

LINEAR MIXING MODEL APPLIED TO AVHRR LAC DATA

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Abstract. A linear mixing model was applied to coarse spatial resolution data from the NOAA Advanced Very High Resolution Radiometer. The reflective component of the 3.55 - 3.93 μ m channel was extracted and used with the two reflective channels 0.58 - 0.68 μ m and 0.725 - 1.1 μ m to run a Constrained Least Squares model to generate vegetation, soil, and shade fraction images for an area in the Western region of Brazil. The Landsat Thematic Mapper data covering the Emas National Park region was used for estimating the spectral response of the mixture components and for evaluating the mixing model results. The fraction images were compared with an unsupervised classification derived from Landsat TM data acquired on the same day. The relationship between the fraction images and normalized difference vegetation index images show the potential of the unmixing techniques when using coarse resolution data for global studies.

Introduction

Satellite level radiances depend upon the sensor's characteristics and the integrated sum of the radiances of all surface materials and atmosphere within the instantaneous field-of-view (IFOV) of the sensor. Assuming the atmospheric effect is constant, the radiation detected will be influenced by a mixture of many different surface materials (mixed pixels) unless the target is

composed of a single material (pure pixel). The radiometric characteristics of the Local Area Coverage (LAC, 1.1 Km pixels at nadir) of the National Oceanic and Atmospheric Administration's (NOAA) Advanced Very High Resolution Radiometer (AVHRR) are more affected by the mixed pixel problem than finer spatial resolution satellite imagery.

Because emphasis is being placed on the LAC AVHRR data for providing global scale

monitoring (Townshend 1992), efforts to address the problem of mixed pixels is of increasing importance. Most investigations have compared the information content of AVHRR data to fine spatial resolution data as from Landsat Thematic Mapper (TM) for example. Typically a classification procedure is used such as presented by Iverson et al. (1989) in the Midwest United States and Cross (1990) in the Southern Amazonia to estimate forest cover. Mixture modeling offers an alternative. Quarmby et al. (1992) presented a linear mixture model for crop area estimation using multitemporal AVHRR channel 1 and 2 data. They assumed that each field within a ground pixel contributes to the signal received at the satellite sensor by an amount that is characteristic of the cover type in that field and proportional to the area of the field. Also, when using multitemporal data, they assumed that the proportions did not change between images. Cross et al. (1991) used a linear mixing model and the first four channels of AVHRR to monitor tropical deforestation in Rondonia, Brazil and Ghana. Two thermal infrared channels (3 and 4) were included because they were considered to contain information for forest/nonforest discrimination. This implies that each cover type is thermally distinct and the sensor response to the surface properties in question behaves linearly with thermal emission.

Thermal emission is governed by Planck's equation, therefore a linear model may not accurately represent the satellite radiometric response

to a surface target. This problem may be minimized by using all reflective bands as is done with Thematic Mapper data or, as in the case of the AVHRR 3.75 μm band which is a mixture of reflected and emitted energy, use only the reflective component (Kaufman and Nakajima 1992). Extraction of this band is detailed in the next section.

There are several techniques to solve the mixture problem, such as Constrained Least Squares (CLS), Weighted Least Squares (WLS), Quadratic Programming (QP) presented by Shimabukuro (1987) and the unmixing methods developed at University of Washington (Smith et al. 1985, Adams et al. 1986, Adams et al. 1989). These techniques have been applied to high resolution data sets such as Viking images of Mars (Adams et al. 1986); MSS (Multispectral Scanner System) and TM data (Adams and Adams 1984, Adams et al. 1990, Shimabukuro 1987); and AVIRIS (Airborne Visible/Infrared Imaging Spectrometer) data (Gillespie et al. 1990). All of the above techniques produce similar results (Shimabukuro 1987) and their use is usually dictated by an investigator's personal preference.

We present a technique to apply mixture models to coarse resolution AVHRR data to generate vegetation, soil, and shade fraction images from the proportion of each component within the pixels. Because of our familiarity with the method, we chose to apply the Constrained Least Squares (CLS) method (Shimabukuro and Smith 1991) to an AVHRR image covering the centralwestern region of Brazil. The

validation of the model for this kind of data will be performed by comparing the resulting fraction images with the classification derived from coincident Landsat/TM and AVHRR NDVI images.

Study Site

The study site is located between $17^{\circ} 50'$ to $18^{\circ} 20'$ south latitude and $52^{\circ} 40'$ to $53^{\circ} 20'$ west longitude on the border of Goiás, Mato Grosso and Mato Grosso do Sul States. The site includes the Emas National Park comprising about 131,000 hectares in which the "cerrado" vegetation is well represented (Redford 1985, IBDF/FBCN 1978, Pinto 1986). Located on the watershed between the La Plata and Amazon River basins, Emas Park is on the western edge of the Central Brazilian Plateau, adjacent to the Pantanal (Redford 1985). It offers a good sample of the Planalto habitats, including a number of small watercourses, the sources of two important rivers, riverine gallery forest and marshes, large areas of grassland (the "campos"), and some open woodland (the "cerrados") consisting of small thinly distributed trees seldom more than three meters high (Erize 1977). The surrounding land of the Park is used for agriculture and cattle grazing. The park is commonly affected by uncontrolled fires during the annual dry season (Shimabukuro 1991). The rest of the study site is covered by "cerrado" vegetation types.

Method

AVHRR $3.75\mu\text{m}$ Reflective Component

The AVHRR $3.75\mu\text{m}$ band signal is a mixture of thermal and reflected energy. Typically the latter represents less than 10% of the signal for bare soil and urban features and less than 3 percent for green vegetation (Kerber and Schutt 1986, Schutt and Holben 1991, Kaufman and Remer 1993). The reflective component may be approximated by assuming the emitted energy (brightness temperature) in the adjacent thermal band (10.5 to $11.5\mu\text{m}$) is related to the emitted energy in the $3.75\mu\text{m}$ band at ambient temperature through the Planck Function as follows (Kaufman and Nakajima 1992):

$$L_3 = L_{3\rho} + L_{3\varepsilon} \quad (1)$$

where:

L_3 = Total radiant energy measured by the satellite at $3.75\mu\text{m}$

$L_{3\rho}$ = The reflective energy at $3.75\mu\text{m}$

$L_{3\varepsilon}$ = The emissive energy at $3.75\mu\text{m}$

The reflective and emitted components may be expanded according to:

$$L_3 = \rho_3 F_{0\mu_0}/\pi + R_3(T_4) * (1 - \rho) \quad (2)$$

where:

ρ_3 = Reflectance in the $3.75\mu\text{m}$ band

F_0 = 3.75 band solar irradiance at the bottom of the atmosphere

μ_0 = cosine of the solar zenith angle

$R_3(T_4)$ = Emitted radiance at $3.75\mu\text{m}$ using the $11.0\mu\text{m}$ brightness computed with the Planck Function

Solving for ρ_3 :

$$\rho_3 = (L_3 - R_3(T_4)) / (F_0 \mu_0 / \pi - R_3(T_4)) \quad (3)$$

This formulation ignores the differential atmospheric transmission in both bands and assumes the target surface is flat and the satellite view direction is nadir.

The digital numbers from the satellite data are converted to

brightness temperatures using the calibration coefficients and Planck Function coefficients given in the NOAA-9 users Handbook (Kidwell 1988). The parameters and variables used for the computation of the R_3 and L_3 radiances are given in Table 1.

Table 1: The Planck Function parameters and constants for the R_3 and L_3 radiance computations

Rad Temp	λ	C1	C2	$F_0 \mu_0 / \pi$
L_3 T_3	$3.75 \mu\text{m}$	37413	14388	0.0008
R_3 T_4	$3.75 \mu\text{m}$	37413	14388	0.0008

Linear Mixture Model

A linear relation was used to represent the spectral mixture of materials within a resolution element. The response of each pixel in any spectral wavelength was taken 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 scale, contains information about the proportion and the spectral response of each component within the ground resolution unit. Hence, if the proportions of the components are known for any multispectral image, then the spectral responses of these components can be obtained. Similarly, if the spectral response of the components are known, then the proportion of each component in the mixture can be estimated. The basic mixture model may be formulated as:

$$r_i = \sum a_{ij} x_j + e_i \quad (4)$$

where:

r_i = measured satellite

response for a pixel in spectral band i

a_{ij} = spectral response of mixture component, j, for spectral band i

x_j = proportion of mixture component, j, for a pixel

e_i = the error term for spectral band i.

Subject to:

$$\sum x_j = 1 \text{ and } x_j \geq 0 \text{ for all.}$$

The Constrained Least Squares (CLS) method estimates the proportion of each component inside the pixel by minimizing the sum of squares of the errors. A linear constraint is added, since the sum of the proportions for any resolution element must be one and the proportion values must be nonnegative. This method was developed for three and four components assumed to be inside the pixel (Shimabukuro 1987). In this study, the CLS method is discussed assuming three components within the pixel. In addition, the error image for each spectral band and the mean error image were generated. They are computed for each pixel as follows:

$$\text{ERROR} = \text{SQRT} (r_i - \sum a_{ij} x_j)^2 = e_i, \text{ and}$$

$$\text{MEAN ERROR} = (\sum e_i)/m$$

where

m = number of spectral bands.

Approach

The CLS method described above was applied using TM and AVHRR data acquired on July 29, 1988. The imagery, centered on Emas National Park, covers approximately 100 by 100 km and 780 by 780 km for TM and AVHRR respectively. For this study, only TM channels 3 (0.63-0.69 μ m), 4 (0.76-0.90 μ m), and 5 (1.55-1.75 μ m) were available. The AVHRR channels used were 1 (0.58-0.68 μ m), 2 (0.725-1.1 μ m), and the reflective component of channel 3 (3.55-3.93 μ m).

The CLS technique requires the pure spectral responses for each mixture component. The selection of the "pure pixel" for each mixture component in the TM scene was evaluated by analyzing the mean error images described in the previous section and by analyzing the pixels that violate the constraint, i.e., pixels with values greater than one or less than zero. The spectral responses for vegetation, soil, and shade for AVHRR were estimated by regressing each AVHRR channel against the corresponding pixels in the TM fraction images (Richardson et al. 1975). The spectral responses were derived from the regression coefficients and used as inputs for the CLS model. The derived fraction images were compared to the TM results, and related to normalized difference

vegetation index NDVI images for model validation. The model performance was also evaluated by analyzing the error images.

Results and Discussion

The unsupervised classification of the TM scene showed the complexity of cover types within the region of Emas National Park. The unsupervised classifier, based on K-means, identified 13 clusters and were rearranged into the following 7 classes according to ground truth reported by Shimabukuro et al. (1991): Water and burned areas, "cerrado", "campo cerrado", "campo limpo", bare soil 1, bare soil 2, and cut areas (Fig. 1). These classes were used to identify areas with most pure pixels of vegetation, bare soil and shade. The spectral response for shade was searched in water and burned areas classes based on similar low spectral responses (Richardson et al. 1975, Adams et al. 1986, Shimabukuro 1987, Gillespie et al. 1990). The spectral responses for vegetation and soil were searched inside the "cerrado" and cut areas classes, respectively.

The coefficient of determination, r^2 , and the spectral responses of the components for AVHRR channels are presented in Table 2. The vegetation, soil, and shade fraction images were generated using these spectral responses in the mixture model for AVHRR data. The advantage of the fraction images is that they contain physical information, i.e., amount of each component within the pixel. For example, in figure 2B and 2C, the light

gray means that a pixel has bare soil, respectively.
high amount of vegetation and

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

Channel	r^2	DN		
		Vegetation	Soil	Shade
1	78.7	21.8	27.8	11.3
2	93.3	46.5	42.2	10.3
3Refl	78.2	5.9	8.4	0.0

n = 50

There was a visual similarity of vegetation fraction and NDVI images (Fig. 2A and B). The NDVI values were well correlated by the fraction images ($r^2 = 95.2$ and 90.0 for TM ($n=75$) and AVHRR ($n=90$), respectively). Also there is good agreement between the higher soil pixel values and the corresponding bare soil clusters from the unsupervised classification. Note that cloud screening was not performed on these data sets yet they are easily detected in the vegetation, soil and mean error images (Fig 2B, C, and D) as a vertical line of light colored cell aggregates.

Figures 3, 4 and 5 show the NDVI, vegetation and soil fraction images, respectively, derived from AVHRR data over a large area (704 by 704 pixels) around the study site. Again the similarity between NDVI and vegetation fraction shows the potential of extending the linear mixture technique well beyond the boundaries of the defining components using coarse spatial resolution data. As stated previously, the disagreement between these images for the cloudy pixels indicates a cloud screening algorithm must

be employed for most large area investigations. In addition, the soil fraction image seems to be useful for deforestation studies since it contains information about bare soil proportion within the pixels.

Conclusion

In the example cited, the reflective part of channel 3 shows ample sensitivity to various covertypes to provide a suitable band for mixture modeling. Further assessment of the influence of the atmospheric transmission in this band is required to fully benefit from its reflective properties. This may require incorporation of ancillary data.

The vegetation fraction image was in very good agreement with the NDVI image, which shows the amount of green vegetation. Also, the soil fraction image containing information about non vegetation areas, seems to have a great potential for tropical deforestation studies using coarse resolution satellite data. In addition, the shade image contains information that can explain the vegetation index response, especially for the tropical forest which from the multilayer structure has a

high amount of shade.

As the information contained in the AVHRR remote sensing resolution elements are mostly a mixture of several materials, the linear mixing models appear to be a useful tool for image analysis. Further quantitative assessment of the pixel proportions is required to fully interpret the results from mixture models. Rigorous evaluation of the technique beyond the region of component definition is required to apply the approach to coarse resolution data such as AVHRR.

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Figure Captions

Figure1: Land cover classification derived from Landsat TM data using unsupervised classification (K-means).

Fig. 2: (A) NDVI, (B) vegetation, (C) soil and (D)

mean error images derived from AVHRR data over the study site.

Fig. 3: NDVI image derived from AVHRR data covering a large area around the study site.

Fig. 4: Vegetation fraction image derived from AVHRR data covering a large area around the study site.

Fig. 5: Soil fraction image derived from AVHRR data covering a large area around the study site.



WATER / BURNED AREAS

"CERRADO"

"CAMPO CERRADO"

LANDSAT TM

■ BARE SOIL 1

29 JUL 1988

■ "CAMPO LIMPO"

■ BARE SOIL 2

■ CUT AREAS







