Identification of agriculture areas in satellite images using Supervised Classification Technique

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Abstract: Indian remote sensing deals with high resolution of geospatial data. It works on the various fields like Agriculture, Water resources, environment forest, land use or land cover, ocean applications, soil, geosciences, disaster warning and management. Finding land use or land covered by studying previous satellite data and gives the analytics is a challenge for remote sensing. In this paper gives a study of identification of agriculture area from satellite image using supervised classification. For the classification purpose various mathematical algorithms are used like Minimum distance, Maximum like hood, Spectral angle mapping, Parallelepiped classification, Land cover signature classification.

***IndexTerms* - Remote sensing, land use or cover, change detection, classification**

I. Introduction

A general definition, "Remote sensing is the science and technology by which the characteristics of object of interest can be identified, measured or analyzed the characteristics without direct contact [1]. Usually remote sensing is the measurement of the energy emanated from the earth's surface [2][3][4][5]. Indian economy is depending on agriculture also the agriculture is important for world to produce huge amount of food for fulfilling's the demand of it [6][7]. It's a challenge to the agriculture department to identify agriculture area and give some statistics or giving suggestions to the farmers about different food production strategies, for that finding agriculture land is very important [8].

Identification of crop area research is carried out by various researchers, Mondal [9]. Qui et al[10]. Masialeti [11] concluded that from single image it is very difficult to map crops. Main problem for that is mixed pixels which causes difficulties during classification. According to Dharval et al [12] various techniques of classification of crop area identification gives the land cover in fine and coarse resolution image. NDVI (Normalized Difference Vegetation Index) is used for classification of vegetation in satellite image. NDVI technique is very famous and useful in remote sensing because it gives very good results while finding vegetation's. This technique is used by Ying et al [13] to find vegetation. Panghrahy [14] used AWiFS technique for the classification of crops from satellite image.

This paper gives the supervised classification technique to identify the crop area as well as different areas present in satellite image. Paper is divided into different sections. Introduction section gives brief introduction about remote sensing and some related work about previously done classification. Second segment gives flowchart of system and methods used. After that third section gives classification algorithm used to find out different area classification within satellite image. Then output result screenshots of classification is given and at last conclusion.

II. Flowchart and Method

2.1 Flowchart:

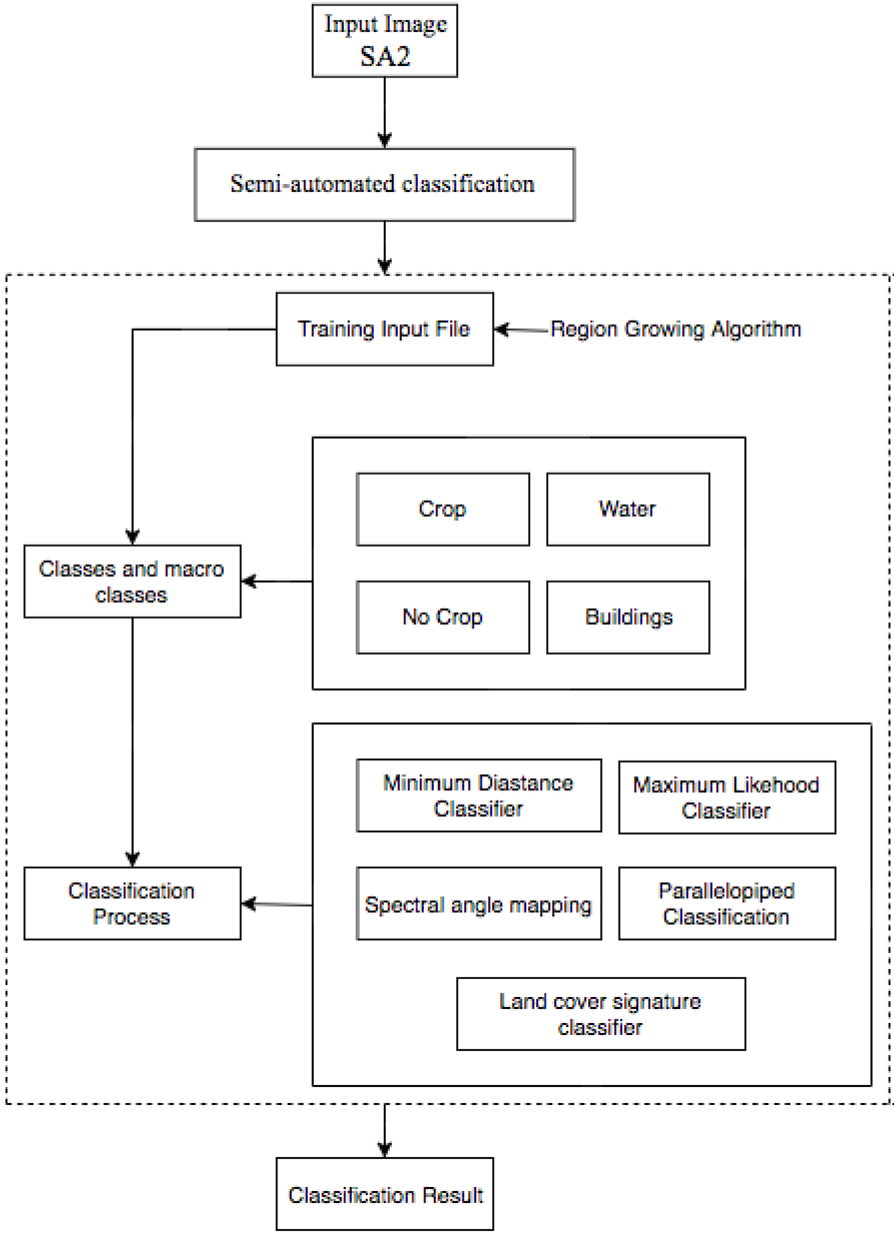

Fig 2.1 Flowchart for Supervised Classification

2.2 Supervised Classification:

Supervised classification is used to identify objects by the value of object's spectral signatures. In remote sensing supervised classification technique used to quantitative analysis. Its basic idea is to divide image by the spectral intensity according to land content. In remote sensing supervised classification divided into two types that is soft classification and hard classification. Supervised classification works on the simple principal, it first decides the classes for classification. Then selecting seed pixel from each ROI (Region of Interest) for training. After that signature of the class is generated by using classification algorithm. Class table is generated next, this table contains all the classes of classification with their class ids. Finally, it gives result of classification which contains all the classes with their defined band color [15].

2.3 Training Input:

In supervised algorithm we need to give ROI (Region of Interest) as input for every area present in satellite image. Region of Interest are box drawn or polygon or user can select any area according to classification need. There is Region of

Interest for each class type of area. This paper contains only four type of classes that is, Vegetation, No Vegetation, Water and Urban area. Here for training area of different types of classes Region growing algorithm is used. Region growing algorithm works on the principle of spectral similarity. It grows area of region by the reference of seed pixel.

Class Name	Class Id	Macro Class	Macro Id
Crop Area	1	Vegetation	1
No Crop	2	No Vegetation	2
Water Bodies	3	Water	3
Building	4	Build Up Area	4

Table 2.3.1 RIO Table for different class

III. CLASSIFICATION ALGORITHM USED:

Signature of each spectral calculated by the pixel value of ROI (Region of Interest) which has the same ids of class. Here algorithm classify image by the comparison of ROI spectral signature with each pixel of satellite image. Distance calculated for pixel is given that class from it is very close. It includes the following algorithm,

3.1 Minimum Distance Classifier:

In this algorithm Euclidean distance is calculated from training data signature to input image pixel signature. Mathematically it is given as,

$$d(I_P, T_P) = \sqrt{\sum_{i=1}^{n} (I_P - T_P)^2}$$

I_P- Input image pixel spectral signature
T_P- Training area pixel spectral signature
n- Number of bands

3.2 Maximum Likelihood Classifier:

It is most important and most used classification technique used in remote sensing. It calculates probability of class using Bayes theorem and then that pixel is sent to its appropriate class. This algorithm need a training pixel to create covariance matrix. So, sufficient number of pixels is present training input to calculate the covariance matrix of that class.

$$g_c(I_P) = \ln P(L_c) - \frac{1}{2}\ln|\sum c| - \frac{1}{2}((I_P - S_C)^t \sum_c^{-1} (I_P - S_C)$$

L_C- Land cover class 'c'
I_P- Input image spectral signature
$P(L_C)$- Probability of class L_C
$|\sum C|$- Determinant of covariance matrix of class LC
S_C- Vector Spectral signature of class 'c'

3.3 Spectral Angle Mapping Classifier:

This algorithm calculates the angle between input image pixel and training area spectral signature. Mathematically, Spectral angle Θ is given as

$$\theta(I_P, T_P) = \cos^{-1} \frac{(\sum_{i=1}^{n} I_P * \ T_P)}{(\sum_{i=1}^{n} I_{Pi}^2)^{\frac{1}{2}} * (\sum_{i=1}^{n} T_{Pi}^2)^{\frac{1}{2}}}$$

I_P- Input image spectra vector spectral signature
T_P-Train area vector spectral signature
n- Number of image band

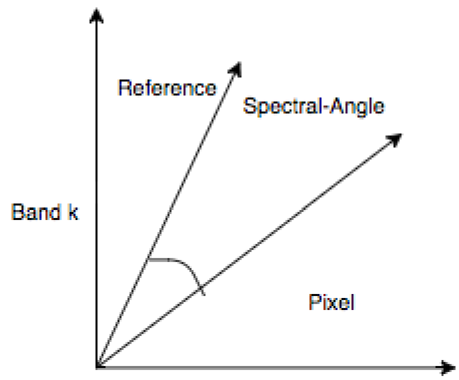

Fig 3.3.1 Calculation of Spectral Angle

3.4 Parallelepiped Classification:

It works on the simple principal of decision rule. It classifies based upon a standard deviation threshold from the mean of each class. If training area pixel value is coming under threshold then it classified in the class. If multiple class threshold occurs, then it classifies into nearest value class or it is not classified.

3.5 Land Cover Signature Classifier:

It gives minimum and maximum value for each band according to its threshold value. Spectral signature of input image object and training area are same then it will come in same class. If pixel is lies in more than one area, then other above classification algorithms are used.

Fig 3.5.1 Land Cover signature classifier- signature plot

IV. **OUTPUT RESULT:**

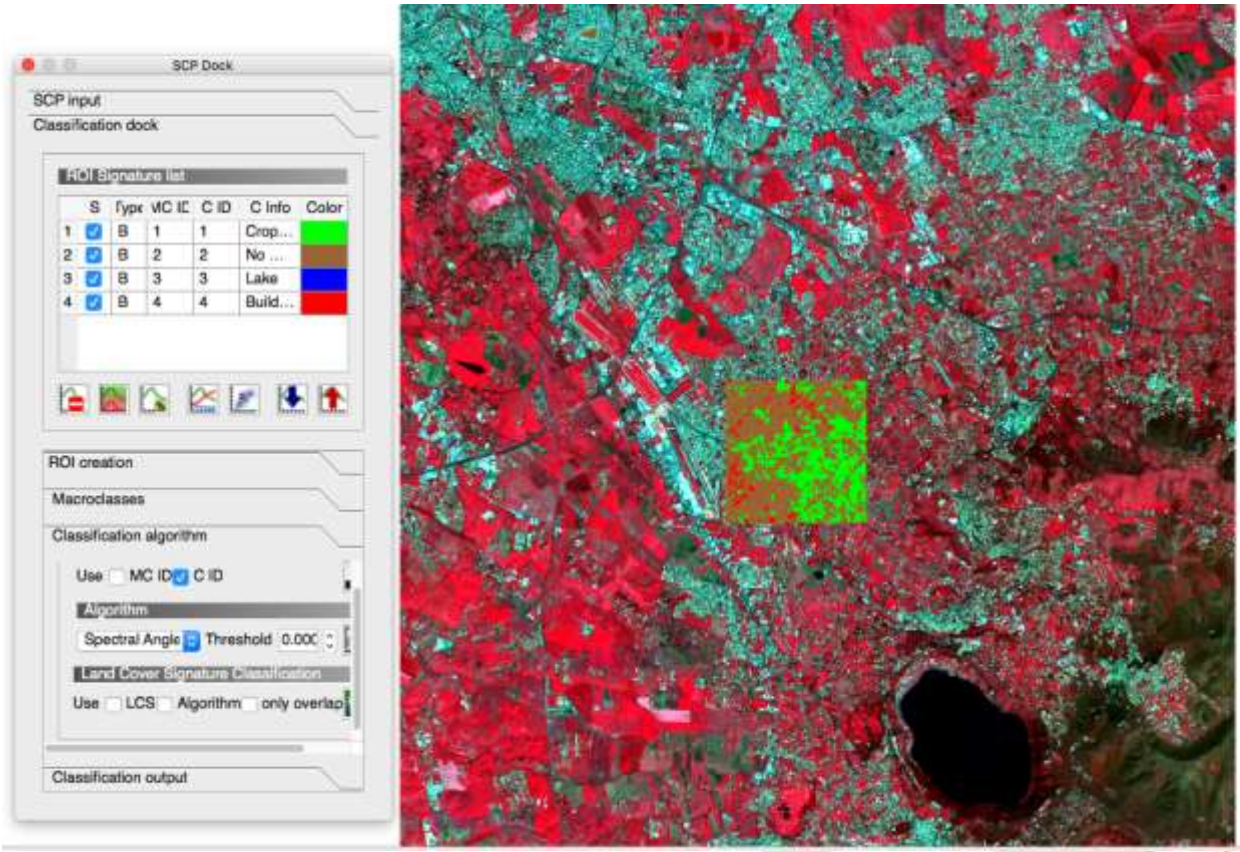

Fig 4.1 Classification mask after classification

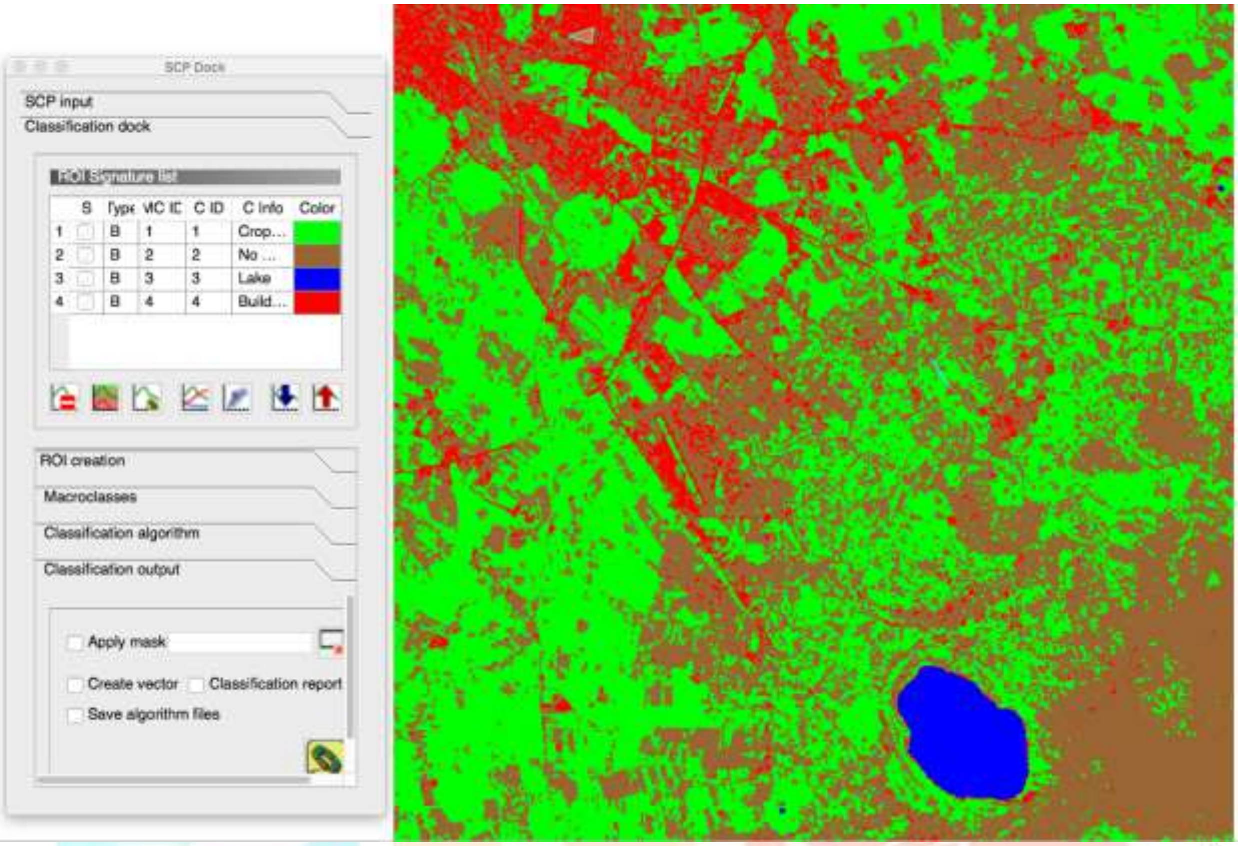

Fig 4.2 Overall Classification output after applying classification mask

V. CONCLUSION

Crop area identification and classification is very important task in remote sensing because it gives rough idea to future planning of production increment or analyse the crop production etc. It also helps in identification of various crop types of selected image region. This paper gives the identification of crop area also various other areas by using supervised classification. This technique is very easy to do and gives 90% accurate classification result.

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