Journal of Geomatics Vol 12 No. 1 April 2018

Comparative analysis of object based and pixel based classification for mapping of mango orchards in Sitapur district of Uttar Pradesh

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(Received: Nov 07, 2017; in final form: April 18, 2018)

Abstract: Pixel based classification often fails to capture the spectral variability in high resolution images while delineating of horticulture crops, especially orchards. It tends to classify individual pixels on the assumption that individual classes contain uniform spectral behaviour but does not include contextual information like texture, shape etc. Salt and Pepper effect is very common in this type of conventional classifiers whenever there is an intra-class variation. These problems can be solved by using Object Based Image Analysis (OBIA) which combines similar neighboring pixels into meaningful geographical objects thereby preserving pixel topology. It takes into account both the spectral as well as spatial properties of the pixels while creating such objects. This study thereby attempts to evaluate the performance of per pixel classification with that of OBIA for mapping of mango orchards in Sitapur district of Uttar Pradesh (UP). High resolution imagery of IRS-Resourcesat 2 - LISS IV for the month of April, May and November have been used. Pixel based classification was performed using Supervised Maximum Likelihood Classifier (MXL) and Object based classification with Segmentation Lambda Schedule. Accuracy assessment carried out after ground truth data collection shows an accuracy of 65% and 92% respectively, which further increased to 96% after visual editing of the later. Comparison of areas obtained from remote sensing estimate and official state figures for last three years (2013-14, 2014-15 and 2015-16) shows a Relative Deviation (RD) of 22% in pixel based and -2.6% in object based, which gets reduced to negligible after post classification editing. Findings of this study concludes object based classification as the state of art for mapping of orchards with high accuracy.

Keywords: Mango Orchards; LISS IV; Classification; Object based image analysis; Accuracy

1. Introduction

Horticulture is one of the fastest growing sectors of agriculture in India and there has been a substantial increase in terms of both area and production of horticulture crops in recent years. However, to promote holistic growth there is a need of a comprehensive and updated database of the current scenario. The traditional approaches of crop estimation involved enumeration based on field surveys, which are time consuming, costly as well as labour intensive. Remote Sensing has evolved as one of the advanced tools to gather accurate information of earth's surface with its repetitive and synoptic coverage in a real time basis and thus can provide an alternative tool for monitoring and studying various aspects of horticultural crops. Studies (Rao et al., 2014) have shown use of remote sensing and geographical information systems to map the potential areas suitable under mango crop cultivation in the parts of Krishna and West Godavari districts of Andhra Pradesh using temporal data sets from AWiFS and LISS-III sensor onboard Resourcesat-1 satellite and IKONOS data. In a separate study horticultural fruit crop mapping was done in Adampur and Hisar-IInd development blocks of Hisar district using the satellite data of World View-2 for the months of March to Dec 2011 and IRS-P6-LISS-III for the month of February (Veena, 2014). The delineation of orchards using geospatial technology can provide additional information for management decision making, such as the determination of fruit yield, the quantification and scheduling of precise and proper fertilizer, irrigation needs, and the application of pesticides for pest and disease management (Panda et al., 2010). Johansen et al., (2009) showed the utility of high resolution data for delineation of banana plantations. However, studies (Whiteside and Ahmad, 2005, Wang et al., 2010, Aggarwal et al., 2013, Hebbar et al., 2014, Yadav et al., 2015, Aggarwal et al., 2016) have shown that conventional per pixel classifiers fails to capture the spectral heterogeneity and contextual information associated with high resolution images and thus results in poor accuracy in delineation of horticulture crops. Object Based Image Analysis (OBIA) on the other hand seeks to create "meaningful" objects by segmenting an image into groups of pixels with similar characteristics based on spectral and spatial properties (Benz et al., 2004). In a study (Basayigit and Ersan, 2015) carried out in Isparta-Turkey for separation of crop pattern using high resolution data of Quickbird-2, object-based classification method was found to give the highest accuracy in higher plants and perennial crops that consist of a mixture of soil and vegetation where elimination of the soil reflection was an essential factor. The accuracy of separation was believed to increase by combining the vegetation index with the object-based classification method. For homogenous patterns such as bare soil, vegetables and feed crops, the supervised classification method was found to be more successful than the object-based method.

In India, the CHAMAN (Coordinated Horticulture Assessment and MAnagement using geoiNformatics) project was initiated with the primary goal of providing area assessment and production forecast of major horticultural crops in selected districts of major states (Ray et al., 2016). This project was launched by Ministry of Agriculture & Farmers' Welfare, under the Mission for Integrated Development of Horticulture (MIDH) and is being coordinated by Mahalanobis National Crop Forecast Centre (MNCFC). Mango is one of the crops identified under CHAMAN project for orchard mapping and area estimation.

Uttar Pradesh (UP) is the leading producer of mango in India and Sitapur district is one of the major mango belts in the state. Very few works have been carried out in mango orchard mapping in this state, using remote sensing data. This study thereby attempts to find the best technique for accurately mapping of mango orchards by comparing the performance of traditional pixel based classifier with that of OBIA in Sitapur district of Uttar Pradesh (UP) as a part of the CHAMAN programme.

2. Materials and methods

2.1 Study area

The Sitapur district of Uttar Pradesh is situated in central plane between 27°.54'- 27°.60' N and 80°.18- 81°.24' E above 100-150m mean sea level (Figure 1). Major horticultural fruit crops cultivated in Sitapur are mango, banana, papaya and guava. The total area under mango in Sitapur district is 15.5 thousand hectares. Other crops include wheat, paddy, urad, sugarcane, mustard, mentha etc.

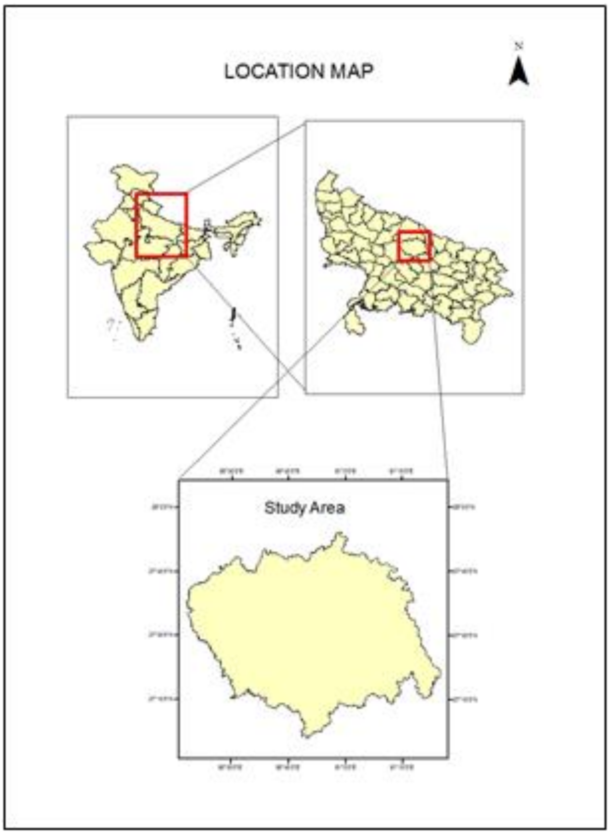

Figure 1: Study Area

2.2 Data

Dataset used, comprised of both spatial and non-spatial nature as discussed below.

Remote sensing data

High resolution ortho-rectified LISS (Linear Self Imaging and Scanning) IV data (with 5.8 m spatial resolution) have been used for this study. The details of satellite datasets are given in table 1.

Months of April, May and November are best suitable for mapping of orchard crops as crop cover is minimal during those time period (Singh et.al., 2016). Also orchards are perennial in nature so that duration of two three years will not make any great difference.

Field data:

Ground truth (GT) survey was carried out in the month of May on the basis of varying spectral signatures as discernible on the satellite image as well as those marked in google earth to identify the competing in the study area. GT was done using CHAMAN App in Android phone for recording the geographic coordinates of orchards or fields, developed by National Remote Sensing Centre. Other ancillary information such as orchard area, row spacing, orchard age, and variety etc. were also recorded during field survey. In total 41 GT points were collected.

Collateral data:

Land Use Land Cover (LULC) map at 1:50k scale, was collected from Uttar Pradesh State Remote Sensing Centre, Lucknow.

Orchard statistics data:

Last 10 years (2006-07 to 2015-16) district level statistical data of mango orchards were collected from the Uttar Pradesh State Horticulture Mission Report and online HAPIS (Horticulture Area Production Information System) portal.

Table 1: Satellite data used

Satellite Data	Sensor	Bands	Path/Row	Date
Resourcesat-2	LISS IV	1,2,3 (Green, Red, NIR)	99-52B	15th April 2013, 12th Nov 2014
			100-52A	15th April 2014,4th May 2015
			100-52C	15th April 2014,4th May 2015

2.3 Satellite data pre-processing

All the scenes of LISS IV were subjected to the following pre-processing steps, viz. geometric correction, conversion of Digital Number (DN) to radiance and radiance to top of atmosphere (TOA) reflectance, before being used for analysis as per the methodology elucidated in Baba Shaeb et al. (2013).

2.4 Normalized Differential Vegetation Index (NDVI) generation

NDVI (Rouse et al., 1974) images were generated from the reflectance images using the equation given below:

$$NDVI = (\rho_{NIR} - \rho_{Red}) / (\rho_{NIR+} \rho_{Red}) \quad \ldots\ldots \quad (1)$$

where ρ is reflectance.

2.5 Pixel based classification

Methodology for pixel based classification has been shown in Figure 2.

Building the vegetation mask

NDVI index is a direct indicator of green cover hence could be used to mask out the urban settlements, water bodies and other non-vegetation classes. The NDVI values ranges from -1 to +1. It is generally below 0 equal for water and non-vegetation classes and shows a positive values for normal to healthy vegetation. Here, the NDVI value of 0. 3 was selected as a threshold and the theme classes having value below the threshold were masked out and a binary vegetation mask was thereby generated.

Use of LULC to delineate forest/natural vegetation class

In this study the target object to be delineated was orchards, hence the possibility of mixing of orchard and forest/ natural vegetation classes could not be overlooked as the near similar spectral signatures and tone/ texture of these two classes may lead to miss classification. The LULC map was used to address this issue and major forest classes were removed.

Image classification

Training samples were generated using ground truth data as well as taking reference from google earth and supervised classification using Maximum Likelihood Classifier (MXL) technique was performed over the masked images. MXL classifier assumes that the population from which training samples are drawn are multivariate normal in their distribution (Navalgund et.al., 2007).

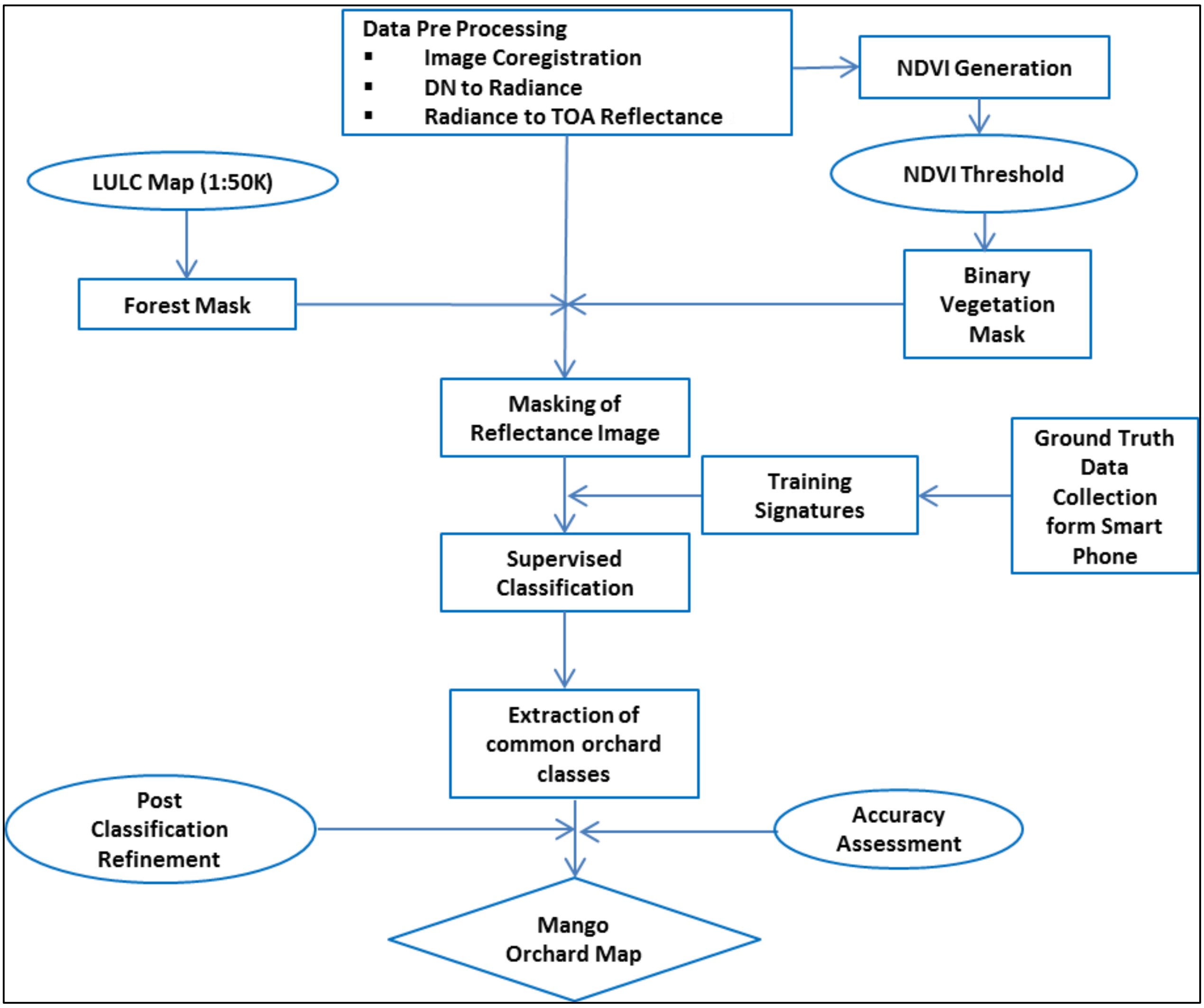

Figure 2: Methodology for Pixel Based Classification

Extraction of common orchard classes

All the scenes were classified separately and the common orchard area found in them were combined to extract the common orchard area. Orchards are perennial in nature and show similar spectral signatures in all the scenes unlike field crops which have peak spectral values at the time of maximum vegetative stage and weak spectral values at the time of harvest.

Post classification refinement

Post classification refinement of the derived area was performed to remove the redundant/misclassified small clusters by re-verifying with google earth images and visual comparison of tone and texture. The final mango orchard map was derived.

Accuracy assessment

Accuracy assessment is an important step in the process of verifying and validating the analysed remote sensing data. The most common way to express classification accuracy is the preparation of error matrix also known as confusion matrix or contingency matrix (Stehman, 1997). Such matrices show the cross tabulation of the classified land cover and the actual land cover reported by ground truth and calculation of overall accuracy of classification.

2.6 Object based classification

Image segmentation is the first step in object-based image analysis (Castilla and Hay, 2008). This process separates the image into segments that are arranged according to the classification of spectral, geometric, textural and other characteristics of the objects (Veljanovski et al., 2011). There are many techniques to perform image segmentation and those techniques can be categorized into three classes: thresholding/ clustering, region based and edge based (Fu and Mui., 1981, Haralick and Shapiro, 1985).

In this study object based classification of orchard areas is based on Segmentation Lambda Schedule algorithm (Govedarica et al., 2015) which is available as part of Objective Erdas Imagine software 2015.

Raster pixel processor

First step is the processing of pixels with Single Feature Probability (SFP) function. It computes a probability metric (between 0 to 1) to each pixel of the input image based on its pixel values and training samples (orchards). Pixels with values similar to those that represent the orchard class, will have a higher probability value. Lower probability value is assigned to pixels that differ significantly from the pixels that represent an orchard class.

Raster object creator

The resultant probability pixel layer is then grouped into meaningful objects based on Segmentation Lambda Schedule (FLS) algorithm. Unlike normal segmentation parameter it considers spectral as well as texture, size and shape while grouping of homogenous pixels depending upon the weights assigned while grouping (Imagine

.

Objective User Guide, 2015). Segment size also depends upon pixel: segment ratio. In this case the average size of the segment is set to 250.

The spectral information was given a higher weightage as compared to texture (Measured as mean of DN values to segment) since the base data is multispectral LISS IV. Segmentation parameters used in this study has been shown in table 2.

Table 2: Segmentation Parameters

Spectral	Texture	Shape	Size
0.7	0.5	0.3	0.3

Raster object operator

In order to improve the results of the segmentation, probability filter was used. This operator removes all raster objects whose zonal probability mean is less than the specified Minimum Probability. In this case, two probability filters were chosen one at 0.3 (P1) and another at 0.1 (P2) as shown in Figure 3. In P1(0.3) The number of orchard pixels captured were less owing to its higher threshold value than in P2. However, lowering the threshold led to inclusion of some non-orchard pixels also which has to be refined by manual editing later on.

Raster to vector conversion

Raster Objects created in previous step were then converted to the vector objects using polygon trace.

Vector object operator

Smooth filter was then applied to smoothen the boundaries of orchard polygons. Smoothening factor of 0.5 was chosen which was found to be optimum.

Vector object processor

This step performs operation on vector layer. Area and Eccentricity factors were considered to clean up the vector objects. Higher values of Eccentricity (0.9) helps to eliminate linear features. In this case row plantations mixing with mango orchard classes were removed.

Vector clean up operator

Cleaning of vector layers was done in Arc GIS by onscreen visual interpretation and applying the non-vegetation mask to remove scrub land/ wetlands and erroneous vector object if any. The final mango orchard map was prepared by combining the orchard areas of all the overlapping/two date scenes.

Accuracy assessment

Mapping accuracy (Hebbar et al., 2014) was carried out with the ground truth points.

$$MA = \frac{No\ of\ correctly\ classified\ GT\ points}{Total\ number\ of\ GT\ points} \quad \ldots\ldots\ldots\ldots\ldots(2)$$

Figure 4 shows the methodology.

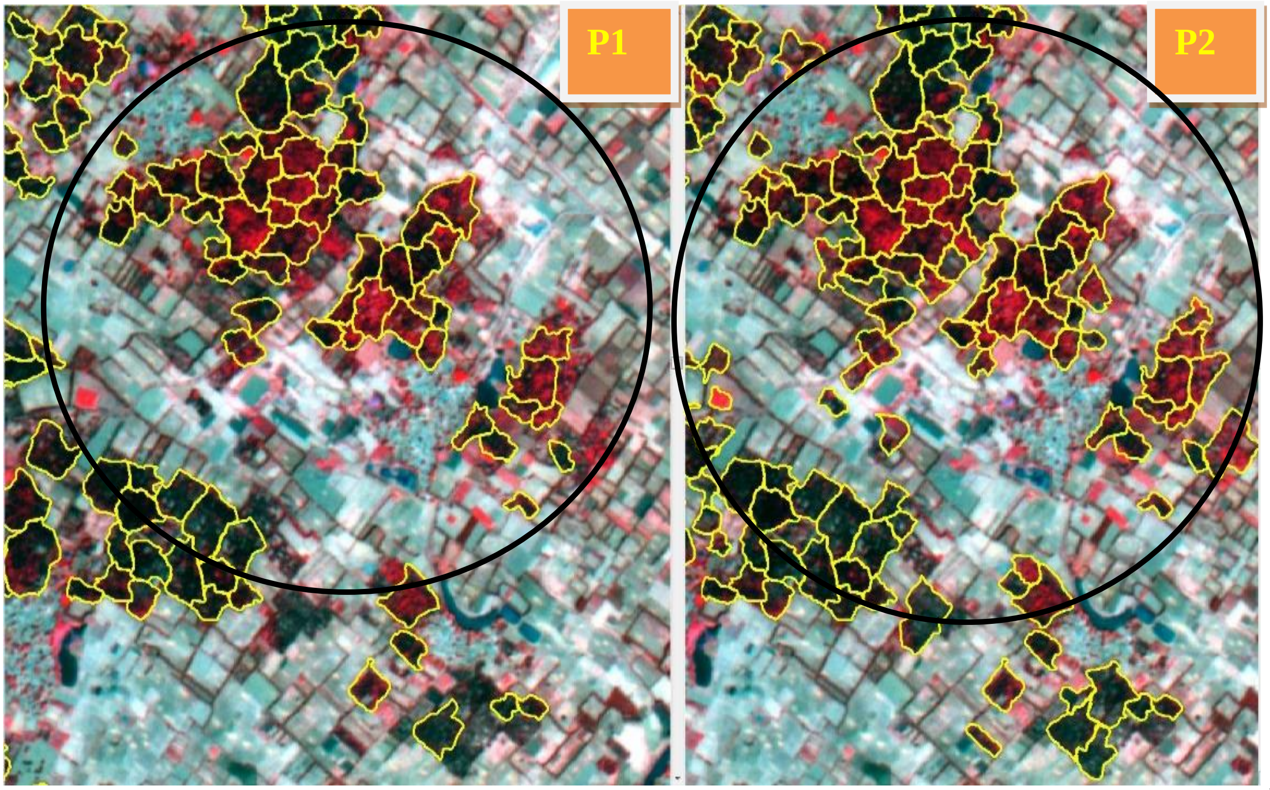

Figure 3: Section of study area showing segmentation at two probability levels (Image: Resourcesat 2-LISS IV, 4th May, 2015)

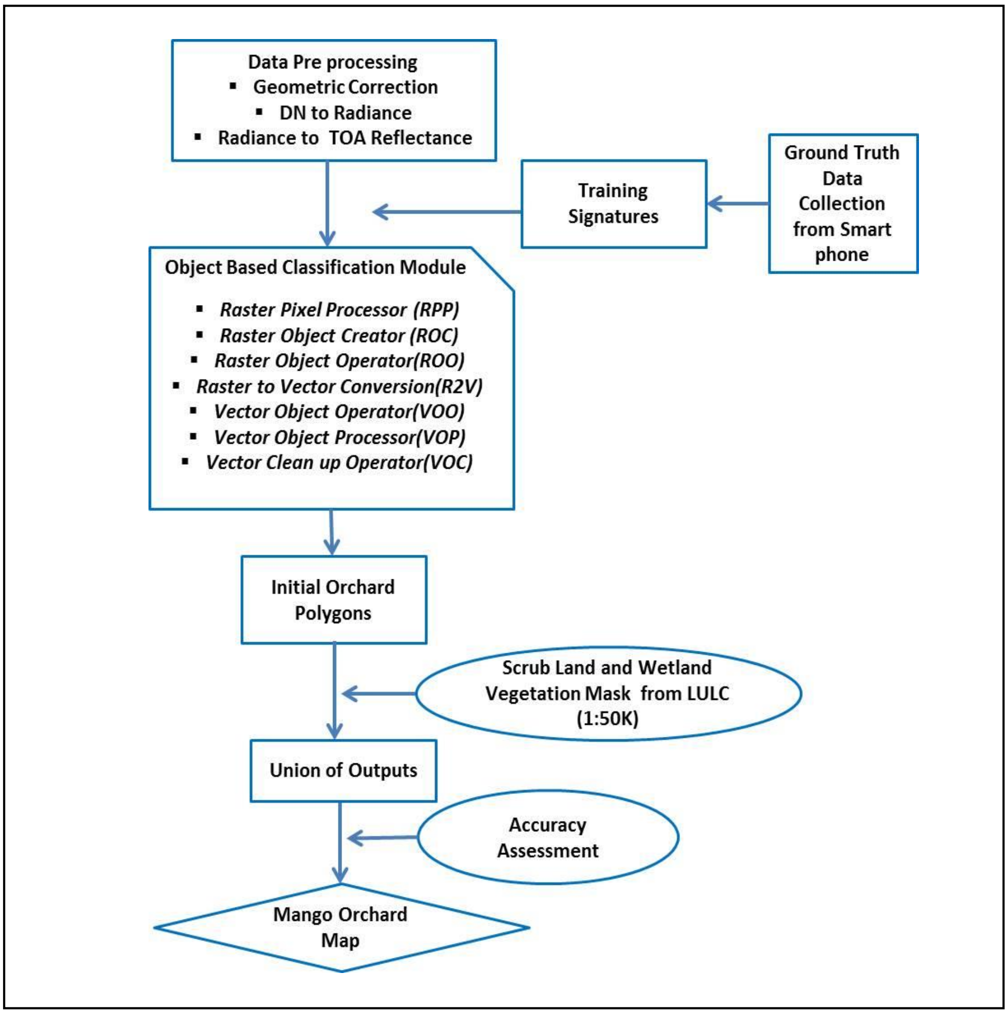

Figure 4: Methodology for Object Based Classification

4 Results and discussions

3.1 Comparison between pixel based and OBIA

Orchard plantations have a characteristic row and column pattern of planting with wide spaces in between two trees which gives soil exposure or weak NDVI values. In pixel based approach pixels are grouped in a class based only on its spectral characteristics, hence those spaces are treated as different class resulting in non-uniform class or gaps in final classified output which led to area under estimation as shown in Figure 5. It also fails to include the boundary and edge pixels. Young orchards exhibiting weak spectral signature and texture almost similar to agricultural field or fallow are also misclassified. On the other hand, OBIA considers group of pixels within an orchard as meaningful objects based on spectral, tonal, textural, size and shape characteristic and thus captures within orchard variability and heterogeneity. The final output shows well demarcated orchard boundaries distinctly different from field and fallow classes as shown in Figure 5. Thus the area estimation is quite reliable in OBIA. Manual digitization on high resolution google earth images gives even more clarity which is however good for a small part of the study area but is a crude and time consuming method for making district level orchard maps. OBIA is semi-automatic in nature and the output can also be overlayed on high resolution images for further refinement if needed.

3.2 Accuracy assessment

Accuracy assessment carried out after ground truth (GT) data collection shows an accuracy of 65% in pixel based and 92% in object based, which upon further refinement increased to 96%. Table 3. shows comparison of area obtained from both the approaches with the average statistics for three years obtained from HAPIS (Horticulture Area and Production Information System) online portal shows a Relative Deviation (RD) of 22% in pixel based and -2.6% in object based approach has been observed. After post classification editing in the latter case the RD got reduced to minimal.

Table 3: Comparison of final Area (Hectares) estimates through different classifiers

Pixel Based Estimate	Object Based Estimate	Horticulture Statistics Average of 3 years (2013-14 to 2015-16)
12117	15435	15379

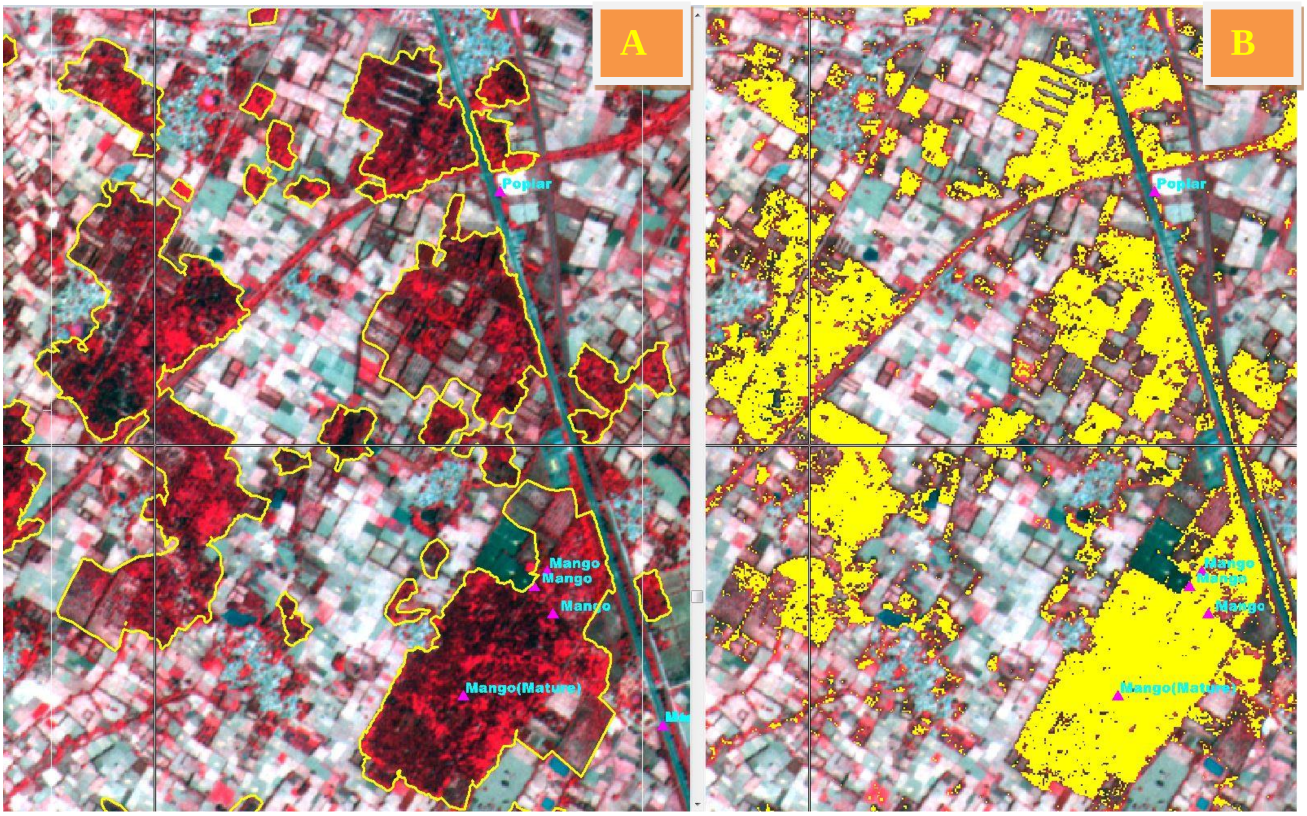

Figure 5: Part of study area showing comparison between two approaches A: Object Based Classification and B: Pixel Based Classification (Image: Resourcesat 2-LISS IV; Date: 4th May, 2015)

Conclusion

The current study shows the comparison of traditional pixel based classifier with that of Object Based Classification (OBIA) for mango orchard mapping in Sitapur. It was observed that conventional per pixel classifiers though convenient to use in homogenous areas, fails to capture the heterogeneity and intra-class variability with the increase of spatial resolution. The property of class uniformity breaks in former case leading to less accuracy, chances of mixed pixels, salt and pepper effects. It often fails to capture the differential canopy reflectance owing to different age groups of trees in an orchard as well as intercropping, soil exposure etc. On the other hand, in OBIA similar pixels are converted into objects, based on texture, spectral and spatial parameters like size, shape, eccentricity, compactness and proves far more superior in terms of capturing orchard heterogeneity. It also reduces the chance of occurrence or redundant and mixed pixels. It can be concluded that OBIA is the state of art in orchard mapping as compare to pixel based classification. The current study is however limited to use of high resolution multispectral data of LISS IV. Further research work is needed to differentiate between different competing orchards viz. mango and litchi by inclusion of very high resolution satellite data of sub meter level spatial resolution where individual tree crowns can be detected.

Acknowledgment

The above study was carried under the CHAMAN project of Department of Agriculture, Cooperation and Farmer's Welfare, Ministry of Agriculture and Farmers' Welfare. Authors wish to thank State Horticulture Department and Uttar Pradesh Remote Sensing Applications Centre (RSAC-UP) for their cooperation and logistic support for carrying out ground truth in Sitapur district. Authors are thankful to Dr Pradeep Kumar, Assistant Director, MNCFC for critically reviewing the paper.

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