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Comparative Evaluation between Multispectral and Hyperspectral Data for Discrimination of Fruit Crops using Statistical Techniques

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SUMMARY

Horticultural crops unlike field crops are perennial in nature, not having distinct phenology. It is difficult to discriminate horticultural crops using temporal multispectral data. Major limitation of multispectral data is lesser number of bands and mixed pixels which may not be able to discriminate fruit crops but the hyperspectral data has the advantage of having relatively large number of narrow, contiguous bands which lead to continuous spectral reflectance curve, making intricate details visible in the spectrum. For comparison of multispectral data with hyperspectral data, the hyperspectral data which have 2151 numbers of bands has been brought to multispectral level as because multispectral data has very less number of bands. Therefore, in the hyperspectral data, average at 50 nm, 100 nm and 250 nm interval was taken to reduces the data set into 42, 22 and 9 bands. The 4 tier statistical procedure which includes one way Analysis of variance (ANOVA), Classification and regression tree (CART), Jeffries-Matusita (J-M) distance and Linear discriminant analysis (LDA) technique was applied in the reduced band data set. The result of J-M distance and LDA were used to observe whether the reduced band data set can be able to discriminate the fruit crops. The study reveals the limitation of multispectral data in fruit crop discrimination. As the number of bands gets reduced the discriminative power of the data set also gets down.

Keywords: Classification and regression tree, Discrimination, Hyperspectral data, Jaffries-Matusita distance, Linear discriminant analysis, Multispectral data, One way analysis of variance.

1. INTRODUCTION

In case of field crops, temporal multispectral data can be helpful in capturing crop phenology hence may discriminate whereas fruit crops being perennial in nature, not having distinct phenology, it is difficult to discriminate them using temporal multispectral data. Major limitation of multispectral data is very less number of bands which may not be able to discriminate fruit crops. Because of lesser number of bands in multispectral data, it gives a discrete spectrum, which fails to identify small differences in reflectance pattern of different crops particularly fruit crops. Hyperspectral data has relatively large number of narrow, contiguous bands which can be able to discriminate fruit crops efficiently. Fruit and nut orchards can be distinguished from the mixed vegetation of tall forest trees and dwarf grass or other small shrubs with advanced image processing techniques and use of high-resolution multispectral imagery if their unique spectral characteristics are known (Peltoniemi *et al.*, 2005; Panda and Hoogenboom, 2009). Manjunath *et al.* (2011) used SDA technique for selection of optimum wave bands and differentiated among cole crops, pulses and ornamental plants using ground-based hyperspectral data. Sahoo *et al.* (2013) made an attempt to discriminate 70 genotypes of wheat from hyperspectral reflectance data (350–2500 nm at 10 nm interval) with the help of SDA as feature selection method and Jeffries–Matusita (J–M) distance (Richards, 1993) for separability. Arafat *et al.* (2013) discriminated two winter crops (Wheat and

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Clover) and two summer crops (Maize and Rice) using field hyperspectral remotely sensed data. They used different statistical techniques which include one-way ANOVA, Tukey's HSD post hoc analysis and LDA for identification and extraction of optimum wavebands. The results showed the optimal wavebands to discriminate between each two crops.

The aim of the present study is to evaluate the discriminating power of hyperspectral data by comparing it with multispectral data and to examine whether field based hyperspectral data could efficiently be used for discrimination of different fruit crops.

2. RESEARCH METHODOLOGY AND DATA USED

The methodology followed to discriminate fruit crops for possible comparison of multispectral data with hyperspectral data is given below in Fig. 1.

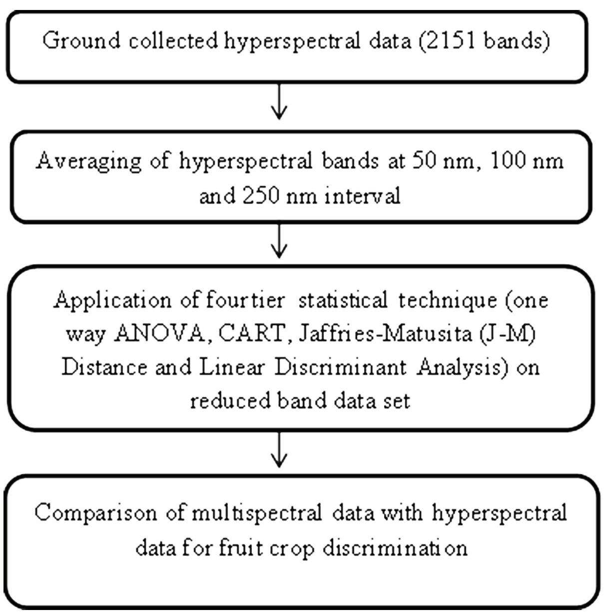

Fig 1. Overall methodology for comparison of multispectral data with hyperspectral data.

2.1 Study area

Experimental orchard farms of Bihar Agricultural University, Sabour, Bhagalpur covering 8 fruit crops were selected for their discrimination through ground based hyperspectral remote sensing using spectroradiometer. Study site details with data collected and purpose is summarized in Table 1.

Table 1. Study Area

SL. No.	Name of the Study area	Sensor Used	Fruit crops	Data collected	Purpose
1	Sabour, Bhagalpur	Spectroradiom-eter	8 fruit crops*	Spectral signa-tures	Discrimi-nation of fruit crops for possible comparison

*Banana, Citrus, Coconut, Guava, Kinnow, Litchi, Mango and Pomogranate

2.2 Spectral data collection

Leaf samples of 8 fruit crops of Sabour, Bhagalpur were collected for spectral measurement in laboratory conditions. Number of leaves of different fruit crops collected varies between 30 to 40. Later this spectral data were used for discrimination of fruit crop orchards at field level.

2.3 Comparison between multispectral and hyperspectral data for discrimination of fruit crops

Leaf samples of different fruit crops were collected by using spectroradiometer for extraction of reflectance for possible discrimination of fruit crops at field level. The wavelength of collected spectral data varies from 350 to 2500 nm which consist of 2151 number of spectral bands. Only the significant bands which could spectrally discriminate the fruit crop orchards were identified and selected from these bands. For this different statistical techniques have been applied. Since in hyperspectral data there is large number of bands (n=2151) any one statistical technique may not be sufficient to reduce the number of bands therefore a four tier statistical method has been proposed in this study for spectral discrimination of fruit crops for possible comparison. These four statistical techniques include one way ANOVA, CART, Jaffries-Matusita (J-M) Distance and Linear Discriminant Analysis. By using one way ANOVA the pre-processed collected reflectance spectra of 8 fruit crops in case of Sabour spectral data were statistically analyzed to find significant wavelengths for discrimination. CART was used to further minimize the dimensions of significant wavebands obtained from one way ANOVA analysis. CART is a nonparametric statistical technique developed by Breiman *et al.* (1984) used to identify most sensitive spectral bands for discrimination of fruit crop.

Jaffries-Matusita distance has been considered as the measure of separability index (Vaiphasa *et al*., 2007). J-M distance analysis quantified the separability of all possible fruit crop pairs. The square of J-M distance varies from 0 to 2 with a higher values indicating greater separability of the class pairs (Richards, 1993). In this study, 1.94 (97% of 2) is selected as a threshold J-M distance value for spectral separability between fruit crop pairs. Finally discriminative power of the selected wavelengths obtained from CART analysis was further assessed on the basis of overall accuracy in Linear Discriminant Analysis (LDA) as because J-M distance only gives us pairwise comparison among the fruit crop pairs.

For comparison of multipsectral data with hyperspectral data, there is a need of bringing hyperspectral data into multispectral level as because multispectral data contain very less number of bands. Therefore, averaging was done at 50 nm, 100 nm and 250 nm interval in hyperspectral data which reduces the data set into 42, 22 and 9 bands. After that the above proposed 4 tier statistical technique has been applied on this reduced band data set to check whether this reduced band data can be able to discriminate the fruit crops.

The result of J-M distance and LDA are given in the following Tables. Table 2 illustrates the result that all the J-M distance values are still greater than the threshold value (i.e. 1.94). Therefore, by taking average at 50 nm interval the reduced band data set (having 42 bands) have the capability to discriminate fruit crop pairs.

Table 3. Illustrate that at 100 nm interval the J-M distance values are still greater than the threshold value (i.e. 1.94). Therefore, this reduce band data set (having 22 bands) still able to discriminate the fruit crop pairs.

Table 4 shows that as average is taken at 250 nm interval, reduced band data set (9 bands) have some J-M distance values which are less than the threshold value (1.94). The Table 4 shows that J-M distance values in case of Coconut-Guava, Guava-Kinnow, Guava-Mango, Guava-Pomegranate and Kinnow-Mango pairs are less than the threshold value. So, it is clear that as number of bands decreased, the discriminative power of bands also gets reduced.

Table 5 shows that misclassification occurred among all the fruit crops. The overall accuracy also decreases to 64.32% as the average is taken at 50 nm.

Table 2. Spectral separability of fruit crops of Sabour using spectral data at 50 nm interval

JM- Distance	Banana	Citrus	Coconut	Guava	Kinnow	Litchi	Mango	Pomegranate
Banana	1.823							
Citrus	1.998	1.823						
Coconut	1.999	1.999	1.823					
Guava	1.996	1.999	1.968	1.823				
Kinnow	1.975	1.999	1.998	1.992	1.823			
Litchi	1.998	1.999	1.999	1.999	1.997	1.823		
Mango	1.996	1.999	1.997	1.992	1.992	1.999	1.823	
Pomegranate	1.987	1.998	1.999	1.993	1.988	1.995	1.996	1.823

Table 3. Spectral separability of fruit crops of Sabour using spectral data at 100 nm interval

JM- Distance	Banana	Citrus	Coconut	Guava	Kinnow	Litchi	Mango	Pomegranate
Banana	1.823							
Citrus	1.996	1.823						
Coconut	1.999	1.999	1.823					
Guava	1.995	1.997	1.979	1.823				
Kinnow	1.978	1.999	1.997	1.993	1.823			
Litchi	1.997	1.999	1.999	1.999	1.995	1.823		
Mango	1.995	1.999	1.999	1.997	1.987	1.999	1.823	
Pomegranate	1.988	1.996	1.998	1.994	1.988	1.998	1.994	1.823

Table 4. Spectral separability of fruit crops of Sabour using spectral data at 250 nm interval

JM distance	Banana	Citrus	Coconut	Guava	Kinnow	Litchi	Mango	Pomegranate
Banana	1.64644							
Citrus	1.95183	1.64644						
Coconut	1.97320	1.97785	1.64644					
Guava	1.97049	1.97740	1.87830	1.64644				
Kinnow	1.94705	1.98796	1.97100	1.91680	1.64644			
Litchi	1.98763	1.99705	1.99307	1.97394	1.95812	1.64644		
Mango	1.98177	1.99560	1.96568	1.89116	1.92581	1.97958	1.64644	
Pomegranate	1.97894	1.97726	1.98413	1.91664	1.94531	1.96366	1.97475	1.64644

Table 5. Linear Discriminant Analysis at 50 nm interval

LDA	Banana	Citrus	Coconut	Guava	Kinnow	Litchi	Mango	Pome-Granate	Row total	User accuracy
Banana	13	2	0	0	8	1	0	2	26	50
Citrus	2	9	0	0	0	0	0	0	11	81.81
Coconut	0	1	14	5	0	0	0	0	20	70
Guava	0	1	6	20	4	0	2	0	33	60.60
Kinnow	4	1	0	2	7	0	0	3	17	41.17
Litchi	0	0	0	0	3	8	0	0	11	72.72
Mango	1	0	0	0	5	1	32	12	51	62.74
Pomegranate	0	0	0	2	1	1	0	16	20	80
Column total	20	14	20	29	28	11	34	33	189	
Producer accuracy	65	64.28	70	68.96	25	72.72	94.11	48.48		

Table 6. Linear Discriminant Analysis at 100 nm interval

LDA	Banana	Citrus	Coconut	Guava	Kinnow	Litchi	Mango	Pomegranate	Row total	User accuracy
Banana	15	1	0	0	3	0	0	0	19	78.94
Citrus	1	11	0	1	0	0	0	0	13	84.61
Coconut	0	1	15	5	1	0	0	0	22	68.18
Guava	0	1	5	18	4	0	1	1	30	60
Kinnow	7	1	0	3	10	0	0	3	24	41.66
Litchi	0	0	0	0	5	9	0	1	15	60
Mango	1	0	0	0	5	1	33	3	43	76.74
Pomegranate	2	0	0	2	0	1	0	15	20	75
Column total	26	15	20	29	28	11	34	23	186	
Producer accuracy	57.69	73.33	75	62.06	35.71	81.81	97.05	65.21		

Table 6 shows that all the fruit crops were still misclassified and overall accuracy was also very low which is about 68.11%.

Table 7 shows that most of the fruit crops has users and produces accuracy less than 50% and all the fruit crops were inaccurately classified. Overall accuracy is also very low which is 52.43%. Therefore, it is clear that this reduced bands data failed to discriminate different fruit crops.

3. CONCLUSION

Being perennial in nature, it is difficult to discriminate fruit crops using multispectral data as it has very few number of spectral bands. Hence, from the above result it is clear that as we reduce the number of bands the discriminative power of spectral bands also get decreased. In case of reduced band data set most of the fruit crops were misclassified. Unlike multispectral data, hyperspectral data has

Table 7. Linear Discriminant Analysis at 250 nm interval

LDA	Banana	Citrus	Coconut	Guava	Kinnow	Litchi	Mango	Pomegranate	Row total	User accuracy
Banana	13	6	0	0	7	1	0	4	31	41.93
Citrus	2	4	0	0	0	0	0	0	6	66.66
Coconut	1	0	13	1	1	0	0	0	16	81.25
Guava	0	0	5	16	6	0	2	2	31	51.61
Kinnow	4	3	1	1	5	0	0	2	16	31.25
Litchi	0	0	0	0	2	3	0	1	6	50
Mango	2	0	1	5	6	1	32	3	50	64
Pomegranate	4	1	0	6	1	6	0	11	29	37.93
Column total	26	14	20	29	28	11	34	23	185	
Producer accuracy	50	28.57	65	55.17	17.85	27.27	94.11	47.82		

huge number of narrow, contiguous spectral bands which can effectively be discriminate fruit crops.It may be concluded that hyperspectral data has more discriminative power than the multispectral data in fruit crop discrimination and can efficiently be used for discrimination of fruit crops.

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