which adequately sample unbiased verification fields, yielding narrow confidence limits. Furthermore, procedures must be implemented which analyze Landsat classifications rigorously with well designed analysis procedures, such as analysis within both heterogeneous and homogeneous areas and methods to reduce effects from spatial misregistration. For a complete analysis, results should be output in contingency tables with supplemental information on classification accuracies along with confidence limits, overall classification accuracy, omission and commission errors, and information quantity assessment.

Overall low classification accuracies caused us to evaluate the class characteristics used in the Landsat classifications and verification fields. One particular problem was that the class descriptions were often inadequate for the diverse study area and the ground cover which was represented by classes often had changing class descriptions between the Landsat classifications and verification data. These errors resulted in overall lower classification accuracies and identifiable need for evaluation at lower classification levels. In many cases the results were merely a measure of the agreement between two data sets and not any valid measure of classification accuracy.

The underlying factor for much of the problems of poor correspondence between the training fields with the verification fields is attributed to the spatial complexity of the ground cover. There are many combinations of ground cover resulting in an infinite possible set of proportions and patterns. Additionally, most comparisons require an accurate spatial registration for the Landsat classifications and verification fields. In heterogeneous areas a slight shift in the location of verification cells will change the ground cover mixture, frequently changing the class designation.

As has been demonstrated, a simple evaluation of results does not usually provide a reflection of the true classification accuracy. More likely, no single procedure will work, what is needed is a rigorous experimental design with procedures objectively pursued.

LITERATURE CITED

Anderson, J. R., E. E. Hardy, and J. T. Roach, (1976), A Land Use Classification System for Use with Remote Sensor Data, U.S. Geological Survey Circular 671, Washington, D.C.

Bendix Aerospace Systems Division, (1978), Landsat Digital Data Classification for Land Use and Wildlife Habitat Inventory, Final Report, BSR-4323, U.S. Fish and Wildlife Service Cr--14-16-0008-2160, Ann Arbor, Michigan.

Berry, B. J. L., and A. M. Baker, (1968), Geographic Sampling in Spatial Analysis: A Reader in Statistical Geography (B. J. L. Berry and P. F. Marble Editors), Prentice Hall, Englewood Cliffs, N. J., p. 91-100.

Biehl, L. L., and L. F. Silva, (1975), Evaluation of Sky Lab Data for Land Use Planning, Paper AAS74-145, American Astronautical Society, p. 1-38.

Brunk, H. D., (1965), An Introduction to Mathematical Statistics, Blaisdell, 177 pp.

Garner, W. R., (1962), Undertainty and Structure as Psychological Concepts, John Wiley and Sons.

Genderen, J. L. Van, and B. F. Lock, (1976), A Methodology for Producing Small Scale Rural Land Use Maps in Semi-arid Developing Countries Using Orbital MSS Imagery, Final Contractor's Report: NASA-CR-151173, Department of Industry, London.

Genderen, J. L. Van, and B. F. Lock, (1978), Remote Sensing: Statistical Testing of Thematic Map Accuracy, Remote Sensing of Environment, Vol. 7, p. 3-14.

Ginevan, J. E., (1979), Testing Land-Use Map Accuracy: Another Look, Photogrammetric Engineering and Remote Sensing, Vol. 45, No. 10, p. 1371-1377.

Hajic, E. J., and D. S. Simonett, (1976), Comparisons of Qualitative and Quantitative Image Analysis, in Remote Sensing of Environment, (J. L. Lintz Jr. and D. S. Simonett, Editors), Addison-Wesley, Reading, Massachusetts, 409 pp.

Hay, A. M., (1979), Sampling Designs to Test Land Use Map Accuracy, Photogrammetric Engineering and Remote Sensing, Vol. 45, No. 4, p. 671-678.

Hord, R. M., and William Brooner, (1976), Land Use Mapping Accuracy Criteria, Photogrammetric Engineering and Remote Sensing, Vol. 42, No. 5, p. 671-678.

Kelly, B. W., (1970), Sampling and Statistical Problems in Remote Sensing with Special Reference to Agriculture and Forestry, Washington, D.C., National Academy of Sciences, p. 329-353.

Krebs, P. V., (1976), Multiple Resource Evaluation of Region 2, U.S. Forest Service Lands Utilizing Landsat MSS Data, Final Report NAS 5-20948, Institute of Arctic and Alpine Research.

Maxwell, E. L., (1975), Information Theory Applied to Remote Sensing in Remote Sensing of Earth Resources, Vol. 4, University of Tennessee Space Institute, p. 43-67.

Rudd, R. D., (1971), Macro Land Use Mapping with Simulated Photographs, Photogrammetric Engineering, Vol. 37, p. 365-372.

Smedes, H. W., (1975), The Truth About Ground Truth Maps, Proceedings of the Tenth International Symposium on Remote Sensing of Environment, Vol. II, Environmental Research Institute of Michigan, Ann Arbor, pp. 821-823.

Till, R., (1974), Statistical Methods for the Earth Scientist, An Introduction, John Wiley and Sons, New York, 154 pp.

Toll, D. L., (1978), Analysis of Certain Procedures for Evaluating the Accuracy of Ground Cover Mapping from Landsat, M.S. Thesis, Colorado State University, Fort Collins, Co., 300 pp.

Tom, C. H., (1977), Spatial Land-Use Inventory, Modeling and Projection, Denver Metropolitan Area, Ph.D. Dissertation, Colorado State University, Fort Collins, Co., 251 pp.

Zonneveld, I. S., (1974), Aerial Photography, Remote Sensing and Ecology, I. T. C. Journal, 1974, p. 553-560.

ACKNOWLEDGMENTS

The research effort described in this paper was supported by a subcontract from the Bendix Corporation (SC-1617) for the U.S. Fish and Wildlife Service under contract number 14-16-0008-2160 and was completed when at Colorado State University. The Landsat derived classification maps were provided by Bendix Corporation. The field data was collected by personnel at Ecology Consultants, Inc. Dr. Dennis Parker provided color infrared photography for evaluation work and allowed access to equipment on many occasions.

I wish to give my sincerest appreciation to Dr. E. L. Maxwell of Colorado State University; without his guidance this paper would not have been possible. I also thank Carol Riordan, Tom Hart, Brian Markham, and Lisette Dottavio for their assistance.

Table 1. Two-way decision table. The possible outcomes of Class A for classification results.

Truth	Decision: A	Decision: Not A
Is Really Class A	Correct Decision	Omission Error (Type 1 Error)
Is Not Class A	Commission Error (Type 2 Error)	Correct Decision

Table 2. The table below depicts the grouping of classes for different levels of classification.

<table>
<tr><th colspan="4">Level of Classification</th></tr>
<tr><th>24 Classes</th><th>12 Classes</th><th>9 Classes</th><th>8 Classes</th></tr>
<tr><td>Fir</td><td>Coniferous</td><td rowspan="4">Forest</td><td rowspan="4">Forest</td></tr>
<tr><td>Cottonwood</td><td rowspan="3">Deciduous</td></tr>
<tr><td>Aspen (Low Vigor)</td></tr>
<tr><td>Aspen (High Vigor)</td></tr>
<tr><td>Mixed Shrub</td><td rowspan="2">Shrub-Sagebrush</td><td rowspan="5">Shrub</td><td rowspan="7">Shrub and Pinyon-Juniper</td></tr>
<tr><td>Mixed Shrub-Sagebrush</td></tr>
<tr><td>Upland Sagebrush (Low Density)</td><td rowspan="3">Sagebrush</td></tr>
<tr><td>Upland Sagebrush (High Density)</td></tr>
<tr><td>Bottomland Sagebrush (High Density)</td></tr>
<tr><td>Pinyon-Juniper (Low Density)</td><td rowspan="2">Pinyon-Juniper</td><td rowspan="2">Pinyon-Juniper</td></tr>
<tr><td>Pinyon-Juniper (High Density)</td></tr>
<tr><td>Grass (Dry)</td><td rowspan="4">Grass</td><td rowspan="6">Grass and Agriculture</td><td rowspan="6">Grass and Agriculture</td></tr>
<tr><td>Grass (Dry Meadow)</td></tr>
<tr><td>Grass (Dry Tundra)</td></tr>
<tr><td>Grass (Wet Tundra)</td></tr>
<tr><td>Agriculture (Dry)</td><td rowspan="2">Agriculture</td></tr>
<tr><td>Agriculture (Wet)</td></tr>
<tr><td>Barren Basalt</td><td rowspan="2">Barren</td><td rowspan="2">Barren</td><td rowspan="2">Barren</td></tr>
<tr><td>Barren Rock</td></tr>
<tr><td>Water Clear</td><td rowspan="2">Water</td><td rowspan="2">Water</td><td rowspan="2">Water</td></tr>
<tr><td>Water Turbid</td></tr>
<tr><td>Uncategorized</td><td>Uncategorized</td><td>Uncategorized</td><td>Uncategorized</td></tr>
<tr><td>Pinyon-Juniper Sagebrush</td><td>Pinyon-Juniper Sagebrush</td><td>Pinyon-Juniper Sagebrush</td><td>Pinyon-Juniper Sagebrush</td></tr>
<tr><td>Agriculture Unknown</td><td>Agriculture Unknown</td><td>Agriculture Unknown</td><td>Agriculture Unknown</td></tr>
</table>

Table 3. A class confusion table with supplemental information showing results for the total sampled area. Results are from a pixel by pixel comparison of verification data with Landsat classifications at the 12 class level.

Name	Symbol	Verification	Landsat
Fir	A	74	39
Deciduous	B	163	209
Shrub	E	1452	725
Sagebrush	G	1044	1382
Pinyon–Juniper	J	887	1057
Grass	L	194	540
Grass (Agric)	P	306	128
Barren	R	33	83
Water	T	13	0
Uncategorized	V	153	23
Pinyon & Sage	W	0	70
AG (Unknown)	X	0	63
		Total Pixels =	4319

		Landsat												Classification Accuracy (%)	Lower[1] Bound (%)	Upper[1] Bound (%)
	Symbol	A	B	E	G	J	L	P	R	T	V	W	X			
Verification	A	20	11	22	14	3	3	0	1	0	0	0	0	27.03	16.5	40.9
	B	4	105	46	0	0	8	0	0	0	0	0	0	64.42	55.6	72.3
	E	9	69	498	392	166	211	48	1	0	13	21	10	34.30	31.9	36.7
	G	2	13	97	464	292	104	19	26	0	3	11	13	44.44	41.4	47.4
	J	1	0	7	294	458	58	9	23	0	0	36	1	51.63	48.1	55.1
	L	1	1	12	57	75	28	6	12	0	1	0	1	14.43	9.7	20.9
	P	1	7	27	102	40	71	34	11	0	3	2	0	11.11	7.7	15.6
	R	0	0	2	13	11	2	3	1	0	1	0	0	3.03	0.3	23.2
	T	1	3	2	4	2	1	0	0	0	0	0	0	0.00	0.0	51.6
	V	0	0	12	42	10	54	9	2	0	2	0	22	1.31	0.3	5.4
	W	0	0	0	0	0	0	0	0	0	0	0	0	0.00	–	–
	X	0	0	0	0	0	0	0	0	0	0	0	0	0.00	–	–
	Commission Error (%)	49.	50.	31.	66.	57.	95.	73.	99.	0.	91.	100.	100.			
												Overall=		37.3	35.8	38.7

Information Quantity Assessment 570 Bits/Square Kilometer

[1] Bounds are provided for the 0.05 confidence level.

Table 4. A class confusion table with supplemental information showing results for the total sampled area. Results are from designating classified 9-pixel cells single classes prior to comparisons between verification data and Landsat classifications at the 12 class level.

Name	Symbol	Verification	Landsat
Fir	A	7	3
Deciduous	B	19	22
Shrub	E	164	83
Sagebrush	G	108	117
Pinyon-Juniper	J	106	151
Grass	L	10	44
Grass (Agric)	P	31	9
Barren	R	0	10
Water	T	0	0
Uncategorized	V	1	2
Pinyon & Sage	W	0	1
AG (Unknown)	X	0	4
		Total Pixels =	446

		Landsat														
	Symbol	A	B	E	G	J	L	P	R	T	V	W	X	Classification Accuracy (%)	Lower[1] Bound (%)	Upper[1] Bound (%)
Verification	A	2	0	4	1	0	0	0	0	0	0	0	0	28.57	1.7	90.2
	B	0	12	7	0	0	0	0	0	0	0	0	0	63.16	29.9	87.5
	E	1	8	57	42	22	25	2	1	0	2	1	3	34.74	30.2	39.5
	G	0	1	10	44	39	7	2	4	0	0	0	1	40.74	30.4	51.9
	J	0	1	2	19	76	6	0	2	0	0	0	0	71.70	60.5	80.6
	L	0	0	0	1	6	1	0	2	0	0	0	0	10.00	0.5	71.1
	P	0	0	3	9	8	5	5	1	0	0	0	0	16.13	5.0	41.2
	R	0	0	0	0	0	0	0	0	0	0	0	0	0.00	—	—
	T	0	0	0	0	0	0	0	0	0	0	0	0	0.00	—	—
	V	0	0	0	1	0	0	0	0	0	0	0	0	0.00	—	—
	W	0	0	0	0	0	0	0	0	0	0	0	0	0.00	—	—
	X	0	0	0	0	0	0	0	0	0	0	0	0	0.00	—	—
	Commission Error (%)	33.	45.	31.	62.	50.	98.	44.	100.	0.	100.	100.	100.			
													Overall =	44.2	35.8	38.7

Information Quantity Assessment 52 Bits/Square Kilometer

[1] Bounds are provided for the 0.05 confidence level.

Table 5. A class confusion table with supplemental information showing results for the homogeneous only cells within the total sampled area. Results are from a pixel by pixel comparison of verification data with Landsat classifications at the 12 pixel level.

Name	Symbol	Verification	Landsat
Fir	A	12	9
Deciduous	B	50	50
Shrub	E	201	171
Sagebrush	G	177	213
Pinyon-Juniper	J	121	152
Grass	L	8	21
Grass (Agric)	P	43	2
Barren	R	0	1
Water	T	0	0
Uncategorized	V	18	0
Pinyon & Sage	W	0	4
AG (Unknown)	X	0	1
		Total Pixels =	630

		Landsat														
	Symbol	A	B	E	G	J	L	P	R	T	V	W	X	Classification Accuracy (%)	Lower[1] Bound (%)	Upper[1] Bound (%)
Verification	A	7	0	5	0	0	0	0	0	0	0	0	0	58.33	16.6	90.7
	B	0	41	8	0	0	1	0	0	0	0	0	0	82.00	64.5	91.9
	E	1	7	140	37	11	5	0	0	0	0	0	0	69.65	62.0	76.3
	G	1	1	22	107	39	5	1	0	0	0	1	0	60.45	52.0	68.2
	J	0	0	0	28	90	0	0	0	0	0	3	0	74.38	64.3	82.3
	L	0	1	2	1	4	0	0	0	0	0	0	0	0.00	0.0	75.2
	P	0	0	0	33	8	1	1	0	0	0	0	0	2.33	0.0	23.2
	R	0	0	0	0	0	0	0	0	0	0	0	0	0.00	--	--
	T	0	0	0	0	0	0	0	0	0	0	0	0	0.00	--	--
	V	0	0	0	7	0	9	0	1	0	0	0	1	0.00	0.0	37.4
	W	0	0	0	0	0	0	0	0	0	0	0	0	0.00	--	--
	X	0	0	0	0	0	0	0	0	0	0	0	0	0.00	--	--
	Commission Error (%)	22.	18.	21.	50.	41.	100.	50.	100.	0.	0.	100.	100.			
												Overall =		61.3	57.1	65.2

Information Quantity Assessment 1320 Bits/Square Kilometer

[1] Bounds are provided for the 0.05 confidence level.

Table 6. A class confusion table with supplemental information showing results for the homogeneous only cells within the total sampled area. Results are from designating classified 9 pixel cells single classes prior to comparisons between verification data and Landsat classifications at the 12 class level.

Name	Symbol	Verification	Landsat
Fir	A	2	1
Deciduous	B	6	5
Shrub	E	23	21
Sagebrush	G	18	24
Pinyon–Juniper	J	14	18
Grass	L	0	0
Grass (Agric)	P	6	0
Barren	R	0	0
Water	T	0	0
Uncategorized	V	0	0
Pinyon & Sage	W	0	0
AG (Unknown)	X	0	0
		Total Pixels =	69

		Landsat												Classification Accuracy (%)	Lower[1] Bound (%)	Upper[1] Bound (%)
	Symbol	A	B	E	G	J	L	P	R	T	V	W	X			
Verification	A	1	0	1	0	0	0	0	0	0	0	0	0	50.00	0.0	100.0
	B	0	5	1	0	0	0	0	0	0	0	0	0	83.33	9.0	99.6
	E	0	0	18	4	1	0	0	0	0	0	0	0	78.26	46.6	93.6
	G	0	0	1	14	3	0	0	0	0	0	0	0	77.78	39.9	94.8
	J	0	0	0	1	13	0	0	0	0	0	0	0	92.86	50.0	99.9
	L	0	0	0	0	0	0	0	0	0	0	0	0	0.00	–	–
	P	0	0	0	5	1	0	0	0	0	0	0	0	0.00	0.0	87.0
	R	0	0	0	0	0	0	0	0	0	0	0	0	0.00	–	–
	T	0	0	0	0	0	0	0	0	0	0	0	0	0.00	–	–
	V	0	0	0	0	0	0	0	0	0	0	0	0	0.00	–	–
	W	0	0	0	0	0	0	0	0	0	0	0	0	0.00	–	–
	X	0	0	0	0	0	0	0	0	0	0	0	0	0.00	–	–
	Commission Error (%)	0.	0.	14.	42.	28.	0.	0.	0.	0.	0.	0.	0.			
													Overall =	73.9	59.3	84.3

Information Quantity Assessment 142 Bits/Square Kilometer

[1] Bounds are provided for the 0.05 confidence level.

Table 7. The change in overall percentage agreement after correcting misregistered Landsat classifications to correspond to 7½' quadrangle maps.

7½' Quadrangle Map	Level of Classifications			
	Classes 24	Classes 12	Classes 9	Classes 8
Big Beaver Reservoir	+4.4%	+10.0%	+11.0%	+5.0%
Hamilton	+4.2%	+7.0%	+7.9%	+5.1%
Hayden	+1.7%	*	0.0%	+0.2%
Jessup Gulch	−0.2%	+2.2%	+2.0%	+1.5%
Sagebrush Hill	+0.5%	*	*	*
Yankee Gulch	+1.4%	+4.9%	+5.8%	+4.6%

*Figure unavailable for Landsat data before it was corrected.

Table 8. Example two-way contingency table.

		Are the spectral and spatial characteristics of a pixel in correspondence with the training field characteristics?	
		Yes	No
Are the class designations for the verification data in agreement with the Landsat data?	Yes	12	3
	No	9	7

Table 9. Significance levels are provided for which the null hypothesis may be rejected.

Class Name	$P(X > x_T)$	
	24 Class Level	12 Class Level
Fir	0.01	0.02
Low Vigor Aspen	0.33	0.50
High Vigor Aspen	0.10	0.09
Mixed Shrub	0.01	0.01
Mixed Shrub-Sagebrush	0.01	0.01
Low Density Sagebrush	0.22	0.15
High Density Upland Sagebrush	0.27	0.16
High Density Lowland Sagebrush	*	0.58
Low Density Pinyon-Juniper	*	0.27
High Density Pinyon-Juniper	0.08	0.01
Dry Grassland	0.03	0.07
Dry Meadow	*	*
Wet Tundra	*	*
Dryland Agriculture	0.28	0.28
Irrigated Agriculture	0.51	0.51

*Insufficient data.

Table 10. Fir class evaluation two-way contingency tables.

		Are the spectral and spatial characteristics of a pixel in correspondence with the training field characteristics?			
		24 Class Level		9 Class Level	
		Yes	No	Yes	No
Are the pixel designations for the verification data in agreement with the Landsat data?	Yes	11	0	13	2
	No	5	5	3	2

Table 11. Mixed shrub-sagebrush class evaluation two-way contingency table.

		Are the spectral and spatial characteristics of a pixel in correspondence with the training field characteristics?			
		24 Class Level		9 Class Level	
		Yes	No	Yes	No
Are the pixel designations for the verification data in agreement with the Landsat data?	Yes	7	5	12	2
	No	11	40	9	39

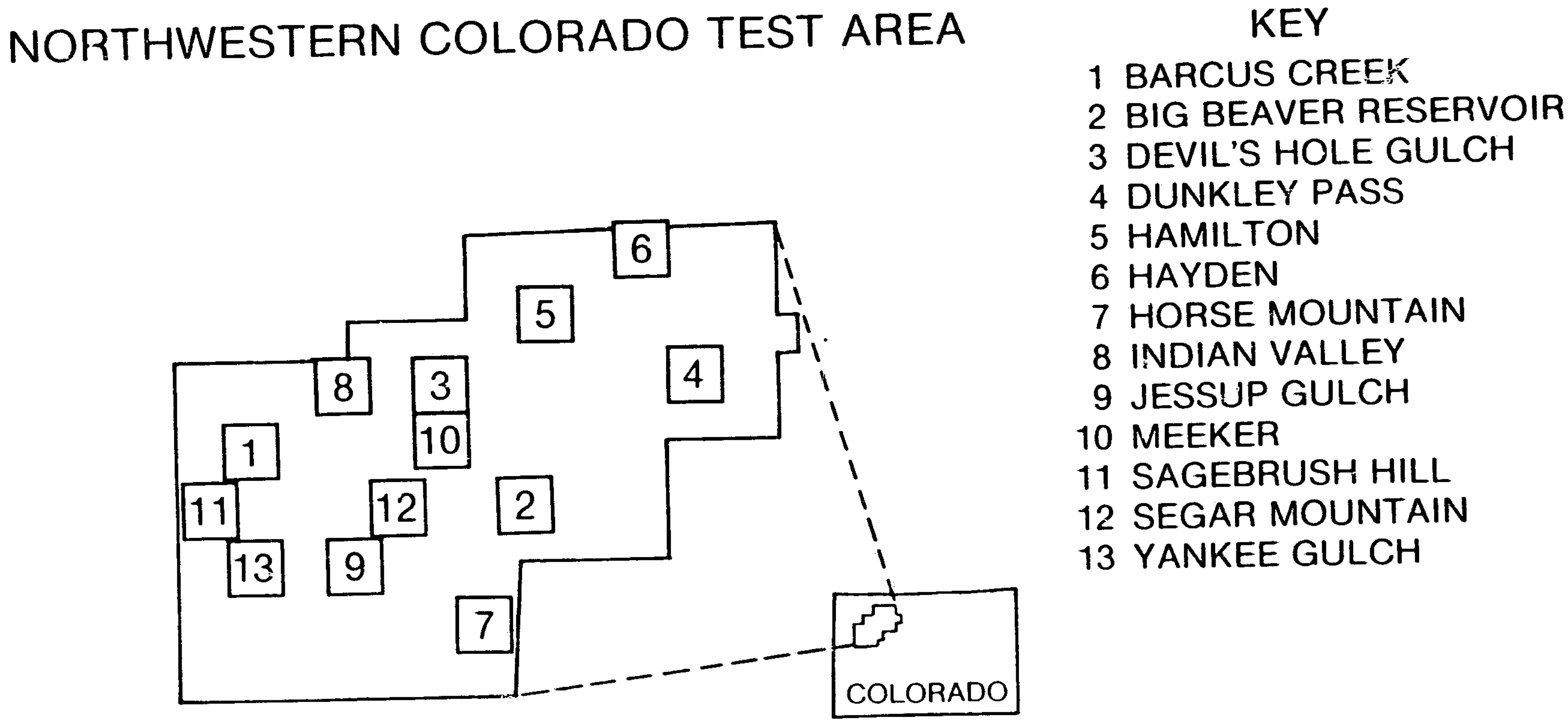


Figure 1. Location of Study Area Along With Distribution of Verification Quads.

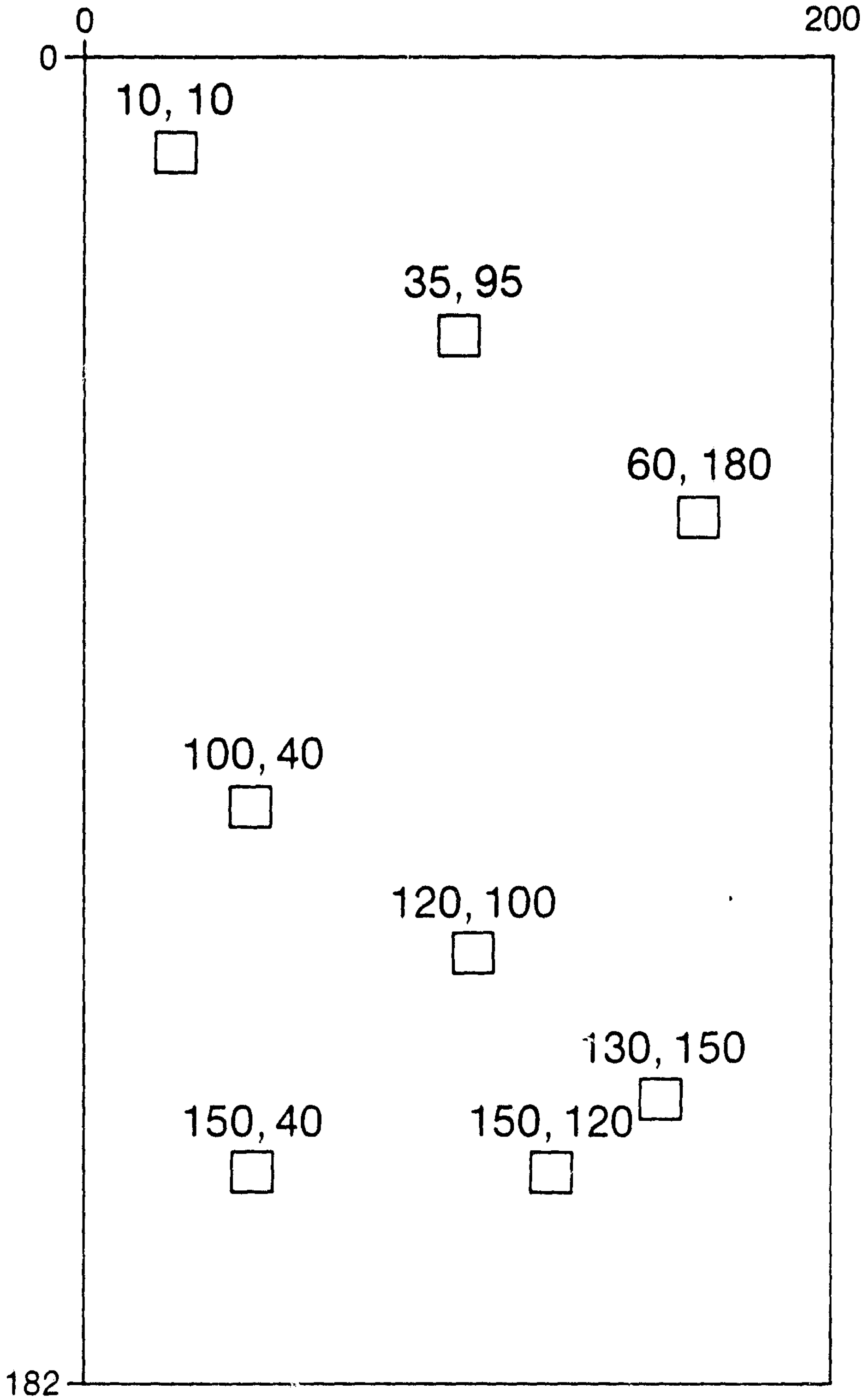
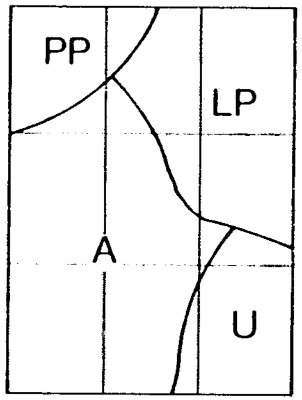


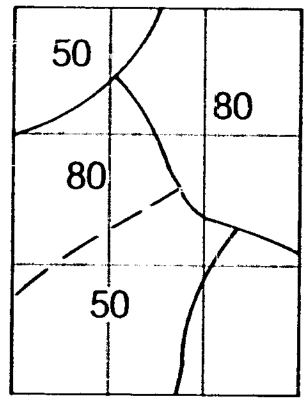
Figure 2. Example of Randomly Located 10-Acre Cells -- Verification Form.

VERIFICATION FORM

QUAD HAYDEN

CELL 63, 86





PP (45)	LP (50)	LP (80)
A (80)	A (55)	LP (50)
A (50)	A (45)	U

LAND USE/COVER

DIVIDE AREA BY CLASSES AND CODES USED ON THE CLASSIFICATION MAP. DESIGNATE UNCATEGORIZED THOSE AREAS NOT IDENTIFIABLE WITH ONE OF THE MAP CLASSES.

COVER DENSITY

DIVIDE AREA SAME AS LAND USE/COVER PLOT. FURTHER DIVIDE THOSE AREAS WITH DIFFERENT COVER DENSITIES. ESTIMATE % GROUND COVER FOR CLASSES DESIGNATED.

PIXEL DESIGNATION

BASED ON PLOTS TO THE LEFT, ASSIGN A CLASS TO EACH PIXEL, BASED ON CLASS DOMINANCE. ALSO INCLUDE THE % OF THE PIXEL COVERED BY THE CLASS DESIGNATED.

TOPOGRAPHY WITHIN CELL M
(E = EXTREME RELIEF, M = MODERATE, L = LOW)
DATA SOURCES USED (CIR, GROUND VISIT, ETC.)

NOTES:

Figure 3. Photointerpretation Form.

Figure 4. Verification cell in Sagebrush Hill quadrangle, having fir, grassland, sagebrush, mixed shrub, and barren classes.

Figure 5. Verification cell in the Segar Mountain quadrangle, having mixed shrub and barren classes.

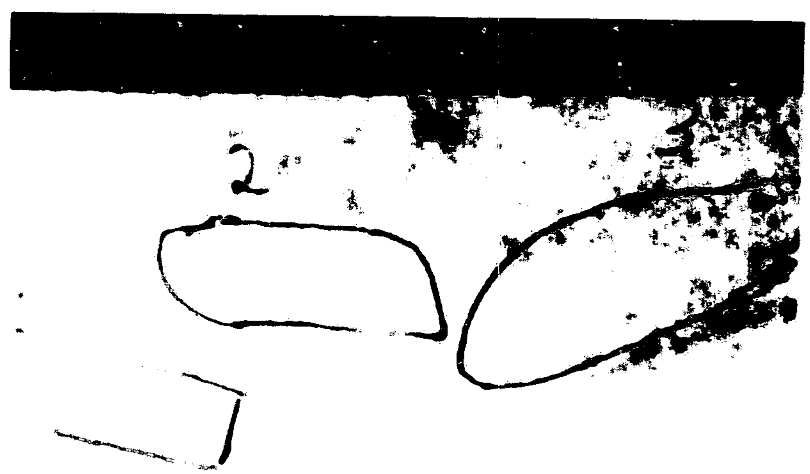


Figure 6. Mixed shrub–sagebrush training fields (three of the four training fields selected), occurring in the Jessup Gulch quadrangle.

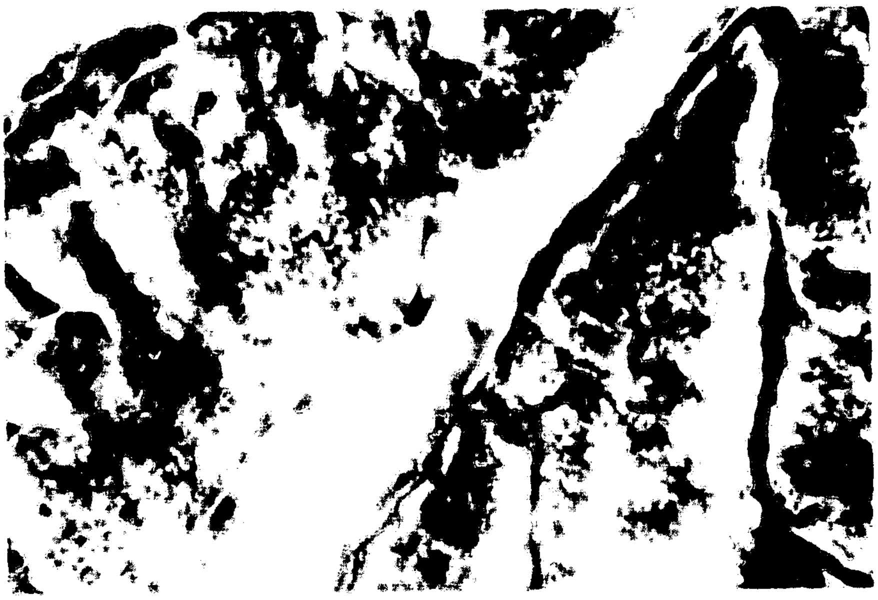


Figure 7. Verification Cell in the Sagebrush Hill quadrangle, having barren, mixed shrub and uncategorized classes. An example of barren class (pixel 2) and an uncategorized class (pixel 5) designated as low density sagebrush for the verification data.

Figure 8. High density pinyon-juniper training field, occurring in the Sagebrush Hill quadrangle.

Table 9. Significance levels are provided for which the null hypothesis may be rejected.

	$P(X > x_T)$	
Class Name	24 Class Level	12 Class Level
Fir	0.01	0.02
Low Vigor Aspen	0.33	0.50
High Vigor Aspen	0.10	0.09
Mixed Shrub	0.01	0.01
Mixed Shrub-Sagebrush	0.01	0.01
Low Density Sagebrush	0.22	0.15
High Density Upland Sagebrush	0.27	0.16
High Density Lowland Sagebrush	*	0.58
Low Density Pinyon-Juniper	*	0.27
High Density Pinyon-Juniper	0.08	0.01
Dry Grassland	0.03	0.07
Dry Meadow	*	*
Wet Tundra	*	*
Dryland Agriculture	0.28	0.28
Irrigated Agriculture	0.51	0.51

*Insufficient data.

Table 10. Fir class evaluation two-way contingency tables.

		Are the spectral and spatial characteristics of a pixel in correspondence with the training field characteristics?			
		24 Class Level		9 Class Level	
		Yes	No	Yes	No
Are the pixel designations for the verification data in agreement with the Landsat data?	Yes	11	0	13	2
	No	5	5	3	2

Table 11. Mixed shrub-sagebrush class evaluation two-way contingency table.

		Are the spectral and spatial characteristics of a pixel in correspondence with the training field characteristics?			
		24 Class Level		9 Class Level	
		Yes	No	Yes	No
Are the pixel designations for the verification data in agreement with the Landsat data?	Yes	7	5	12	2
	No	11	40	9	39

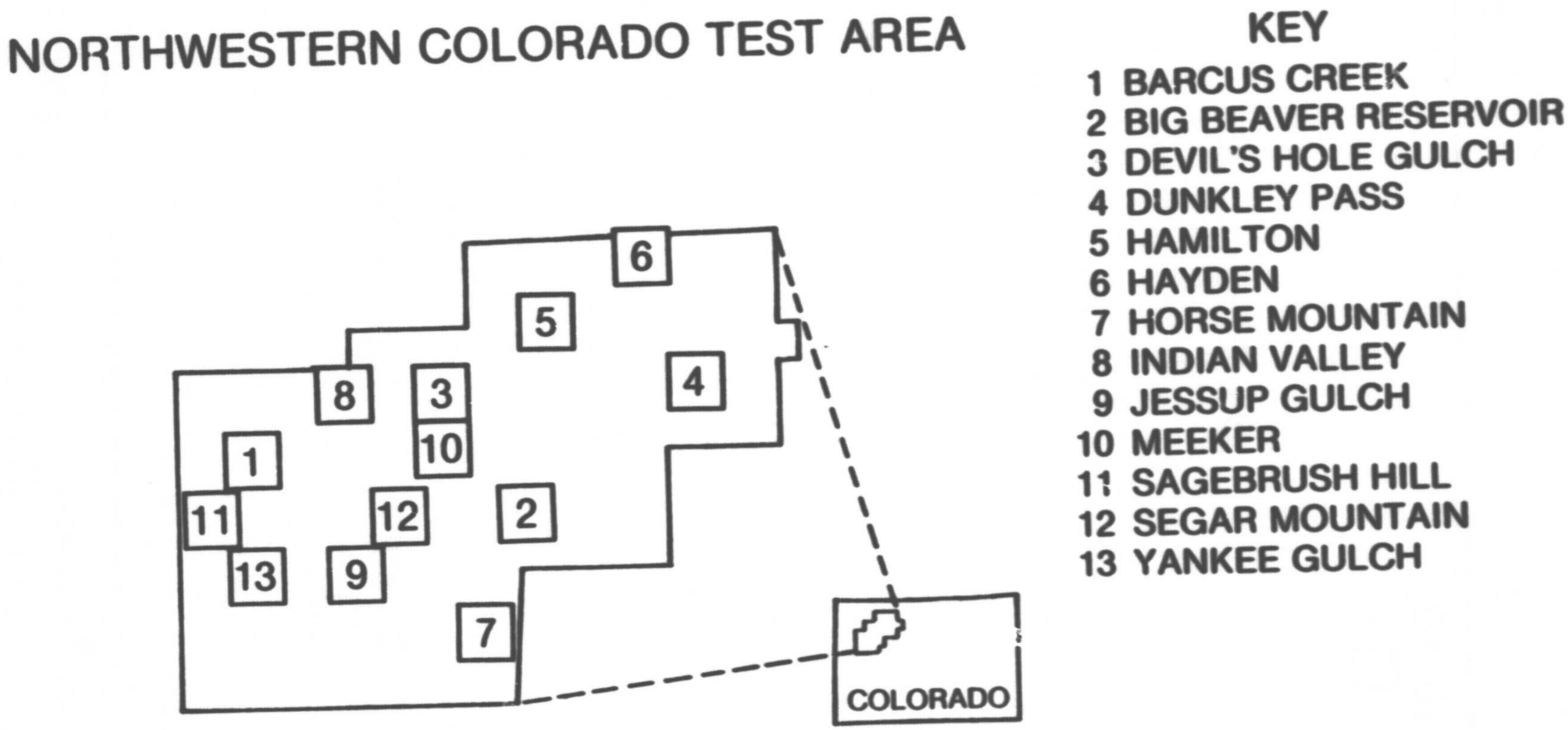


Figure 1. Location of Study Area Along With Distribution of Verification Quads.

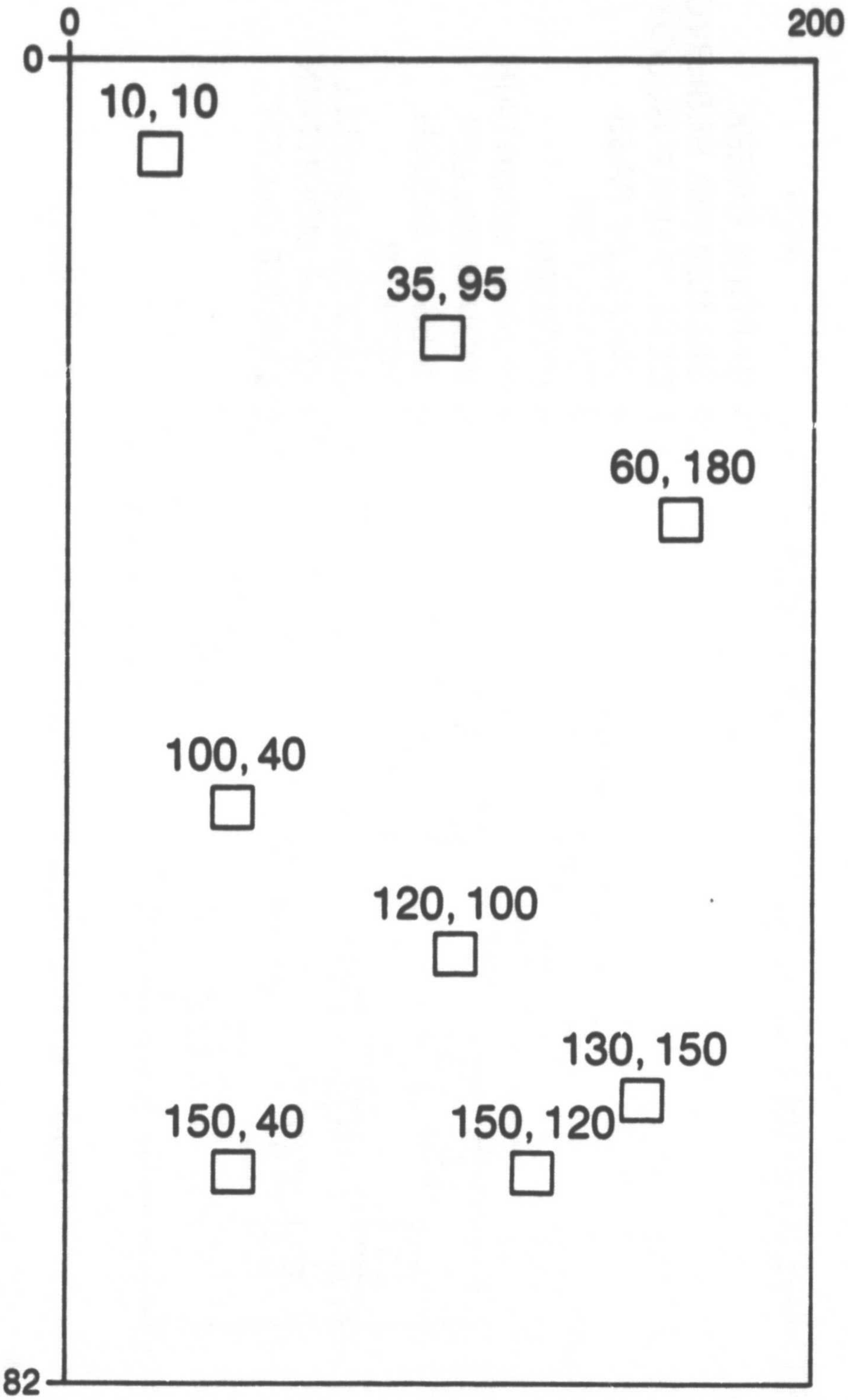
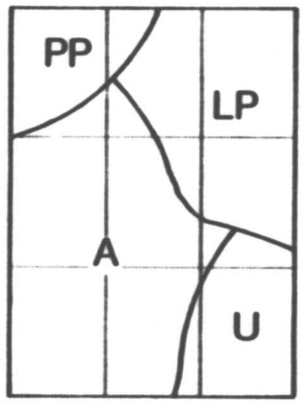


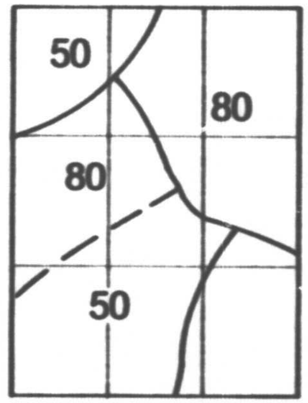
Figure 2. Example of Randomly Located 10-Acre Cells – Verification Form.

VERIFICATION FORM

QUAD H A Y D E N

CELL 63, 86





PP (45)	LP (50)	LP (80)
A (80)	A (55)	LP (50)
A (50)	A (45)	U

LAND USE/COVER

DIVIDE AREA BY CLASSES AND CODES USED ON THE CLASSIFICATION MAP. DESIGNATE UNCATEGORIZED THOSE AREAS NOT IDENTIFIABLE WITH ONE OF THE MAP CLASSES.

COVER DENSITY

DIVIDE AREA SAME AS LAND USE/COVER PLOT. FURTHER DIVIDE THOSE AREAS WITH DIFFERENT COVER DENSITIES. ESTIMATE % GROUND COVER FOR CLASSES DESIGNATED.

PIXEL DESIGNATION

BASED ON PLOTS TO THE LEFT, ASSIGN A CLASS TO EACH PIXEL, BASED ON CLASS DOMINANCE. ALSO INCLUDE THE % OF THE PIXEL COVERED BY THE CLASS DESIGNATED.

TOPOGRAPHY WITHIN CELL M
(E = EXTREME RELIEF, M = MODERATE, L = LOW)
DATA SOURCES USED (CIR, GROUND VISIT, ETC.)

NOTES:

Figure 3. Photointerpretation Form.

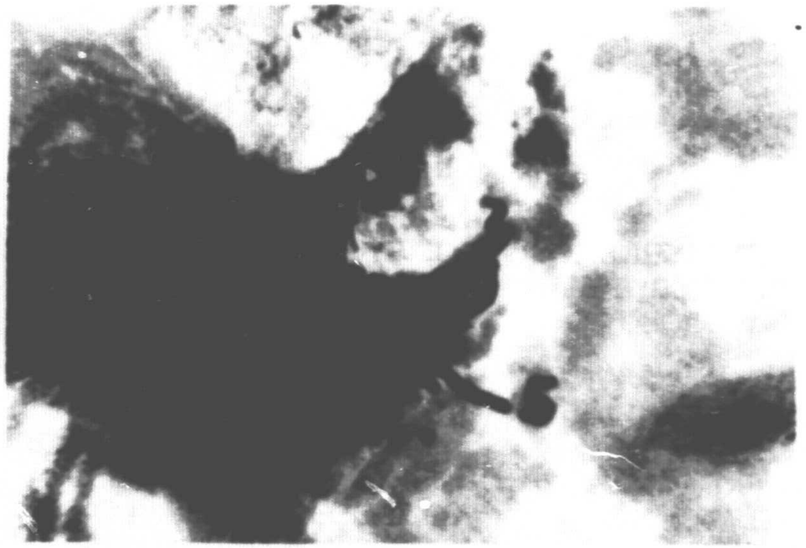


Figure 4. Verification cell in Sagebrush Hill quadrangle, having fir, grassland, sagebrush, mixed shrub, and barren classes.

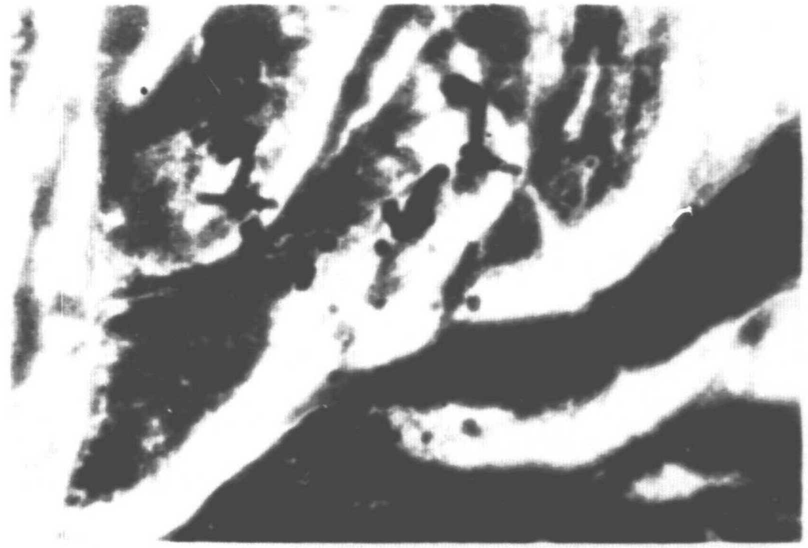


Figure 5. Verification cell in the Segar Mountain quadrangle, having mixed shrub and barren classes.

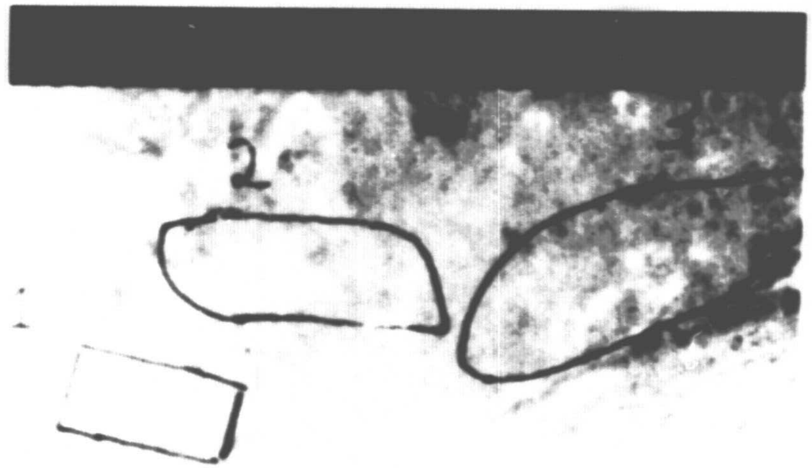


Figure 6. Mixed shrub–sagebrush training fields (three of the four training fields selected), occurring in the Jessup Gulch quadrangle.

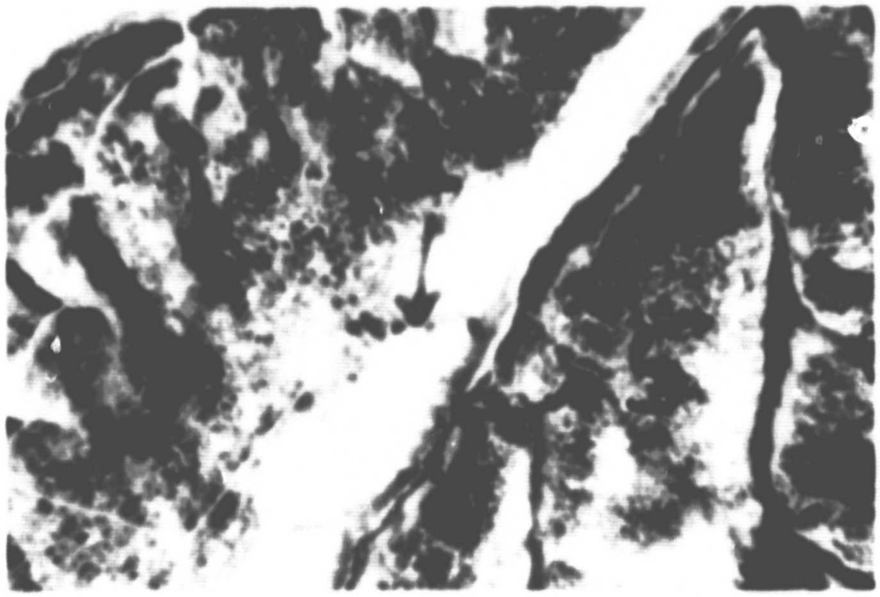


Figure 7. Verification Cell in the Sagebrush Hill quadrangle, having barren, mixed shrub and uncategorized classes. An example of barren class (pixel 2) and an uncategorized class (pixel 5) designated as low density sagebrush for the verification data.

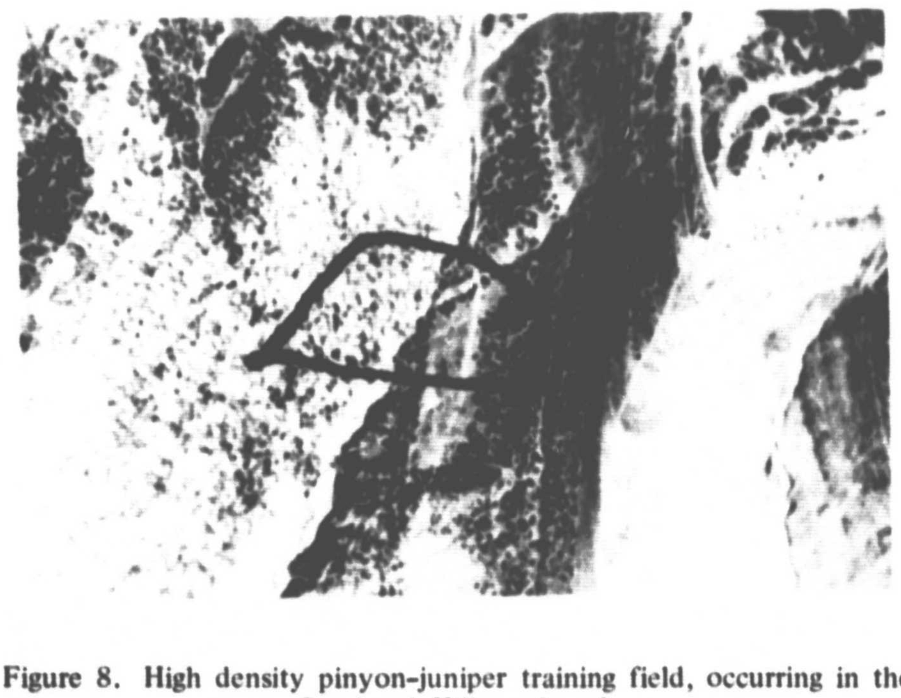


Figure 8. High density pinyon-juniper training field, occurring in the Sagebrush Hill quadrangle.