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Techniques for Combining Landsat and Ancillary Data for Digital Classification Improvement

The advantages and disadvantages of preclassification scene stratification, postclassification class sorting, and classification modification are discussed.

ABSTRACT: *Digital classification of Landsat data for use in natural resource inventory has produced mixed results. In attempts to improve classification, ancillary data, such as digitized maps and terrain (elevation) data, have been combined with Landsat data in various ways. These data have been used in (1) preclassification scene stratification; (2) postclassification class sorting; and (3) classification modification through increasing the number of observation channels, modifying prior probabilities, or adding a second stage to the classification. Preclassification stratification and postclassification sorting are found to be efficient, but lacking in sophistication due to their reliance on deterministic decision rules. Classification modification through the simple addition of observations does not appear to improve classification results reliably; however, stratification of the sample used for training by the ancillary data does improve accuracy. Classification modification by altering prior probabilities or by incorporating distribution models increases accuracy, but requires considerable additional sampling.*

INTRODUCTION

A LANDSAT scene of the Earth's surface is composed of a two-dimensional array of cells or picture elements (pixels). Associated with each pixel are observations of Earth surface radiance as measured in four relatively narrow bands of the electromagnetic spectrum. Digital classification of these data requires that representative samples of object classes on the Earth's surface (e.g., types of vegetation, soils, geology, land use) be carefully selected and described so that the remaining pixels in the scene can be examined and accurately classified.

The assumption that each of the objects of interest has a unique set of attributes is implicit in the process of classification. Drawing on past experiences, we are able to recognize objects by their unique set of sensible attributes (size, color, shape, feel, smell, sound, surroundings). Digital classification of Landsat data seeks to recognize Earth objects using four observations of one attribute—color. The argument made for digital multispectral classification is that, when considering the spectrum as a whole, different objects have different patterns of reflection and emission. Further, it is assumed that these spectral patterns are sufficiently unique to make objects consistently distinguishable from one another using statistical classification techniques. However, even within a single multispectral classification, accuracy is highly variable [see, for example, Todd *et al.* (1980)].

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Aside from the development of new classification algorithms, any number of methods might be used to improve classification accuracy. One obvious approach would be to increase the number of spectral observations used in classification. However, the addition of spectral observations does not necessarily add more usable information to the classification exercise (Ready *et al.*, 1971).

Another obvious method for improving classification would be to consider a greater number of object attributes. This might include consideration of conventional image attributes, such as size, shape, pattern, and association of objects, and result in a process similar to that performed by a photo-interpreter (see Colwell, 1960). However, many of these attributes are not easily derived from the digital image. A more immediate method would be to incorporate information about object attributes derived from ancillary data sources.

Ancillary Data

Ancillary data used to improve digital Landsat classification are primarily map-based. Examples are maps of geology, soils, vegetation, or topography. These data are readily available and are widely understood. However, they present several problems when used with digital Landsat data in an automated classification.

The most significant difficulty in using maps for digital classification improvement derives from the nominal nature of the data they usually contain. Techniques exist for combining continuous and nominal or categorical data (Strahler *et al.*, 1980). However, it is difficult to deal with the variation contained in categories. For example, on a choroplethic map—such as a soil or vegetation map—each polygon is discrete. Each point contained within the polygon, by definition, must be of special value (Duecker, 1979). Spatial variation of factors within the mapping unit, such as vegetation cover, percent rock outcrop, or soil color, can be described within the legend but cannot be expressed on the map itself. Obviously, these spatial variations will have an effect on the spectral response of a class of objects, but there is no convenient way to accommodate them when comparing or combining Landsat and map data.

Locational accuracy is a major consideration if two spatial data sets (maps) are to be merged. Two factors make the locational accuracy of ancillary data highly variable. First, many attribute maps are not subject to rigid accuracy standards. For example, many older soil surveys published by the U.S. Soil Conservation Service are still in use, but were based on uncontrolled photomosaics. Second, the precise location of boundaries between mapping units of any attribute is always uncertain. For example, in vegetation mapping, Kuchler (1967) has pointed out that boundaries between vegetation types may or may not exist on the ground. In soil mapping, Bie and Beckett (1973) showed dramatically the extreme variation in different mappers' perception of the same landscape and the same sample data.

Most maps are not in digital form and must be digitized. Although this may not be a significant technical problem, it does require considerable effort in addition to specialized digitizing hardware and supporting software.

Digital terrain (elevation) data, available from the USGS National Cartographic Information Center (NCIC), have a number of advantages for use in improving Landsat classification. These data are (1) available for all of the United States, (2) inexpensive, (3) in a grid cell format more or less compatible with Landsat or other digital image data, and (4) essentially continuous rather than nominal in nature.

Approaches to Use of Ancillary Data

Classification improvement with ancillary data has followed one of three paths: incorporating those data either before, during, or after classification, through stratification, classifier operations, or postclassification sorting.

Stratification

Use of ancillary data prior to classification involves a division of the study scene into smaller areas or strata based on some criterion or rule, so that each stratum may be processed independently. Statistically, the purpose of stratification is to increase the homogeneity of the data sets to be classified. Because of its simplicity, stratification is a widely used technique. From a practical standpoint, stratification is employed for classification improvement either to divide a large study area into smaller homogeneous units, or to separate different things which are spectrally similar.

There are two advantages to dividing a large study area into smaller subareas. First is the simple convenience of dealing with smaller data sets at each stage of analysis. This, in fact, may be an overriding practical consideration in especially large studies (Bryant *et al.*, 1979). The second advantage is a reduction of variation within strata. This is the statistical basis for stratification (Snedecor and Cochran, 1967). The spectral characteristics of any set of objects, such as specific soil or vegetation types, are likely to vary over distance. As variance increases, the likelihood of confusion between spectrally similar objects also increases. Criteria selected for stratification should be significant in describing the variation of the objects of interest within the study area. For example, a regional study of soils might be stratified by rock type, or a vegetation study might be stratified by elevation.

A more specific and pragmatic application of stratification is its use in separating different objects that cannot be distinguished spectrally. For example, obviously different things, such as older residential areas and rural woodlands, may be spectrally identical. To avoid confusion, urban and non-urban areas may be separated by manual photo-interpretation or by using a general land-use map. Training and classification then can proceed independently on each stratum and finally the two may be merged in a final product. Confusion is thus avoided and accuracy improved (see Gaydos and Newland, 1978).

Stratification is a conceptually simple tool and, carefully used, can be effective in improving classification accuracy. However, it is not sensitive to subtle distinctions. Differences between strata are absolute and the lines between them are abrupt; there are no gradations or fuzzy boundaries between mapped classes. Thus, considerable care should be taken when (1) deciding to stratify, or not and (2) selecting stratification criteria.

Imprudent selection of stratification criteria can have far-reaching implications in classification. Differences in training set selection for individual strata and/or the vagaries of clustering algorithms, if used, may produce markedly different spectral classes on either side of strata boundaries. Merging strata for a final product with class boundary offsets or missing classes is difficult, at best.

CLASSIFIER OPERATIONS

Use of ancillary data during classification has followed several approaches. The first, and most obvious, is to increase the number of attributes or channels of information used in the classification process. Thus, instead of four bands of spectral data, n bands of spectral and ancillary data are combined and used for classification. This technique had been called the "logical channel" approach (Strahler *et al.*, 1978). The hoped-for improvements have generally not materialized (Anuta *et al.*, 1976). It appears that the "simple addition" of new non-spectral observations or channels without modifying conventional spectral sampling routines adds little to classification accuracy and can create new problems in developing class statistics.

Another approach involves the modification of the maximum likelihood decision rule. In most classifications, prior probabilities are ignored or are assumed to be equal for all classes. However, the classifier can be modified by developing prior probabilities before classification based either on the estimated areal composition of the known object classes in the study area or on the known association between object classes and the ancillary data. The "modified priors" concept was demonstrated by Strahler *et al.* (1978) and has been described more fully in Strahler (1980).

Several difficulties exist in the use of prior probabilities for classification improvement. First, maximum likelihood classifiers assume Gaussian distributions for the data classes, an assumption that is commonly not valid for ancillary data. Second, it is also assumed that new observations should improve classification. However, new observations require new samples to describe not only their signatures for the object classes, but also their association (covariance) with all other observations. Strahler *et al.* (1978) emphasized the difficulty of ensuring that the full range of elevations associated with a particular tree species could be sampled. In their study, a single set of 93 samples from a 220 sq km study area was used to describe both the spectral and topographic characteristics of forest cover types. To ensure that this sample was sufficient, elevation and aspect data were reduced to categories. Classification accuracies were improved, but it was necessary to adjust class mean elevation values to obtain best results.

Fleming and Hoffer (1979) developed two techniques for mapping forest cover type in Colorado that used topographic data but avoided some of the sampling difficulties discussed above. To describe the relationship between cover types and topography, a topographic stratified random sample (TSRS) of 4,550 points was drawn from a 3,750 sq km study area. (Only 3,379 sample points were suitable for training.) The strata were defined by classes of elevation, slope, and aspect. Cover type for each point was determined by photointerpretation.

One classification improvement technique was a variation of the logical channel approach. It used the TSRS to derive both spectral and topographic training statistics for use in a conventional "single stage" supervised application. The use of additional channels produced a more accurate classification than spectral data alone. By using the ancillary data to stratify the sample, all significant variation in the ancillary data was represented.

The other technique developed by Fleming and Hoffer makes more sophisticated use of the TSRS in a "layered" approach to classification. Based on the sample data, a "topographic distribution model" was developed to determine the probability of each forest cover type occurring at any given elevation, slope, and aspect. In parallel, spectral training statistics were developed independently using the "modified clustering" technique. In a two stage, or layered, approach the spectral statistics were used to classify major cover types (e.g., coniferous forest, deciduous forest), and the topographic statistics were used to further subdivide cover types to the species level. Accuracies of the layered and single stage approach were not significantly different in terms of computer time.

However, the layered approach was over four times faster than the single stage.

The use of ancillary data directly in the classification process improves accuracy but also increases cost. Simple addition of new observations that accompany the spectral sample can improve accuracy, but the results are unpredictable. Addition of topographic observations derived from a TSRS as logical channels improves accuracy but requires both intensive sampling and an increase in computer time. Both the layered and modified priors approaches offer improvements in accuracy but require a level of added sampling that is considerably beyond conventional spectral classification.

POSTCLASSIFICATION SORTING

The use of ancillary data after multispectral classification is based on the observation that a single class of objects seldom can be represented by a single spectral class. To accommodate this, a large number of spectral classes commonly is created. Spectral classes may then be merged into groups which represent object classes. The problem, as has been discussed, is that one spectral class may often represent subsets of more than one object class. In postclassification sorting, these problem spectral classes are treated as separate special cases. Based on a sorting rule, individual pixels of the problem spectral class are assigned to the appropriate object class using ancillary data. The approach and techniques used in postclassification sorting are derived from methods for overlay analysis found in grid-based geographic information systems (Tomlinson *et al.*, 1975).

EXAMPLE OF POSTCLASSIFICATION SORTING

An example of a spectral classification of Landsat data for a desert area in California is shown in Plate 1a. In a subjective evaluation of the classification, results were compared visually with the original unclassified scene. A number of cases of confusion between proposed classes was found. For example, there was confusion between the bright surfaces of a dry lake bed (playa) and the steep sunny slopes of large sand dunes. It was felt that, by using slope data derived from digital terrain data, it would be possible to separate the steep sunny sand dunes from the flat playa surface. Other areas of confusion in the scene were found to exist among dark classes, such as shadow, basalt, and surfaces with desert varnish. If information describing slope and aspect were used in a postclassification operation, it would be possible to distinguish steep north or northwest facing slopes (shadows) from other dark surfaces. These dark surfaces might also be further subdivided on the basis of slope to recognize different types of alluvial fans.

Decision rules were developed, based on the arguments suggested above, to distinguish between the types of terrain that appeared to be confused most commonly (Table 1). Using these rules, the class assignment of each pixel was examined and was either assigned a new class or left unchanged.

The first refinement of the spectral classification using these decision rules was unsatisfactory. The elevation data from which slope values were derived contain systematic errors in the estimates of the elevations of cells between contours (Figure 1). Erroneous slope values therefore resulted between contours in the elevation data. This caused a banding of classes across the relatively low gradient alluvial fans and erroneously created areas of the dry lake class in the region of sand dunes. Similar problems of accuracy in these terrain data have been reported by others (Fleming and Hoffer, 1979; Stow and Estes, 1981). However, it is hoped that the reformatted terrain data now made available by NCIC are improved.

In an attempt to eliminate the errors in this particular data set, a 25 by 25 pixel averaging filter was applied to the slope calculations. A classification refinement was again performed using the smoothed slope data and the decision rules suggested above. Plate 1b shows the results. Dry lake areas again are erroneously inserted in the region of dunes. Also, a part of the dissected cobbly alluvial fan class (red) has been reassigned to the low gradient undissected basalt alluvial fan class (lavender). Both errors appear to be a product of the smoothing process which created low estimates of slope on some fan surfaces.

Another prominent feature of the refined classification is the abruptness of the boundaries created on the major alluvial surfaces (coded red). These are a product of the deterministic nature of the techniques used to refine the classification: decisions made at any point are "either/or," and thus, while the data used for sorting are essentially continuous, the rules employed use interval classes with discrete differences.

In summary, the postclassification technique is crude in its deterministic sorting approach to classification improvement. However, it offers several advantages. First, it is simple, quick, and easily implemented. Second, it is efficient because it deals only with "problem" classes. Third, it is relatively simple to include several types of ancillary data in developing decision rules. Finally, because it is performed after classification, errors made in rule selection can be corrected easily as opposed to those made prior to classification using scene stratification. The sample presented, though, would suggest two guidelines for using the technique. First, the ancillary data used for improvement must be reliable, and second, the decision rules must model the natural situation.

(a) (b)

PLATE 1. (a) Multispectral classification of a portion of Landsat scene 1700-17422, 28 June 1974, corresponding to Flynn, California 15′ quadrangle. (b) Refinement of classes displayed in (a), through postclassification sorting, using slope and aspect data (see Table 1 for explanation). The edge around the refined classification marks the limit of the terrain data.

TABLE 1. DECISION RULES APPLIED TO SPECTRAL CLASSES

Initial Assignment (Class)	Rule**	Final Assignment (Class)
Active sand dunes (1)	If slope is less than 1%	dry lake (10)*
	otherwise	active sand dunes (1)
Stabilized sand (2)	If slope is less than 1%	dry lake (10)*
	If slope is greater than 1%, but less than 15%	stabilized sand (2)
	otherwise	active sand dunes (1)
Low gradient undissected sandy alluvial fans and washes (3)	If slope is less than 1%	dry lake (10)*
	otherwise	low gradient undissected sandy alluvial fans and washes (3)
Low gradient cobbly alluvial fans (4)	If slope is less than 8%	low gradient cobbly alluvial fans (4)
	If slope is greater than 8%, but less than 15%	dissected cobbly alluvial fans (5)
	otherwise	mountain scrub (8)
Dissected cobbly alluvial fans (5)	If slope is less than 3%	low gradient undissected basalt alluvial fans (14)*
	If slope is greater than 3%, but less than 15%	dissected cobbly alluvial fans (5)
	otherwise	mountain scrub (8)
Mountain scrub (8)	If slope is greater than 15%	mountain scrub (8)
	otherwise	highly dissected alluvial fans (15)*
Shadow and basalt (9)	If slope aspect is north or northwest	shadow (9)
	If slope is less than 3%	highly dissected alluvial fans (14)*
	If slope is greater than 3%, but less than 8%	slightly dissected basalt alluvial fans (13)*
	If slope is greater than 8%, but less than 15%	dissected basalt alluvial fans (12)*
	otherwise	basalt mountains (11)*

* Derived classes.

** Slope values of 3 percent, 8 percent, and 15 percent were found to be useful for separating different degrees of alluvial fan dissection in a reconnaissance soil survey of the region (Desert Plan Staff, 1976).

SUMMARY AND CONCLUSIONS

Improvement in digital classification of Landsat data can be achieved through the incorporation of ancillary data. These data may be choroplethic maps of various land attributes or digital terrain (elevation) data. The incorporation of ancillary data in the classification process can be approached in several ways. The general characteristics of these approaches are summarized below.

- The use of ancillary data for scene stratification has been widely used in many different types of applications. Stratification is statistically sound, easily implemented, effective, and inexpensive in computer time. However, it is deterministic and thus cannot accommodate gradations between strata. In addition, because it is performed before classification, incorrect stratification criteria can invalidate the entire classification.
- Use of ancillary data as another logical channel to be considered during classification has been examined frequently. Although easily implemented and conceptually straightforward, the simple addition of new observations increases computer time considerably and does not appear to improve classification accuracy with any consistency. The careful selection of samples alleviates some of this difficulty, but requires considerable additional sampling.
- The modified priors and layered approaches to the use of ancillary data during classification rep-

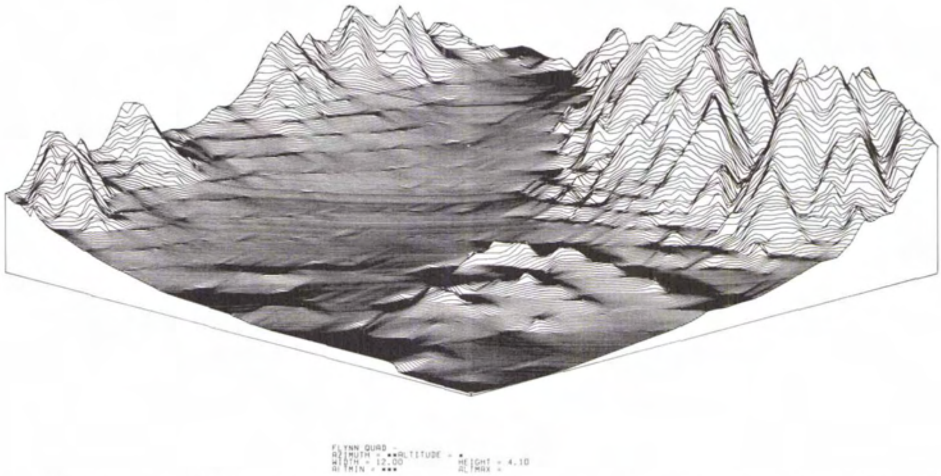

FIG. 1. Perspective plot of digital terrain data for Flynn quadrangle viewed from the northwest; "steps" seen on slopes are present in the raw data.

resent a new and sophisticated development. They are probabilistic and thus may have the greatest potential for improving accuracy and making efficient use of ancillary data. However, because they are based on statistical parameters, many samples must be drawn to characterize object relationships with both ancillary and spectral data. Thus, they require a level of sampling intensity that is somewhat beyond that which is conducted in normal spectral classifications.

- Postclassification sorting is a new application of a technique that has been used in geographic information systems. It, like stratification, is conceptually simple and easily implemented, but it is also deterministic. However, it does offer some advantages: it deals only with problem classes rather than all classes and, unlike stratification, errors made in the selection of sorting rules are easily corrected and do not require that the classification be redone.

Each of the techniques for classification improvement has advantages that will recommend its use in particular situations. Thus, it is not useful or proper to offer a judgment as to what the "best" technique might be. However, it is appropriate to make some general observations. Because of their simplicity, stratification and postclassification sorting will likely continue to be used in spite of their limitations. Both techniques are most effective when the confused objects are relatively discrete in their distribution, as is the case in many urban applications.

The simple addition logical channels is difficult to recommend because results cannot be consistently predicted. However, with careful preliminary work it can prove useful for specific applications, as demonstrated in the use of the topographic stratified random sample.

For natural resource applications, both the modified priors and layered approaches hold much promise. They would be reasonable to use on problems where objects were not always discrete in their distribution, such as vegetation or soils, and where a number of ancillary data sources were being used.

All techniques for classification improvement, with the possible exception of the simple addition logical channels, require that the analyst have a detailed understanding of the objects of interest and their relationship with ancillary data before attempting to improve the classification. Further, the more sophisticated the technique, the better the analyst must understand these relationships. However, in large-area, natural resource applications, these relationships are not likely to be well-known until after the classification or inventory is completed. Thus, significant improvement in large-area classification may not always be possible by the means described above, and errors must either be tolerated, explained in the legend, or corrected through more conventional means as the inventory proceeds.

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