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DATA RESOLUTION VERSUS FORESTRY CLASSIFICATION AND MODELING*

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ABSTRACT

This paper examines the effects on timber stand computer classification accuracies caused by changes in the resolution of remotely sensed multispectral data. This investigation is valuable, especially for determining optimal sensor and platform designs.

Theoretical justification and experimental verification support the finding that classification accuracies for low resolution data could be better than the accuracies for data with higher resolution. The increase in accuracy is construed as due to the reduction of scene inhomogeneity at lower resolution. The computer classification scheme was a maximum likelihood classifier.

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I. INTRODUCTION

Two topics on data resolution versus forestry analysis are discussed:

- theoretical effects on classification accuracies caused by changes in data resolution;
- verification of the theoretical conclusions by performing a timber stand classification using real and simulated data with various reduced resolutions.

It is intuitive that multispectral data with different data resolution (i.e., the actual ground area of a picture element (pixel) recorded by a multispectral scanner) permit different classification accuracies for varied hierarchies of ground features. The question, "How does the computer classification accuracy vary with data resolution, and what is the optimal data resolution for computer classification of remotely sensed data?", naturally arises and needs to be answered.

The ground features of interest to this study are timber stands of different forest types and/or condition classes. Species composition defines the forest type, while the age, size and, sometimes, condition determine the condition class of the timber stand.

Forest scenes are particularly complex, especially when viewed from low altitudes, because of the nonhomogeneity of tree patterns, the nonuniformity of the species composition of trees in the stand, the variation in the undergrowth and spacing between individual trees, and the texture effects caused by shadows. All these effects would be significant for multispectral data with resolution less than, for example, (10 meters)^2.

Present machine processors cannot utilize information extractable from low-altitude data as photointerpreters can. Photointerpreters can use to advantage nonspectral information (such as texture, shape of tree crowns, shadows of trees indicating their profiles) from high resolution data; but machine processing systems like LARSYS (a system developed at the Laboratory for the Applications of Remote Sensing (Phillips, 1973)) cannot. Thus, forest scene complexities in high-resolution data make stand identification difficult. Smoothing out the complexities would be expected to improve classification accuracies.

The complexities in forest scenes are smoothed by simulating lower resolution data from high resolution data with an averaging process. This simulates the photographic scale reduction process and derives data sets equivalently scanned at higher altitudes. With this kind of modeling, the theoretical effects on classification accuracies caused by resolution reduction were examined, and experimental work was performed to verify the theoretical conclusions.

II. TECHNICAL APPROACH

II.1 Simulation of Data at Reduced Resolution

To simulate data at lower resolution from data at high resolution, an averaging relationship is assumed between data at different resolutions. This electronically simulates the photographic scale reduction process, and also simulates data scanned equivalently at higher altitudes.

For example, data $\{x_{ij}\}$ has a resolution of (8 meters)^2; data $\{y_{ij}\}$ has a 2X (2 times) reduced resolution, i.e., coarser resolution of (16 meters)^2. (See figure 1; x_{ij} and y_{ij} denote the spectral measurements at line i and column j.) Thus, the same (16 meters)^2 ground area covered by one y measurement will be covered by four (8 meters)^2 x measurements. The averaging relationship is

$$y_{11} = \frac{1}{4}\left(x_{11} + x_{12} + x_{21} + x_{22}\right)$$

for the reduced pixel in line 1 and column 1. In general,

$$y_{m,n} = \frac{1}{4}\left(x_{2m-1,2n-1} + x_{2m-1,2n} + x_{2m,2n-1} + x_{2m,2n}\right)$$

The same averaging is done over individual channels; i.e., the 2X reduced data has the same number of channels as the original unreduced data, and has effectively half as many lines and half as many pixels per line.

This simple averaging process is assumed in the theoretical derivation and forestry application discussed in sections III and IV. The more general process of weighted averaging is also discussed in section III.2,

where

$$y_{m,n} = w_1 x_{2m-1,2n-1} + w_2 x_{2m-1,2n} + w_3 x_{2m,2n-1} + w_4 x_{2m,2n}$$

with

$$w_i \geq 0$$

and

$$\sum_{i=1}^{4} w_i = 1.$$

II.2 Classification and Evaluation Procedures

The classification technique is the widely used scheme of supervised pattern recognition. That is, training fields are selected to train the maximum likelihood classifier, such as in LARSYS (Phillips, 1973). Normal statistical distributions are assumed on the training classes. Equivalently, the Bayes' classifier using equal *a priori* probability is employed (Anderson, 1958).

The evaluation procedure is the calculation of classification accuracies of training fields/classes. The classification accuracy is a measure of the statistical probability of correct classification (PCC) (Anderson, 1958) which is a widely accepted evaluation parameter. Also, the divergence measure (Marill and Green, 1963) is calculated to convey the extent of separability between classes. In special cases, it has been established that the divergence measure has direct relationship with PCC.

III. THEORETICAL RESULTS

III.1 Probability of Correct Classification

The following discussion shows that there is a gain in the PCC when the data resolution is lowered. Actually, the probability of misclassification (PMC) for the 2-class classification case is computed below; PMC = 1 - PCC. Data sets {X} and {Y} are studied, where {Y} is a mX (i.e., m times) reduction of {X}; i.e., a generic data point in {Y} is an average of m^2 data points in {X}. (In this section, {X} and {Y} are shorthand notation of $\{x_{ij}\}$ and $\{y_{ij}\}$.)

Assume the following notations for the means and covariance matrices for the two classes C_1 and C_2 in the data sets {X} and {Y}:

$$C_1: \ \mu_{X1}, \ \Sigma_{X1}; \ \mu_{Y1}, \ \Sigma_{Y1}$$

$$C_2: \ \mu_{X2}, \ \Sigma_{X2}; \ \mu_{Y2}, \ \Sigma_{Y2}.$$

These parameters can be estimated from the {X} and {Y} data sets, using the normal method of training field selection and statistics calculation. By the averaging process which simulates {Y} from {X}, it follows that:

$$\mu_{X1} = \mu_{Y1}$$

$$\Sigma_{X1} = m^2 \Sigma_{Y1}$$

$$\mu_{X2} = \mu_{Y2}$$

$$\Sigma_{X2} = m^2 \Sigma_{Y2}.$$

Using these statistics to train the classifier, the Bayes' regions (Anderson, 1958) for equal *a priori* probabilities are established and denoted by R_{X1}, R_{X2} for data set {X} and by R_{Y1}, R_{Y2} for data set {Y}. For the case when $\Sigma_1 = \Sigma_2$, it follows that:

$$R_{X1} = R_{Y1}$$

$$R_{X2} = R_{Y2}.$$

By the definition of PMC, which is (Anderson, 1958)

$$\text{PMC} = \tfrac{1}{2}\text{Prob}\left(R_1/C_2\right) + \tfrac{1}{2}\text{Prob}\left(R_2/C_1\right)$$

and because the relationship between the covariance matrices implies that the distributions in data set {Y} taper off quicker than those in {X}, it follows that:

$$(\text{PMC})_X \geq (\text{PMC})_Y.$$

That is, PMC is lower for data set {Y} than for {X}. In other words,

$$(\text{PCC})_Y \geq (\text{PCC})_X.$$

For the case when $\Sigma_1 \neq \Sigma_2$, but are not very different, the same relationship between $(\text{PCC})_Y$ and $(\text{PCC})_X$ can be shown to be true.

In other words, the classification accuracy will be better for the lower resolution data {Y} than for the high resolution data {X}.

III.2 <u>Separability: Divergence Measure</u>

The following establishes that the divergence between C_1 and C_2 increases with the lowering of the data resolution; the same situation as in section III.1 is assumed. The divergence measure is used because it has been shown (Marill and Green, 1963) that the divergence value relates to PCC. In fact, when $\Sigma_1 = \Sigma_2$ for C_1 and C_2, the divergence $J(C_1,C_2)$ between C_1 and C_2 has a one-to-one relationship with PCC; and, $J(C_1,C_2)$

increases if and only if PCC increases. Generally, the larger the divergence value, the more separable C_1 is from C_2.

The divergence $J(C_1,C_2)$ between C_1 and C_2 is defined as:

$$J(C_1,C_2) = \frac{1}{2}tr\left[\Sigma_1 - \Sigma_2\right]\left[\Sigma_2^{-1} - \Sigma_1^{-1}\right]$$

$$+ \frac{1}{2}\left[\mu_1 - \mu_2\right]^T\left[\Sigma_1^{-1} + \Sigma_2^{-1}\right]\left[\mu_1 - \mu_2\right] \quad .$$

By the relationship established in section III.1 between μ_{X1} and μ_{Y1}, Σ_{X1} and Σ_{Y1}, μ_{X2} and μ_{Y2}, Σ_{X2} and Σ_{Y2}, $J_X(C_1,C_2)$ and $J_Y(C_1,C_2)$ for data sets {X} and {Y} can be related by the following inequalities:

$$J_X(C_1,C_2) \leq J_Y(C_1,C_2) \leq m^2 J_X(C_1,C_2) \quad .$$

$J_Y = m^2 J_X$ in the special case when $\Sigma_1 = \Sigma_2$; and $J_Y = J_X$ when there is no averaging, i.e., when data set {Y} is identical to data set {X}.

In general, when {Y} is a weighted average of {X}; i.e., a generic data point, y, in {Y} relates to the generic data points, x_i, in {X} in the following manner:

$$y = \sum_{i=1}^{m^2} w_i x_i, \qquad \sum_{i=1}^{m^2} w_i, = 1, \; w_i \geq 0;$$

the m^2 factors in the above discussion will be replaced by $1/\sum w_i^2$, which is a constant between 1 and m^2. That is,

$$J_X(C_1,C_2) \leq J_Y(C_1,C_2) \leq k \, J_X(C_1,C_2)$$

where $1 \leq k \leq m^2$.

In other words, the separability between classes as measured by the divergence measure will be larger for the lower resolution data {Y} than for the high resolution data {X}.

IV. FORESTRY APPLICATIONS

This experimental investigation on data resolution versus forestry classification is part of the Forestry Applications Exploratory Studies Project (FAP). The FAP project is conducted by the Earth Observations Division at the Lyndon B. Johnson Space Center (JSC) of the National Aeronautics and Space Administration, and by the Southern Region of the Forest Service, U.S. Department of Agriculture. Detailed information on the project can be found in (Anon., 1974).

IV.1 Study Area

The study area is located in Sam Houston National Forest, which is located 90 miles north of Houston, Texas. This forest is in the "East Texas Piney Woods", the heavily forested portion of East Texas. The "Piney Woods", also called "Flatwoods", occupy the physiographic province known as the Gulf Coastal Plains. Topography is flat to gently rolling with forest soils that are generally deep sandy soils or shallow sandy soils over a heavy clay subsoil with clay outcrops.

Forest cover generally consists of shortleaf pine (*pinus echinata Mill.*) on the ridges and upper slopes, loblolly pine (*Pinus taeda L.*) and hardwood on the lower slopes, and hardwoods in the bottoms. The most common hardwood species are mixed oaks: (a) laurel oak (*Quercus laurifolia Michx.*), and willow oak (*Quercus phellos L.*); and (b) sweetgum (*Liquidambar styraciflua L.*), nuttal oak (*Quercus nutallii Palmer*), and willow oak. On some high, dry sites post oak (*Quercus stellata Wargenh.*) and black oak (*Quercus veluntina Lam.*) predominate. Further descriptions of these timber types can be found in (Anon., 1954).

There are seven timber types/condition classes studied in this application; these features are contained in the data sets described in the following subsection. Using a numbering system that is used in the FAP project, these seven features are tabulated in table 1.

IV.2 Data Sets

An area of approximately 11 square kilometers (5 square miles) in Sam Houston National Forest was studied; this area was also known as Edit 9 in the FAP project. Multispectral scanner data over Edit 9 was collected during Mission M230 of the NASA C-130 aircraft, flown on March 21, 1973 at 3 kilometers (10,000 feet) altitude. The Bendix 24-channel multispectral scanner (MSS/24) on board M230 had only 12 operating channels at the time of flight. The channels are numbered in this investigation 1 through 12; their spectral coverages are shown in table 2.

A three-channel color rendition of the Edit 9 multispectral scanner data is shown in figure 2, with the timber stand and compartment boundaries delineated on the imagery. The boundaries were transferred onto the imagery from U.S. Forest Service maps.

The original unreduced data plus two simulated data sets were studied: 1X, 2X and 3X; where 1X has a data resolution of approximately (8 meters)^2; 2X, (16 meters)^2; and 3X, (24 meters)^2. The simulation was performed by the simple averaging process described in section III.1. 1X has approximately 250 scan lines and 700 pixels/scan line.

IV.3 Field Selection

The fields selected for classification and divergence studies are shown in figure 3. The entire Edit 9 area is divided into 3 sections, left (L), middle (M) and right (R); hence the labels of fields, e.g., L2.5, R2.5.

In order to avoid scan-angle problems (Crane, 1971), the left fields, middle fields, and right fields were studied separately. The same physical fields were selected from 1X, 2X, and 3X. Thus, the field coordinates in 1X, 2X, and 3X are directly related.

IV.4 Data Processing

The 1X, 2X, and 3X data were processed on the Earth Resources Interactive Processing System (ERIPS) at NASA/JSC. The left four field, middle two fields, and right three fields, and right three fields were studied separately.

Statistics of these fields were generated; pairwise classification and divergence calculations* were made. For example, for the right three fields R1.3, R2.3 and R2.5, there are three pairs: R1.3/R2.3, R1.3/R2.5 and R2.3/R2.5.

Classification and divergence calculations were performed using three different channel sets: (1) 8 channels - numbers 2, 4, 5, 7, 8, 9, 10, and 11; (2) 4 channels - numbers 3, 5, 8, and 11; (3) 4 best channels as dictated by the channel selection processor on ERIPS - numbers 2, 7, 10, 12 for 1X and 3X; numbers 2, 3, 7, and 11 for 2X.

In case 1, the 8-channel set was chosen arbitrarily because of the limitation of ERIPS in the divergence calculation. Channels 1 and 3 were arbitrarily dropped, because

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*In this application on ERIPS, the transformed divergence J' was used instead of the divergence J defined in section III.2, where $J' = 99.9\ (1 - \exp(-J/16))$. J' and J are equivalent (Swain, 1973); any conclusion drawn from J' computations applies to J computations, and vice versa.

channel 2 contains very similar information (at least visually); channel 2 was retained; channel 6 was dropped because of data drop-out; channel 12 was dropped because data values were very low. In case 2, the 4-channel set was arbitrarily chosen, and spaced throughout the 12 channels. The channel set in case 3 was dictated by the channel selection processor on ERIPS, which uses the divergence measure to determine between-class separability.

IV.5 Analysis Results

The results of performing the classification and divergence measurements are summarized in figures 4 through 6. Each figure is in bar-chart form.

Each bar-chart shows the classification accuracy for the pairwise classification (on the ordinate) versus the specific pairs of classes used in classification (on the abscissa). The classification accuracy is a measure of PCC and is given by 1/2 (classification accuracy of C_1 + classification accuracy of C_2)*; classification accuracy of C_i = the number of points of C_i correctly classified into C_i/the number of points of C_i.

The pairwise divergence values are also indicated in the bar-charts. The values are written in the bars. Internal settings on ERIPS have limited the maximum between-class separability to 99.9.

Figure 4 through 6 correspond to cases 1, 2, and 3 of data processing discussed in section IV.4. The 1X, 2X, and 3X results are shown side-by-side.

IV.6 Inference from Analysis Results

Figures 4 through 6 lead to the following conclusion: For the data sets and forest classes studied in this investigation, classification accuracies increased with the lowering of data resolution. Also, classes were more separable at lower resolution.

This conclusion reinforces the theory discussed in section III.

V. REMARKS

V.1 The Paradox

The theoretical and experimental results conclude that classification accuracies increase with the reduction in fidelity of data resolution. This gives rise to the following paradox:

> "If ground features can be classified using high resolution (e.g., low altitude) data, they can also be classified, and even with higher accuracies, using low resolution (e.g., high altitude) data."

The paradox should not cause any alarm, because the statement is asserted for computer classification accuracies alone, and because the classification technique employs spectral information alone. Also the classification and identification of timber stands, not individual trees, are considered.

The accuracy measure used in the analysis comes form evaluating training/test data which are well defined and delineated due to prior knowledge. The loss in boundary accuracy and mensuration accuracy in the analysis of higher altitude data has not been accounted for. These two factors are most often deciding factors on optimal data resolution. Also, the gain in details at higher resolution is not an asset to the spectral classification rule. In fact, the details in texture, etc., add to the complexity in machine processing in this case.

Another explanation for the increase in classification accuracies for lower resolution data is that a "PERFIELD" classification (Gupta, 1973) is performed on the lower resolution data, compared to a "PERPOINT" classification on the high resolution data.

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*Beside this definition of classification accuracy, other measures have also been commonly used; for example: number of correctly classified points of C_1 and C_2/total number of points of C_1 and C_2.

A "PERFIELD" classification rule has been suggested to be superior to the "PERPOINT" classification rule. That is, scene nonhomogeneity in the high resolution data is reduced by the averaging process, which gives the lower resolution data. This explanation is readily acceptable, especially for the forest scenes studied in this investigation, where complexities abound with high resolution.

V.2 A Conjecture on Detection

An interesting conjecture follows from the conclusion of the above analysis. For detection purposes, a satellite could outperform aircraft data analysis, as long as the features to be detected have physical sizes sufficiently larger than the satellite resolution (preferably at least four times larger, in order to assure total containment of the feature in at least one pixel). Detection here means the detection of the presence of the feature, disregarding its size.

V.3 Decision on Optimal Data Resolution

An optimizing criterion can be set up where the optimal choice of data resolution is a compromise between classification accuracy, boundary accuracy and mensuration accuracy. The criterion, D, could then be written as

$$D = d_1\theta_c + d_2\theta_b + d_3\theta_m \quad ,$$

where d_1, d_2, and d_3 are weights in the criterion, and θ_c, θ_b, θ_m are respectively the accuracies in classification, boundary location, and mensuration. An optimal solution for data resolution will be obtained by achieving maximum value of the criterion D. Different applications will call for different weights d_1, d_2, and d_3; and will produce different solutions. Other factors such as the cost of data acquisition, cost of data processing, etc., can be also incorporated into the criterion as follows:

$$D' = d_1\theta_c + d_2\theta_b + d_3\theta_m + d_4C_a + d_5C_p \quad ,$$

Where C_a and C_p are the respective costs.

An optimal decision on data resolution will lead to an optimal design of sensors and platforms.

V.4 Signal-to-Noise Considerations

The effects of sensor noise, thus signal-to-noise ratio, on classification accuracies were not addressed in this work. Rather, in this paper, the relation between scene homogeneity and data resolution was modeled, and the increase in classification accuracy due to lowering the data resolution was construed as the result of smoothing the scene.

Nevertheless, it is recognized that the same data reduction process smooths out the noise in the sensed signals. In fact, (Thomson et. al., 1974) pointed out the same kind of conclusion for land-use classifications; and the gain in accuracy was construed as due to the increase in the signal-to-noise ratio.

One problem remains to be solved, i.e. how can the increase of accuracy be partitioned into (a) the increase due to smoothing scene nonhomogeneity; and (b) the increase due to the gain in signal-to-noise ratios. The subtle distinction between (a) and (b) will influence the design of optimal sensors and platforms. That is, to achieve the reduction of scene nonhomogeneity, the data could be taken at high altitudes. And, to achieve the gain in signal-to-noise ratios at a specific data resolution, new designs of sensors might have to be called for.

V.5 Forestry Modeling

The theoretical and experimental findings indicate that forest scenes at different data resolution need to be appropriately modeled by different statistical models. Specifically, a pure pixel model could be developed for high resolution (e.g. low altitude) aircraft data. The second model, for mixed pixels, could also be developed for low resolution (e.g. high altitude aircraft and satellite) data.

In the model of pure pixels, only one tree crown is contained in an individual pixel. In the model of mixed pixels, crowns of many trees and openings between trees might be contained in one pixel.

Analysis approaches for the two models are intuitively different. (Basu and Kan, 1974) proposed that forest types be distinguished by their "proportion vectors" which characterize the mix of tree species in the forest. Also, a "compound distribution" approach or a linear regression approach was proposed for the mixed pixel model.

VI. CONCLUSIONS

Theoretical results and experimental verification have led to the conclusion that computer classification accuracy could increase with the lowering of data resolution. The theory applies to general remote sensing problems; while the verification was performed on forestry data where timber stand classification/identification was of concern.

The increase in classification accuracy is construed as due to the smoothing of scene nonhomogeneity. For forestry data such as the sets studied here, the modeling of lower resolution data from high resolution data (e.g. from (8 meters)^2 resolution reduced to (16 meters)^2 and (24 meters)^2 resolution) readily lends credence to the present conclusions. Such considerations are important and would lead to optimal designs of sensor and platforms.

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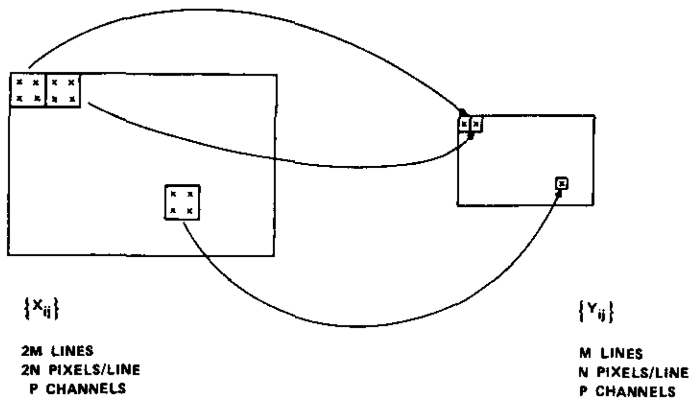
Table 1. Timber Types/Condition Classes of Interest in Study Area

Type ID	Description
1.3	Shortleaf pine, immature sawtimber
2.3	Loblolly pine, seedling and sapling, adequately stocked
2.5	Loblolly pine, immature sawtimber
2.6	Loblolly pine, mature sawtimber
3.1	Laurel oak - willow oak, immature sawtimber
4.2	Sweetgum-nuttal oak - willow oak, immature sawtimber
7.2	Cutover land, not site prepared

Table 2. Spectral Coverages of 12 Channels of MSS/24 Data Over Study Area

Channel no.	Spectral coverage (micrometer)
1	0.375-0.405
2	0.40-0.44
3	0.466-0.495
4	0.53-0.58
5	0.588-0.643
6	0.65-0.69
7	0.72-0.76
8	0.770-0.810
9	0.82-0.88
10	0.981-1.045
11	1.20-1.30
12	2.10-2.36



$$y_{m,n} = \frac{1}{4}\left[x_{2m-1,2n-1} + x_{2m,2n-1} + x_{2m,2n-1} + x_{2m,2n}\right]$$

Figure 1. Illustration of data resolution reduction: a 2X reduction.

TIMBER STAND AND COMPARTMENT MAP OVER

SAM HOUSTON NATIONAL FOREST MSS/24 EDIT

MISSION NO. 230 – EDIT NO. 9

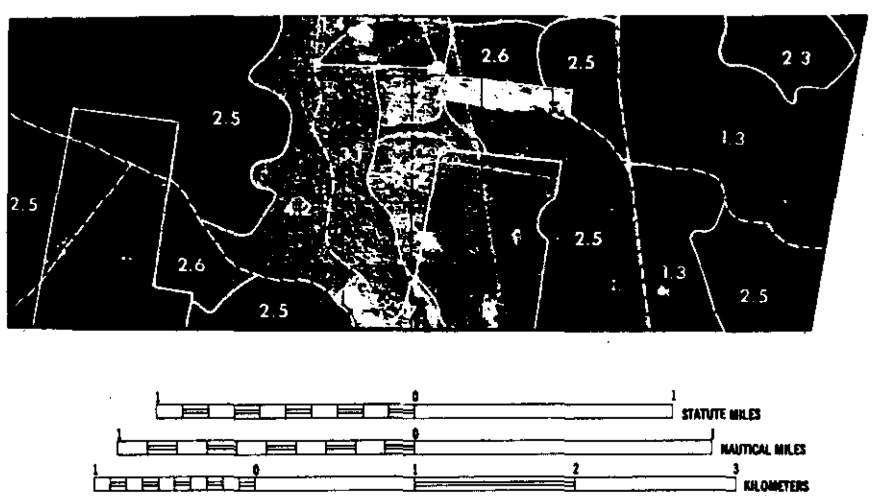


Figure 2. Timber stand and compartment map over Sam Houston National Forest Edit 9; a 3-channel color rendition of the MSS/24 data of M230. (Refer to table 1 for timber type codes.)

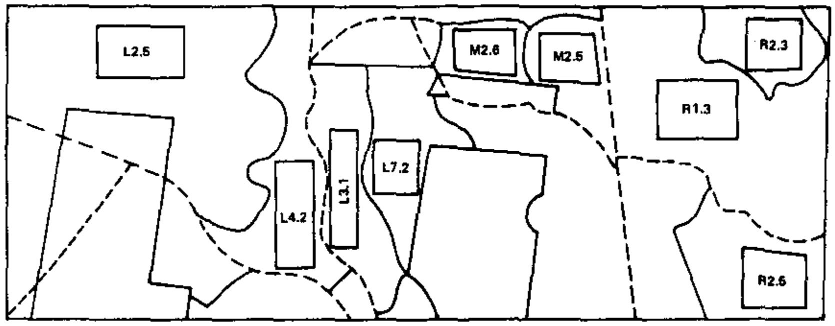


Figure 3. Locations of fields selected on Edit 9 (used in classification and divergence studies).

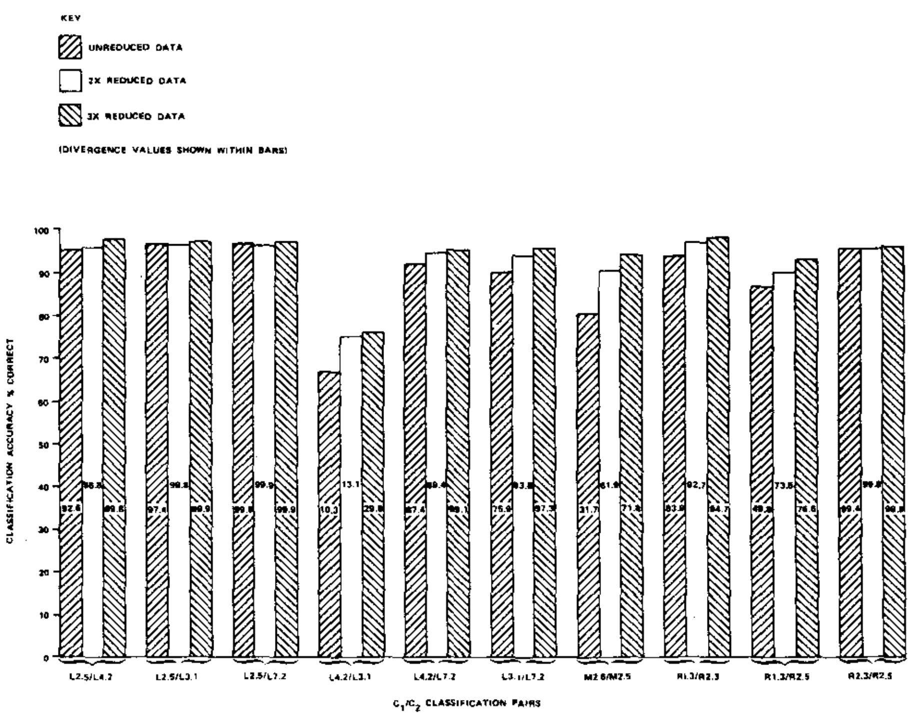


Figure 4. Bar charts of pairwise classification accuracies: case 1.

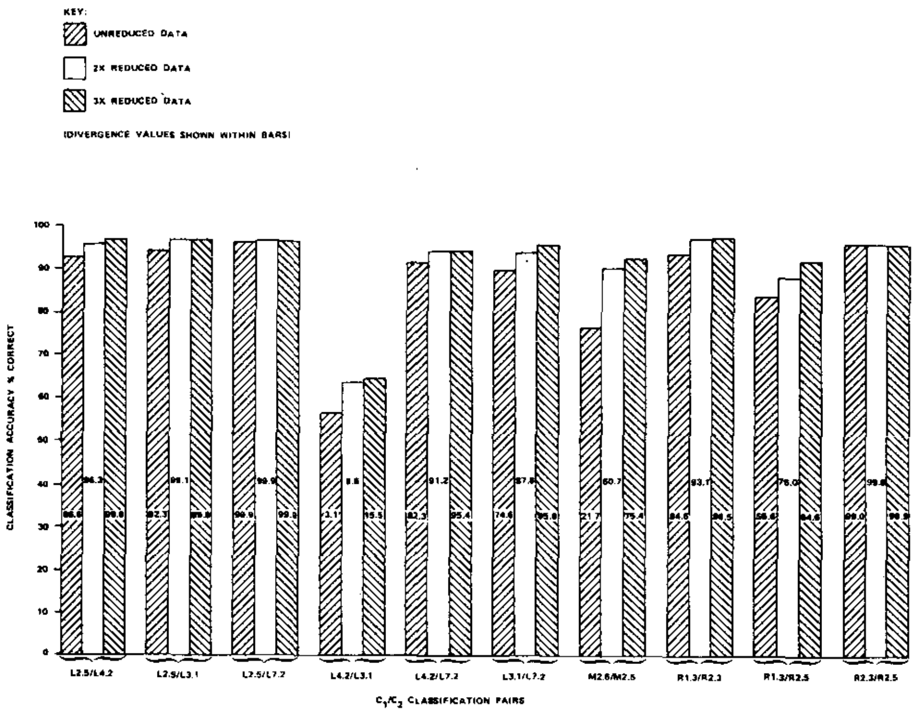


Figure 5. Bar charts of pairwise classification accuracies: case 2.

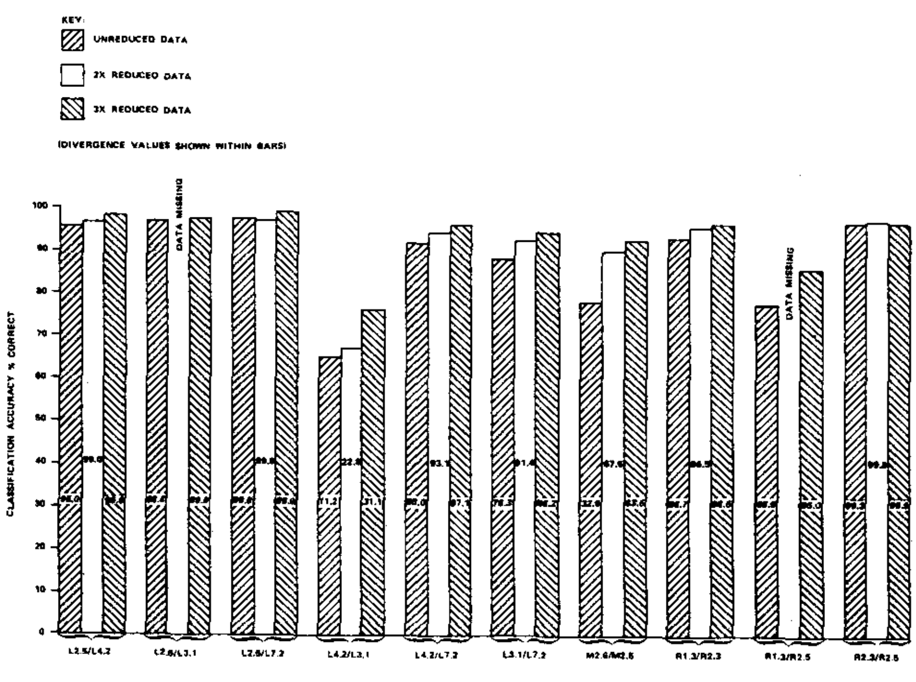


Figure 6. Bar charts of pairwise classification accuracies: case 3.