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Signature Extension Versus Retraining for Multispectral Classification of Surface Mines in Arid Regions

Signature extension proved to be at least as accurate as retraining, and was lower in cost.

Abstract: *Because governmental agencies are responsible for conducting mined land inventories on a regular basis, it is desirable to standardize the manipulation of the digital Landsat data for this purpose. Supervised classification of Landsat images was used in this study to map Arizona copper mining activity in order to demonstrate the utility of these images for dynamic, regional inventories of mined lands. A set of spectral signatures derived at a single, large mining complex were extended spatially and temporally to discriminate mining activity from natural terrain features at other sites. Accurate classifications were obtained using signature extension, and, in some cases, the accuracy exceeded that obtained by retraining the classifier for individual mines.*

Introduction

Increasing demand for raw materials and energy, together with increased public awareness and demand for environmental protection, has resulted in the enactment of a variety of federal legislation designed to regulate waste disposal and provide protection to the environment and to nearby population. All legislation designed to regulate mine waste requires the acquisition of large quantities of information at periodic intervals. The most recent legislation enacted by Congress to regulate mine waste is the Surface Mining Control and Reclamation Act of 1977. This act requires each state to inventory hazardous mining areas and to establish a periodic monitoring program to include a complete inspection of each active mine quarterly and a partial inspection monthly. The requirement for frequent monitoring places a severe demand on limited state personnel and operating budgets, particularly in the western states where mining operations are often large and widely spaced.

Three sources of data that can support the inventory and monitoring requirements of the Surface Mining Act are

- Field surveys,
- Aerial photographs, and
- Satellite images.

Of these, only the last offers the advantage of automatic multidate, multispectral coverage providing direct digital formats compatible with computerized data base mapping. The major disadvantage of commercial satellite imaging systems, such as

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Landsat, is their relatively low spatial resolution compared to aerial and ground survey techniques. This disadvantage, however, will be partially overcome with recently developed high-resolution imaging systems, such as the Thematic Mapper on Landsat 4 and the HRV on the French SPOT satellite.

Multispectral Classification of Mined Lands

Landsat provides multidate coverage on an 18 (16 for Landsat-4) day repeat cycle and a digital image format (Landsat Data Users Handbook, 1979). Four separate images constitute a Landsat scene, two in the visible spectrum (bands 4 and 5 corresponding to green and red wavelengths, respectively) and two in the near infrared (bands 6 and 7). The digital format with 80-m pixels (picture, or ground resolution elements) permits the direct application of automated computer classification and other computer processing techniques to the images.

Automated classification algorithms for multispectral images can be either unsupervised or supervised (Swain, 1978). Unsupervised classification develops terrain class signatures by iterative clustering of a set of image pixels representing the classes of interest. This type of classification is useful for an image where limited field information exists to accurately locate and identify terrain training sites, or where a large number of spectral classes are present. An unsupervised classification is also suitable for automatic retraining of multitemporal images to correct for variations in atmospheric haze.

In mined-lands applications, where numerous scenes are to be classified, where there are few terrain classes of interest, and where field information is available to aid training site selection, a supervised classification technique is most appropriate. Training sites, consisting of small contiguous groups of pixels representing each terrain class, are chosen based on field information and visual image examination. More than one training site may be needed for some terrain classes in order to include their spectral variability. The supervised classification algorithm uses the statistical properties of pixels in the training sites to develop criteria by which the entire scene can be classified into a thematic map of the chosen terrain classes.

Conventional supervised classification techniques for mined lands applications require retraining the classifier at each mine. This retraining is not a severe handicap for monitoring or change detection applications at specific mines. For an inventory, however, retraining requires a knowledge of suitable training sites at all mine locations, i.e., a *preliminary* inventory to enable subsequent inventories to proceed. Clearly, such prior knowledge would defeat the purpose of a satellite inventory.

To avoid a preliminary inventory, this study was designed to assess the effectiveness of multispectral signature extension techniques in which a large number of similar mines are classified using one universal training data set. Signature extension involves calculating spectral signatures for mine classes using a large number of representative training sites at one mine location. These signatures are then used to classify mining areas in other Landsat images, acquired on other dates. The scope of this research was restricted to classification of three open-pit copper mine sites and associated tailings waste in Arizona (Figure 1).

Formation of a Comprehensive Training Set

The mines at Twin Buttes were used for the selection of a comprehensive training data set. This copper mining complex south of Tucson is the world's largest, with four major open-pit mines and extensive tailings. Because of its size, this mining area contains a wide variety of candidate training sites representing the full range of spectral variability for mining classes of interest. Plate 1 illustrates this spectral variability. Enlarged portions of the image shown in Plate 1a reveal the wide range of radiances that occur within a single tailings pond (Plate 1b) and a single mine (Plates 1c and 1d). Bright tailings ponds (rectangular fea-

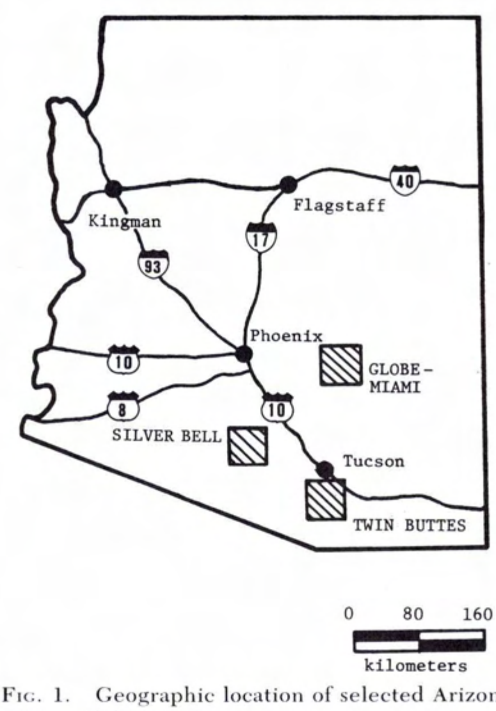


Fig. 1. Geographic location of selected Arizona copper mining areas.

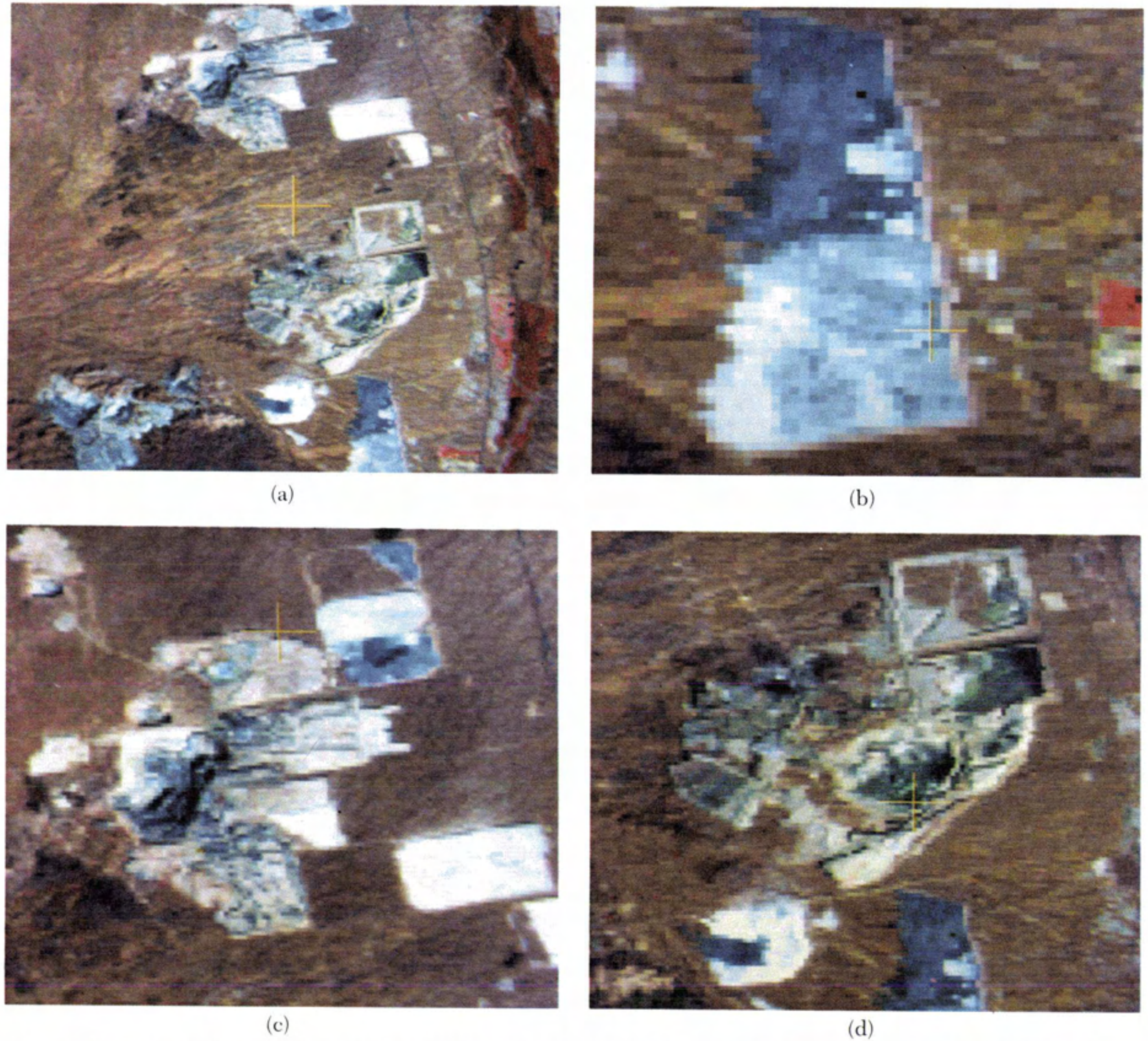


PLATE 1. Representations of spectral variability associated with the Twin Buttes mining complex. Landsat MSS #1358-16593; 11 October 1978. (a) Twin Buttes mining complex (approx. scale, 1:312,500). (b) Enlargement of tailings pond (approx. scale, 1:75,000). (c) Enlargement of open pit mine and tailings pond (approx. scale, 1:125,000). (d) Enlargement of open pit mine (approx. scale, 1:125,000).

tures) can also be seen in Plate 1c. Thirteen training sites were chosen to represent tailings, and six training sites were chosen to represent mining and waste rock.

A wide variety of spectral signatures exists in the image of the Twin Buttes mines. Figure 2 shows the reduced spectral variability encountered in images of smaller mines. The images in this figure are all at the same scale. Figure 2b, of the Globe-Miami mines, shows that, whereas dry tailings ponds are easily recognized, wet tailings, except for pools of water, are not distinguishable from other mine areas. The definition of mine classes is even more difficult for mines smaller than those at Globe-Miami. Figure 2c shows that wet tailings are easily differentiated from surrounding terrain at Silver Bell, but the mines are more difficult to confidently delineate. Both the Silver Bell and Globe-Miami examples illustrate the problems that would be encountered with retraining at each mine.

Difficulties encountered in applying training statistics derived from the Twin Buttes area to other mining areas include variations in atmospheric haze and solar irradiance for different Landsat images and different local rock types in the vicinity of each mine. Each of these topics is addressed below in relation to scene classification in arid regions.

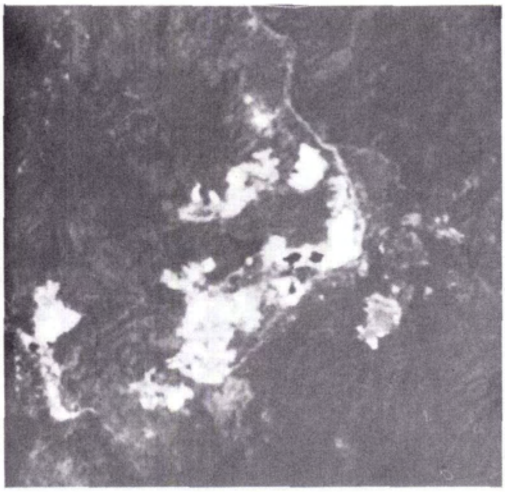
ATMOSPHERIC HAZE

A common atmospheric correction technique consists of a simple bias level adjustment based upon pixel values representing shadows or deep bodies of water (Chavez, 1975). Deep bodies of clear water and true shadows are often difficult to identify with certainty in the vicinity of Arizona mines. Furthermore, to facilitate classification, cloud-free scenes were chosen that possessed high solar elevation angles in order to *minimize* shadows within the open-pit mines. The combination of cloud-free images and high solar elevations resulted in few shadows for use in atmospheric correction. Consequently, we elected to minimize atmospheric effects by selecting an appropriate subset of the Landsat bands. Of the four Landsat MSS bands, band 4 is the most severely affected by atmospheric effects while having little impact on classification accuracy for mines as determined by test classifications of our study sites. Band 4 was therefore deleted from the classification feature set. Atmospheric scattering was still present in band 5 but was less than five grey levels out of the range of 128 gray levels in scenes where bodies of water made verification possible. Because the gray level range of pixels in band 5 was typically 100 or more, the atmospheric component was relatively low.

SOLAR ANGLE

To correct for solar angle variation, the Earth's surface was assumed to be a Lambertian reflector.

(a)



(b)

(c)

FIG. 2. Example of the reduced spectral variability encountered in the smaller mines at Globe-Miami and Silver Bell. (a) Twin Buttes mines, Landsat MSS image #1358-16593; 11 October 1978 (approx. scale, 1:300,000). (b) Globe-Miami mines, Landsat MSS image #2512-17092; 17 June 1976 (approx. scale, 1:300,000). (c) Silver Bell mines, Landsat MSS image #2873-17010; 13 June 1977 (approx. scale, 1:300,000).

This model is known to be invalid for certain types of terrain, e.g., forests (Smith *et al.*, 1980), but may be considered a first-order representation for most other surfaces. The surface radiance for a Lambertian reflector is given by

$$L_R = \frac{E}{\pi}\,\rho\,\cos(i),$$

where $L_R(i)$ = surface radiance,
E = solar irradiance,
ρ = target reflectance, and
i = angle of incidence of solar irradiance relative to surface normal vector.

The solar correction factor, SC, is given by the ratio of the radiance for a reference image to the radiance of the image to be corrected as shown below:

$$SC = \frac{L_R\,[^i\text{reference}]}{L_R\,[^i\text{image}]} = \frac{\text{Cos}\,[^i\text{reference}]}{\text{Cos}\,[^i\text{image}]}$$

All pixels in the scenes to be corrected are multiplied by SC to normalize their values to those of the reference image. Alternatively, all scenes may be normalized to an incidence angle of zero degrees (Chavez, 1975).

GEOLOGIC SIGNATURE

Rock-type variation can adversely affect signature extension. The major Arizona copper mines and the "country" and ore rock type at each mine are listed in Table 1. Most copper occurrences in Arizona are, as a very simple overview, disseminated chalcopyrite (with associated chalcocite enrichment) in quartz monzonite associated with volcanic rocks. Locally, sedimentary and metamorphic rock constitute the country rock.

Hunt and Salisbury (1978), in a laboratory study of reflectance values for various rock types, noted that non-altered, non-ferric oxide-stained silicic and intermediate rocks, most sedimentary rocks, and some metamorphic rocks (marbles and gneisses) have similar spectral reflectance curves between 0.5 and 1.1 μm. No spectral pattern exists that would allow discrimination among these rock types using the Landsat MSS bands. In Arizona mining locales, country and ore rock types are spectrally similar at the spectral and spatial resolution of the Landsat MSS and hence do not pose difficulties for spectral signature extension. Our classification results support this conclusion, although, as Hunt and Salisbury caution, at higher spectral or spatial resolutions a liberal extrapolation of their results might cause errors because textural, alteration, geomorphic, and vegetation effects can produce patterns that could cause considerable spectral variability among rock types.

Example Classifications Using Signature Extension

Tests were conducted using a supervised maximum-likelihood classifier to assess the errors introduced by using a universal training set, rather than retraining at each mine.

Errors were estimated for six test sites at Morenci and Globe-Miami, located with the aid of 1:24,000-scale orthophoto quadrangles. The test site classes were then compared to the classification results obtained with retraining at these

Table 1. Major Arizona Copper Mines

Mine	Elements Mined	Major Country Rock Type
1. Twin Buttes mines, Twin Buttes	Cu	quartz monzonite with volcanics
2. Mission/Cyprus Pima, Twin Buttes	Cu, Mo	quartz monzonite with volcanics
3. Esperanza and Sierrita, Twin Buttes	Cu, Mo	quartz monzonite with volcanics
4. Cities Service Company, Miami	Cu	quartz monzonite with shales, slates, schists, granites and volcanics
5. Inspiration Consol Company, Globe/Miami	Cu	quartz monzonite with shales, slates, schists, granites and volcanics
6. Kennecott Copper, Ray	Cu	quartz monzonite with shales, slates, schists, granites and volcanics
7. Ranchers Exploration & Development Co., Globe/Miami	Cu	quartz monzonite with shales, slates, schists, granites and volcanics
8. Silver Bell Unit, Silver Bell	Cu	quartz monzonite with volcanics
9. Hayden Unit, Hayden	Cu	quartz monzonite with volcanics
10. Cyprus Bagdad, Bagdad	Cu	granites, schists, volcanics
11. Mineral Park, Kingman	Cu, Mo	Pre-Cambrian gneiss
12. Magma Copper Co., San Manuel	Cu	granites
13. Phelps Dodge Corp., Morenci	Cu	quartz monzonites with granite
14. Phelps Dodge Corp., (New Cornelia Branch, Ajo)	Cu	quartz monzonite
15. Phelps Dodge Corp., (Copper Queen Branch, Bisbee)	Cu	schists, limestone, quartz monzonite

TABLE 2. COMPARISON OF CLASSIFICATION RESULTS USING SIGNATURE EXTENSION AND RETRAINING.

Test Site	Class	Location	Retraining			Signature Extension		
			% Correct	% Misclass.	% Threshold	% Correct	% Misclass	% Threshold
1	Mine	Morenci	33	62	5	44	52	4
2	Mine	Globe	32	2	66	47	45	8
3	Tailings	Morenci	79	2	19	71	26	3
4	Tailings	Globe	60	2	38	62	21	17
5	Tailings	Globe	0	0	100	100	0	0
6	Reclaimed Tailings	Globe	0	0	100	33	67	0

mines and with signature extension using training data from Twin Buttes. Table 2 summarizes the results by tabulating mine pixels that are classified as tailings or vice versa. Misclassification of tailings appeared to be due to topographic shading differences caused by the steep tailings embankments, or to signature mixing caused by the use of waste rock or alluvial material as starter dikes for the ponds. Misclassification of mining areas was probably due to specular reflection from rock surfaces and benches within the mines. This misclassification is inevitable when using 80-m resolution Landsat MSS data, but is of little concern for inventory purposes because both terrain types are mine-related. Of more concern are known mine features that are not classified; i.e., errors of omission. This is usually caused by the threshold algorithm (Swain, 1978, p. 156) used to reduce errors of commission. It was desirable to have the percent of mine pixels deleted by the threshold algorithm (Table 2) as low as possible to avoid omitting mine areas from the final classification map.

Table 2 indicates that the classification accuracy using signature extension was superior to retraining in five of the six test sites. Furthermore, the percent of pixels lost to the threshold operation was lower in all six test sites using signature extension. This was due to the wide variety of training sites at Twin Buttes used in the signature extension compared to limited training opportunities at the other, smaller mines.

Test site number 6 in Table 2 corresponds to the Solitude tailings pond which was abandoned in the late 1950's by the Miami Copper Company. Because the pond was enclosed by mountains, an attempt was made to establish a cover of vegetation to make the pond more aesthetically pleasing. A mixture of seed varieties was applied to the pond and enough of the vegetation reportedly survived to support wildlife and stabilize blowing dust. Training signatures in the Globe-Miami area, other than the Solitude pond itself, are insufficient to correctly classify the Solitude pond because of the alteration of its spectral properties by reclamation attempts. The pond was therefore put into the threshold class. The signature extension approach misclassified 67 percent of the pixels in the Solitude pond, but nevertheless classified the pond as a mine-related area composed of tailings and mine rock. None of the Solitude pixels was lost due to the threshold algorithm using signature extension.

SUMMARY AND CONCLUSIONS

Recently enacted federal legislation requiring inventories and frequent monitoring of widespread mined lands has effectuated the need for economical and rapid ways to gather necessary data. As repeated field reconnaissance and aerial surveys are both expensive and labor intensive, satellite imaging systems appear to be promising tools for future inventories and monitoring programs.

The most effective techniques for performing inventories and monitoring of mined lands using satellite systems is supervised classification of high resolution, multispectral images. A major disadvantage inherent in supervised classification techniques is the need to retrain the classifier for each mine and each scene.

This study was designed to assess the effectiveness of multi-spectral signature extension techniques as a way to avoid retraining. Signature extension involves calculating statistical signatures from a large set of training sites at a single mine and applying these signatures to mines from different scenes and dates. In this way, it is possible to include most of the within-class variability without retraining at each mine.

Mined lands classification using signature extension proved to be at least as accurate as retraining, and lower in cost because the training process does not need to be repeated for each mine, scene, or date. In one case (Globe, Arizona), signature extension was successful in classifying tailings poinds that were missed by retraining.

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