Pixel Based and Object Based Land Cover Classification analysis for a High-Resolution UAV Image

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Abstract

Remotely sensed image takes in a digital number (DN) value as input per pixel, in according to the reflectance received by sensors. Traditionally, these pixel-values are used to separate clusters and classify different objects or land covers accordingly. It often creates discontinuity for a particular land cover, resulting in creation of small objects within a pixel-based image analysis (PBIA) land cover due to some change in reflectance value or object shadows. It is called salt and paper effect. To smoothen this discontinuity object-based image analysis (OBIA) was introduced which first creates possible small objects and then classifies land cover based on its texture, shape, neighbors, and other algorithms like NDVI & NDWI. With the advancement of drone technology and increasing better image resolution, how both of this method still reacts with better resolution especially in context of Bangladesh that is to be find out. For this study a high-resolution drone image with R, G, B and NIR bands is used. The study finds out that OBIA still has 12% more accuracy than PBIA, indicating an overall accuracy of 93%. This study also tries to find out what happens on the edge of different objects in both methods and how can it be made better for a continuous object extraction.

Keyword: Object based Image analysis, land cover classification, accuracy assessment, eCognition, NDVI

1 Introduction

Remote sensing has long become the desired mode for land monitoring, information collection, land cover classification rather than using traditional method of extensive and cumbersome field survey. The classification of land use and land cover (LULC) from remotely sensed imagery can be divided into two general image analysis approaches: i) classifications based on pixels, and ii) classifications based on objects. While pixel-based analysis has long been the main stay approach for classifying remotely sensed imagery, object-based image analysis has become increasingly commonplace over the last decade (Blaschke, 2010).

Pixel-based image analysis (PBIA) has been used, which was not as efficient and reliable in the HSRS image processing. Gradually, object-based image analysis (OBIA),which employs groups of pixels, namely objects, as the processing units, has received considerable attention in the HSRS image processing. (Khosravi and Momeni 2018). Object-based image analysis, using a software program called eCognition was conducted to divide photographs into different vegetation classes (based on similarities among neighboring pixels) to estimate percent ground cover for each category (Luscier, Thompson et al. 2006).

How much the classification is accurate with the ground truth that can be found out using kappa statistic which is a measure of how closely the instances classified by the machine learning classifier matched the data labeled as ground truth, controlling for the accuracy of a random classifier as measured by the expected accuracy. Another method is error matrix which uses the same principle and provides both user and producer accuracy.

Pixel-based and object-based image analysis approaches for classifying broad land cover classes over agricultural landscapes are compared using three supervised machine learning algorithms: decision tree (DT), random forest (RF), and the support vector machine (SVM). Overall classification accuracies between pixel based and object-based classifications were not statistically significant. Using pixel-based image analysis, there was no statistically significant difference ($p>0.05$) between results produced using different classification algorithms (Duro, Franklin et al. 2012). Hossain et al. (2019) discussed different types of recent algorithms, its strength and limitations in image analysis. Based on that, it is evident that remote sensing field is flourishing very quickly. The purpose of this study is to find out the difference between accuracy of those both methods in a UAV image with correspondence to the landscape of Bangladesh. In different types of landscape and for different classes there are variations seen in image classification algorithms and logic development. For feature extraction, what type of methods have what type of result is important for image processing for a particular landscape.

2 Methodology and Data Collection

For this study, first the raw image is processed using different tools. Then, pixel based, and object-based image analysis method is used for classification. Object based image classification is done using eCognition and pixel-based image classification is done using Arc GIS. Image classification accuracy, land cover area calculation and overlapping boundaries are accessed for comparison of both techniques. For accuracy assessment Kappa statistics, user's and producer's accuracy is used.

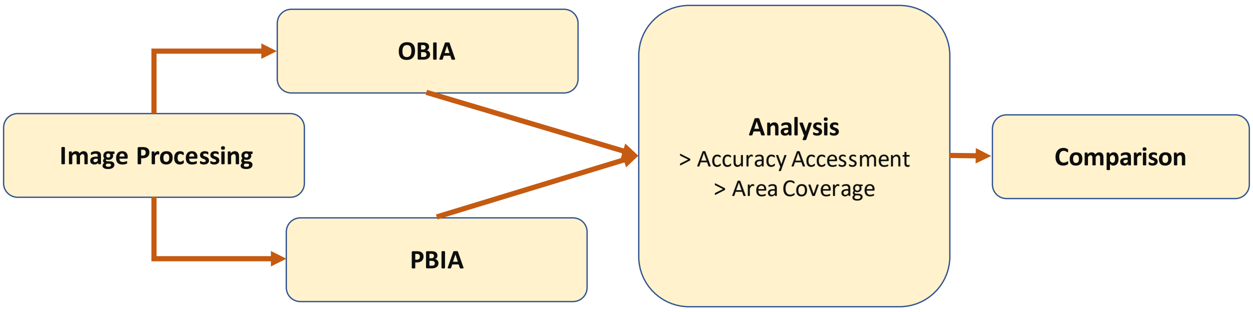

Fig: Flow of the Study

As Study area, Barisal district (Babuganj Upazilla) of Bangladesh is selected where a reseacch is going by International Maize and Wheat Improvement Center (CIMMYT) and drone is being used for measuring the health of Wheat plant. The image is collected form that source.

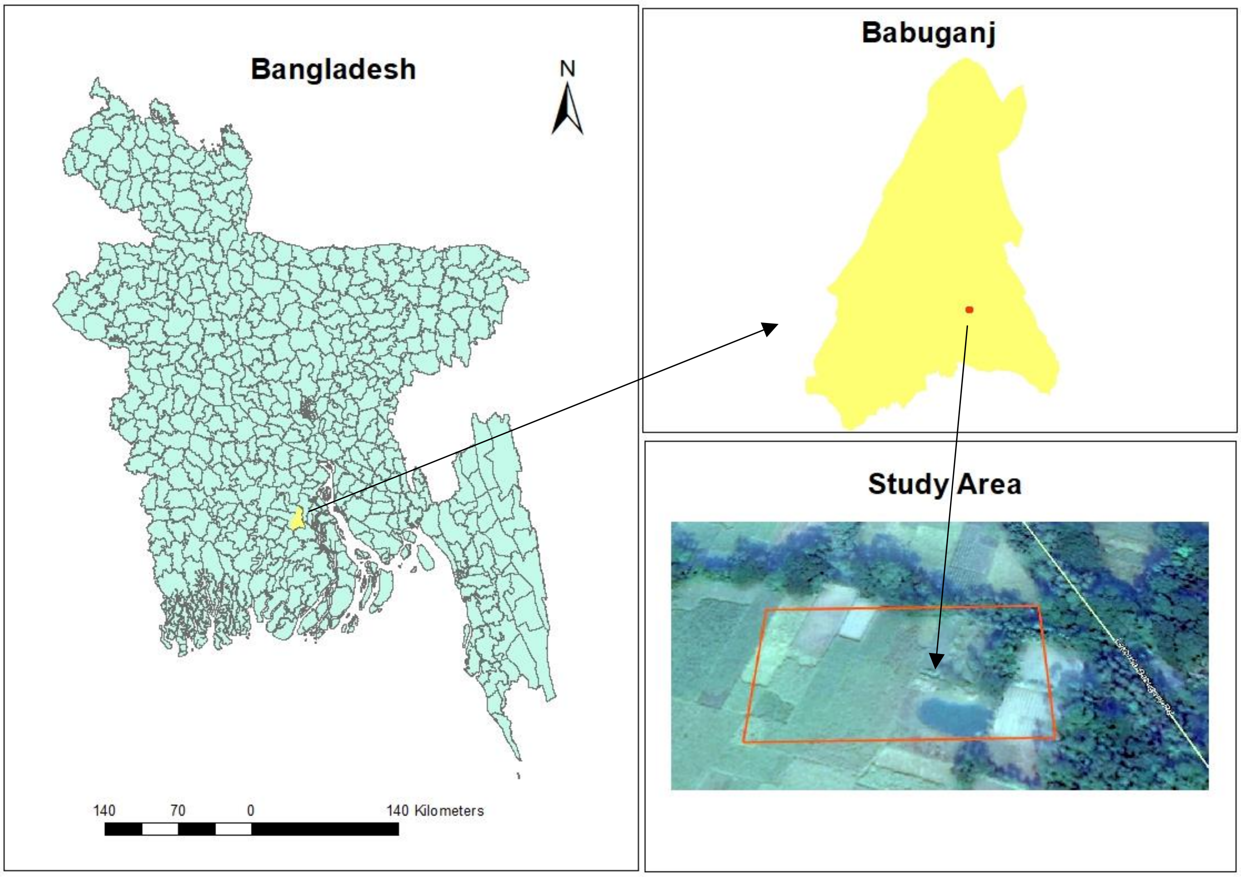

Fig: Study area location

The raw image used in this study has 4 bands including Red, Green, Blue and Infrared. This image was captured by a UAV drone, under the project of International Maize and Wheat Improvement Center (CIMMYT) which is further analyzed for understanding wheat plant growth and its health condition. It has a spatial resolution of .0125 m and mostly there is agricultural land in that area composing some water body as well.

For accuracy assessment, Kappa statistics are used which follow the following formula.

Kappa = (total accuracy – random accuracy) / (1- random accuracy)

3 Data Processing

3.1 Image Processing

The image has been captured using Slant Range sensor that consists of four bands and processing has been done in two steps to create high resolution mosaic multispectral image of the field that can represent satellite image in terms of their character. Firstly, the captured TIFF images are converted to GeoTIFF image file using Slant View software. Basically, it converts the image pixel value into reflectance value and eliminates the unexpected images that are outside the flight path of UAV. Secondly, the GeoTIFF image is further processed using Agisoft Photo scan software. UAV image processing in Agisoft has several steps. The steps are aligning images, sparse cloud creation from alignment of photos, dense cloud preparation, mesh creation for 3D visualization and sharpen the image, orthorectification and finally exporting the mosaic image. Then GPS coordinate is taken carefully for georeferencing.

3.2 Classification Logic Development

For object-based classification, bottom-up approach is used in this study as it helps in separating land cover by first creating lot of small objects. The size and shape of those objects depend on the choice of compactness and scale factor. By trial-and-error method a good combination is necessary to be found using multi resolution segmentation analysis algorithm. Then using spectral difference objects with similar spectral value are merged to create a larger object. Several indexes like NDWI, NDVI (Table 1) are used to extract the boundaries and some logics based on shape parameter, closeness to other objects or neighbors, small unnecessary noises in a neighbor are used to smoothen then classification of 5 land cover types. Finally, all of them are merged to create merged land cover.

For pixel-based classification supervised and unsupervised techniques are used. Pixel are classified in 5 categories for unsupervised classification and training data is used to classify using supervised method.

Steps	Water	Structure	Shadow	Crop	Vegetation
1	Brightness 0 - 15	From Unassigned Brightness 20 – 35 & NDWI > .8	From Unassigned Class Brightness < 15	NDVI .65-1.5	From Unassigned Class NDVI < .65
2	NDWI 0 - .21	Rectangle Shape > 70%	-	-	From Unassigned Class Brightness >30
3	Unclassified Area with <1000 pixel & Has border > 80% with water classify as Water	Unclassified Area with <1000 pixel & border > 80% with Structure classify as Structure	Unclassified Area with <1000 pixel & border > 80%with Shadow classify as Shadow	Unclassified Area with <1000 pixel & Has border > 80% with Crop classify as Crop	Unclassified Area with <1000 pixel & border > 80% with Vegetation classify as Vegetation
4	Merge Region	Merge Region	Merge Region	Merge Region	Merge Region

Table 1: Land classification logic for OBIA

4 Discussion

4.1 Image classification

Unsupervised (Fig c) and Supervised (Fig b) classification is used to find out the pixel-based classification output. Classified image (Fig d) is the output of object OBIA. Visually PBIA looks like having a lot of salt and paper effects which is having a lot of small boundaries within a class or object. It creates a more unnecessary effect on the object. May be the pixels that are showing different value are the true ones. But there is less likelihood of being a different object. So, considering its neighboring pixels mostly helps to differentiate these objects. If we look closely at the water body in OBIA and PBIA method (Fig b & d) we can see that PBIA has water body as a scattered plot in some cases but we know from filed verification that it is a pond and, in a pond, usually water body in a continuous figure. So, this supervised classification clearly has a salting effect which OBIA manages to avoid. As there are lots of features with different heights like vegetation, wheat crop, forest & structure, taking this into account analysis of shadow is necessary to find out if that object has height in order to make visual classification better. Image with height data or cloud point data, is better to classify more precisely using another phenomenon of height.

4.2 Accuracy Assessment

Using the convolution matrix, the accuracy is counted which is not suitable for PBIA method output. In the case of OBIA methods output it is more suitable to have an accuracy of 94% (Table) while PBIA has an accuracy of 73.6% (Table) which is 20% lower.

Class	Structure	Shadow	Water	Crop	Vegetation	Total	U_Accuracy	Kappa
Structure	5	0	0	0	5	10	0.5	0
Shadow	0	8	0	0	2	10	0.8	0
Water	0	0	9	0	1	10	0.9	0
Crop	0	0	0	15	2	17	0.882	0
Vegetation	0	0	0	5	5	10	0.5	0
Total	5	8	9	20	15	57	0	0
P_Accuracy	1	1	1	0.75	0.333	0	0.7368	0
Kappa	0	0	0	0	0	0	0	0.663

Table 2: Accuracy assessment of PBIA (Supervised)

Class	Water	Shadow	Vegetation	Crop	Structure	Total	U_Accuracy	Kappa
Water	10	0	0	0	0	10	1	0
Shadow	0	9	0	1	0	10	0.9	0
Vegetation	0	0	9	1	0	10	0.9	0
Crop	0	0	0	19	0	19	1	0
Structure	0	0	0	1	9	10	0.9	0
Total	10	9	9	22	9	59	0	0
P_Accuracy	1	1	1	0.86	1	0	0.949	0
Kappa	0	0	0	0	0	0	0	0.934

Table 3: Accuracy assessment of OBIA

Another parameter for accuracy assessment is Kappa Statistics which is .663, quite low in PBIA output (table 2) and It’s a lot better for OBIA having a value of .93 (table 3). It also indicates a sharp rise in accuracy as well for OBIA.

4.3 Land Cover Area Comparison

Among the five-land use categories, change in land cover area indicates the difference and shift of areas from one land use to another. It is found (table 4) that more pixels are found with the same reflectance of structure because usually structure roof has high reflectance value and on barren lands.

land Use Type	OBIA Area (X sq km)	PBIA Area (Y sq km)	Change in Coverage (X-Y)
Structure	45	120	-74
Shadow	215	317	-102
Water	264	138	126
Vegetation	2165	2558	-393
Crop	4680	4227	453

Table 4: Area of different land cover in PBIA and OBIA

4.4 Comparison of Boundary Overlapping

In terms of different object boundaries tend to vary. This study shows better classification of OBIA method in terms of water boundary classification (Fig A). It also works good for structure (Fig C) extraction because of being able to use shape parameters.

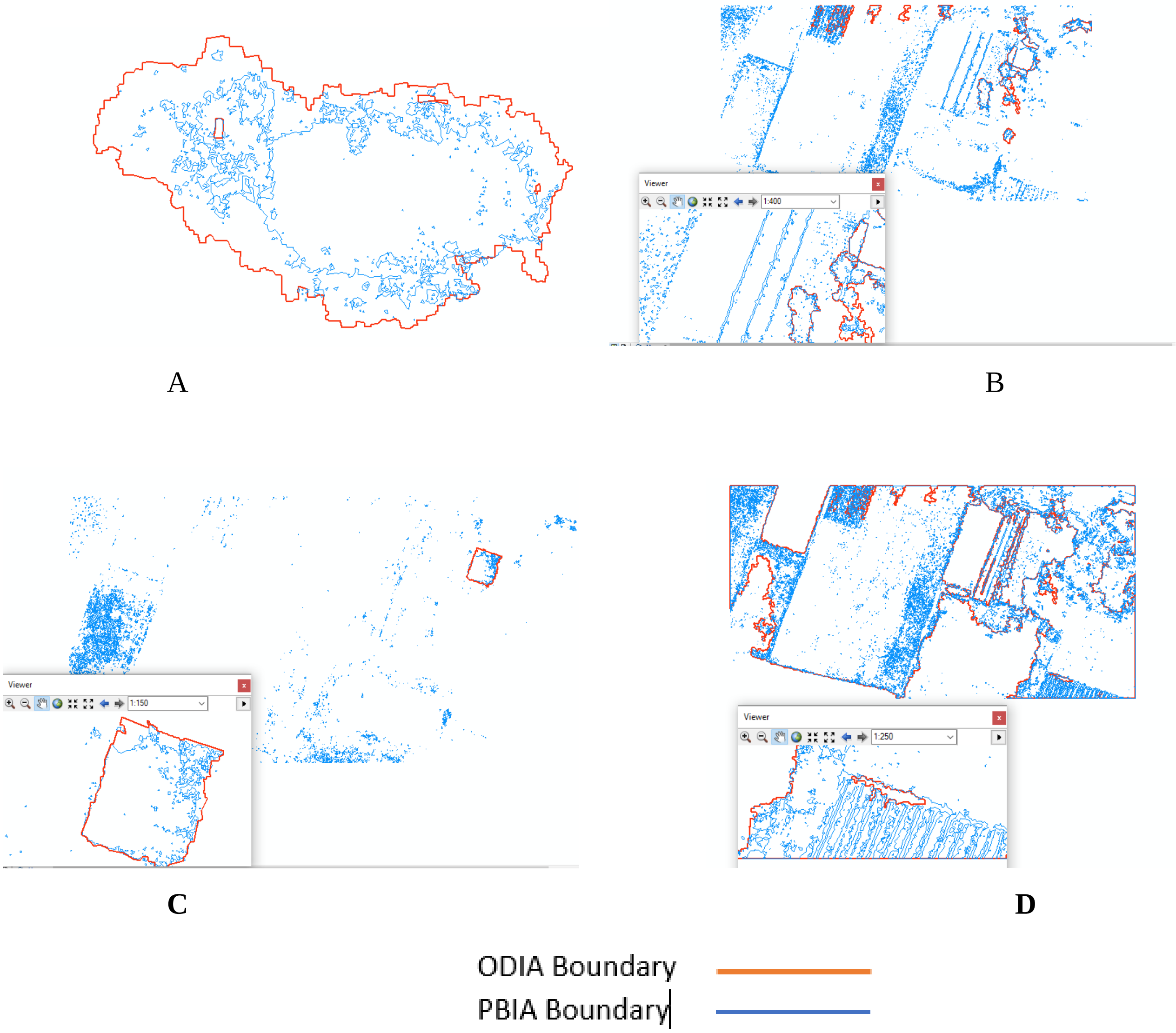

Fig: Comparison of boundary in OBIA & PBIA of Water (A), Shadow (B), Structure (C), Crop(D)

On the contrary, PBIA has more success in delineating shadows (Fig B) as they tend to appear frequently in many places and as it is better responsible to pixel values, it works fine for shadow analysis. For crop classification (Fig D) OBIA provides better continuous boundary. In overall scenario OBIA can create more meaning full objects.

5 Conclusion

Extracting information from image analysis has been a major tool of remote monitoring in recent decades. For more accurate and precise monitoring, advanced methods and tools are being developed constantly. Based on the limitation and new perspective different methods are being applied. In terms of image analysis OBIA has been adapted due to some limitations in the application of PBIA and it has been able to carry attention for the users and researchers. In terms of the land scape of Bangladesh it also seems to be working fine. For further development of this method, more automation tools need to be prepared and tested. As time passes by higher resolution is going to replace the old one and more elevation data from different angel will be more available. Based on that, we will be able to classify objects with height more easily and integrate them with ground reflectance for integrated land classification. It will enable us to have better land monitoring system and we will be able to observe change and growth data on real time in rear future as well.

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