

Discrimination and Plot Wise Area Estimation of Seasonal Crops from High Resolution World View 2 Multispectral Image

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Abstract

In the present study a semi-automated process model, named as ‘Accelerated Plot Based Crop Discrimination’ (APCD), has been developed for identifying and discriminating seasonal crops as well as estimating their plot level coverage area using very high resolution satellite image as this type of information plays a vital role in any agricultural policy making. The overall accuracy calculated is 89.10% with Kappa coefficient being 0.87. The plot wise crop coverage area estimated from the process model is also very closely matching with area obtained from detailed GPS survey data. To cross check the discrimination achieved from WV 2 multispectral data, hyperspectral measurements of the same crops are also collected by the field spectroradiometer and the statistical indices calculated from it shows similar spectral pattern as well as good co-relation ($R^2 > .90$) with the same indices generated from the image. Findings of this study suggest that (1) plot level crop discrimination is achievable through pixel based approaches, (2) best discrimination can be achieved from NIR 1, NIR 2, Red Edge and Green bands combinations of WV 2 and (3) crop wise coverage area can be correctly estimated through the application of Raster Statistics for Vector (RSV) operation.

Key words: Crop discrimination, band indices, FCC, ISODATA, Co-Occurrence, J-M distance, liner regression, area estimation, Raster Statistics for Vector.

1. Introduction

Reliable information on crop type identification, production, area and yield estimation is essential for agricultural and environmental policy making and overall economic development (Beach *et al.*, 2008; Pena-Barragan *et al.*, 2011; Leeuw *et al.*, 2010; Hayes & Decker, 1996). In India various regional level projects have been carried out to estimate crop acreage and production at regional level. Application of remote sensing technology could not be used for plot level seasonal crop discrimination due to limitations in spectral and spatial resolutions. World View II 8 band multispectral data have opened up the possibility for crop type identification and acreage estimation at plot level.

A semi automated process model termed Accelerated Plot-based Crop Discrimination (APCD) has been developed for plot wise identification and area estimation of seasonal crops using one time high resolution data. The first step to develop the process for crop discrimination is to generate image composites for visual separation of different crops. Three custom spectral indices are generated between NIR 1, NIR 2, Red-Edge and Green bands showing maximum spectral separation. The indices computed by utilizing NIR and Red-Edge bands have generally shown to be more accurate in case of crop type classification than the traditional ones (Ustunera *et al.*, 2014; Novotná *et al.*, 2013). Category raster output formed by the ISODATA algorithm is compared with the composites and the band indices for acquiring the spectral discrimination between the crops. Once the visual and

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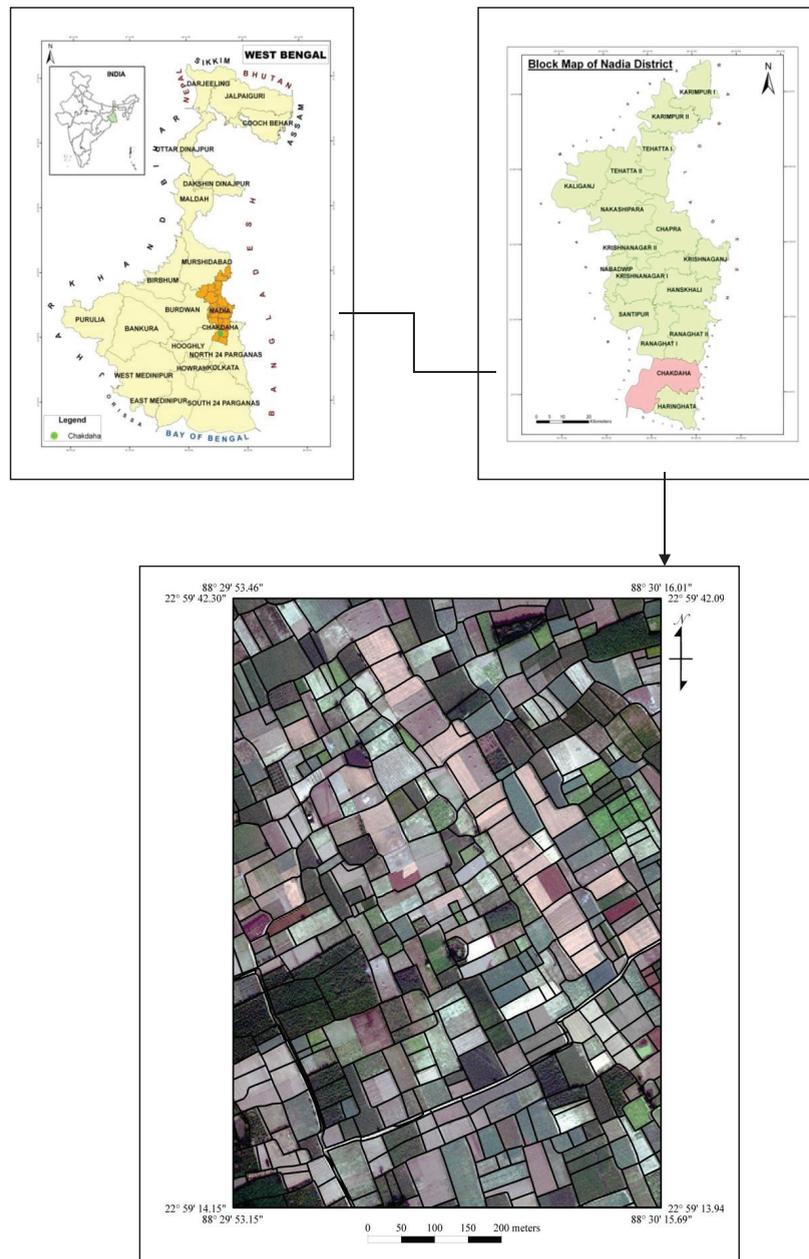


Figure 1. Location map of the study area.

spectral separation is achieved between the crop classes, co-occurrence statistics along with Jeffries-Matusita distance (squared form) is calculated to verify the presence of classification bias and to judge the inter class separability (Sebastian *et al.*, 2012; Lee and Bretschneider 2010; Swain *et al.*, 1971; Banerjee *et al.*, 2014). The above separated classes are then correlated with the plot level GPS survey data. In order to see the viability of the achieved discrimination over any seasonal remote sensing data regardless of the crop types sown in an area, the WV-2 custom indices are correlated with the same indices calculated from field-spectroradiometer data as the crop discrimination using hyper spectral data are regarded as very accurate irrespective of temporal variability

(Wilson *et al.*, 2014; Wang, 2008). Lastly Raster Statistics for Vector (RSV) is applied over the category raster output and the plot boundary vector and the desired crop wise coverage area is achieved.

The proposed method has been applied over an agricultural belt of West Bengal, India where different types of vegetables are grown in various small plots which cannot be differentiated by low resolution satellite data. This leads to use of WV 2 (8 bands) high resolution satellite data in this study with the following objectives: 1) to establish the suitable band ratios and methodology by which plot level crop identification can be achieved with limited field survey, 2) to show the types of crops are being cultivated in different

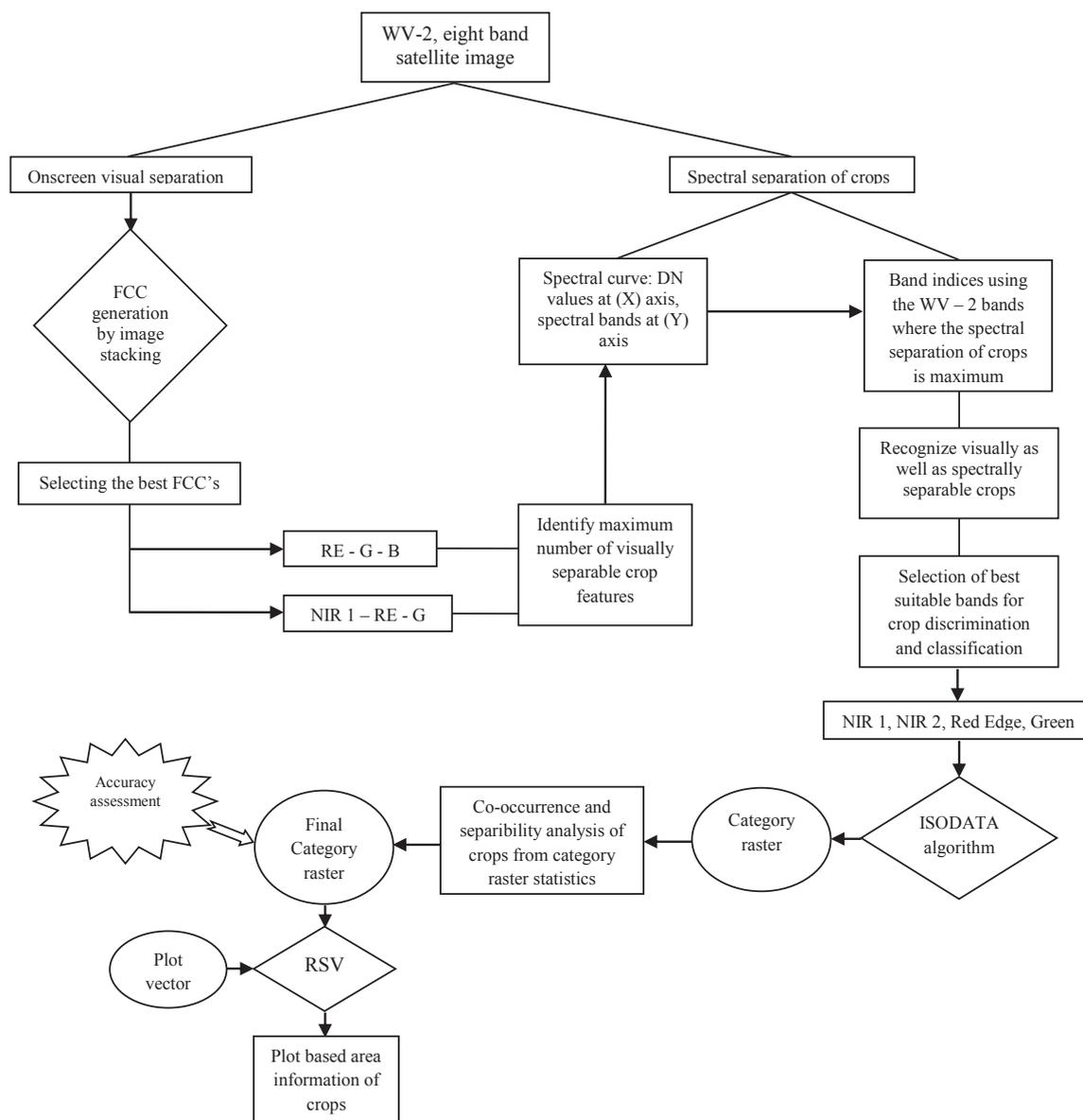


Figure 2. Process diagram for APCD process model.

areas at different seasons, 3) their acreage estimation and 4) to generate an up-to-date plot based agricultural land use information database.

2. Study Area

The study area is located between 22° 59' 14.15" to 22° 59' 42.30" N and 88° 29' 53.46" to 88° 30' 16.01" E in Chakdah block of Nadia district. The entire area lies on the flood plain of the river Bhagirathi and its tributaries which provides ideal condition for growing various agricultural crops and that is why it has become one of the major agricultural hubs of West Bengal, India. In the present study 554910 square meters of land of Saguna and Alaipur mouzas of Nadia district have been represented (Figure 1).

3. Data Used

- World View -2 eight band image having spatial resolution of 0.5 meter for panchromatic and 2 meter for Multispectral.

Sensor Bands:

Panchromatic: 450 - 800 nm

8 Multispectral:

Coastal: 400 - 450 nm, Blue: 450 - 510 nm, Green: 510 - 580 nm, Yellow: 585 - 625 nm, Red: 630 -690 nm, Red Edge: 705 - 745 nm, Near-IR1: 770 - 895 nm, Near-IR2: 860 - 1040 nm

Date of pass 02-12-2012.

- Field Spectroradiometer (Spectral Evolution Inc, Model: PSR – 1100 with 4 degree FOV lens, sampling interval: 1.4

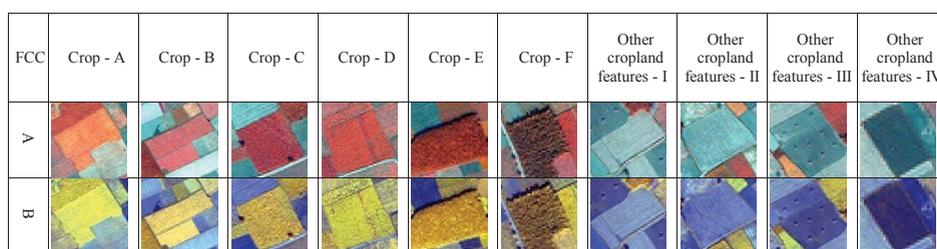


Figure 3. Plot level Visual separation of crops types through composite A and B.

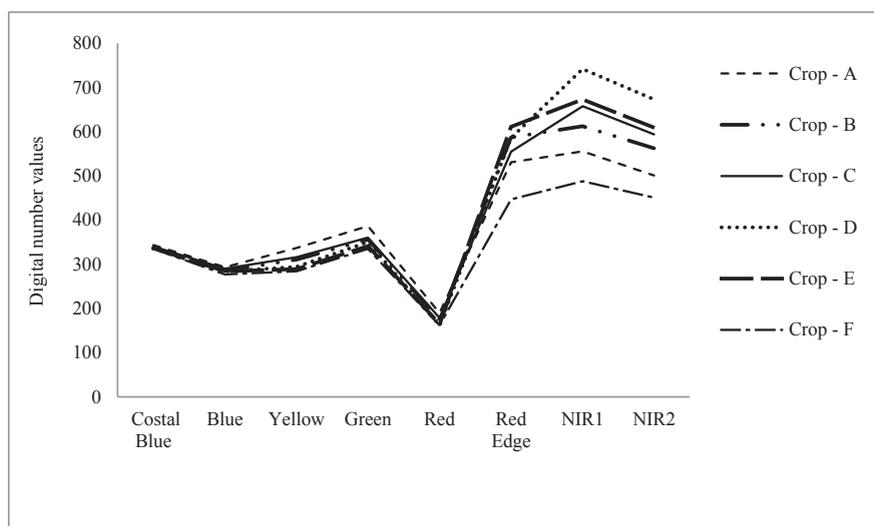


Figure 4. Spectral curve of all crop types generated from WV-2.

Table 1. NDCI ranges for different crops.

Crop	Normalized Difference Crop Index		
	(NDCI I)	(NDCI II)	(NDCI III)
Crop A	.037 - .086	.020 - .087	0.10 - 0.28
Crop B	.050 - .080	0.10 - 0.14	0.30 - 0.40
Crop C	.031 - .088	0.040 - 0.15	0.23 - 0.34
Crop D	0.013 - .023	0.072 - 0.12	0.30 - 0.40
Crop E	0.011 - 0.081	0.11 - 0.19	0.34 - 0.36
Crop F	0.011 - 0.066	0.019 - 0.090	0.12 - 0.25

- 1.7 nm between the spectral wavelength range: 320 – 1100 nm).

- Handheld GPS (Trimble, Juno SB).
- Survey of India topographical maps (1: 50,000), Police station maps (1 inch = 1 mile), Cadastral maps (16 inches = 1 mile), District Statistical Handbook, Census data etc.

4. Methodology

The methodology of the work is based on a number of semi-automated processes such as Generation of Image

Composites, NDCI, ISODATA algorithm, Classification Co-occurrence Statistics and Raster Statistics for Vector. To achieve the ultimate result the sequential applications of the above processes have been presented through a process model (Figure 2) which is termed as Accelerated Plot-based Crop Discrimination (APCD).

4.1 On screen visual interpretation

Prior to any image classification technique can be applied on a certain remote sensing imagery, particularly for any kind of discriminative analysis, it is essential to understand the basic topographic features of the concerned area. In order to

observe the different features present in the WV-2 satellite data of the study area, ‘False colour composite’ (FCC) images have been generated along with the true colour image composite.

Additionally the panchromatic image is also used to observe the textural pattern of the distinct crop features. Preliminarily a nomenclature i.e. Crop A, B, C, D, Other cropland features (OCF I, II, III, IV) etc are assigned to the visually separable crop and non-crop features based on various tones, textures and patterns of the composite images (Figure 3).

4.2 Onscreen Spectral separation through custom band indices

As the visual separation of the crop types is the direct result of their spectral properties we first generated spectral curve (Figure 4) for all the visually separable crop features from the eight bands of WV 2. From that curve we find out the spectral regions where maximum separation between the crop features are noticed.

Based on that spectral separation we have computed three numbers of indices (NDCI- I, II & III) using those particular bands which yielded good normalized differences as well as enabling us to calculate distinct normalized index ranges between the crop types (Table 1). These normalized difference indexes for the purpose of crop discrimination are termed as ‘Normalized Difference Crop Index’ (NDCI). The generated three indices are as follows:

$$NDCI\ I = (NIR\ 1 - NIR\ 2 / NIR1 + NIR\ 2)$$

$$NDCI\ II = (NIR\ 1 - Red-Edge / NIR1 + Red-Edge)$$

$$NDCI\ III = (NIR\ 1 - Green / NIR1 + Green)$$

These grey scale rasters are minutely compared with Composites by raster overlay technique to verify the spectral separation of the crop features by observing and noting the per pixel values. For each crop feature, 15 to 20 image pixels are chosen randomly from the associated plots (number of pixels chosen is directly proportion to the size of the plot). On an average 4 to 6 plots are chosen for every crop feature.

4.3 Automatic crop-feature extraction by applying ISODATA algorithm

The ISODATA algorithm is applied subsequent to the visual and spectral separation for generating the category raster output utilizing the bands where maximum spectral separation is achieved. The classification parameters for the above algorithm are shown below –

- Number of classes : 50
- Maximum Iterations : 10
- Maximum Standard Deviation: 4.5000

- Minimum Distance to Combine : 3.2000
- Minimum Cluster Cells : 30
- Minimum Distance for Chaining : 3.2000

The number of classes to be considered is entirely depending on the variety of features present in the satellite image.

4.3.1 Co-occurrence Statistics and Jeffries-Matusita distance computation

To observe whether random bias is involved in the classification process and to judge which classes are spatially as well as spectrally associated with each other, ‘Classification Co-occurrence Statistics’ (TNTmips tutorial, 2011) is computed from the category raster output which represents both the co-occurrence value (upper number) and the separability value (lower number) for each pair of classes. A positive co-occurrence value between two classes with a relatively low separability value indicates that they tend to occur together in the same spectral space. The normalized values for above co-occurrence are produced by comparing the raw frequencies of adjacency with the values expected from a random distribution of class cells. The ‘Jeffries-Matusita distance’ based on the ‘Bhattacharya Distance’ is used to measure the separability of classes, as each pair represents two probability distributions across the same spectral space.

4.3.2 Construction of ‘Normalized co-occurrence matrix

A co-occurrence matrix or Gray-Level Co-occurrence Matrices (GLCM) is a matrix or distribution that is defined over an image to be the distribution of co-occurring values at a given offset. Therefore, if ‘I’ be a given grey scale image and ‘N’ be the total number of grey levels in the image then the Co-occurrence Matrix is a square matrix ‘G’ of order ‘N’, where the (i, j)th entry of G represents the number of occasions, a pixel with intensity, ‘I’ is adjacent to a pixel with intensity ‘j’, as defined by ‘Haralick’ (Alam and Faruqui 2011).

So mathematically, a co-occurrence matrix ‘C’ is defined over an n × m image ‘I’, parameterized by an offset (Δx, Δy), as:

$$C_{\Delta x, \Delta y}(i, j) = \sum_{p=1}^n \sum_{q=1}^m \begin{cases} 1, & \text{if } I(p, q) = i \text{ and } I(p + \Delta x, q + \Delta y) = j \\ 0, & \text{otherwise} \end{cases} \dots \text{Equation 1}$$

Where, i and j are the image intensity values, ‘p’ and ‘q’ are the spatial positions in the image ‘I’ and the offset (Δx, Δy) depends on the direction used ‘d’ and the distance at which the matrix is computed, ‘d’. As ‘N’ is the total number of grey levels in the image, thus the normalized co-occurrence matrix, ‘C_N’ is calculated as:

$$CN = (1/N) C \Delta x \Delta y (i, j) \dots \dots \dots \text{Equation 2}$$

Table 2. Classification Co-occurrence Statistics.

Co-occurrence and Separability analysis										
Class	Crop A	Crop B	Crop D	Crop C	OCFI	OCFII	OCFIII	OCFIV	Crop E	Crop F
Crop A	188.719, 0.000									
Crop B	35.745, 1.116	213.585, 0.000								
Crop D	-32.829, 1.880	-19.521, 1.855	231.411, 0.000							
Crop C	-52.081, 1.809	-36.919, 1.760	51.491, 1.160	222.719, 2.000						
OCFI	-17.000, 1.545	-80.006, 1.926	-44.778, 2.000	-69.140, 1.998	257.386, 0.000					
OCFII	-55.762, 1.601	-79.767, 1.861	-46.670, 2.000	-72.338, 1.999	-63.831, 1.801	224.811, 0.000				
OCFIII	-25.176, 1.324	-69.054, 1.772	-47.389, 1.999	-73.627, 1.986	-21.602, 1.445	-3.093, 1.295	199.706, 0.000			
OCFIV	-31.960, 1.853	-41.623, 1.952	-27.463, 2.000	-39.077, 2.000	-38.524, 1.974	33.240, 1.336	-41.202, 1.945	278.692, 0.000		
CropE	-10.402, 2.000	-11.988, 2.000	-6.997, 2.000	-9.432, 2.000	-11.493, 2.000	-10.630, 2.000	-12.148, 2.000	13.599, 1.999	266.138, 0.000	
CropF	-36.740, 1.929	-36.259, 1.906	12.136, 1.667	11.517, 1.193	-47.979, 1.998	-50.335, 2.000	-51.625, 1.996	-27.496, 1.992	13.090, 1.591	233.385, 0.000

4.3.3 Bhattacharyya distance for measuring separability of classes

In statistics, the Bhattacharyya distance measures the similarity of two discrete or continuous probability distributions or classes by extracting the mean and variances of two separate distributions or classes.

In its simplest formulation, the Bhattacharyya distance between two classes under the normal distribution can be mathematically calculated as:

$$D_B(p, q) = \frac{1}{4} \ln \left(\frac{1}{4} \left(\frac{\sigma_p^2 + \sigma_q^2}{\sigma_p^2 \sigma_q^2} + 2 \right) \right) + \frac{1}{4} \left(\frac{(\mu_p - \mu_q)^2}{\sigma_p^2 + \sigma_q^2} \right) \dots\dots\dots \text{Equation 3}$$

Where, $D_B(p, q)$ is the Bhattacharyya distance between p and q distributions or classes,

σ_p is the co- variance matrix of the p-th distribution,

σ_q is the co- variance matrix of the q-th distribution,

μ_p is the mean vector for the p-th distribution

μ_q is the mean vector for the q-th distribution and,

p ,q are two different distributions or classes.

4.3.4 Jeffries-Matusita distance for measuring separability of classes

The Jeffries-Matusita distance (J-M) is a transformation of the Bhattacharyya distance ($D_B(p, q)$), which has a fixed range $[0, \sqrt{2}]$. Here the J-M distance is squared so that the range lies between 0 and 2. Mathematically the J-M is calculated as:

$$J - M = \sqrt{(1 - e^{-D_B(p,q)})} \dots\dots\dots \text{Equation 4}$$

Based on the above equations (Eqn.1-4) the ‘Classification Co-occurrence Statistics’ have been calculated for all the classes. The classes having high positive co-occurrence (> 50) value with low separability value (< 1.1) are merged together (Table 2).The final category raster output is reduced to 12 numbers of classes from the number of 50 classes (Figure 5).

4.4 Plot based GPS survey and ground truth verification

A detailed GPS survey followed by farmer’s interview was carried out during the growing season of the winter crops. This survey data was compared with the ISODATA output and accordingly the crop types A, B, C, D were verified as Mustard, Cauliflower, Brinjal and Cabbage respectively. Crop classes E and F were identified as Berry and Banana plantations and that is why their spectral signatures are not included in the present study. The remaining classes such as OCFI, II, III and IV were verified as agricultural plots under preparation for the next crop (Table 3). The information regarding non crop features such as water body and shadow areas are not given here.

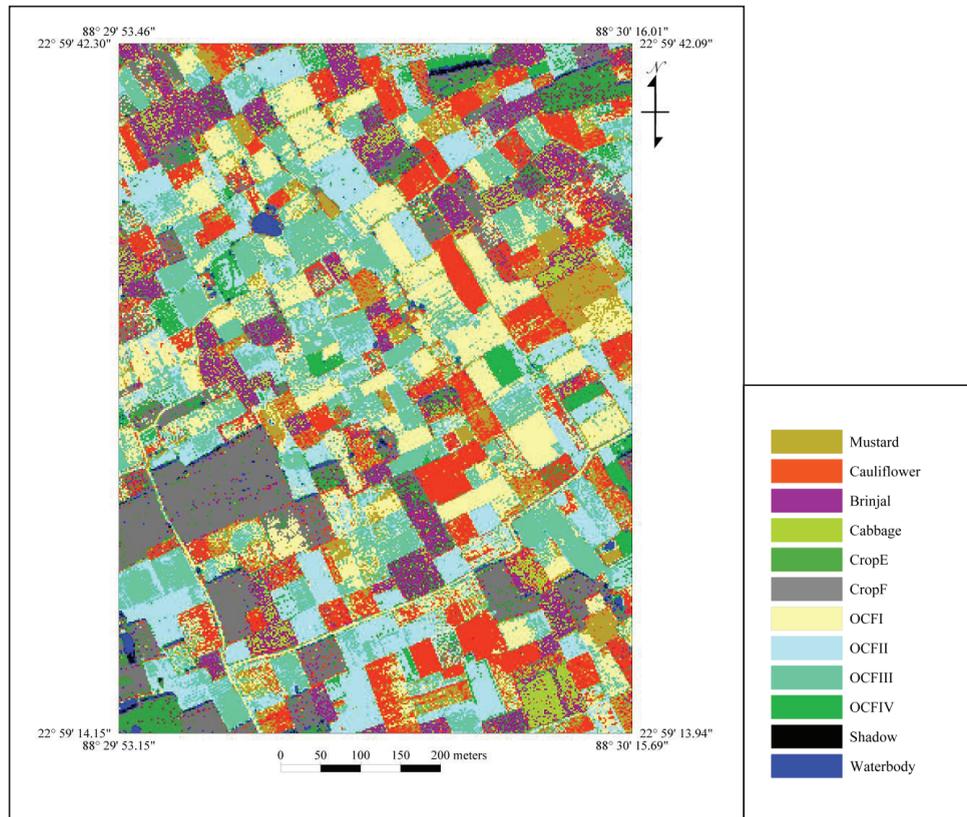


Figure 5. ISODATA output: category raster with associated classes.

Table 3. Crop types and their associated class information after field verification.

Crop	Class number	Field information
Crop A	2	Mustard
Crop B	3	Cauliflower
Crop C	4	Cabbage
Crop D	5	Brinjal
Crop E & F	11 & 12	Plantations
Other cropland features	6, 7, 8 & 9	Cropland under preparation

4.5 Accuracy assessment

Error matrix is an effective way to perform classification error analysis. That is why based on the field information training cells of known classes were created on the ground truth raster and compared to their counterparts in the category raster output. Each row in the error matrix represents a certain class of the classified output and each column a ground truth class. The Error matrix (Table 4) shows two measures of accuracy for individual classes which are User’s accuracy and Producer’s accuracy. The User’s accuracy signifies the percentage of cells correctly classified in the

classified output while the Producer’s accuracy shows the percentage of sample cells correctly classified in the ground truth raster or training set. The overall accuracy of the classification process adopted for the APCD model is calculated as:

$$\begin{aligned}
 & 100 \times (\text{Number of correctly classified raster cells}) / (\text{Total number of cells in ground raster}) \% \\
 & = 100 \times (\text{The sum of leading diagonal values}) / 10334 (\%) \\
 & = 100 \times (9208 / 10334) (\%) \\
 & = 89.10 \%
 \end{aligned}$$

The Kappa coefficient is 0.8727. The result indicates a good deal of efficiency of the classification process.

5. Verification of the WV 2 Image Discrimination with Hyperspectral Data

5.1 Spectral data acquisition

To cross check the above discrimination a portable field-spectroradiometer was used to collect spectral signatures of the same winter crops as it takes measurement of absolute radiometric quantities in narrow wavelength intervals irrespective of temporal and spatial variations and provides valuable assistance in quantifying biophysical characteristics

Table 4. Error matrix of ISODATA classification in APCD process.

Class	Ground Truth Data												Total	User's accuracy
	Waterbody	Mustard	Cauliflower	Cabbage	Brinjal	OCFI	OCFII	OCFIII	OCFIV	Shadow	CropE	CropF		
Waterbody	169	0	0	0	0	0	5	0	0	1	2	15	192	88.02%
Mustard	0	693	42	1	0	3	7	0	1	0	0	0	747	92.77%
Cauliflower	0	28	1049	1	7	0	0	0	0	0	3	4	1092	96.06%
Cabbage	0	0	5	318	290	0	0	0	0	0	21	2	636	50.00%
Brinjal	0	0	1	41	724	0	0	0	0	0	146	46	958	75.57%
OCFI	0	3	0	0	0	1172	17	6	0	0	0	0	1198	97.83%
OCFII	0	0	0	0	0	0	943	6	18	0	0	0	967	97.52%
OCFIII	0	7	0	0	0	15	12	244	0	0	0	0	278	87.77%
OCFIV	0	0	0	0	0	0	23	0	365	0	0	16	404	90.35%
Shadow	16	0	0	0	0	0	0	0	0	32	0	0	48	66.67%
CropE	0	0	0	1	157	0	0	0	0	0	653	66	877	74.46%
CropF	6	0	13	1	18	0	1	0	6	0	46	2846	2937	96.90%
Total	191	731	1110	363	1196	1190	1008	256	390	33	871	2995	10334	
Producer's accuracy	88.48%	94.80%	94.50%	87.60%	60.54%	98.49%	93.55%	95.31%	93.59%	96.97%	74.97%	95.03%		

Table 5. Coefficient of determination R² values for each crop in the linear regression model.

Crop	R ² value for NDCI - I	R ² value for NDCI - II	R ² value for NDCI - III
Brinjal	0.911	0.9425	0.949
Mustard	0.928	0.950	0.889
Cauliflower	0.855	0.970	0.937
Cabbage	0.903	0.918	0.910

of agricultural crops (Arifat *et al.*, 2013; Blackburn, 1998; Shibayama and. Akiyama, 1991; Curran *et al.*, 1990). At least twenty to twenty-five spectral signatures of each crop were collected between 11 am to 1 pm at a fixed height of 12 cm over the leaf (at nadir position, 90 degrees) from the individual plots along with GPS coordinates. A white reference Spectralon calibration panel was used at every 20-25 measurements. Thereafter those spectroradiometer data were spectrally analyzed and compared with the WV 2 image data. The curve generated from the spectroradiometer data (Figure 6) shows similar spectral separability of the crops at the same spectral region noticed in the image data.

5.2 Co-relation and regression analysis

To statistically verify the above separation regression and correlation analysis has been done between the three NDCIs generated from the spectroradiometer data as well as WV-2 imagery which again shows good co-relation in the 'Linear Regression Model' with R² value for each crop variable ranges from 0.85 to 0.97 (Table 5).

6. Application of Raster Statistics for Vector for Plot based crop area calculation

In plot level crop area calculation from high resolution satellite data the presence of 'Mixed pixels' is a major problem which is generally found along the edges of image features. In the present ISODATA output the mixed pixels problem arises due to the spectral conflict between the crops having relatively similar spectral properties although they are distinctly different from each other that have been reflected in the NDCI ranges. Henceforth to solve this problem and to achieve exact plot wise crop area information a GIS application named Raster statistics for Vector (RSV) has been applied on the category raster output using 'TNT mips 2014' software instead of simple attribute transfer, raster to vector operation or other theoretical approaches (Czaplewski & Catts, 1992). It utilizes the Hough histogram technique for feature separation and subsequently calculates, extracts and links the maximum occurring class number (Mode or majority value) of a particular crop with its associated polygon from the plot boundary layer. For example in the present study if a plot gets the mode value '2' from the ISODATA raster through RSV, it means that particular plot is covered by mustard (Crop A) and its area will be obtained from the corresponding plot boundary vector (Figure 7).

7. Results and Discussion

7.1 Visual separation

To understand the visual characteristics of the various crop features present in the study area from WV 2 a number of False Colour Composites (FCC) were formed. Out of the generated composites the two most distinct false colour composites (Figure 3) where maximum visual separation between the crop features were observed are:

- Composite –A formed by combining Red-Edge, Green and Blue and
- Composite – B which was the result of NIR 1, Red-

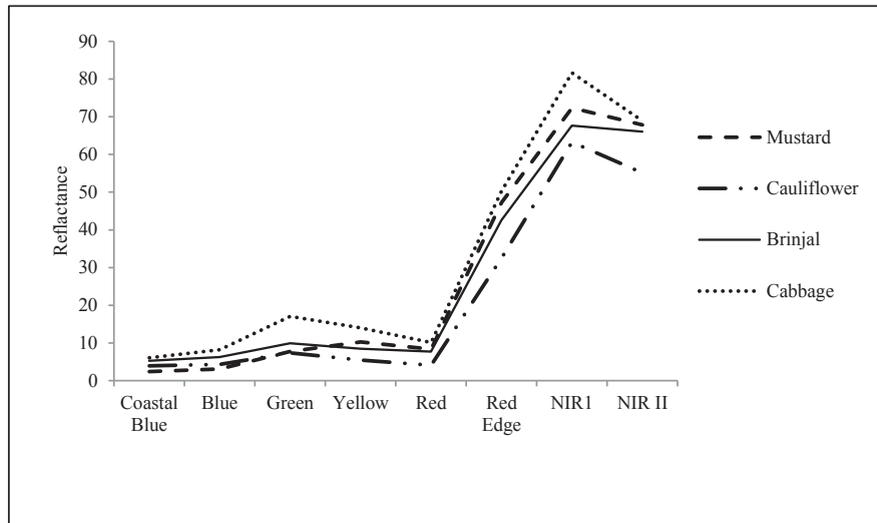


Figure 6. Spectral curve of all crop types generated from Spectroradiometer data.



Figure 7. Final vector output with mode value.

Edge and Green bands respectively.

7.2 Spectral discrimination

Once the visual separation of the crop features is obtained their spectral nature is known through the generation of respective spectral curve. The generated spectral curve (Figure 4) shows that the crop features have greater spectral

discrimination between Red edge, NIR1 and NIR 2 and also are clearly distinguishable at the Green (VNIR) region of the spectrum which is very closely matching with visually separated bands. Accordingly by considering those selected bands three numbers of indices (NDCI I between NIR 1 - NIR 2 / NIR1 + NIR 2, NDCI II between NIR 1 - Red-Edge / NIR1 + Red-Edge and NDCI III between NIR 1 - Green / NIR1 + Green) have been generated and from there

Table 6. Crop wise coverage area comparison between RSV and survey data.

Crop name	Area (Sq.m) obtained from GPS survey.	Area (Sq.m) obtained from RSV	Area accurately estimated (%)
Mustard	22517.95	25508.21	88.28%
Cauliflower	85075.18	91084.23	93.40%
Cabbage	10639.41	12219.97	87.07%
Brinjal	52835.18	57361.52	92.11%
Total Area	172648.28	184593.37	93.53%

good normalized differences as well as distinct normalized index ranges are achieved for the crops (Table 1).

7.3 Statistical analysis of the ISODATA output

The Co-occurrence and Separability analysis (Table 2) shows that all the visually separable crop features and the other cropland features are distinctly different from each other as they have negative to low co-occurrence and high spectral separability between them. The co-occurrence value is generally greater than 200 and the separability (square of J-M distance) is expectedly zero (on a scale of 0 – 2) for the same crop classes. Crops which are visually distinct in the image composites as well as have different indices ranges are mostly associated with negative co-occurrence. Moderately positive spatial and spectral adjacency were observed between the pair of Mustard and Cauliflower (Co-occurrence: 35.745, square of J-M distance: 1.116) as well as for Cabbage and Brinjal (Co-occurrence: 51.491, square of JM distance: 1.160). Based on the results in Table 2 it can be predicted that the crops should be discriminable by most of the pixel based approaches such as ISODATA, Maximum Likelihood etc. using WV 2.

The ISODATA classification process adopted for the APCD process model shows an overall accuracy of 89.10% while the Kappa coefficient is 0.8727.

The Error matrix (Table 4) reveals that the User's accuracy and the Producer's accuracy for all the classes are mostly above 85% which indicates that each individual class was correctly classified in both the training raster (ground truth) and in the ISODATA (classified) output. Among the crops Mustard and Cauliflower have the highest User's and Producer's accuracy, 92.77%, 94.80% and 96.06%, 94.50% respectively. Cabbage has the lowest User's accuracy, 50%, among the crop classes though its Producer's accuracy is significantly higher, 87.60%. For Brinjal the percentage of cells correctly classified in the ISODATA output is 75.57% while it's Producer's accuracy is lower than that i.e. 60.54%.

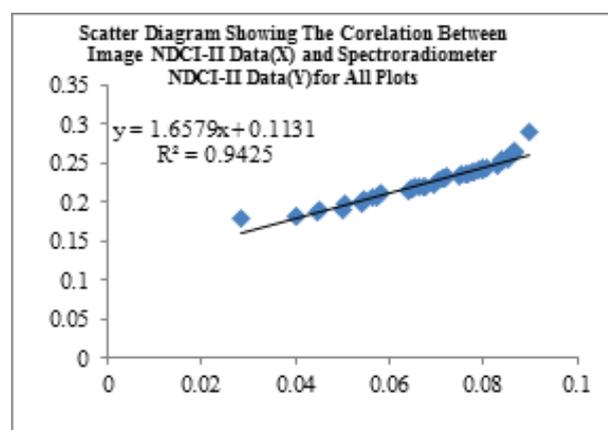


Figure 8. Brinjal : image data in X axis and Spectroradiometer data in Y axis.

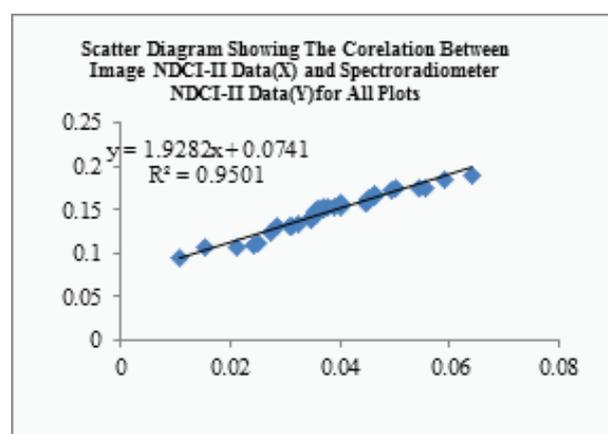


Figure 9. Mustard : image data in X axis and Spectroradiometer data in Y axis.

Crop E and F which were verified as Berry (in early growth stage) and Banana plantations respectively have User's and Producer's accuracy of 74.46%, 74.97% and 96.90%, 95.03%.

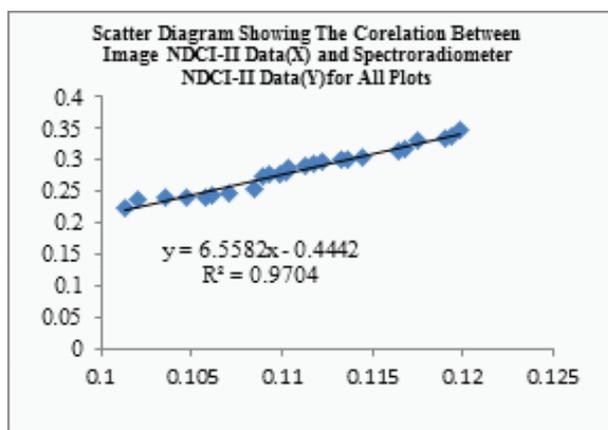


Figure 10. Cauliflower : image data in X axis and Spectroradiometer data in Y axis.

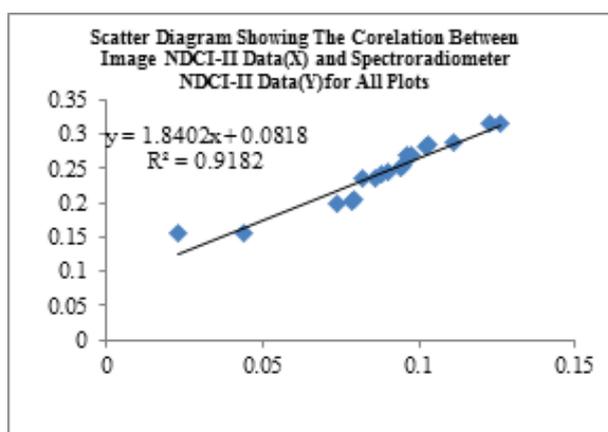


Figure 11. Cabbage : image data in X axis and Spectroradiometer data in Y axis.

The total plot level coverage area of the winter crops i.e. Mustard, Cauliflower, Brinjal and Cabbage obtained through RSV (Table 6) is 93.53% of the area calculated from the detailed plot level GPS survey data. Out of which Cauliflower and Brinjal has the highest amount of accuracy i.e. 93.40% and 92.11% respectively.

7.4 Comparison of image data with Spectroradiometer data

By comparing the spectral curve generated from the image (Figure 4) as well as spectroradiometer (Figure 6) data we have noticed that the spectral pattern of all the crops is same in both the cases with maximum reflection occurring in NIR 1 band. It was also found that indices generated from image data as well as from spectroradiometer data have good correlation in 'Linear Regression Model'. Out of three NDCIs, the NDCI-II calculated using NIR I and Red-Edge bands have greater co-relation with the R^2 existing between the values 0.92 to 0.97 (Figure 8 to 11).

8. Conclusion

The techniques utilized for APCD such as generation of image composite, NDCI, automatic feature extraction by ISODATA, classification co-occurrence statistics and RSV, are all semi-automated processes which require less user intervention. Not only this through the calculation of statistical 'Mode' over seasonal satellite data one can get an overview about the agricultural practices carried out in a certain region which is necessary for agro-economic development of that particular area. Lastly, based on the above findings we can conclude that the proposed process is potentially a time saving and cost effective solution for generating plot based up-to-date agricultural land use information database.

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