Comparative Analysis of Pixel-Based and Object-Based Classification of High Resolution Remote Sensing Images – A Review

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Abstract: *We delineate an overall performance comparison between the two most popular classification techniques: Pixel-Based and Object-Based of remote sensing. Object based image analysis has been widely used as a common paradigm in the analysis of high resolution remotely sensed satellite data which is used to extract the meaningful information for updating the GIS data. Both techniques have their own pros and cons in finding the solutions of many applications. To create land cover thematic maps with higher accuracies then the image classification analysis is a big challenge in the remote sensing. However, the pixel based classification technique works only on spectral features and neglects the spatial features but in object based classification have ability to work on both spectral and spatial features. OBC has also characteristic features like mean, standard deviation etc. which can be used to differentiate the classes properly. In paper, we observed that the object-based technique shows higher accuracy in classification process than the pixel-based technique because pixel based can't satisfy the high resolution satellite data properties and it produced data redundancy.*

Keywords: *Pixel-Based Classification (PBC), Object-Based Classification (OBC), Remotely Sensed Images.*

I INTRODUCTION

High Resolution (HR) Remote Sensing images have demonstrated to be very useful in land use/ land cover (LULC) mapping which includes energy, water and environment (Bio-mass energy, Forest Inventory, Hydroelectric, Snow Cover Monitoring, water quality, observations of the temporal and spatial variations in water volumes stored in rivers, lakes, wetlands, detection of pollution, climate changes, urban growth and management of urban planning) [1]. However, to explore the full value of these data, the useful information has to be extracted and represented in standard format so that to import it into geo-information systems (GIS) [3]. Remote sensing imagery data of our earth surface has been captured by spaceborne and airborne sensors. These remotely sensed images are composed by the collection of rows and columns of pixels. But a single pixel is to be an individual unit which carries several spectral layer values.

The pixels of an image having different spectral values are assigned to one class of thematic mapping; this is called Image Classification [2-4]. The processing steps of Image Classification are: 1) Choice of a suitable classification system, 2) Selection of training samples, 3) Image preprocessing and feature extraction, 4) Selection of suitable classification methods, 5) Post-classification processing, and 6) Accuracy assessment [4].

Image classification is done by these two techniques: pixel based and object based. The Pixel-based approaches work on each individual pixel and also extract information from remotely sensed data based on spectral information only [28]**.** The increased variability implicit within high spatial resolution imagery confuses traditional pixel based classifiers resulting in lower accuracies. The problems faced by pixel based approaches are overcome by the Object Based image classification. Object-Based information interprets an image not only by single pixel but also in meaningful image objects and their mutual relationships. Object-based information extraction not only depends upon spectrum character, but also on geometry and structure information. This approach provides the truly revolutionary data and can easily accessible [27].

Classification is one of the processes of image analysis that can be used to meet the challenges in remote sensing. This paper is mentioned as follows: in section 2 discuses the classical pixel-based and object based classification, in section 3 demonstrates the related work in the survey of remote sensing data, in section 4&5 summaries the results of the presented papers.

II. CLASSICAL PIXEL-BASED AND OBJECT BASED CLASSIFICATION

The overall image classification procedures have objectives to automatically allocate all pixels into land use/ land cover (LULC) classes in an image. Variety of multispectral image is used in remote sensing to perform the classification of image and thus, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization. High resolution image provides more deep information and hence can be used to classify the image with very accurate boundaries of the classes. The classifications of high resolution images can be analyzed by pixel-based and object-based techniques.

Image analysis by Pixel-Based Classification (PBC): The traditional pixel-based image analysis works on the spectral value similarities between the classes of multispectral data for mapping a pixel to a class [2]. Spectral pattern recognition refers to the family of classification procedures that utilizes the pixel by pixel spectral information as the basis for land cover classification [11]. Pixel-Oriented methods have reached their limits with the development of high and VHSR (very high-spatial resolution) remote sensing images. At VHSR, each pixel represents a region ranging from 0.25 to 2m, which means that the complexity and variety of identifiable objects increase considerably [20]. It is limited due to following reasons: image pixels are not true geographical objects and the pixel topology is limited. The pixel-based image analysis has high spectral information but low spatial information which neglects texture, context and shape information. This technique can't applicable on high resolution image classification precision and produced large data redundancy [27]. The accuracy in this is affected by the salt and pepper noise. Normally ERDAS Imagine, ENVI, ILWIS software are used for analysis the satellite data using pixel based classification [7]. The extraction of data by conventional methods for creating and updating the data rely heavily on manual work and therefore are very expensive and time consuming [10]. The classification techniques of pixel based for the analysis of the image are supervised and unsupervised classification.

Supervised classification: Supervised networks have the information of input data and target data. Training typically consists of computerized adjustment of parameters to optimize performance on the training set. Performance on new data depends on how well the training data are classified and how representative they are. Representative training areas are used to combine a numerical "interpretation key" that describes the spectral attributes for feature type of interest. There are many classifiers that come under the category of supervised classification that are Parallelepiped, Maximum Likelihood (MLC) and Minimum Distance etc. This technique may also cause over-segmentation due to mismatching of homogeneity criteria [15].

Unsupervised classification: Unsupervised networks only have the information of input data. Data are clustered together if they look similar to other members of the cluster. When new data are not similar enough to any existing cluster, a new cluster is formed unsupervised networks.
After the completion of classifying operation the examiner determines the land-cover type for each class based on ground-truth information, image interpretation, maps, field reports etc. then assigns each class to a specified category (aggregation). The most popular classifiers which use this process are *K*-means and ISODATA (iterative self-organizing data analysis). There are following steps under unsupervised classification:

1. Define Classification Scheme
2. Configure and Run Classifier
3. Aggregate Classification
4. Label Classes
5. Check Accuracy

Unsupervised normally requires only a small amount of initial input that is why clustering does not require training data. This metrics rely on intrinsic properties computed directly from the resulting segments. But in case of supervised classification, they provide efficient solutions to quantify similarity between pixels of the image, thus training samples are to be taken which plays an important role. In general, the results of the supervised classification have higher accuracy than unsupervised classification. In unsupervised similar concepts get lumped together [21].

Image analysis by Object-Based Classification (OBC): Object based classification is different from the pixel based classification approach as it works on the group of pixels instead of direct pixels. OBC has two steps: (i) Image Segmentation to generate segmented image and (ii) classification of segmented image. Image segmentation is the basic and crucial step in object based classification. The performance of the classification is affected by the results of image segmentation process. Image segmentation divides an image into objects. But in OBIA systems, the bottom-up principle is mostly used because it compares all the features of small objects to get bigger object after merging. There are lots of segmentation techniques available under the Bottom-up principle but normally multi-resolution region growing segmentation approach is used in the analysis of remote sensing image. Merging of two neighboring segments follow certain homogeneity criteria based on scale parameter, spectral and spatial information [5]. The main problem of region growing is the threshold setting which may causes over or under segmentation, also cannot create desired objects for various different targets [17]. No results of segmentation will be proofed if it is not satisfied to the human eye [6]. The huge bandwidth of segmentation applications approached that has also been outlined here will certainly lead to further progress which is needed in order to use the full potential of remotely sensed data [39].

Image analysis includes spectrum character, geometry, shape, size and structure information. Object-based image analysis approaches try to overcome the drawbacks occurred in PBC by grouping pixels into higher level objects [19]. Object based classification can be realized by using the Definiens eCognition software which is very much reliable which also includes segmentation step before the classification as shown in Fig. 1.

1) By using the multi-resolution segmentation, creating a hierarchical network of image objects. The upper level segments represent large-scale objects while the lower-level segments represent small-scale objects.
2) By using class hierarchy, classifying the derived objects based on their physical properties then assigns the class to each object and gives their class name.
3) Describing the relationships of the hierarchical objects by using the homogeneity and heterogeneity Criteria of neighborhood relationships or being a sub or super objects [11].

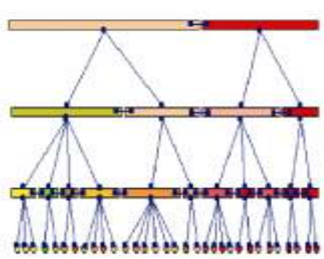

FIGURE 1. HIERARCHICAL PROCESS [11].

There exist many segmentation algorithms in the literature; one can cite for example fuzzy c-means, level set, and watershed transformation [2]. An object based classification have characteristics like mean value, standard deviation, length/width ratio, etc. that can help in the calculations of image differential classes. Features like textural, contextual and spatial along with spectral information helps in the extraction of meaningful object information which further reduces the salt & pepper noise, lost of data, and increases accuracy [6].

III RELATED WORK

There is a large number of current works as well as efforts that are on the go, the development of various Classification techniques are used for the better data extraction from the satellite data. These approaches are based on the features of the application and its requirements. However, there are factors that should be taken into consideration when developing the methods or classifier for remote sensing.

In [5] the authors explained that the segmentation results were evaluated with an objective function that aims at maximizing homogeneity within segments and separability between neighboring segments. The accuracy assessment results presented similar distribution as that of the objective function values that is segmentations with the highest objective function values also resulted in the highest classification accuracies or vice-versa. This result shows that image segmentation has a direct effect on the classification accuracy. With the optimal segmentation, object based classification achieved accuracy significantly higher than that of the pixel based classification, with 99% significance level.

In [8] the authors described the survey of building damage detection after earthquake. An efficient method was proposed using pre-event vector map and post-event pan-sharpened high spatial resolution image**.** A decision-making system based on these features and an adaptive network-based fuzzy inference system (ANFIS) model was designed to attain building damage degree. The results of our method indicate that an overall accuracy of 76.36% and kappa coefficient of 0.63 were achieved to identify building damage degree. The obtained results indicate that the post-event geometrical features along with the ANFIS model can help to reach better results in building damage detection**.**

In [9] the authors proposed the hierarchical object based classification which combined the object based and pixel based classification techniques. In this, the vegetation and shadow areas were extracted by pixel based classification and post classification processing but the non-vegetation classes were examined by object based classification. This work showed better results in the accuracy of segmentation and hierarchical object based classification method produced higher overall accuracy as compared to other survey methods.

In [10] the authors studied that the automatic and accurate road extraction approach based on OBC depends upon the spectral and geometric characteristic features of roads. This approach mentioned in three processing steps: rough classification of roads, road connection algorithm, and result grooming. The proposed approach of automatic road extraction images could improve the accuracy of road extraction and reduce the effects of occlusions on roads such as shadows.

In [11] the authors explained that the detailed accuracy results were found as error matrices and they showed that the overall accuracy of object based classification is better than pixel based techniques like parallelepiped classification, minimum distance classification and maximum likelihood classification.

In [12] authors demonstrated that the evaluation of feature-type segmentation in object based technique gives an insight to the decision-making process in choosing the exact parameters towards the quality of segmentation rather than the point based or pixel based approach and also optimal segmentation process should be achieved for the better classification process.

In [13] the authors showed that in the pixel-based analysis the maximum likelihood method and the ISODATA method were applied. The results showed that in both methods misclassification tended to increase due to shadows. The pixel-based classification also experienced difficulty due to factors such as the varied shapes of the forest canopy and mixing of vegetation, etc. The object-based classification, in contrast, relies on abstraction of comparatively homogenous areas, and proved capable of extracting the boundaries among all the forest types. Some misclassification problems remained, which have to be addressed by future trial and error experiments in parameter setting. The results showed that object based is much better than pixel based techniques.

In [19] the authors presented that object-based image analysis (OBIA) method strongly depends on the segmentation analysis. They proposed a novel of unsupervised metric, which evaluates local quality by using segment of nearest neighborhood, thus quantifying under or over segmentation based on a certain homogeneity criterion. Also they proposed two variants of this metrics, for estimating global quantity of remote sensing image segmentation by the aggregation of local quality. The complexity of pixel-based is higher in remote sensing images as compare to object based.

In [25] the authors explained that the developed LULC classification based mapping of accuracy may serve as a better solution for numerical accuracy assessment and also provide a initial point for further changes in LULC maps. This method used the three different techniques MLC, ANN and RF, from which RF has higher accuracy than both other techniques.

IV Results of some presented techniques

Table 1: Comparative Analysis Of Classifiers Used In Different Study Areas:

Satellite Data	Study Area	Classifier	Classes	Results/Accuracy
Land sat-7 EMT + [2]	North of Algeria (Coastal area)	OBC, PBC with SVM	5 classes (water, dense urban, bare soil, vegetation, less dense urban)	Kappa Coefficient, Overall Accuracy and F- measure of OBC is 0.89, 92.97% & 0.9078 respectively but in PBC 0.85, 88.24 & 0.8867 respectively. The ROC of OBC is better than the pixel based technique
Land sat-7 EMT + [4]	Central west of Mexico	OOC, MLC of PBC	8 classes (lavaflow, orchards, Rain-fed agriculture, irrigated agriculture, Temperate, forest, grassland, tropical dry forest)	McNemar's test = 10.27 with optimal segmentation, object based classi fication achieved accuracy significantly higher than PBC with 99% significance level.
SPOT-5, Land sat-7 EMT +, MODIS [6]	South-East of Tancitaro mountain peak	MLC and NN of PBC, OBC	7 classes (forests, orchards, irrigated agriculture, Tropical dry forest, rain fed agriculture, Human settlement)	Object based classific ation has better accuracy of 63.5% than pixel based classifiers (MLC and NN) of the image.
Quickbird Imag	BAM	ANFIS model	3 classes Moderate damage, very	Building detection maps the overall

e [8]		of OBC, PBC with MLL	heavy damage, slightly damage	accuracy and kappa coefficient of ANFIS model (OBC) are 76.36% & 0.63 respectively that is higher than PBC with MLL.
Quickbird Image [9]	Beijing urban	Water shed of PBC, OBC	2 classes (vegetated, non-vegetated)	The Hierarchical method of OBC showed that Kappa Coefficient and overall accuracy are 0.8411 & 86.21% respectively which is better than PBC that showed 0.8047 kappa coefficient & 83.04% accuracy.
Quickbird Image [10]	Beijing city	k-mean, Morphology with OBC	2 classes (Main- Roads and Sub-Roads.	Accuracy analysis of main roads and secondary roads using OBC method are 96.7% and 74.3% respectively.
Landsat-7 EMT + [11]	Zonguldak, Turkey	Parellelpiped, MDC & MLC of PBC, OBC	7 classes (dam lake sea, settlement areas, dense forest, wood Land, coal waste, Open areas)	Kappa Statics and overall accuracy are 0.76 & 81.30% respectively in object based better than pixel based.
IKONOS [13]	Yokaichiba city, Japan	MLC & MDC of PBC, OBC	Vegetation community	Misclassification produced by pixel based classification but OBC can abstract the exact shapes & height of the trees.
SPOT-5 [14]	Gardland country, Arkansas	Supervised & Unsupervised of PBC, OBC	13 classes (urban, grass, forest, shadow, clearcut-new, clearcut-old, water, barren land	Object-based has better results than other two techniques of PBC in accuracy. The accuracy of OBC at different levels are CIROff- 78.2%, On-Off- 66.1%, LeafOn 58.9%, CIROn Off- 82.02%.
Landsat-7 EMT + [15]	National forest inventory of Mexico	MLC of PBC, OBC	Land cover map	Overall Accuracy of OBC is 2.3% higher than PCB.
Landsat TM [21]	Peninsular Malaysia	PCB, OBC	3 classes (water, Vegetation, Urban)	Land use features can be easily extracted by OBC and saved time to Connect the polylines & Convert to polygons than Pixel based technique.
Landsat & IRS [22]	Algiers	Land sets as classifiers	Build up areas	IRS land set as classifier is better than landsat images due to accuracy and sensitivity parameters
Quickbird [24]	City of Cologne	PBC, OBV, OBR	6 classes (roof, bush/tree, façade, Shadow, Meadow, Sealed)	Kappa coeffiecent- 0.8253 and overall accuracy- 0.7547 in OBR that is better than PBC & OBV.
Quickbird [26]	Suburban of Bombay	ANN, NN, SVM	9 classes (lake, pool, road, field, Mountain, shadow, Bright roofs, dark- Roofs, vegetation)	Modified CBFNN+ RLP in OBC shows better overall accuracy- 89.72% & kappa coefficient- 0.89 than other classifiers.
Quickbird [27]	Beiging	OBC, MLC of PBC	5 classes (water, vegetation, Road, Buildings, bare)	OBC overcomes the limitations of MLC which produced noise and shadow. The overall accuracy in OBC is 0.9576 than PBC.
Landsat-7 EMT + [28]	San Antonia	OBC, NN	4 classes (water, builtup, forest, Agriculture)	Improves mean, standard deviation and overall accuracy of the system in OBC.

CONCLUSION

This paper focuses on the study of the classification approaches or techniques based on pixel-oriented and object-oriented. The comparative examination is based on various complementary statistical measures. The growing availability of high spatial resolution imagery has focused on the limitations of pixel based and need for more advanced study. Image classification plays an important role in the analysis of image in remote sensing. Optimal and efficient classification approach can enhance the performance as well as the overall accuracy of the classified image. By the study of various research papers showed that object based have spectral, temporal and spatial properties which can easily deal with high resolution remotely sensed data that overcomes the limitations of pixel based classification which depends only spectral values of the data. Hence, the comparison between these two techniques from which it is analyzed that object based technique classification is more accurate and have many advantages over pixel based classification for high and very high spatial resolution images in most of the applications.

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