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Performance of RGB and L Base Supervised Classification Technique Using Multispectral Satellite Imagery

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ABSTRACT
In the present growth of sensor technology is to improve the new chance and applications in GIS. This enhances the technology law a new method that should not focus on real time available products, but it must automatically lead to new ones. The aim of the paper is to make a maximum use of remote sensing data and GIS techniques to access land use and land cover classification in the Kiliyar sub basin sector in palar river of northen part of Tamil Nadu.IRS P6 LISS III is merged data to perform the classification using ERDAS Imaging. The RGB and L base supervised classification was based up on a Multispectral analysis, land use and land cover information's (maps and existing reports), which involves advanced technology and complex data processing to find detailed imagery in the study region. Ground surface reflects more radar energy emitted by the sensor from the study region, which makes it easy to distinguish between the water body, hilly, agriculture, settlement and wetland.
Keywords - Multispectral, Classification, RGB&L, SAM, SCM,

I. INTRODUCTION

A procedure that use the satellite imagery data to produce maps and/or tables shows the study region and point of different selected land cover types or ground characteristic is called image classification[2]. This is the next step of the imagery enhancement or post processing. This is the most common ways to use remotely sensed data for generate land cover maps. This technique requires minimal prior knowledge of the area where a map is needed and easily incorporates ancillary data. Remote sensing image classification can be viewed as a joint venture of both image processing and classification techniques. Generally, image classification, in the field of remote sensing is the process of assigning pixels or the basic units of an image to classes. It is likely to assemble groups of identical pixels found in remotely sensed data into classes that match the informational categories of user interest by comparing pixels to one another and to those of known identity. Several technique of image classification exists.

Image classification is an important part of the remote sensing, image analysis and pattern recognition. In some instances, the classification itself may be the object of the analysis. For example, classification of land use from remotely sensed data produces a map like imagery as the final product of the analysis [6]. In other cases, the classification can serve only as an intermediate step in more intricate analyses, such as land degradation studies, process studies, landscape modeling, coastal zone management, resource management and other environment monitoring applications. The image classification therefore forms an important tool for examination of the digital images. Using this classification tool, we can extract our own representation of land use/land cover information. As a result, image classification has emerged as a significant tool for investigating digital images. Moreover, the selection of the appropriate classification technique to be employed can have a considerable upshot on the results of whether the classification is used as an ultimate product or as one of numerous analytical procedures applied for deriving information from an imagery for additional analyses[5].

Multispectral imagery is used for imagery classification based on unsupervised and supervised classification algorithm. In the preprocessing stage, RGB and L based spectral sharpening method is applied to sharpen and resample for achieving pixel size based on high resolution. The performance evaluation metrics proved that spectral sharpening performs better than sharpening the RGB and L between the boundaries. The minimum distance to mean classifier, the maximum likelihood classifier and the box classification were used. According to the land cover reflectance characteristics of the surface material, the land use and land cover classification indicated 5 classes that belong to 30 classes. The land use and land cover map contains 5 classes. It has been shown, within the limitation, threshold parameters and classification algorithms containing significant influence on the classification results and should be selected carefully based on the study region.

II. STUDY AREA

Palar is a southern India river, originated from Nandidurg hills of Karnataka state and flows through Karnataka, Andhra Pradesh, Tamil Nadu and finally convergence into the Bay of Bengal at Vayalur, Tamilnadu.

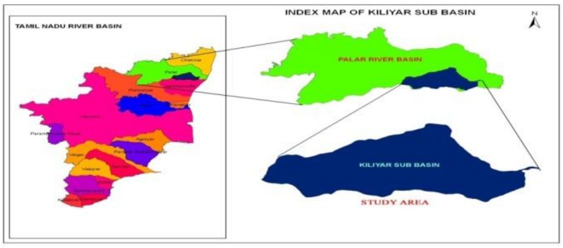

Fig. 1. Study Area

Palar River Basin is one of the 17 major rivers of Tamil Nadu. This basin is divided in to 8 sub basins. Kiliyar is one of the sub basins, which mostly covers Thiruvannamalai and Kanchipuram districts about 914.45 sq. km total geographical area.

III. METHODOLOGY

Satellite Imagery
↓
Imagery is to be processed
↓
Color based pixels Identified
↓
Classification Technique Selection
↓
Identifying the Classes
↓
Display the Result

Fig. 2. Methodology Diagram for Image Classification

This methodology involves both the primary and the secondary information. This research focuses land use and/or land cover classification in Kiliyar sub basin in Northern Tamilnadu. Land use types of 2008 have been categorized on the basis of land use category classified by district resource map, agriculture, forest, built-up area, water bodies and barren land. Similarly, for land use data of 2008 toposheets (scale 1:50000 to topographic map) generated by Survey of India. Different land use categories have taken and classified by department of survey during preparation of topographic map viz agriculture, forest, settlement, water bodies, landslide. All the necessary data set for the research work such land use map 2008, land cover map 1972 to 1976, roads, rivers, settlements contours have been converted into 'digital' form through using ERDAS Imaging. The study region satellite imagery is shown in following fig. 3.

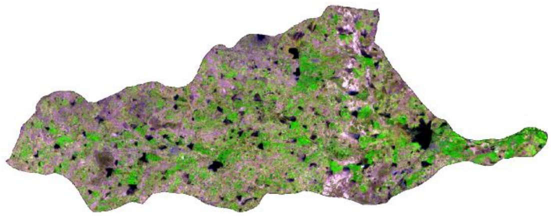

Fig. 3. Unclassified Satellite Imagery for Study Area

To obtain the study area map during the year 1972-1976 (scale 1:50000), geology map (scale 1:50000) prepared District resource map of geological survey of india in 2008 and Resource map bhoovan sample data, NRSC website during the year 1990 to 2010.

IV. IMAGE TRAINING PROCESS

The overall goal of this step is to group a set of raw data that describe the natural result pattern for each land use land cover types to be classified in an imagery of the study area. Locate and classify using RGB & L based, to several relatively blocks of imagery, dispersed over the entire study site, each containing as a segregate of land cover type of interest. These are known as candidate training sets. The training set is to create and analyze the image pixels we must describe the each class or category that are to be mapped in the imagery; and we should identify the pixel values by which the category is to be recognized and identified, differentiate varying pixel values for each category as a result we can get most appropriate and accurate results.

We define the brightness level or the density of color intensity of the classing color; we must also describe the tolerance level of each channel or of the composite color by which the comparison can make an adjustment while examination at each pixel. Clusters in the feature space were used to determine the spectral classes in to which the imagery is resolved, and to perform representative subset of raw data by sampling method to acquire sets of ground truth that can be used to establish decision system for the classification of every pixel in the satellite imagery data set.

Training data set is called signature file creation is shown in the following fig.4.

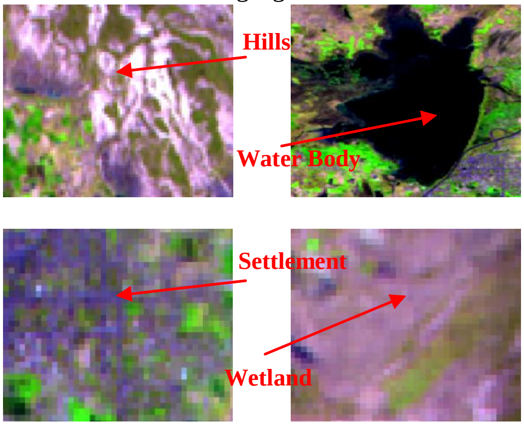

Fig. 4. Image Pixel Identification for Signature File Creation

In the fig. 4, various category of classes like Hills, Water body, Agriculture Land, Wetland, Settlement were chosen as training area. In this process the block pixels are trained as water body or tank, the dark gray pixels selected as Hills, the ash green pixels are trained as barren land and the red pixels are trained as cropland, continue in this process according to our classification method. Thus under the hole system we will require to provide the following data as training data set.

- Name or label of the group
- RGB channel values of the color for the group
- Tolerance of the color from the described color

4.1. Input the Imagery to Process

Imagery for analysis must be specified as RGB and L base techniques deal with the pixel values, regardless of the type of the imagery or any imagery can be analyzed. In this satellite imagery, details are given below Table 1.

Table1: Satellite Imagery Details

Image Type	Pan and Liss III Merged Data
File Format	Geo TIFF
Projection Type	UTM
Spheroid Name	WGS 84
Datum Name	WGS84
UTM Zone	1
North or South	North

4.2. Color Based Pixel Identification

From the top left corner of the input imagery, the pixels are grip and are used for assessment. While grievance the pixel values, we transform the pixels color values into the separate channel values and the brightness level or identify its density level.

4.3. Proposed Classification Method

The remote sensing presents with a number of supervised and unsupervised technique, that have been developed to undertake the multispectral data classification problem. In this paper RGB & L base supervised technique is used. The statistical method in use for the previous studies of land use land cover classification is the maximum likelihood classifier. Nowadays, various studies have applied artificial intelligence techniques as substitutes to remotely sensed image classification applications. In addition, diverse ensemble classification method has been proposed to significantly improve classification accuracy. Scientists and practitioners have made great efforts in developing efficient classification approaches and techniques for improving classification accuracy. The image quality of a supervised classification [3] depends on the quality of the training sites. All the supervised classifications usually have a sequence of operations that must be followed.

- ❖ Defining of the Training Sites.
- ❖ Extraction of Signatures.
- ❖ Classification of the Imagery

The training sites are done with digitized features. Usually two or three training sites are selected. The more training site is selected, the better results can be gained. This procedure assures both the accuracy of classification and the true interpretation of the results.

After the training site areas are digitized then the statistical characterizations of the information are created. These are called Signatures. Finally the classification methods are applied. At present, there are different image classifications procedures are used for different purposes by various researchers. These techniques are distinguished in two main ways as supervised and unsupervised classifications. Additionally, supervised classification has different sub classification methods, which are named as parallelepiped, maximum likelihood and minimum distances. These methods are named as Hard Classifier. In this work RGB& L Base method is used for supervised classification methods. Its result and performance given below.

4.4. Identifying the Classes Categories

After picking up pixel and splitting up channels, each channel must be compared with the channels of each groups training data. On examining that the pixel value contains the value of training data, we consider the following constraints.

- If each channel has the accurate values as the training data, then it must signature file.
- If each channel or any of them fails to prove, to be the exact values in the signature value then the pixel's values must be compared with the abide color values form the color of the group.
- If in, the pixel a value does not matches any of the above conditions then the pixel is labeled to be an "unknown" pixel and must start comparing again with next class.

Assessment of a pixel must run until a category is found for a pixel or all the class found unmatched for the pixel.

4.5. Display the Result

After all the pixels were examined, we can display the result. With the result, we can easily plot classified map imagery, according to the supervised classes. All the unknown pixels from this plotting will be the borders of the category specified in any way and we can easily draw the borders of each group without any fail.

V. RESULT AND DISCUSSION

The main aim of the study is to evaluate the performance of the different classification algorithms using the multispectral data. This is implemented with ERDAS Imaging 2014 [14]. In a similar way, the classification algorithms can be applied for the multispectral data [15].

There are three existing classification method classified and tested in unclassified satellite Imagery. Beginning of the classification, Analysts could not locate which is water body, hills, crop, fallow and other classes. The satellite unclassified imagery shown in above fig.3.

5.1. Proposed Classification Algorithm

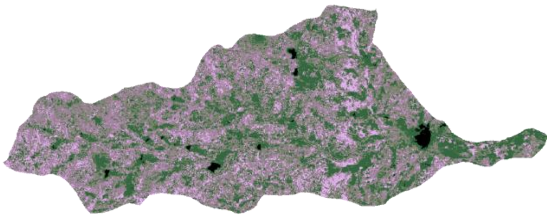

Fig. 5. Classified imagery for RGB & L Based Method

5.2. Maximum Likelihood Classification Algorithm

First the unclassified satellite imagery was tested with maximum likelihood classification technique. This Classification uses the training data by means of estimating means and variances of the classes, which are used to estimate probabilities and also consider the variability of brightness values in each class.

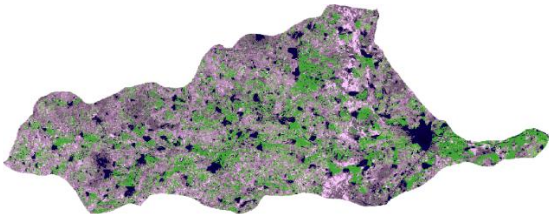

Fig. 6. Classified imagery for Maximum Likelihood Method

This classifier is based on Bayesian probability theory. It is the most powerful classification methods when accurate training data is provided and one of the most widely used algorithm. The classified imagery is shown in above figure 6.

The Maximum Likelihood classification is calculated as:

$$d_{i=1}(x) = \ln|v_i| + \frac{y^t y}{v_i} \qquad (1)$$

Where d_i denote as distance between feature vector (x) and a class mean (m_i) based on probabilities, v_i denote as the n x n variance-covariance matrix of class i, where n is the number of input bands, y denote as $x - m_i$; is the difference vector between feature vector x and class mean vector m_i and y^t denote as the transposed of y.

5.3. Minimum Distance Classification Algorithm

Second the unclassified satellite imagery was tested with minimum Distance classification technique. It is based on the minimum distance decision rule that calculates the spectral distance between the measurement vector for the imagery pixel and the mean vector for each sample. Then it assigns the candidate pixel to the class having the minimum spectral distance. The classified imagery is shown in figure 7.

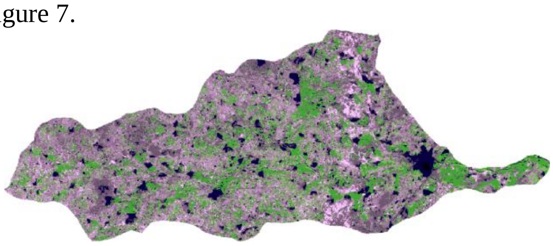

Fig. 7. Classified imagery for Minimum Distance Method

For each feature vector, the distances towards class means are calculated.

- The shortest Euclidian distance to a class mean is found.
- If this shortest distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel.
- Else the undefined value is assigned.

5.4. Parallelepiped Classification Algorithm

Finally the unclassified satellite imagery was tested with parallel piped classification technique. This is a widely used decision rule based on simple Boolean “and/or” logic. Training data in ‘n’ spectral bands are used in performing the classifications. Brightness values from each pixel of the multispectral imagery are used to produce an n-dimensional mean vector, $Mc = (\mu_{ck}, \mu_{c2}, \mu_{c3}, \ldots \mu_{cn})$ with μ_{ck} being the mean value of the training data obtained for class c in band k out of possible classes, as previously defined. S_{ck} is the standard deviation of the training data class c of band k out of m possible classes.

The parallelepiped algorithm is a computationally efficient method for classifying remote sensor data. Unfortunately, because some parallelepiped overlap, it is possible that an unknown candidate pixel might satisfy the criteria of more than one class. In such cases it is usually assigned to the first class for which it meets all criteria. A more elegant solution is to take this pixel and can be assigned to more than one class and use a minimum distance by means of decision rule to assign it to just one class. The parallelepiped classifier uses the class limits and stored in each class signature to determine, if a given pixel falls within the class or not. The class limits specify the dimensions of each side of a parallelepiped surrounding the mean of the class in feature space. If the pixel falls inside the parallelepiped, it is assigned to the class. However, if the pixel falls within more than one class, it is put in the overlap class. If the pixel does not fall inside any class, it is assigned to the null class. The classified imagery is shown in figure 8.

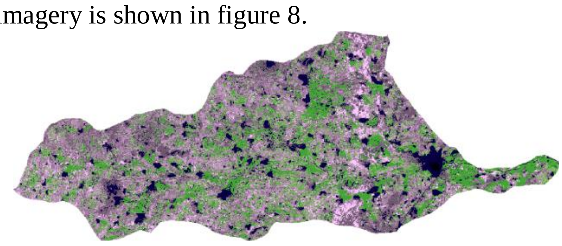

Fig. 8. Classified imagery for Parallel Piped Method

5.5. Mahalanobis distance Classification Algorithm

Mahalanobis distance classification is similar to minimum distance classification except that the covariance matrix is used. The Mahalanobis distance classification algorithm assumes that the histograms of the bands have normal distributions. The classified imagery is shown the figure 9.

The Mahalanobis distance is calculated as:

$$d_{i=1}(x) = \frac{y^t y}{v_i} \qquad (2)$$

Clarification of the limits as follow

- For each feature vector x, the shortest Mahalanobis distance to a class mean is found.
- If this shortest distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel.
- Else the undefined value is assigned.

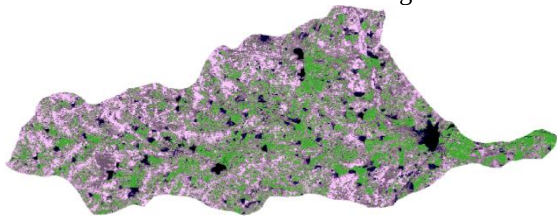

Fig. 9. Classified imagery for Mahalanobis distance Method

5.6. Spectral Angle Mapper Classification Algorithm

The Spectral Angle Mapper (SAM) method is an automated method for directly comparing imagery spectra to known spectra. This method cares for both spectra as vectors and compute the spectral point of view between them. This method is insensitive to illumination since the SAM algorithm uses only the vector direction and not the vector length. The result of the SAM classification is an imagery show in figure 10.

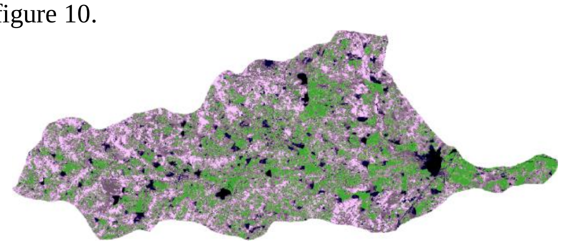

Fig. 10. Classified imagery for Spectral Angle Mapper Method

SAM Presents the following formula

$$\alpha = \cos^{-1} \frac{\sum xy}{\sum(x)^2 \sum(y)^2} \qquad (3)$$

α denote as Angle formed between reference spectrum and image spectrum, x denote as image spectrum, y denote as reference spectrum.

5.7. Spectral Correlation Mapper Classification Algorithm

The Spectral Correlation Mapper (SCM) method is a derivative of Pearsonian Correlation Coefficient that eliminates negative correlation and maintains the SAM characteristic of minimizing the shading consequence resulting in improved result shown figure 11.

The SCM algorithm method, similar to SAM, uses the reference spectrum defined by the researcher, in agreement with the imagery user wants to classify. SCM presents the following formula

$$R = \frac{N\sum xy - \left(\sum x\right)\left(\sum y\right)}{\left(N\left(\sum x^2 - \left(\sum x\right)^2\right)\right)^{\frac{1}{2}}\left(N\left(\sum y^2 - \left(\sum y\right)^2\right)\right)^{\frac{1}{2}}} \quad (4)$$

The function cos (SAM) is similar to the Pearsonian Correlation Coefficient above equation. The big difference is that Pearsonian Correlation Coefficient standardizes the data, centralizing itself in the mean of x and y.

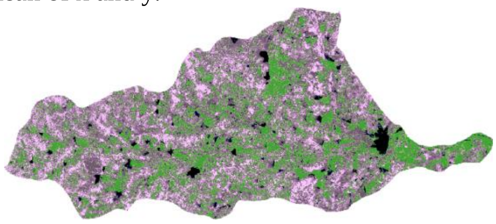

Fig. 11. Classified imagery for Spectral Correlation Mapper Method

VI. CONCLUSION

The proposed supervised classification method gave better accuracy than the other classification methods. It is observed that the spectral means of the classes in all bands was improved. The proposed method compares with existing method namely Parallelepiped, Maximum Likelihood, Minimum Distance, Mahalanobis distance, SAM and SCM. If the result is better, it indicates that the training samples were spectrally separable and the classification works well in the study region. This aids in the training set refinement process, but indicates little about classifier performance elsewhere in the scene.

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