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Incorporating Biophysical Parameters of the Terrain to Improve Classification Accuracy of Multispectral Images

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ABSTRACT

Background: Image classification procedure requires sets of information and parameters from the image and other sources. Particularly, soil and information on greenness are important for the improved performance of landuse/landcover classification. This paper attempts to incorporate the biophysical parameters such as brightness, greenness and NDVI information in the classification procedure to improve accuracy. Objective: Wavelet based information fusion was attempted with Maximum Likelihood Classification (MLC) and Support Vector Machine (SVM) classification on satellite image of Yercaud Hills. Results: The information fusion method yielded better accuracies of classification than the conventional (MLC and SVM) classification techniques. Conclusion: The proposed method of information fusion for image classification by Incorporating biophysical parameters improves the accuracy of landuse/landcover of hilly terrain.

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INTRODUCTION

Image classification is performed based on the spatial and spectral value of the image. However, image have limitations in conveying information about the landuse classes due to the limitation of image information, which will decrease the classification accuracy. This could be overcome by information fusion, a recent image classification technique, and gives better information about the area. The information derived from the multispectral image, when appropriately fused with spectral data, yields accurate information on landuse/landcover (LULC). Information range based fusion algorithm has been proposed and compared with the conventional classification technique. Many researchers have carried out fusion based classification algorithms. (i.e.) focus on combining – or fusing – data from multiple sources or multiple sensors. The definition of information fusion is as follows information process dealing with the association, correlation, and combination of data and information from single and multiple sensors or sources to achieve refined estimates of parameters, characteristics, events, and behaviors for observed entities in an observed field of view (Bostrm *et al.*, 2007).

2. *Related Work:*

Many researchers have carried classification of remotely sensed images. For example, ten landcover types of the Shervarayan hill were prepared from IRS 1C LISS III satellite data. Slope map was prepared and superimposed on the vegetation map. Thus, different vegetation types in different slope categories were identified (Balaguru *et al.*, 2003). In another study Houda chaabouni *et al* (2013) proposed fully automatic 3-D change detection for urban area using IKONOS image by incorporating Digital Elevation Model (DEM). A fusion, both in feature and decision levels, is experimented in order to automatically detect the buildings, shadowed areas, water bodies, ground, low and high vegetation categories. Robin Pouteau and Benoit Stoll (2012) introduced a Selective Fusion (SELF) scheme based on SVM which used a single source for source-specific classes. The tested area is French Polynesia (south pacific) on the island of Moorea.

Saha *et al.* (2005) proposed NDVI and DEM data layers for multispectral classification of IRS LISS III of Himalayan region using the maximum

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likelihood classifier. Qingsheng and Gaohua (2010) paper combined the tasseled cap transformation (TCT) and SVM method on Landsat TM imagery. First, the Brightness, Greenness and Wetness component are inputted into SVM and the different Classes of water, wetland, shrub, farm and grassland are identified. The overall improved accuracy is 91.2%. Pakorn Watanachaturaporn *et al.* (2005) discussed the classification of IRS-1C LISS III image along with NDVI and DEM data layers in the Himalayan region. Xavier *et al*. (2010) discussed the SVM fusion ensemble, the rule images and MCS concept. AVIRIS hyperspectral data set is decomposed and processed separately by SVM classification. Finally all the outputs are used as input for the final decision fusion performed by an additional SVM classifier. Le Yu *et al*. (2012) used ASTER-DEM and aeromagnetic data with SVMs for different combinations of 47 data inputs, including the original 14 ASTER bands and 33 derivative datasets extracted from the ASTER image. This combination of the ASTER-derived independent components provided the highest overall classification accuracy of 92.34% for lithological classes.

The above listed literatures indicate that multispectral data alone cannot yield the expected accuracies while generating landuse/landcover maps. Hence, from an understanding of the above studies, we propose to incorporate biophysical parameters in the process of image classification.

3. *Study Area And Methodology:*

The area of study is the Yercaud Hills near Salem, south India. IRS P6 LISS IV image of this area, acquired on 04 January 2008, was used. This multispectral image has 3 Bands (Green (0.52-0.59 µm), Red (0.62-0.68 µm), and NIR (0.77-0.86 µm)) with a resolution of 5.8m and the total area covered is 800 sq. km. The centre latitude of the study area is 78°5'18"E and longitude is 11°56'8E (see Fig. 2).

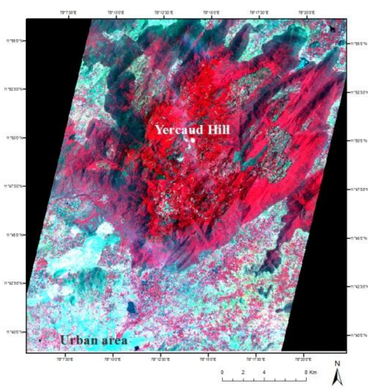

Fig. 1: IRS P6 LISS IV FCC (False Color Composite) of Study area (Yercaud, Salem, Tamil Nadu, India).

In this study, an attempt is being made to reduce the classification accuracy error by incorporating biophysical information (brightness, greenness and image itself. Using this information fused based on wavelet method; a procedure was followed to generate accurate landuse/landcover maps of the Yercaud hills. In the study area, the land cover types are defined in six categories as shown in Table 1.

Table 1. Characteristics of land cover classes present in the Yercaud Hills, south India.

S. No	Class	Land-uses and land-cover included in classes
1	Urban/built-up land	Structures of all types residential, industrial, agricultural, commercial and services. Transportation and utilities mixed urban or built-up land
2	Agricultural	Cropland, orchards, vineyards and nurseries
3	Forest	Deciduous, evergreen and mixed forests
4	Water bodies	Reservoirs, coastal water, canals, tanks
5	Barren land	Uncultivable lands, disturbed grounds at building sites and dirt roads
6	Bauxite/Mining	Exposed rocks, quarries.

The methodology is shown in Figure 2.

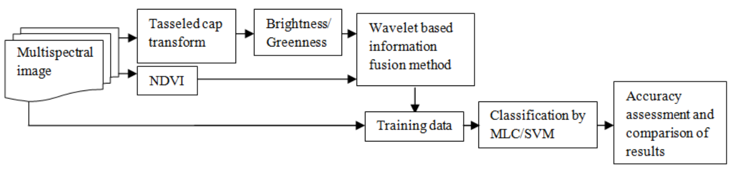

Fig. 2: Methodology of proposed information-fusion fusion based classification.

Brightness, greenness and NDVI information derived and fused to the multispectral image using wavelet based information fusion approach. Thus the methodology in this research uses MLC and SVM classification approaches of the given IRS P6 LISS IV imagery.

4. *Tasseled Cap Transform:*

Image transformation is the technique used to re-produce the information content within several bands/wavelengths of remote sensing images. This technique developed by Kauth and Thomas (1976), produces an orthogonal transformation of the original multispectral band. Tasseled cap has found most use in agricultural fields and it gives four indices-the brightness index (BI), the greenness index (GI), the wetness index (WI) and a non such index (NSI). In the study area, Yercaud hill is mostly occupied by agricultural and forest area and hence only the brightness and greenness information and NDVI range are used. The brightness index represents variations in soil information in the study area such as barren land, mining area and build-up area. Figure 3 shows the brightness(a) and greenness(b) image.

5. *Normalized Difference Vegetation Index (Ndvi):*

The NDVI (Normalized difference) information is to separate the healthy vegetation from other land cover types, mostly forest and vegetation, in Yercaud area. The NDVI is defined as:

$$NDVI = \frac{\rho NIR - \rho RED}{\rho NIR + \rho RED}$$

Where, ρNIR is the near-infrared reflectance (Multispectral band 4) and ρRED is the red reflectance (Multispectral band 3). High NDVI indicates healthy vegetation and low NDVI indicates unhealthy vegetation or the absence of vegetation. This vegetation index essentially used the sum and differences of bands rather than the absolute values which makes it more suitable for Yercaud(Fig. 3 NDVI(c) image.

6. *Wavelet Based Information Fusion Using Ihs Transform Method:*

Wavelet-based image fusion is similar to a Fourier transform analysis. In the Fourier transform, long continuous (sine and cosine) waves are used as the basis. The wavelet transform uses short, discrete "wavelets" instead of a long wave (Strang *et al*, 1997). This algorithm works at the pixel level. The results of pixel-level fusion are primarily for presentation to a human observer/analyst (Rockinger and Fechner, 1998). However, in this case biophysical information parameters (Brightness, Greenness and NDVI) are fused with a multispectral image. First, images are resampled and decomposed. Using the high-pass images derived during the decomposition the multispectral image is reconstructed. Finally, the reconstructed images are fused into a new output image using IHS transform. This method is used to the differentiate color combination of fused information image. Fig. 3 shows the various fused images.

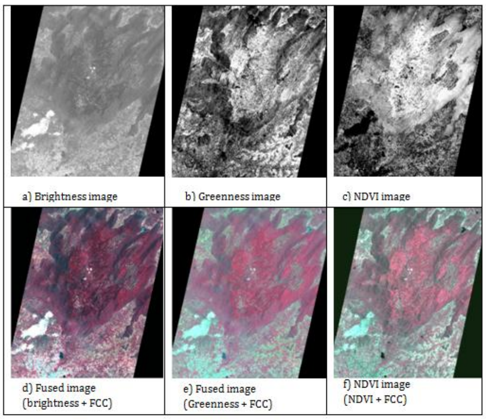

Fig. 3: showing results of various fusion approaches.

7. *Maximum Likelihood Classification (Mlc):*

Maximum Likelihood (ML) estimation of class membership (probability) for an unknown pixel, using multivariate normal distribution models for the classes. The classifier evaluates both the variance and covariance spectral-response patterns of the class, when classifying an unknown pixel. In this classifier, a set of normalized probability values, $Pi(\lambda_k|X)$, are calculated for each pixel vector X, one for each class λ_k. The normalized probability for a pixel a_i to be assigned the class label λ_k is calculated by the following equation:

$$Pi(\lambda_k|X) = \frac{p(X|\lambda_k)P(\lambda_k)}{\sum_{j=1}^{M} p(X|\lambda_j)P(\lambda_j)} \quad (1)$$

$p(X|\lambda_k) = \frac{1}{(2\pi)^{d/2}|S_{\lambda_K}|^{1/2}}[\exp(\mu_{\lambda_K} - 1/2(X - \mu_{\lambda_K})^{t}a_{\lambda_K}^{-1}(X-\mu_{\lambda_K}))]$ (2)

where, M is the total number of classes $(p(\lambda_k)$ is the probability of class λ_k, and $p(X|\lambda_k)$ is the probability density for class λ_k, which is given by

where, d is the number of spectral bands S_{λ_K} and μ_{λ_K} are covariance matrix and mean vector respectively for class λ_k, $s_{\lambda_K}^{-1}$ is the inverse of the covariance matrix for class λ_k.

The probability p ($\omega_i|x$) gives the likelihood that the correct class is ω_i for a pixel at position x. classification is performed according to x$\epsilon\omega_i$

p ($\omega_i|x$) > p ($\omega_j|x$) for all j≠i (3)

i.e) the pixel at x belongs to a class ω_i,for which p ($\omega_i|x$) is maximized (Richards 1986). MLC has been used in this study as the conventional classification technique and the results are presented in the next section.

8. *Support vector machine (svm):*

One of the recent methods of supervised classification technique is a Support Vector Machine (SVM). Introduced by Vapnik in 1979, this technique has been more frequently used in the past few years. In this technique the classes are separated with an optimal hyperplane. The data points nearest to the surface (hyperplane) are called support vectors. Training and classification are performed using the ENVI/IDL image processing package. Generally SVM classifies four types of kernels: linear, polynomial, radial basis function (RBF), and sigmoid. The Radial basis function (RBF) kernel gives better results.

$K(x_i, x_j) = \exp(-\gamma|x_i - x_j|^2), \gamma > 0$ (4)

Where, γ is the gamma term in the kernel function and training data set (Xi -Xj) , i=1,2 ... n

$K(x_i, x_j) = \varphi(x_i).\varphi(x_j)$is called kernel function. φ is replaced by kernel K.

Usually RBF kernel (equation (3)) is used. Because, this kernel maps data points into space with higher dimensions nonlinearly and less numerical difficulties (Hsu *et al*., 2007).

9. *Results Of Conventional Classification:*

In the study area, six landuse categories were recognized namely-agriculture, forest, mining area, water bodies, forest, built-up/urban area and barren land. First, implementation of the conventional(MLC and SVM) classification of the original multispectral image leads to an overall accuracy of 68.16 % for MLC and 70.31% for SVM. The classified map is mostly covered by forest (90.91%), vegetation (69.78%) and built-up areas (35%). Water and barren land are the smallest classes with accuracy of 75% and 80.00% respectively. Accuracy was low for barren land and water bodies with the MLC classification when compared to the SVM classification. MLC has perhaps misclassified many pixels of barren land as agricultural areas. The SVM classification produces a little increase in overall accuracy when compared to the MLC classification.

10. *Results Of Information Fusion With Mlc/Svm Classification:*

By incorporating brightness, greenness and NDVI, image classification resulted in deriving better information about the LULC. In the image, six sample locations were selected as training sites. The number of training pixels for each class was assigned based on the area occupied by corresponding classes in the entire image. After performing MLC and SVM classification on the image containing the information fusion method was implemented through wavelet based image classification. The following classification accuracy assessment was performed by comparing the classified output with existing LULC maps, ground truth information, and information from large scale satellite images. Figure 4 shows the result of MLC/SVM classification and incorporating biophysical information with MLC/SVM classification.

A total of 512 pixels were selected by the stratified random approach for accuracy assessment. The results of classification are shown in Table 2.

Table 2: Results of the Classification after information fusion.

Information Layer	Accuracy in % MLC	Kappa value	Accuracy in % SVM	Kappa value
Conventional classification	68.16	0.5348	70.31	0.5599
Brightness + FCC	70.31	0.5599	86.72	0.7864
Greenness + FCC	72.29	0.5825	81.12	0.7096
NDVI + FCC	74.09	0.6199	86.91	0.7658

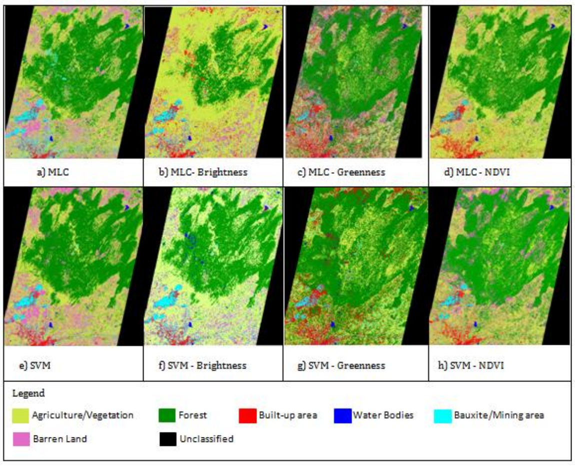

Fig. 4 Results of information fusion - SVM/MLC Classification Techniques.

It is seen from the table that when brightness information is incorporated with multispectral information, the classification process resulted in improving accuracy from 68.16% to 70.31% for MLC approach and from 70.31% to 86.72% for the SVM approach. Similarly, individual class information, especially soil information for barren land, built-up area and mining area have also improved appreciably after incorporating brightness information. The brightness information enhances the feature with no vegetation. It only exposes soil related information.

Greenness and NDVI fused information is mainly used for differentiating forest-vegetation and agriculture-vegetation. The Greenness information accuracy is improved up to 72.29% for MLC and 81.12% for the SVM classification. NDVI information classification accuracy increased upto 74.09% for MLC and 86.91% for SVM classification. The greenness information enhanced the feature with agriculture-vegetation and NDVI enhanced feature of forest vegetation. Fig. 6 shows the overall accuracy chart.

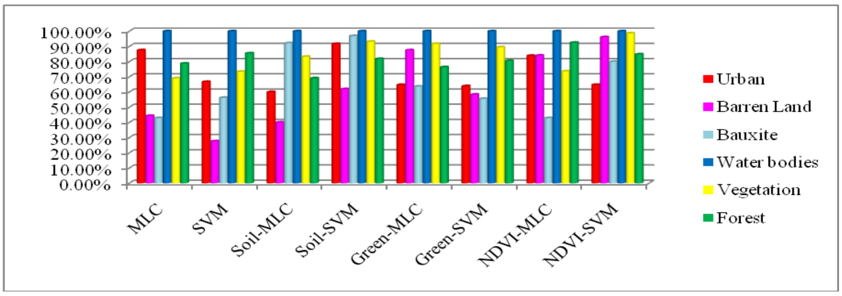

Fig. 5: Overall accuracy of classification.

Conclusions:

In this study, two steps of improving the image classification accuracy was proposed. In the first step, the biophysical parameters (brightness, greenness and NDVI) are derived from the multi-spectral image. The second step incorporated these biophysical information by using the wavelet based information fusion method. Results of the conventional classification (MLC and SVM) methods provide less accuracy for land cover types. An improvement of 18.75% in the overall classification accuracy is achieved using the SVM approach by incorporating the brightness, greenness, NDVI information.

Thus, the necessity for adopting the information fusion approach for image classification rather than the simple MLC/SVM is emphasized here. It is suggested that the similar approach of incorporating biophysical parameters can results in accurate landuse/landcover of hill terrain.

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