Predicting Landsat MSS Endmember Signatures From Corresponding Higher Resolution TM Fraction Images

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Abstract. The approach to predicting Landsat Multispectral Scanner System (MSS) endmember signatures from fraction images derived from high resolution Landsat Thematic Mapper (TM) data is presented. The purpose of this study, conducted in the Mogi-Guacu study site located in Sao Paulo State, Brazil, was to determine if information derived from a mixture mo el applied to higher resolution TM data could serve as ground truth for the lower resolution MSS sensor. The Constrained Least Squares (CLS) method was used to generate vegetation, soil, and shade fraction images from the TM data. The resulting images were then used to estimate the endmember spectral response for MSS data by regressing each MSS spectral channel against the corresponding proportion values estimated for the same resolution cells from the TM mixture model. The evaluation of the predicted signatures was performed by comparing the corresponding fraction images derived from both the MSS and TM data acquired on September 14, 1986. The technique serves as a potential tool for integrating information in global studies where remote sensors with different spectral and spatial resolutions have been used.

Introduction

The radiance recorded by the satellite depends basically upon the recording sensor's characteristics and the spectral and spatial characteristics of the target material that is seen by the sensor. The radiance recorded at the satellite is an integrated sum of the radiances of all materials within the instantaneous field of view (IFOV) of the sensor plus the atmospheric contribution. Thus, the radiation detected will be influenced by a mixture of many different materials (mixed materials (mixed pixels) unless the target is composed by a single material (pure pixel).

According to some investigators, the limited usefulness of multispectral data arises partly from the mixture problem. This problem has been discussed by Horwitz et al. (1971); Detchmendy and Pace (1972); Ranson (1975); Heimes (1977); and others. The mixture problem arises when a sensor images an instantaneous ground resolution element or field of view (IFOV) which contains several different materials (mixed target) or when the instantaneous field of view overlaps the boundary between two or more larger different materials. In both cases, the signals recorded at the sensor are not representative of any one of the materials present. The spectral characteristics of the resolution elements or pixels of Landsat MSS (approximately 0.45 hectares) and TM (approximately 0.10 hectares) at the earth's surface can be affected by one or both of the phenomena described above.

Several works (Shimabukuro, 1987; Adams et al, 1990; Shimabukuro and Smith, 1991) have applied linear mixing models to extract information about the shadow/shade amount within the pixels for vegetation studies. Also, the linear mixing models have been used to extract information about the other materials within the pixels for image analysis purpose. Richardson et al (1975) used linear regression model to infer the amount of vegetation, soil, and shadow for Landsat MSS data.

The existing linear mixing models have been applied to Viking images of Mars (Adams et al, 1986), applied to MSS and/or TM data (Adams and Adams, 1984; Shimabukuro, 1987; Adams et al, 1990) applied to AVIRIS data (Gillespie et al, 1990). However, there is a few works relating mixing models results derived from different sensor data (Holben and Shimabukuro, 1993).

The objective of this paper is to determine if information derived from a mixture model applied to higher resolution TM data could serve as ground truth for the lower resolution MSS sensor. The vegetation, soil, and shade fraction fraction images are derived from Landsat TM data by applying the Constrained Least Squares (CLS) method. The resulting images are then used to estimate the endmember spectral response for MSS data by regressing each MSS channel against the corresponding proportion values estimated for the same resolution cells from the TM mixture model. The evaluation of the predicted signatures is performed by comparing the corresponding fraction images derived from both MSS and TM data acquired on September 14, 1986.

Study Area

The study area "Mogi-Guacu" is located between 22°05' to 22°20' South latitude and 47°00' to 47°15' West longitude in the Sao Paulo State and is representative of pine and eucalyptus plantations common to that region. This site includes the Campininha Pine Experimental Station of the Forestry Institute of the state of Sao Paulo (IFSP) and the Santa Terezinha Eucalyptus Plantation of the Champion Cellulose & Paper Company (CCP). The major Pinus species in Campininha are Pinus elliottii and Pinus taeda. Other species, such as

Pinus caribaea, Pinus bahamensis, Pinus oocarpa, and Pinus palustris, are also planted in small amounts. The prominent Eucalyptus species in Santa Terezinha are Eucalyptus alba and Eucalyptus saligna.

The field data and forest cover maps were provided by IFSP and CCP and can be grouped into four forest classes. These classes refer to (1) Pinus elliottii, (2) Pinus species other than Pinus elliottii, (3) Eucalyptus spp. from eight months to two years, and (4) Eucalyptus spp. over two years (Shimabukuro et al, 1978, 1980). For the images analyzed, pine plantation are represented by forest stands varying from more than 10 years to 30 years and the eucalyptus plantation are formed by forest stands with age varying from one year to 7 years.

Linear Mixing Model

A linear relation is used to represent the spectral mixture of materials within the resolution element. Following this approach, the response of each pixel in any spectral wavelength can be thought of as a linear combination of the responses of each component assumed to be in the mixed target. Thus, each image pixel, which can assume any value within the image gray level, contains information about the proportion and the spectral response of each component within the ground resolution unit.

Hence for any multispectral image provided by any remote sensor system (e.g., Landsat MSS and TM), if the proportions of the components are known, then the spectral responses of these components can be obtained. Similarly, if the spectral responses of the components are known, then the proportion of each component in the mixture can be estimated. In this study, for TM data it is assumed the known spectral responses for the endmember. On the other hand, to predict the MSS endmember signatures the proportion of the components are assumed to be known as estimated from the TM data.

The mixture model is represented as:

$$r = Ax + e$$

where:

r = measured satellite response for a pixel in all spectral bands
A = spectral response matrix of mixture components for a pixel
x = proportion vector of mixture components for a pixel
e = the error term

The function to be minimized is:

$$f(x) = eeT$$

subject to the following constraints:

$$xp = 1$$
$$0 < xp < 1$$

where the sum is carried out over p components in a pixel, here assumed equal to 3, corresponding to vegetation, soil, and shade.

There are several techniques available to solve this problem: Quadratic Programming, Constrained Least Squares, Weighted Least Squares presented by Shimabukuro (1987), Principal Components

(Smith et al, 1985, Adams et al, 1986, Adams et al, 1989), Regression Model (Richardson et al, 1975). The Constrained Least Squares (CLS) method was used in this study to estimates the proportion of each component inside a pixel giventhe corresponding spectral responses in each spectral band for TM and MSS data. This method has been simplified by not constraining the proportion values inside the interval zero and one (Shimabukuro and Smith, 1993). It makes the computer program faster and the pixels that violate the constraint can be easy identified by using any scaling procedure. The Regression model (Richardson et al, 1975) was used to estimate the MSS endmember signatures given the component proportion derived from TM data.

Methodological Approach

For this study, the TM and MSS Landsat data, path 220/row 75, corresponding to the overpass of September 14, 1986 were used to generate fraction images for reforested areas in the study site. The composite response (ri's) data are the digital numbers on the CCT converted to the apparent reflectance (Markham and Barker, 1986). Three components are considered within the pixel: vegetation, soil, and shade. The vegetation type is considered including pine and eucalyptus plantation.

The spectral response (Aij's) for TM data were extracted from the images by finding the purest pixel for each endmember in a iterative process by analyzing the pixels that violate the constraints. The purest pixel for vegetation was searched in the eucalyptus stand, for soil in the baresoil areas, and for shade in the clear water site. Then the vegetation, soil, and shade fraction images were generated for the reforested areas and compared with the ground information available for this study area (Shimabukuro et al, 1978, 1980; Shimabukuro et al, 1989).

The resulting fraction images were then used to estimate the endmember spectral responses for MSS data by regressing each MSS spectral channel against the corresponding proportion values estimated for the same resolution cells from the TM mixture model. The evaluation of the predicted signatures was performed by comparing the corresponding fraction images derived from both MSS and TM data acquired on the same day.

The residual values for each spectral channel can be used to evaluate the results derived from the model. These values are the absolute difference between the original and the estimated pixel response.

Results And Discussion

The availability of Landsat TM and MSS data acquired on the same day allowed to perform this experiment. These data present different spatial and spectral resolution.

The vegetation, soil, and shade fraction images (Fig. 1A, B, and C, respectively) were derived from TM data using the apparent reflectances (Table 1) which correspond to the purest pixel assumed for these endmembers.

Table 1: Spectral responses for vegetat
ion, soil, and shade for TM channels corresponding to the purest pixel assumed for these endmembers

Channel	App. refl. (%)		
	Veg.	Soil	Shade
1	9.41	13.73	9.41
2	7.06	15.29	8.24
3	5.88	20.00	6.27
4	30.59	26.67	3.53
5	10.59	42.35	0.00
7	3.14	35.69	0.00

In the fraction images, the abundance of each component is represented from dark gray (low amount) to light gray (high amount). The vegetation fraction image (Fig. 1A) shows the difference between eucalyptus (light gray) and pine (medium gray) plantations. Also, it shows the variation within eucalyptus site that is related to the age difference, i.e., young eucalyptus presents higher amount of vegetation proportion than the old eucalyptus. The variation within pine site is related to the species difference, i.e., pine elliottii presents higher amount of vegetation proportion than the other species.

The soil fraction image (Fig. 1B) contains information about amount of baresoil component. It is very clear the areas that were clearcut in the eucalyptus site (light gray).

The shade fraction image (Fig. 1C) like as vegetation fraction image shows the difference between eucalyptus and pine plantations and the variation caused by age difference for eucalyptus and species difference for pine (Shimabukuro, 1987, Shimabukuro and Smith, 1991).

The resulting fraction images were used to estimate the MSS endmember signatures by regressing them against each MSS channel using the corresponding resolution element for both MSS and TM data. Table 2 presents the estimated vegetation, soil, and shade spectral responses for MSS channels.

Then the vegetation, soil, and shade fraction images (Fig. 2A, B, and C, respectively) were generated using these apparent reflectances (Table 3) in the mixture model for MSS data. Comparing figure 2 with figure 1, there are a good agreement between the model results derived from both remote sensors data.

Table 3 presents the histogram results for the same area covered by TM and MSS sensor. The average filter was applied to the images to make the results compatible for both sensors. It was used 5 x 7 pixels size for MSS and 13 x 13 pixels size for TM.

Table 2: Spectral responses for vegetation, soil, and shade for MSS channels estimated regressing with the TM fraction images

Channel	r2	Apparent reflectance Vegetation	Soil	(%) Shade
4	90.2	11.25	18.47	11.96
5	96.5	4.20	17.76	5.53
6	97.3	54.98	57.65	19.84
7	97.4	38.75	30.35	2.35

N = 30

Table 3: Histogram results for MSS and TM data

	LANDSAT TM		
	MEAN	MEDIAN	STANDARD DEVIATION
VEGETATION	35.71	36	14.57
SOIL	27.23	27	15.75
SHADE	35.57	35	11.54

	LANDSAT MSS		
	MEAN	MEDIAN	STANDARD DEVIATION
VEGETATION	35.58	36	15.21
SOIL	28.50	28	16.99
SHADE	34.40	34	11.65

There is a good agreement between the statistics for corresponding fraction images derived from MSS and TM data as seen in Table 3.

These results can be extended for a large area in the MSS imagery. Figure 3 shows the soil fraction image as an example. These results show the potential of linear mixing model to relate information provided by sensors with different spectral and spatial resolution. This approach is very important for global studies, that need information from different remote sensors with different spectral and spatial resolutions.

Conclusion

The fraction images showed to contain information to discriminate the forest types. The young eucalyptus presents higher proportion of vegetation component and lower proportion of shade when compared to old eucalyptus. Pine forest presents higher proportion of shade when compared to eucalyptus forest.

The high r values and the similarity of fraction images derived from both TM and MSS data showed the feasibility to predict endmember signatures for lower resolution sensor data from higher resolution sensor data and different spectral wavelength.

The technique serves as a potential tool for integrating information in global studies where remote sensors with different spectral and spatial resolutions are required.

Acknowledgement

During the preparation of this manuscript , the author was serving as a Visiting Scientist at NASA Goddard Space Flight Center under the auspices of the Universities Space Research Association (USRA). Appreciation is also expressed to the Forestry Institute of Sao Paulo and the Champion Cellulose and Paper Company for providing supporting ground data.

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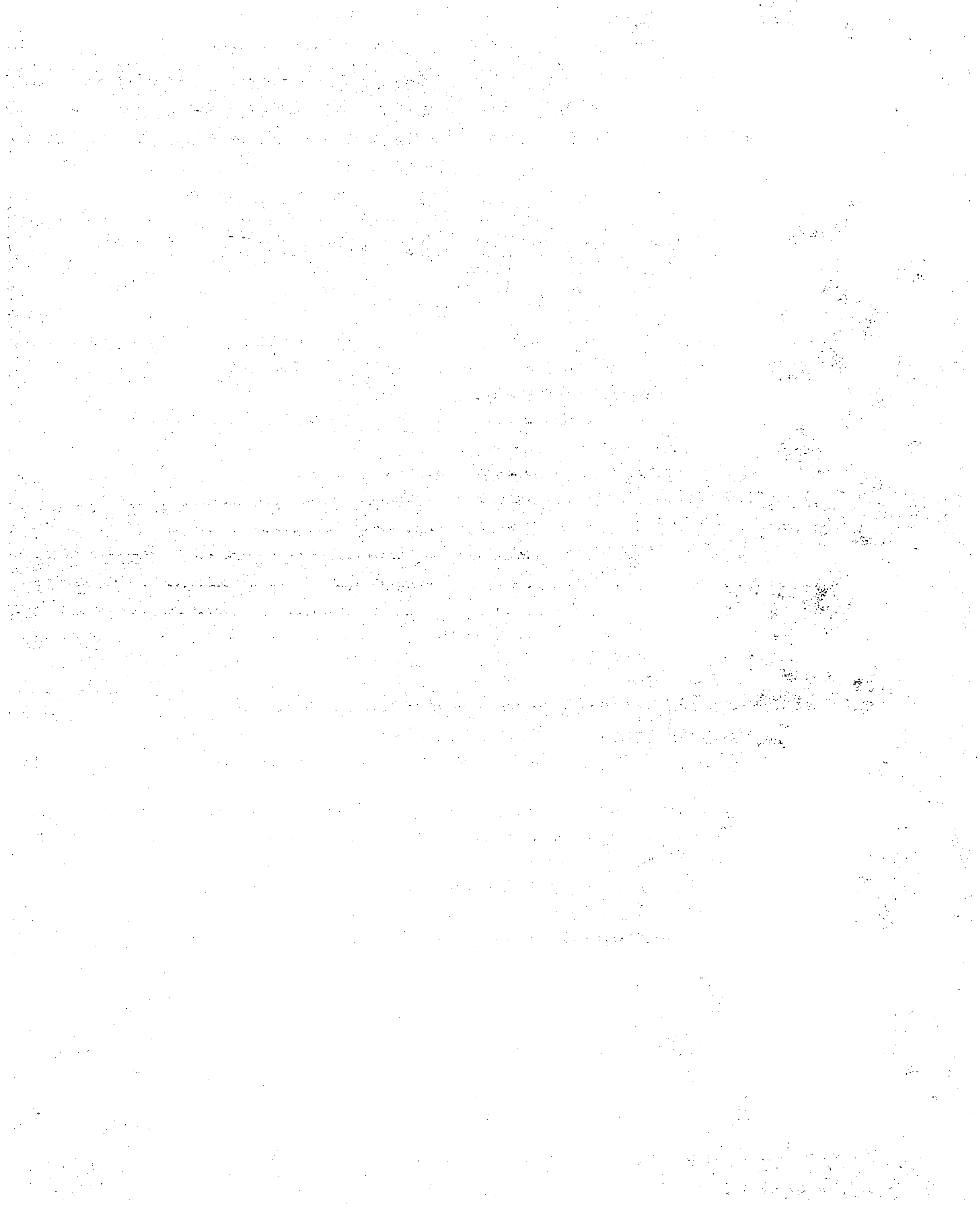
Figure captions:

Fig. 1: Fractions image derived from Landsat TM data: A) vegetation, B) soil, and C) shade.

Fig. 2: Fractions image derived from Landsat MSS data: A)

vegetation, B) soil, and C) shade.

Fig. 3: Soil fraction image derived from Landsat MSS data including the study site.



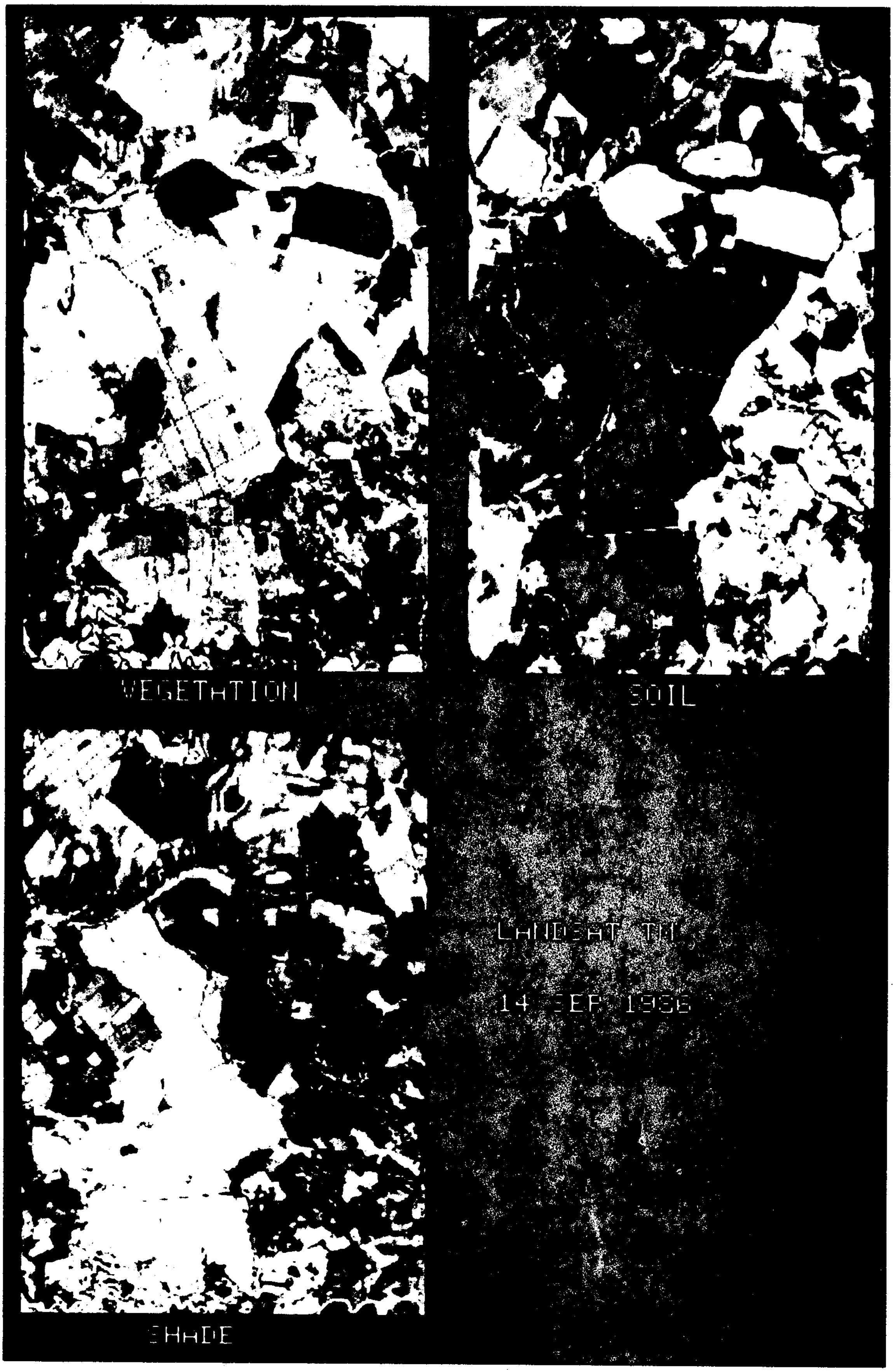


FIG. 1

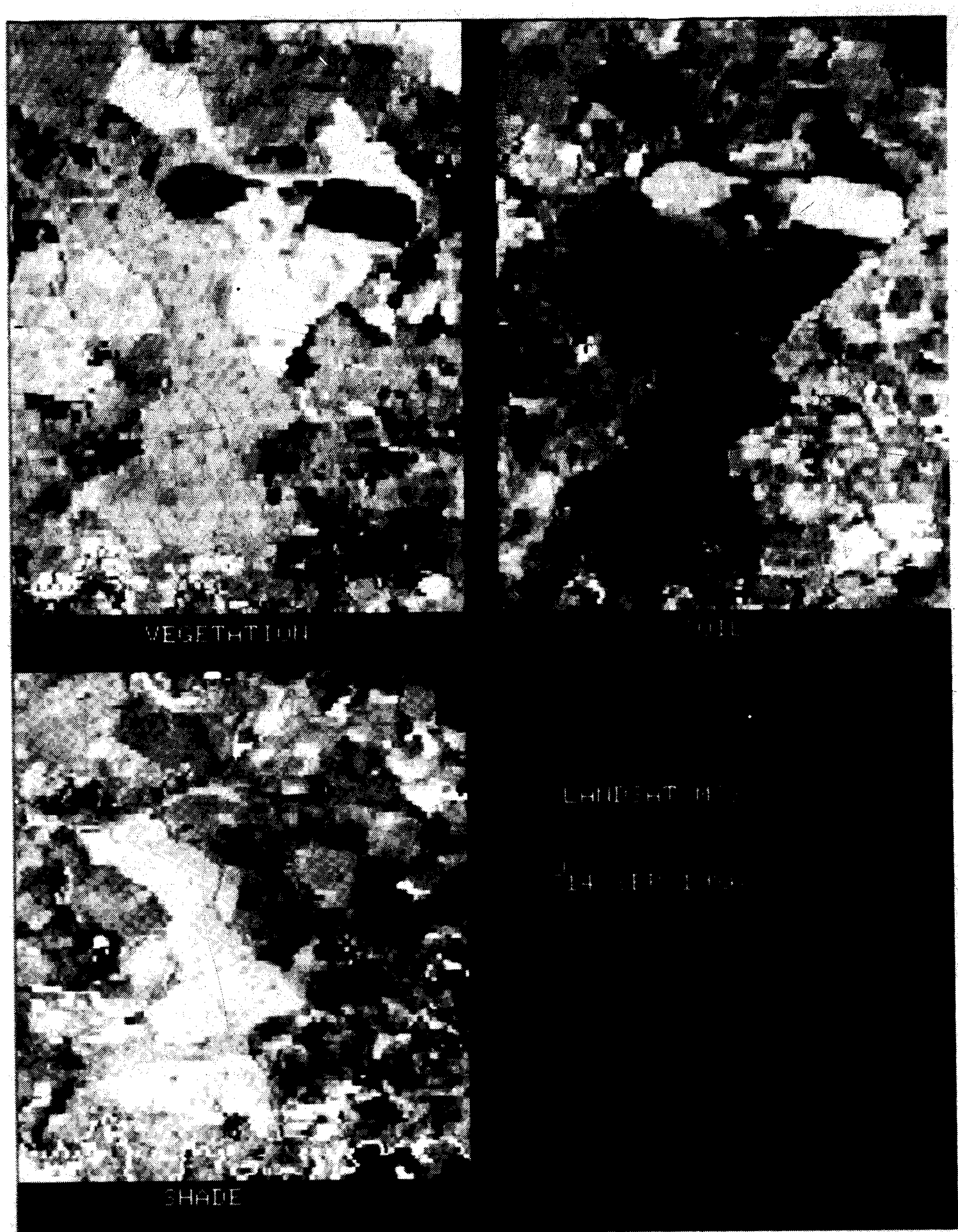
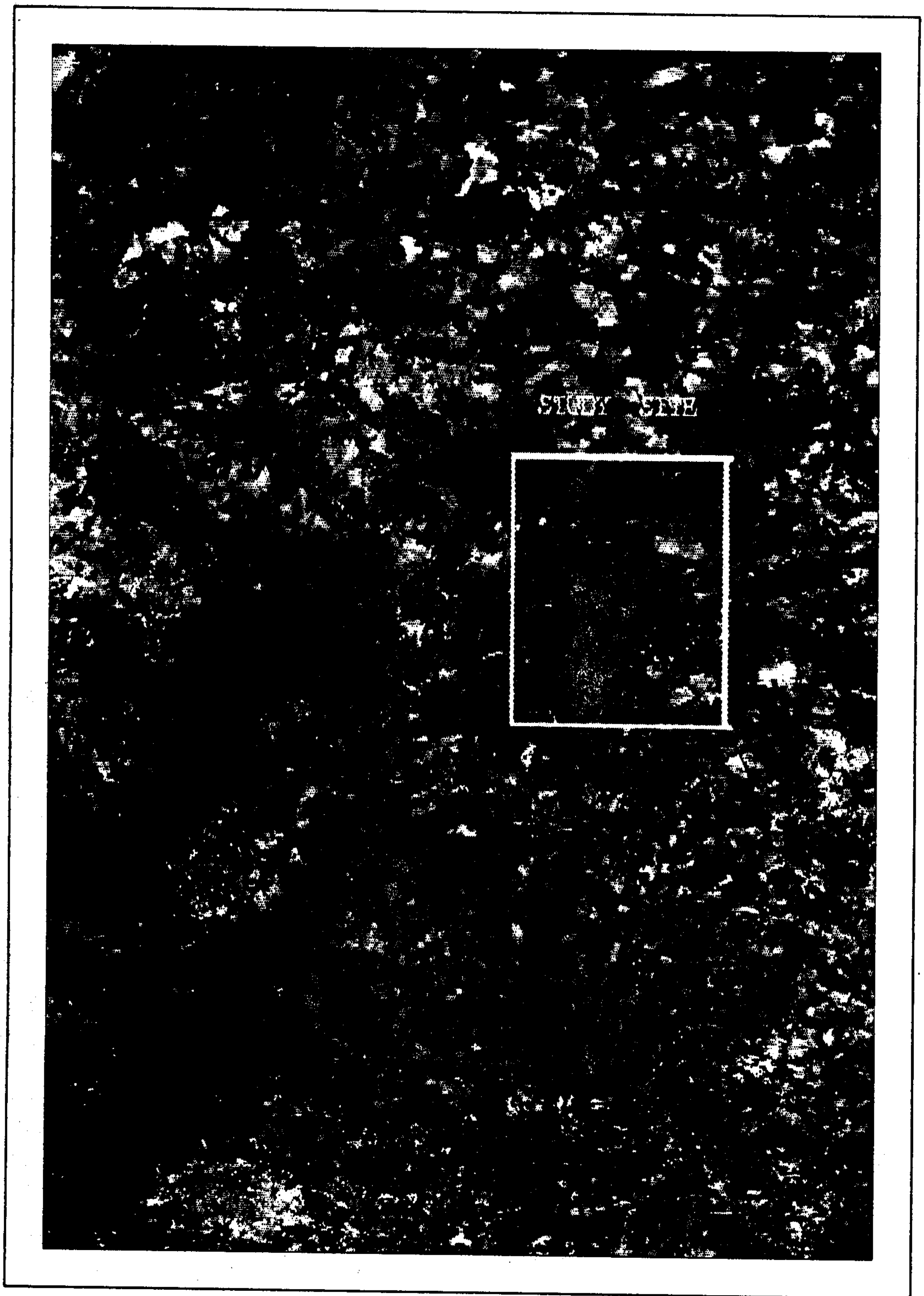


FIG. 2



LANDSAT MSS -SEPTEMBER 14, 1986 - SOIL FRACTION IMAGE

FIG. 3