HIERARCHICAL CLASSIFICATION FOR ASSESSMENT OF HORTICULTURAL CROPS IN MIXED CROPPING PATTERN USING UAV-BORNE MULTI-SPECTRAL SENSOR

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ABSTRACT:

Assessment of horticultural crops under mixed cropping system has been a challenge, both for horticulturists and also to the remote sensing communities. But the recent developments in wide range of sensors onboard Unmanned Aerial Vehicles (UAVs) has opened up new possibilities in identification, mapping and monitoring of horticultural crops. This paper presents the results made from a pilot exercise on horticultural crop discrimination using Parrot Sequoia multi-spectral sensor onboard a UAV. This exercise was carried out in Nongkhrah village, Ri-Bhoi district of Meghalaya state located in the north eastern part of India having mixed horticultural crops. A two level hierarchical classification system was followed for identification and delineation of the major horticultural crops in the village. Parrot Sequoia multi-spectral sensor having four bands has been found to be effective in discrimination of horticultural crops based on variation in spectral response of six horticultural crops *viz.,* pineapple, banana, orange, papaya, ginger and turmeric using three commonly used indices *viz.,* Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge Index (NDRE) and Green Normalized Difference Vegetation Index (GNDVI). NDVI and GNDVI showed nearly similar spectral response, whereas separability among the horticultural crops significantly improved with the use of NDRE. The first level of classification involving the five broad land cover classes has resulted an overall accuracy of about 91%, whereas the second level of classification for delineating the five selected horticultural crops has provided an overall accuracy of 79.8%.

1. INTRODUCTION

The horticulture sector has become one of the major drivers of growth in agricultural sector, and over last few years, India has witnessed a rise in horticulture production, which has even surpassed total production of food grains. The area under horticulture has grown by 2.6% per annum over the last decade and annual production has increased by 4.8%. Horticultural crop production was 311.71 million tonnes from an area of 25.43 million hectares during 2017-18 as per record of Ministry of Agriculture and Farmers Welfare, Govt. of India, 2018-19 (http://agricoop.gov.in/statistics/state-level). Timely availability of the horticultural statistics is of paramount importance to the administrators, policy makers and research workers, but there is no established methodology for collection of reliable statistics under horticultural crops in hilly terrain like in the part of the north east India (Sahoo et al., 2005). Remote sensing approaches have been employed in different aspects of horticulture *viz.,* horticultural crop identification (Panda & Hoogenboom, 2009; Thomas et al., 2008; Usha & Singh, 2013 and Yang et al., 2008), acreage and production estimation (Yadav et al., 2002; Johnson et al. 2003 and Nageswara Rao et al., 2004), identification of suitable sites for horticultural crops (Krishna Rao et al., 2014) etc. There is still requirement in terms of plot level management of horticultural crops using very high resolution images (Panda et al., 2010) employing advanced algorithms, thereby improving the accuracy of assessment (Min et al., 2008; Palaniswami et al., 2006 and Yang et al., 2008). It is in that sense the UAV remote sensing technology adding new dimensions in assessment and monitoring of horticultural crops through the use of multi-spectral digital airborne sensors (Pinter et al., 2003; Bühler et al., 2007; Whitehead & Hugenholtz 2014; Morris, 2013; Gini, 2014 and Pajares, 2015). UAVs enable users for many agricultural and horticultural applications such as crop acreage and production estimation (Stroppiana et al., 2015), growth and quality assessment (Thenkabail et al., 2002; Herwitz et al., 2004), generation of detailed map of vegetation assemblages at the species level (Schuster et al., 2012), crop stress detection (Carter, 1993 and Smith et al., 2004), damage assessment (Kim et al., 2002; Handique et al., 2016 and Zhang et al., 2002) etc. With the possibility of increased spatial and temporal resolution provided by UAV-borne sensors, there has been a shift towards precision, or site specific, crop management activities with remote sensing inputs such as acreage estimation of multiple horticultural crops and also to study within-field variability (Petrie & Walker, 2007 and Hunt et al., 2014).

In hilly terrain like north eastern region (NER) of India, there are challenges for remote sensing applications due to small and fragmented land holding, terrace cultivation, mixed cropping pattern, cloud cover, hill shade etc. (Sahoo et al., 2005). Under such conditions, UAVs have emerged as an alternative and complementary solutions for remote sensing based acreage estimation and crop condition assessment (Ustuner et al., 2014). Different sensors developed with optical, microwave and thermal region of electromagnetic spectrum provide new possibilities for studying within field variations (Hunt et al., 2010 and Karpina et al., 2016). A wide range of vegetation indices have been found to be effective in delineating crops based on their spectral responses. There is also scope of improved statistical estimates for using very high resolution data acquired from satellites and UAVs (Handique, 2012). It is of interest to delineate horticultural crops at village level following a hierarchical classification approach and assess the accuracy of the classification. This paper presents the results and observations made from a pilot exercise on identification of horticultural crops in mixed cropping pattern using UAV-borne multi-spectral sensor.

2. METERIALS AND METHODS

2.1 Study Area

The study was carried out in the Nongkhrah village located in the eastern part of Meghalaya state of India. The study village lies between longitude 91°52'26.96"E and 91°53'49.60"E and between latitude 25°54'44.92"N and 25°55'49.80"N (Figure 1). The physiography and the climate favour a large number of crops in the district. Among horticultural crops, pineapple, orange, banana, papaya, ginger and turmeric are important. The horticultural crops are mostly grown in and around the houses without following any systematic pattern. Pineapple is grown abundantly in the village and is the main commercial crop for the villagers. Some crops are grown as multi-storeyed crops such as top canopy is covered by orange and the lower canopy by turmeric or ginger. In few households, inter-cropping of pineapple and orange was also observed.

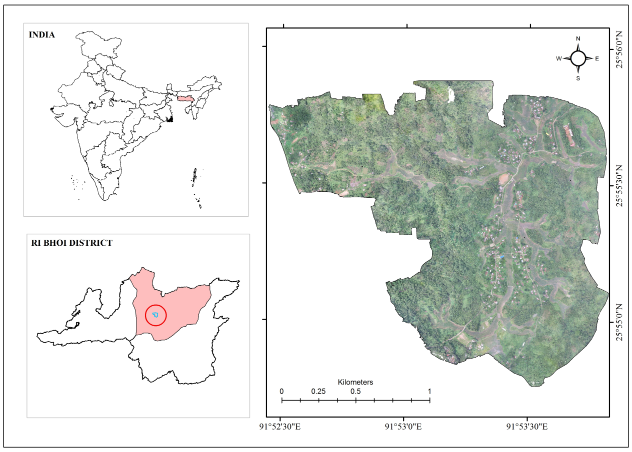

Figure 1. Location map of study village

2.2 Sensor platform and sensors

A light weight hexacopter DJI Matrix 600 was employed for the survey (Figure 2). The M600 is a six-rotor system with a payload capacity of 6.0 kilograms, making it ideal for the full range of DJI's Zenmuse gimbals. The M600's propulsion system is dustproof to simplify maintenance and durability. The M600 features an extended flight time and a 5 km long range, ultra-low latency HD image transmission for accurate image composition and capture. The M600 uses sine-wave driven, intelligent to ensure that it performs accurately, safely and efficiently.

It was important to ensure the location accuracy of the pixels captured by the camera mounted in the drone on the ground. The UAV is equipped with GPS, for inflight recording with accuracy of +/- 1.5 meter. During each flight, the camera was fixed on a two-axis gimbal, pointing vertically downwards covering the entire field to generate the ortho-mosaic images in post-processing (Percivall et al., 2015 and He et al., 2012). Absolute camera position and orientation uncertainties obtained during the flight was within the error limit (1-3 meters).

Figure 2. DJI Matrix 600 (Source: www.dji.com)

2.4 Parrot Sequoia sensor

The Sequoia sensor comprised of two sensors i) the multi-spectral sensor and ii) the sunshine sensor. (Figure 3) The multi-spectral sensor containing five bands *i.e.* Green, Red, Red Edge, Near Infrared (NIR) and one RGB Sensor mounted underneath the drone facing towards the Nadir. The sensor has length of 59 mm, width of 41 mm and height of 28 mm. The central wavelengths of the four bands are given in Table-1.

Table 1. Details of bands in the multi-spectral sensor
(Source: www.parrot.com)

Band Name	Central Wavelength (in nm)	Band width (in nm)
Green	550	40
Red	660	40
Red edge	735	10
NIR	790	40

Figure 3. Parrot Sequoia sensor and sunshine sensor
(Source: www.parrot.com)

The sunshine sensor was mounted above the drone facing towards the zenith or the sky. The sunshine sensor assisted in adjusting the light variability, which occurred during the same acquisition or two different acquisitions taken at two different times of the day of the earth features. This sunshine sensor was very important in the clear as well as overcast conditions of north east India thus improving the results. The sunshine sensor has length of 47 mm, width of 39.6 mm and height of 18.5 mm.

The Parrot Sequoia sensor has a built-in GPS module. While the GPS modules integrated into UAV made it possible to keep an eye on their position during a flight, the Sequoia GPS module allowed the position of each captured image to be identified. The GPS module made it possible to significantly increase the precision of the data collected by the sensor without using data collected by the transport platform: plane, drone, tractor, etc. The integration of a GPS module into the sensor fulfilled the objective of rendering Sequoia fully autonomous, thus dispensing with image monitoring by the autopilot of the drone. As a result, it could be used in any drone.

The survey in the village was consisted of four key steps: acquisition of high resolution UAV images using the low altitude UAV-camera system; post-processing of UAV images including ortho-mosaicing, geo-referencing, extraction of colour vegetation indices from post-processed othomosaic images. We have adopted World Geodetic System 1984 (WGS 84) datum with UTM coordinate system for geo-referenced images.

The height of the UAV was maintained at 120m. At this height ground resolution obtained was about 5cm. Multiple images were obtained at the speed of one image per 5 seconds. The images and the videos were transferred to the computer and processed with Pix4D software (https://www.pix4d.com/). Mosacing of the images was done to have seamless boundaries of the scenes.

2.3 Hierarchical classification approach

A hierarchical classification approach was applied for delineating the horticultural crops based on object based image analysis approach (OBIA). In the first step, through segmentation, all pixels within a segment was assigned to one class, eliminating the within-field spectral variability and mixed pixels problems associated with pixel-based approaches using eCognition software Ver 4.0 (https://geospatial.trimble.com/). Segmentation is based on pre-defined parameters *viz.*, compactness, shape, and scale. It required the understanding of size and shape of farm fields in the study village. Extractions of image objects depend on the approach of a trial-and-error, and the scale parameters segmentation values are specified according to proceeding experience (Ma et al., 2017). Several studies have confirmed the superiority of OBIA over pixel-based classifications, especially in case of heterogeneous agricultural and horticultural crop areas (Blaschke, 2010; Myint, 2006; Laliberte & Rango, 2009; Myint et al., 2011 and Peña-Barragán et al., 2011). Segmentation was followed by grouping of the homogenous segments to derive the broad land-use classes in the village (Aguilar et al., 2015 and Park et al., 2016). This is followed by digital classification of the horticulture class based on spectral response of the selected horticultural crops through generation of three important vegetation indices *viz.,* Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge Index (NDRI) and Green Normalized Difference Vegetation Index (GNDVI) to observe the possibility for discrimination of the selected horticultural crops. Details of the three vegetation indices are given in Table 2. During classification, 70/30 proportion of samples for training and validation purposes was used. A random selection of 70% of the samples were used for training (the RF bootstrap sample), and the remaining 30% of the samples were used in the validation (the RF out-of-bag sample) of the classification accuracy. Validation in the identified sample locations points made with the help of the farmers in the selected village. Standard class-based confusion matrix and subsequent accuracy metrics (including omission error, commission error, overall accuracy and kappa co-efficient) were derived and interpreted (Congalton & Green, 1999).

3. RESULTS AND DISCUSSION

3.1 Level-1 classification for broad land-use classes

The first level of classification involving the five broad land-use classes *viz.,* agriculture, horticulture, fallow land, forest, scrub, settlement, road and water body resulted overall accuracy of about 91% of accuracy. The class under agriculture include the field crops like rice and maize in the village. Since the UAV images were acquired during the period of beginning of transplantation of the rice crops, rice fallow areas are put under the fallow land class. Farmers were seen preparing the land for different vegetable crops. But these areas have not been taken into account in the selected horticultural crops under the study and put in the fallow lands. Dominant horticultural crops in the village *viz.*, pineapple, banana, orange, papaya, other few standing vegetable crops are taken in the horticulture class. Ginger and turmeric which are prominent horticulture and also the spice crops in the village have been put in the horticulture class. Forest class include the community forest attached to the village and also the bamboo areas. Significant amount of scrub lands in the village include short bushes and wild grasslands. Other three categories *viz.,* settlements (houses), Roads and water bodies could easily be separated (Figure 4, Figure 5, Figure 6). As it is observed from the contingency matrix (Table 4), there was overlapping of segmented polygon for agriculture and horticulture classes, particularly in the vegetable growing

Table 2. Details of vegetation indices used in the study

Index	Formula	Spectral Bands or Wavelengths(nm)	Sensor	References
Normalized Difference Vegetation Index	NDVI = (NIR- Red)/ (NIR+Red)	Red : 660 NIR :790	UAV Based Parrot Sequoia Multi-spectral Sensor	Tucker, 1979
Normalized Difference Red Edge Index	NDRE = (NIR- Red Edge)/ (NIR + Red Edge)	Red Edge :735 NIR : 790	UAV Based Parrot Sequoia Multi-spectral Sensor	Schuster et al., 2012
Green Normalized Difference Vegetation Index	GNDVI = (NIR- Green)/ (NIR + Green)	Green : 550 NIR : 790	UAV Based Parrot Sequoia Multi-spectral Sensor	Ustuner, et al., 2014

Figure 4. Part of Nongkhrah village with different land use

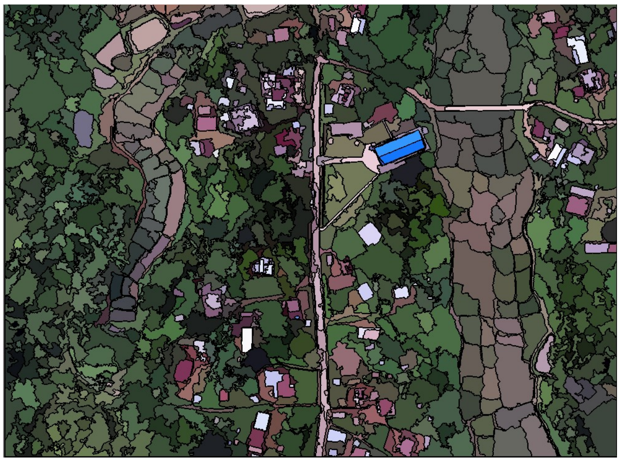

Figure 5. Segmented image of part of the Nongkhrah village

areas resulting a user's and producer's accuracy for horticulture class as 0.89 and 0.93 respectively. Orange plantations in the village resembles to the forests in the village thereby contributing the omission error of the horticulture class (0.15).

This level-1 classification for the broad land-use classes yielded acceptable accuracy with regards to our class of interest, that is the areas under various horticulture crops. Similar results were reported by Ahmed et al., 2017 following a two-level hierarchical classification approach.

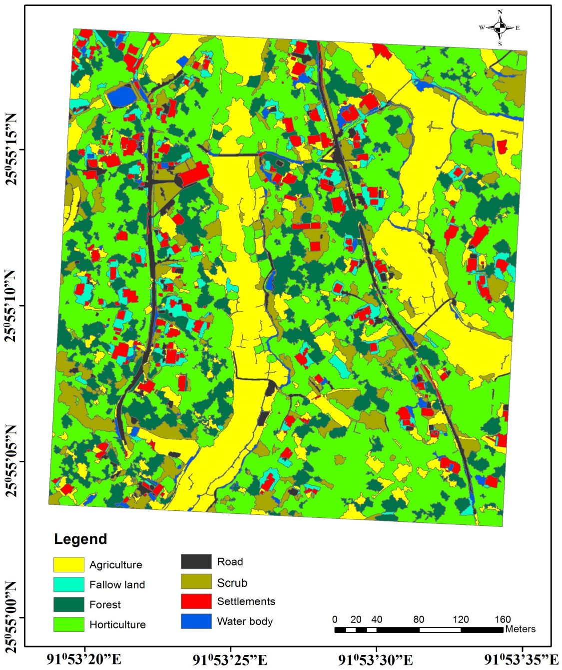

Figure 6. Classified image of land cover classes for part of the village (level-1)

3.2 Level-2 classification for selected horticultural crops

The level-2 classification for delineating the major horticultural crops was carried out in the villages. Four fruit crops *viz.,* pineapple, banana, orange and papaya and two spice crops *viz.,* ginger and turmeric were considered for identification through spectral analysis using the three commonly used indices (NDVI, NDRE and GNDVI). NDVI and GNDVI showed nearly similar spectral response. Pineapple, which grows abundantly in the village with row plantations, has exhibited highest values for all the three indices. (NDVI=0.694, GNDVI=0.584 and NDRE= 0.232). Ginger and turmeric grown in small scale in the village have values in the lower ranges in all the three indices. Ginger has the least values in NDVI (0.356), GNDVI (0.245) and NDRE (0.025).

The lower vegetation index value for ginger and turmeric crops due to the fact that these two crops are towards the maturity stage, leaves started yellowing. Another reason for lower values in the vegetation indices is due to sparse pattern of the leaf structure having exposed soil. When we considered the separability of the selected crops with the indices, it was observed that pineapple and the orange crops were closely placed in terms of NDVI and GNDVI (difference ranges from 1% to 11% respectively). On the other hand, there were significant differences observed in case of GNDVI, between orange and ginger crops. Separability among the crops improved significantly with the use of NDRE. The difference among the selected horticultural crops ranged between 34% to 78%, the highest between the papaya and the ginger. The major gain in using the NDRE is that average difference of its range of values went up to 51% as compared to 19% in case of NDVI and 34 % in case of GNDVI (Figure 7). Similar observations reported earlier by Hunt et al., 2010.

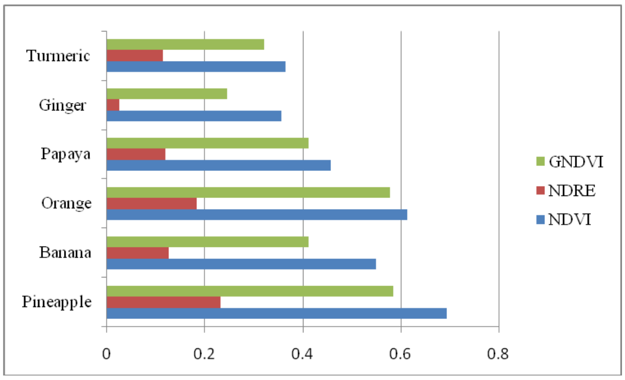

Figure 7. Mean values of vegetation indices for the selected horticultural crops

Correlation among the selected indices revealed that there is closer relation with NDVI and GNDVI (r=0.91) against r=0.74 between NDVI and NDRE and r=0.71 between GNDVI and NDRE.

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Table 4. Confusion matrix for Level-1 classification (Land cover classes)

	Agriculture	Horticulture	Fallow land	Forest	Scrub	Settlement	Road	Water body	**Sum**	User's accuracy	Commission Error
Agriculture	42	5	0	0	0	0	0	0	**47**	0.89	0.11
Horticulture	0	34	1	3	0	0	0	0	**38**	0.89	0.11
Fallow land	2	0	27	0	0	0	0	0	**29**	0.93	0.07
Forest	0	0	0	14	0	0	0	0	**14**	1.00	0.00
Scrub	1	1	0	0	16	1	1	0	**20**	0.80	0.20
Settlement	0	0	1	0	1	8	0	0	**10**	0.80	0.20
Road	0	0	0	0	0	0	16	0	**16**	1.00	0.00
Water body	0	0	0	0	0	0	0	14	**14**	1.00	0.00
Sum	**45**	**40**	**29**	**17**	**17**	**9**	**17**	**14**	**188**		
Producers Accuracy	0.93	0.85	0.93	0.82	0.94	0.89	0.94	1.00		Overall accuracy =91%	
Omission Error	0.07	0.15	0.07	0.18	0.06	0.11	0.06	0.00		Kappa co-efficient= 0.89	

Table 5. Confusion matrix for Level-2 classification (horticultural crops)

	Pineapple	Banana	Orange	Papaya	Ginger	Turmeric	**Sum**	User's accuracy	Commission Error
Pine Apple	23	0	0	1	2	3	**29**	0.79	0.21
Banana	0	20	0	3	0	0	**23**	0.87	0.13
Orange	1	0	13	0	0	0	**14**	0.93	0.07
Papaya	0	2	0	11	0	0	**13**	0.85	0.15
Ginger	2	1	0	0	13	3	**19**	0.58	0.42
Turmeric	2	0	1	0	2	11	**16**	0.69	0.31
Sum	**28**	**23**	**14**	**15**	**17**	**17**	**114**		
Producer's Accuracy	0.82	0.87	0.93	0.73	0.76	0.65		Overall Accuracy= 79.8%	
Omission Error	0.18	0.13	0.07	0.27	0.24	0.35		Kappa co-efficient = 0.75	

This suggests that employing of either NDVI or GNDVI will result in similar classification accuracy as there is no significant gain in additional information due to the use of GNDVI, whereas there is no close relation between NDVI and NDRE and between GNDVI and NDRE (Table 3).

Table 3. Correlation matrix of vegetation indices

	NDVI	*NDRE*	*GNDVI*
NDVI	1		
NDRE	0.743113	1	
GNDVI	0.914581	0.709312	1

The second level of classification for delineating the six selected horticultural crops has resulted overall accuracy of 79.8% (Table 5). Ginger and turmeric have contributed in reducing both user's and producer's accuracy. The highest omission errors have been observed in case of turmeric and papaya (0.35 and 0.27 respectively), where as highest commission error has been observed in case of ginger (0.42) followed by turmeric (0.31). Orange crop, which is grown as plantation with distinct tree spacing was easy to delineate, which has also exhibited highest users and producers accuracy (93%).

Considering the observations of the study, it may be felt the necessity of using more spectral bands for spectral separation of horticultural crops as separability of minor crops yet to reach to level of acceptance for operational use. Use of hyper-spectral sensors onboard UAVs may be explored in such conditions (Yang et al., 2007).

CONCLUSION

Horticultural statistics at large scale (village level/field level) is extremely important for the administrators and famers for production estimation, processing, marketing etc. The conventional satellite remote sensing approaches could not yield the desired level of accuracy due to distinct physiographic and social features of north eastern region of India under small & fragmented holding, shifting cultivation, terrace farming in steep slope, persistent cloud cover during most part of the year etc. Use of UAV remote sensing technology in horticultural system may significantly improved the efficiency in terms of providing a solution for rapid assessment of horticultural crops at the plant/species level with acceptable accuracy. Use of UAV borne hyperspectral images may further enhance the scope of delineation of multiple crops including the minor crops such as vegetable crops. However for various operational applications in horticulture sector, issues like long endurance period, procedures for classification of large volume of heterogeneous very resolution data need to be effectively addressed.

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