

## Object-Oriented Approach of Information Extraction from High Resolution Satellite Imagery

Kanta Tamta<sup>1</sup>, H.S.Bhadauria<sup>2</sup>, A.S.Bhadauria<sup>3</sup>

<sup>1</sup>MTech CSE Dept., G.B. Pant Engineering College, Ghurdauri, Pauri Garwal, Uttarakhand, India

<sup>2</sup>HOD, CSE Dept. G.B. Pant Engineering College, Ghurdauri, Pauri Garwal, Uttarakhand, India

<sup>3</sup>Assistant professor, CSE Dept. G.B. Pant Engineering College, Ghurdauri, Pauri Garwal, Uttarakhand, India

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**Abstract:** The aim of this paper is to present a detailed step by step method for classification of high resolution satellite imagery into defined classes such as high dense vegetation, water, wet land, Agricultural land etc., using fuzzy rule set. In this area, object based analysis is used for image classification. An Objectoriented approach is based on the segmentation that is being followed for information extraction of variety of thematic information from high-resolution satellite imagery. In this method, fuzzy rule set is defined for every class based on the class hierarchy; every defined class is assigned associated segments with high similarity degree, using eCognition Software. Object-oriented classification rule set provide a complete accurate and efficient method of information extraction. In compared the object-oriented with traditional pixel-based classification and proved that object-oriented method has provided high accuracy classification. Nearest Neighbor (NN) classification method was used to discriminate the land cover classes. The overall accuracy is obtained 99.99% and kappa coefficient obtained 99% for the satellite image of Landsat-8.

**Keyword:** Classification, eCognition, Fuzzy rule based, High resolution satellite image, Segmentation.

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### I. Introduction

Landsat TM imagery is the most common data source for land-cover classification, and much previous research has explored methods to improve classification performance, including the use of advanced classification options such as neural network, extraction and classification of homogeneous objects. Historically, remote sensing imagery has been an important source for the extraction of land use/cover information. In [1] remotely sensed data are widely having been using for land cover classification in order to environment monitoring and natural resources and urban area monitoring. High resolution satellite imagery offers a new quality of detailed information. When the image resolution increases, the spectral variability also increases, which can affect the accuracy of further classification. In object based image classification, an image is divided into non overlapping segments which are then assigned to different classes using specific method. Object based image analysis is a new method that not only uses spectral data but also use spatial data. In this method, fuzzy logic is defined for every class based on the class hierarchy; every class is assigned associated segments with high similarity degree, using eCognition developer 8.9 Software [2]. The main motivation is on construction fuzzy membership function for information extraction. Vegetation extraction methods are probably among the most straightforward object identification techniques in remote sensing.

Object based image classification [3] deliberates the group of pixels as one segment for analysis. There are two traditional methods for information extraction from remote sensing images viz. Pixel based approach and object based approach [1]. Pixel-based supervised image classification recognizes the class of each pixel in image [4] data by comparing the n-dimensional data vector of each pixel with the prototype vector of each class. The main disadvantage of the pixel based approach is that it does not consider the spatial and contextual information of the pixel. Image classification is completely based on the pixel spectral information [3] [4]. Texture information is necessary for producing the accurate classification results. Satellite images with operate spatial resolution also contains rich amount of texture information [17] that can be efficiently applied for the purpose of extraction of various earth features.

### II. Study Area And Data

This paper deals with object-oriented approach that takes into account the form, textures, scale and spectral information. This method was implemented using the Landsat-8, OLI (Operational Land Imager) satellite image courtesy of the U.S. Geological survey covering the part of Sunder ban (West Bengal), India, acquired in December 2014. Generally the OLI requirements specified a sensor that collects image data for nine spectral bands with a spatial resolution of 30m (15 panchromatic bands) over a 185 km swath from the nominal 705 km LDCM spacecraft altitude. Landsat satellite image comprise a Panchromatic band (PAN) and four multispectral (MS) bands Blue, Green, Red, Near-infrared (NIR), all of these are used in this study. The original satellite image shown in fig 1. Object-oriented analysis has been executed using eCognition software.

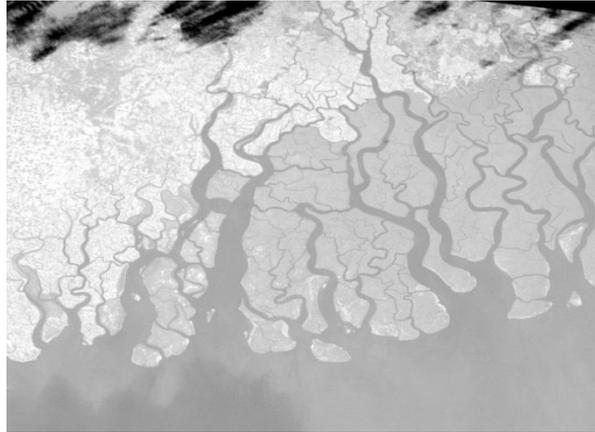


Fig. 1 Original Image to Classify

### III. Methodology

Object oriented approach to image analysis, include three processes: image segmentation, class hierarchy or fuzzy classification and establishing class membership functions [5]. Segmentation [7] is the subdivision of an image into separated regions. In this paper the image is classified into six major classes: High Dense Vegetation, Low Dense Vegetation, Wet land, Agricultural land. Fuzzy classification states an idea that at the same time an object belongs to different categories and degree of this belongingness defined by membership value which is lies between 0 and 1 to classify the desired high resolution image specifically. During image segmentation the pixels that are similar in spectral context are grouped into meaningful image object and this process continues to

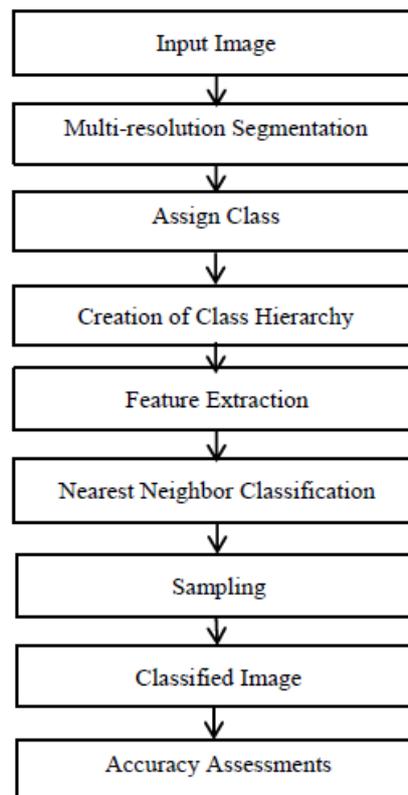


Fig.2 Flowchart for presented method

A subjective degree to obtain desired objects [8]. The desirable thresholds of the parameters used in classification are determined. In this hierarchal classification, first water is extracted then, from water and unclassified data, high dense vegetation is extracted .After that all other classification done, respectively. Fig 2 shows the flow chart of the presented method.

#### IV. Object Oriented Classification Approach

The eCognition software tools offer various object based classification approach that begins with initial image segmentation process to segment the remote sensing image into homogeneous image object followed by fuzzy classification based on the value of membership function.

##### A. Image Segmentation

Object-based image classification is based on image segmentation [7], which is procedure of dividing an image into separated homogenous non –overlapping regions based on the pixel gray values, texture [17], or other adjunct data [1]. Multi-resolution segmentation [15] is one of the most popular segmentation methods. In multi-resolution segmentation, there are three parameters to be defined: scale parameter, shape parameter and compactness [10]. The default values for shape and compactness are used for initial segmentation, which is 0.1 and 0.5 respectively. Scale parameter is also defined so that the resulting segments are smaller than real objects. In proposed method scale, parameter is 25. Multi-resolution segmentation algorithm, which sequentially merge existing image, objects. It is a bottom up segmentation based on a pairwise region merging technique [12]. Multi-resolution segmentation is an optimization process, which, for a given number of image objects, derogates the mean heterogeneity and maximizes their respective homogeneity. Spectral heterogeneity [12] can be calculated by summation of the standard deviations of weighted spectral values in each layer:

$$h_s = \sum_{a=0}^n W_a \sigma_a \tag{1}$$

Where  $h_s$  =spectral heterogeneity;

$n$  =number of band;

$\sigma_a$  =standard deviation of digital number in spectral band;

$W_a$  =weight assigned to a spectral band;

For deviation reduction from smooth or compact shape the spectral heterogeneity criterion are mixed together.

$$h_{sf} = \frac{L}{\sqrt{p}} \tag{2}$$

Where  $h_{sf}$  =spatial heterogeneity fractal factor;

$L$  =length of border;

$p$  =number of image pixel;

During the procedure of multi resolution segmentation, spatial and shape features are also taken into condition along with the spectral characteristics. The shape parameter is composed of compactness heterogeneity and the smoothness heterogeneity [9]. The mathematical equation [5] for calculating the heterogeneity criteria can be expressed as shown in equation

$$f = W_{color} * h_{color} + (1 - W_{color}) * h_{shape} \tag{3}$$

$$h_{shape} = W_{compact} * h_{compact} + (1 - W_{compact}) * h_{smooth} \tag{4}$$

Where,  $W_{color}$  denotes the weight of spectrum information

$h_{color}$  denotes the spectrum heterogeneity

$h_{shape}$  denotes the shape heterogeneity

$W_{compact}$  denotes compact weight

$h_{compact}$  denotes compact heterogeneity

$h_{smooth}$  denotes the smoothness heterogeneity

$$h_{compact} = n_{merge} * \frac{l_{merge}}{\sqrt{n_{merge}}} - (n_{obj1} * \frac{l_{obj1}}{\sqrt{n_{obj1}}} + n_{obj2} * \frac{l_{obj2}}{\sqrt{n_{obj2}}}) \tag{5}$$

$$h_{smooth} = n_{merge} * \frac{l_{merge}}{\sqrt{n_{merge}}} - (n_{obj1} * \frac{l_{obj1}}{\sqrt{n_{obj1}}} + n_{obj2} * \frac{l_{obj2}}{\sqrt{n_{obj2}}}) \tag{6}$$

Multi-resolution segmentation merges a number of pixels into one image object in a reasonable way; there are a large number of features outside the simple spectral values, which can be used for the description of image objects, such as form or texture [6].

(1) Form features

(2) Texture features

(3) The relations between networked image objects

The feature [9] resolution assigns the distinctive properties of image objects to the respective classes. In this paper, we assign the different characteristic of each class .The feature definition of classes is structured hierarchically.

## B. Fuzzy Classification

In pixel based classification methods such as minimum distance method, each segment in the image will have an attribute equal to 0 or 1. In fuzzy rule classification[4], rather of a binary decision-making the possibility of each pixel belonging to a define class is considered, which is defined using a membership function.[7] A membership degree values ranging from 0 to 1.Where 1 means belonging to the class and 0 means not belonging to the class[8].

When implementing fuzzy rule [7] ensures that the boundaries are not crisp the thresholds any more, but fuzzy membership functions within which all parameter value will have a precisepossibility to assigned to a define class are used. Appending more parameters to this image classification, for example, using NDVI and NIR band for every vegetation image classification, better results will be reached. Using fuzzy rule [13], image classification accuracy is less medium to the thresholds.

In the proposed method, the specifications of each object are tested using the fuzzy rules [3] defined for each class based on the class hierarchy mentioned in figure 1.The parameters, which are used for object-based image classification they are Longer wave length visible and near-infrared (NIR) radiation is absorbed more by water than shorter visible wavelengths.Thus water mostly appears blue or green due to stronger reflectance at these shorter wavelengths and darker if viewed at red or NIR wavelengths NDVI and NIR is good for water and vegetation classification[17].Vegetation extraction is one of the most straightforward methods in image classification. In this proposed method, two parameters are used for vegetation and water body's detection.NDVI and near infrared(NIR) ratio, which are explained in this section.NDVI: Normalized Difference Vegetation Index (NDVI) is a proper tool for vegetation extraction. NDVI compare reflectivity of NIR and Red wavelength bands. NDVI has always range between -0.9 to +0.9.NDVI can be calculated as:

$$NDVI = \frac{(\text{meanNIR} - \text{meanRed})}{(\text{meanNIR} + \text{meanRd})} \quad (7)$$

The value of the NDVI and the NIR ratio in vegetated areas slightly differ from one image to another. Generally, the NDVI values for vegetation are around -0.2 to 0.4 and the NIR ratio is around 10 to 30, depending on the density of vegetation.

## V. Result And Analysis

### A. Multi-Resolution Segmentation

Multi resolution segmentation approaches [15] the main concern in the framework of object-based classification. All the parameters are set based on data rule set[8]. In this method all image object layer weight are equal to 1.The homogeneity criterion for compactness and shape are set as default value to 0.5 and 0.1[13] respectively. The scale parameter is 25 in proposed method. The resulting segmentation image is shown in fig 3(scale parameter is 5, 10 and 25). The parameters of the segmentation, as used in eCognition developer [16] were the following:

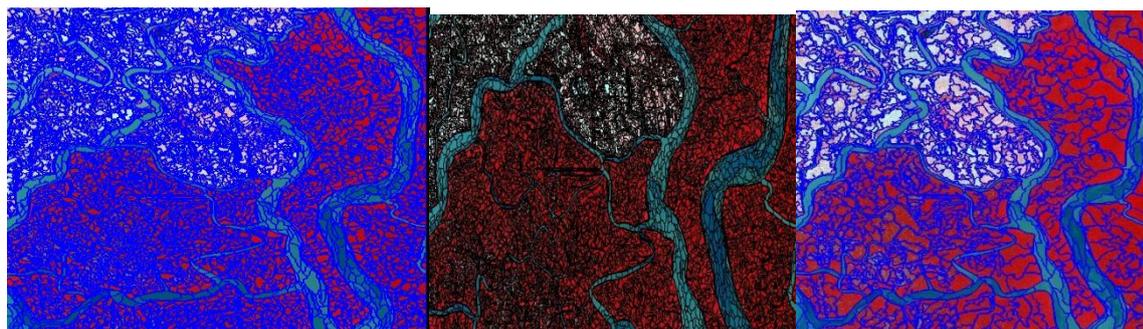
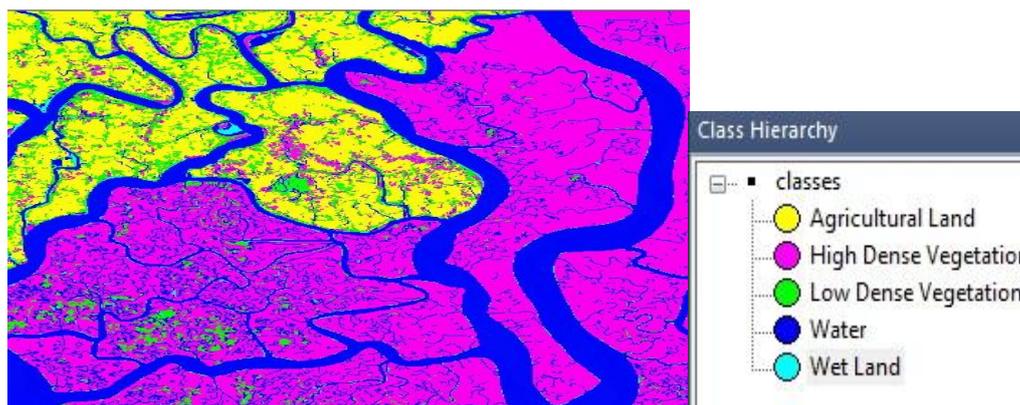


Fig 3 Different Scale Parameters Segemented Results

### B. The Results Of Classification And Assessment Of Accuracy

After the segmentation step, we classify the image object based on certain threshold condition. There are two approach image classification in eCognition software tool a Nearest Neighbor (NN) classifier and membership function. In order to classify water feature from other regions, assign class algorithm will be evaluated with  $NDVI \leq 25$  followed by region merging algorithm. Merge region algorithm [12] merge all the neighboring image object of a class into one larger object. The class hierarchy is created consisting five classes: water, low dense vegetation, high dense vegetation, wet land, agricultural land. Class hierarchy is shown in figure 4.



**Fig.4** Classification of Land Cover Based on Object Oriented Classification and Class Hierarchy

This section presents the results of application of the genetic fuzzy object-based technique [11] on the study area. Through the methods above-mentioned, the suitable parameters were found. Making use of the NIR ratio and border contrast  $NIR > -2$  from water to unclassified area on NIR band, the water could be extracted from the Level 1. Assign member functions with nearest neighbor method on the basis of the image object, we could get the information of water body, wet land and green vegetation. The results of object-oriented classification were compared with the reference data and Google earth. The land cover classes of sample points were also investigated and used as references to compare against the class assignment by the above methods [14]. The image classification accuracy of the results has been calculated with reference to the Training or Test Areas (TTA) mask which is produced from the original image. Accuracy assessment is a very important step of the object based image Classification. In this presented method, Error matrix has been used to calculate the classification accuracy.

**Table I Confusion Matrix for the Presented Method**

Use class	water	Wet land	High dense vegetation	Low dense vegetation	Agricultural land
water	240486	0	0	0	0
Wet land	0	568	0	0	0
High dense vegetation	0	89	103816	35	0
Low dense vegetation	0	0	0	4837	0
Agricultural land	0	0	0	0	68062
Sum	240486	657	103816	4872	68062

**Table II Accuracy Assessment**

Use class	Water	Wet land	High dense vegetation	Low dense vegetation	Agricultural land
producer	1	0.8645	1	0.99281	1
user	1	1	0.998801	1	1
KIA per class	1	0.8643	1	0.99273	1
Total overall accuracy = 0.997933 KIA = 0.9994887					

The overall accuracy and kappa coefficients of the classification results achieved at various scales. Using the manual classification result as sample information, the confusion matrix is generated for the present method [17]. The overall accuracy is 0.99. The confusion matrix was used to make an accuracy rating for the result of the information extraction. The classification result displayed in a confusion matrix. The confusion matrix is calculated by the position of each object and classification of the corresponding image. The accuracies for agricultural land and water extraction in this paper are high as other classes. From the experiment, it can be seen that with newly arisen fuzzy [11] based object oriented approach, the classification accuracy has been improved. The error matrix is generated for the classified image and a general view of image is shown in Table I Table II contains the overall accuracy and kappa statistic for image classification.

## VI. Conclusion

The present study shows that remote sensing based land cover/use mapping is more effective. The high resolution satellite data such as Landsat TM and ETM+ are good source to offer data correctly. The object-oriented approach, together with spectral and spatial feature, such as shape, texture, etc., was used to extract green vegetation information. Using the e-Cognition Developer 8.9, the multi resolution segmentation parameters (scale 25, shape 0.2 and compactness 0.8) were used to carry segmentation and create a classification method and to use the nearest- neighbor and fuzzy membership functions to extract land cover information from images. The method and rules in paper is helpful to the classification of high-resolution images, and in it, the rule set is simple and efficient to information extraction. The object-oriented method demonstrated to be more wide-ranging, more precise and more accurate compared with the traditional classification methods.

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