Sindh Univ. Res. Jour. (Sci. Ser.) Vol.47 (2):335-340 (2015)

SINDH UNIVERSITY RESEARCH JOURNAL (SCIENCE SERIES)

A Comparative Study of Crop Classification By Using Radiometric and Photographic Data

E. A. REHMANI[++], M. S. NAWEED*, M. SHAHID*, S. QADRI*, MUTIULLAH*, Z. GILANI*, ISLAH-U-DIN*.

Department of Physics, the Islamia University of Bahawalpur, Pakistan

Received 8th June 2014 and Revised 3rd January 2015

Abstract: The aim of this study is to compare the performance of two types of remote sensing data, radiometric and photographic, obtained from five different crops; canola, radish-plants and three varieties of wheat crop (Ass, Meraj, and Bhakkar).Radiometric data was acquired by using a handheld crop scan device 'MSR5',in the form of five spectral bands, from 450nm to 1750nm, with five types of wavelength blue, green, red, infrared and far-infrared, whereas, photographic data was obtained by a digital camera with14.1Mpixels resolution. Both types of data were classified by using *ANN* classifier in MaZda software environment. It was observed that the radiometric data gave better classification results as compared to the photographic data. In training phase we received an accuracy of 94.50% and 91.43% with radiometric and photographic data respectively, and when classifier was tested it gave an accuracy of 96.00% and 93.14% respectively.

Keywords: Radiometric data, Photographic data, Artificial neural network, Infrared and far- infrared

1. INTRODUCTION

The information on spatial distribution of various types of crops is crucial for economic planners, agriculture scientists, and government and private agencies to initiate and encourage farmers to practice cropping systems based on soil potential, to maintain relevant product prices in market, and to achieve export targets of a country. Statistical information regarding the cultivated crops (% of cash crops and% food crops) plays a key role to achieve these objectives. In third world countries like Pakistan, India, Bangladesh, etc. where cultivation of crops is usually planned on personal level, collection of such data by ground based conventional techniques is tedious, time consuming, and subjective in nature. A reliable, high quality and objective data source is required to be used to acquire above mentioned objectives. Satellite or aerial remote sensing (ARS) technology can play a very important role in this regard as the temporal data of remotely sensed images has been proven to be an extremely important factor in generating accurate crop type map (Wardlow *et al.* 2007, Ozdogan *et al.* 2010).Moreover, information of the spatial distribution of crops as retrieved form satellite data is highly compatible for analysis in GIS environment (Ramarao 2003, Sudhanshu *et al.* 2010).

Usually the data acquired from satellites or other remote sensing devices is either in photographic format or in radiometric format.

AWIFS, LISS (IRS series), SPOT-5, LANDSAT and also MODIS are popular sources of radiometric data (Dhumal *et al.* 2013).Radiometric data is numeric one, which consists of reflected portion of electromagnetic radiations in visible, infrared and far-infrared regions of spectrum, from the surface of objects. Literature survey reveals that various researchers have been working for the classification of different crops, differentiation of crops of the same type, trees and other objects on the basis of radiometric data acquired from these sources (Badhwar 1984, Shifa *et al.* 2011).

Badhwar used LANDAT multispectral scanner data to classify corn and soybean, on the greenness profile of the crops. The author claimed to have his objective with an accuracy of 90% and 84% for corn and soybean respectively (Badhwar 1984). Similarly, Senay *et al.*, 2000) classified corn and soybean corps by using such type of data, acquired by multispectral scanner mounted on aircraft. The output of the scanner was consisted of visible, near-infrared, and infra-red regions of electromagnetic radiations.

[++]Corresponding author: Ejaz Ahmed Rehmani: ejazahmedrehmani69@gmail.com
*Department of Physics, the Islamia University of Bahawalpur, Pakistan
Department of CS and IT, the Islamia University of Bahawalpur, Pakistan
Department of CS and IT, G C University Faisalabad Layyah Campus, Pakistan
Department of Physics Balochistan University of IT, Engineering and Management
Department of Physics, G. C. University Lahore, Punjab 54000 Pakistan

The authors reported that maximum distinction between corn and soybeans was achieved using the near-infrared bands when the crops were matured (Senay *et al.* 2000).Four crops (wheat, clover, maize, rice) were discriminated by Arafat *et al.*, 2013 on the basis of hyper spectral wavebands, ranges from 400nm-2500nm, and concluded that the near infrared (700nm-1300nm) spectral zone is the best to discriminate the crops (Arafat *et al.* 2013).

Vaiphasa, *et al.*, discriminated 16 Thai tropical mangrove species on the basis of hyper spectral data acquired by spectro-radiometer (Field Spec. Pro. FR, Analytical Spectral Device Inc.) in laboratory environment, within the range of 350 nm-2500 nm of electromagnetic radiations. The researchers proved that with this method the said species can be discriminated with an accuracy of 80% (Vaiphasa *et al.* 2005).

Shifa *et al.*, classified cotton and sugarcane crops by using multispectral data, and received an accuracy of 98%. The required data was collected by using MSR5 radiometer, within five spectral bands (blue, green, red, infra-red, and far-infrared), consisted of 450 nm to 1750 nm wavelength (Shifa *et al.* 2011).

Some other authors performed such type of classification on the basis of imagery data (photographic data) acquired by satellites or other remote sensing devices, like Airborne 3D Imager. By Shrivastava and Gebelein, classification of land cover by citrus crops in Florida using LANDSAT imagery data was performed. Authors concluded that the estimation of citrus crop, with this methodology, can be used very successfully to forecast on-tree incomes for farmers (Rahul 2007). Similarly, with the implementation of photographic data, classification for weed detection in canola, wheat, and peas crops was performed by Eddy *et al.*, where the data was acquired by a camera mounted at the height of 1meter above the canopy of plants, in the range of 400nm-1000nm wavelength. The researchers have reported an accuracy of 97%, when the data was classified by applying neural network algorithm (Eddy *et al.* 2006). Xia *et al.*, classified the land cover area in 5 classes namely, croplands, forests, grasslands, urban/built-up, and water bodies, with the implementation of photographic data. The MODIS-EVI time series data was used for this purpose and by applying decision tree algorithm an overall accuracy of 75.50% was achieved (Xia *et al.* 2008).More recently, a study is published on the behalf of Callego *et al.*,2001 in which the authors estimated the land cover area of maize, wheat, barley, and soybeans crops in Ukraine, by using multi-sensor satellite imagery data of MODIS, LANDSAT-5/TM, AWIFS, LISS-III, and Rapid eye. To compare the cost and time efficiency the data obtained by all sensors was classified separately and the authors concluded that MODIS and LANDSAT data was the best in this regard (Gallego *et al.* 2014).

By integrating imagery data acquired by satellite and airborne laser scanner, urban land-use was classified into five categories buildings, streets, grass-covered area, water bodies, and bare land by Yu *et al.*, and the authors proved that the classification of urban scene is significantly improved with this method (Yu *et al.* 2002). Recently, Hu and Wang, classified the urban land-used in four classes office, industrial, civic, and transportation, by using photographic data. The data was acquired by Airborne Laser Terrain Mapper (ALTM), mounted on air craft. The acquired data was classified by applying decision tree method and received an accuracy of 61.88% (Hu *et al.* 2013).

In present study, we aim to compare the performance of both types of data (radiometric and photographic) for the classification /discrimination of crops or other objects, as, prior to this work no such evidence is available in literature where a study for the estimation of data efficiency for the said purpose has been conducted. For this purpose both types of data has been utilized for the classification of five crops canola, radish-plants, and three wheat crops (Aas, Meraj, and Punjand).

2. MATERIALS AND METHODS

2.1 Acquisition And Analysis Of Radiometric Data

Radiometric data was acquired with a handheld multispectral radiometer MSR5 (Crop, Scan, Rochester, MN, USA), which records the incoming radiation and light reflectance from the canopy in fives spectral bands, similar to LANDSAT Thematic Mapper satellite (CROPSCAN 2001, Shifa *et al.* 2011, Shamudzarira *et al.* June, 2014).The output data consists of blue (450 to 520nm), green (520 to 600nm), red (630 to 690nm), near infrared (760 to 900nm) and far-infrared (1550 to 1750nm).Each band has a half peak band of approximately 5 to 15nm, depending on the specific band. In this way, MSR-5 describes a complete scene on the basis of five numeric digits, i.e., five energy bands. It means that only five real valued pixel data describes a complete captured scene. This device has already been employed for crop classification (Shifa *et al.* 2011), to measure water status (Tsirogiannis *et al.* 2013), and to measure nitrogen contents and biomass in plants (Svotwa *et al.* 2013), very successfully.

For the present research, a study site located at latitude $29^0 23^/$N and longitude $71^0 46^/$ was selected at the agriculture forms of The Islamia University of

Bahawalpur,where, 250 scans from five fields of above mentioned crops i.e., Canola,radish-plans and three wheat varieties namely Aas, Miraj, and Punjnad, have been acquired at the height of 10 feet from the ground level. The scanned data was stored in the memory of Data Logger Controller (DLC) device.

To analyze the data, it was transferred to Excel sheets into a personal computer, by using the routines provided by the vendor of MSR-5. The B11 software was implemented for further statistical analysis. B11 is an application which is integrated with MaZda (popular software for medical image analysis) (Szczypiński *et al.* 2009). The original excel sheets were deployed to B11software for classification. Prior to further analysis, it was necessary to verify the data credibility. For this purpose three approaches, principle component analysis (*PCA*), linear discriminant analysis (*LDA*), and non-linear discriminant analysis (*NDA*), available in B11 were applied.

We received data clustering accuracy of 69.20% and 76.40% with *PCA* and *LDA* respectively. In fact, *NDA* based on artificial neural network (*ANN*) approach and in B11 software a number of options are available to configure the *ANN*. Therefore, to have better results in *NDA* projection space we configured the *ANN* on the basis of numbers of neurons in input layers and learning rate ‘η’ (which is the measure of information deployed per neuron), while keeping all other parameters at default values. We received the best clustering accuracy of 97.32% when ANN classifier was configured by applying 4 neurons in hidden layers and learning rate ‘η’ was set at 0.35.

On the basis of these settings the *ANN* was trained and tested, available in B11 software under n-class training and testing option. For this purpose 200 scans data (40 scans from each class) was used to train the classifier and the remaining 50 scans data (10 scans from each class) was employed to test the classifier, and we received average accuracy of 94.50% during training and 96.00 accuracy for testing the classifier.

2.2 *Acquisition And Analysis Of Photographic Data*

Photographic data was acquired by a digital camera (BenQ, Model DC AE-110) having a resolution of 14.1megapixels. To meet the data acquisition compatibility for both types of data (radiometric and photographic), the camera was also kept at the height of 10 feet from the ground level. In this way, 20 colored images(24-bits) having dimensions 4288×3216 pixels in JPEG format from each above mentioned field were obtained. Sample image of each crop is presented in **(Fig.1)**.

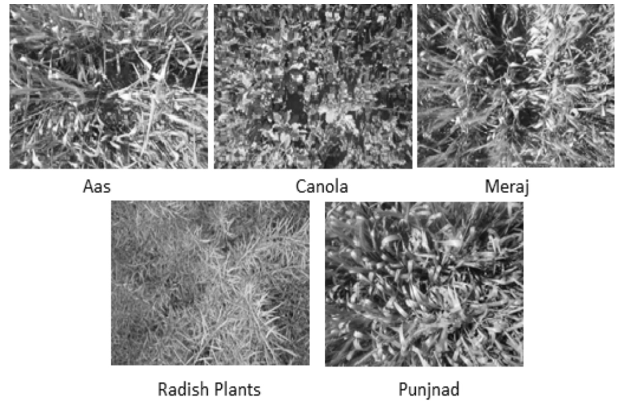


Fig.1 Samples of photographic data

With the implementation of IrfanView software these images were converted to grey scale images (8-bit) and were stored in bitmap (BMP) format, because, the MaZda software, which was used to calculate textural parameters/features, only supports this format. To minimize the shadow effect this data was acquired at noon time (11.30am to 2.00pm) under clear sky. To increase the sample data set, 7 non-over lapping sub-images or regions of interest (ROIs) with window size 512x512 pixels, were developed in each image. In this way, a data set of 700 images was obtained.

Similar to radiometric data, image analysis was carried out using MaZda version (4.6) software. For this purpose, a total number of 254 statistical texture features were calculated from all ROIs, which may be grouped as; 9 histogram features (first-order statistical parameters), 11 Haralick parameters (second-order statistical parameters) derived from *Gray Level Co-occurrence Matrix (GLCM)* in all directions (0^{o},45^{o},90^{o} and 135^{o}) up to 5 pixel distance, 5 Auto regression parameters, and 5 higher-order statistical parameters derived from *Gray Level Run-Length Matrix (GLRM)* in radial and axial directions. In this way, each ROI was defined by 254 textural features, and statistically it means that the data was interpreted in 177800 (700×254) dimensional features vector space.

It is worth mentioning that all of the 254 calculated features were not equally important for the classification of crops under observation. Moreover, a statistically, a huge data is required to have reliable results on the basis of such large number of features, which is practically important impossible. Therefore, it was necessary that the dimensionality of features vector space should be reduced by selecting the most relevant features, which have the ability to discriminate and classify the crops

For the selection of most appropriate set of features three approaches; *Fisher Coefficient (F), Probability Of Error + Average Correlation Coefficient*

(POE + ACC), and *Mutual Information Coefficient (MI)*, available in MaZdasoftware, were adopted. With the implementation of each feature selection approach, available in this software 10 features were selected.In this way total 30 features (10featuresb yeach above mentioned method) were selected. A s , it has been proved by a number of researchers that a hybrid set of features gives the better classification results (Shahid *et al.* 2014), so, for this research, a set of 22 features, by merging the all above mentioned 30 features, was selected.

Similar to radiometric data, clustering capability of photographic data under these 22 features was verified by applying three approaches *PCA*, *LDA*, and *NDA*, and we received an average accuracy of 72.21% and 83.01% by *PCA* and *LDA* approaches respectively. For *NDA*, its accuracy was 91.45% when the classifier was configured by applying 4 neurons in input layers with learning rate was set at 0.22.

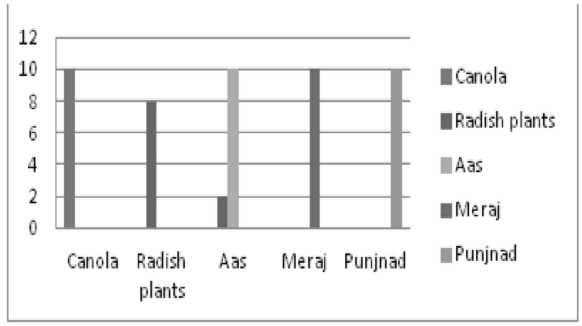
With this procedure it was observed that there were some images which were absolutely misclassified, by each applied approach (*PCA*, *LDA*, and *NDA)*, these images were excluded from data and were not part of further analysis. In this way, to train the ANN classifier a data set of 13 images (ROI=280) for each crop was deployed and a data set of 8 images (total ROI=280) of each class was used to train the classifier. Under the n-class training and testing option, available in B11, a training accuracy of 91.47% and testing accuracy of 93.14% was achieved.

3. RESULTS AND DISCUSSION

In this work, with the implementation of two types of data (radiometric and photographic), five crops were classified. In radiometric only 11 scans out of 40 for wheat crop Meraj were misclassified while all other crops were 100% accurately classified, during training phase as shown in Table1. In this way we received an average accuracy of 94.50% when classifier *ANN* was trained by applying the configuration mentioned in Section 2.1.

Table 1: Classified table of data classification for training

Class	Canola	Radish plants	AaS	Meraj	Punjnad
Canola	40	0	0	0	0
Radish plants	0	40	0	0	0
AaS	0	0	40	0	0
Meraj	0	0	3	29	8
Punjnad	0	0	0	0	40



Graph 1: Classified output testing report of radiometric data

Under the same architectural settings when the classifier was tested for radiometric data, by deploying the data of 50 scans, we received an accuracy 96.00%, only 2 scans of radish- plants crop were misclassified as they belong to Aas, while all other were 100% correctly classified, as shown in Table 2.

Table 2: Confusion table of data classification for testing

Class	Canola	Radish plants	AaS	Meraj	Punjnad
Canola	10	0	0	0	0
Radish plants	0	8	2	0	0
AaS	0	0	10	0	0
Meraj	0	0	0	10	0
Punjnad	0	0	0	0	10

For photographic data, only 24 data samples out of 280 were misclassified, when *ANN* classifier was trained on the basis of 22 selected textural features and was configured by applying the settings discussed in Section 2.2.In this way an accuracy of 91.43% was obtained. Details of misclassified data are presented in Table3. For photographic data the classifier was tested by deploying a data set of 175 samples under the same settings and parameters. In this testing phase 12 samples of photographic data were misclassified and an accuracy of 93.14% was achieved. Details of misclassified data samples are presented in Table 4.

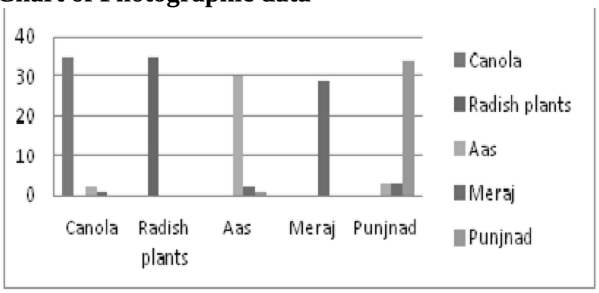
Table 3: Training for photographic data

Class	Canola	Radish plants	AaS	Meraj	Punjnad
Canola	53	0	2	1	0
Radish plants	0	56	0	0	0
AaS	0	8	45	2	1
Meraj	0	0	2	0	54
Punjnad	0	0	2	0	54

Table 4: Misclassification of photographic data testing the classifier

Class	Canola	Radish plants	Aa S	Meraj	Punjnad
Canola	35	0	0	0	0
Radish plants	0	35	0	0	0
AaS	2	0	30	0	0
Meraj	1	0	2	29	3
Punjnad	0	0	1	0	34

Chart of Photographic data



Graph 2: Classified output testing report foe photographic data

The results presented here show that the classification rate of radiometric data is greater than the photographic data for the same crops.

Another point, worth to be discussed here is that for this work each scan in radiometric data is defined on the basis of only five parameters, which consist of reflectance values of blue, green, red, infra-red and far-infrared bands. The classifier was trained and tested by the implementation of these discussed five parameters. On the other hand in the case photographic data a classifier was trained and tested on the basis of 22 statistical parameters, for which prior to implementation, of this data requires a lengthy procedure of features extraction and features selection, whereas, no such procedure is required for radiometric data.

4. CONCLUSION

During this study, classification results from two types of remote sensing data (radiometric and photographic) obtained from five different crops were compared. It was observed that the radiometric data gives better classification results as compared to photographic data, perhaps, due to difference of wavelength range present in data. The radiometric data ranges from 400nm to 1750nm covering the visible as well as, infrared and far-infrared regions, while photographic data delivers information which is based on only the wavelengths corresponding to visible region. We conclude that the presence of infrared and far-infrared wavelengths make the radiometric data more efficient for classification/differentiation as compared to photographic data. Another reason which makes radiometric data preferable in machine vision domain is that, it is easy to manipulate, because, it does not require any preprocessing procedures like features extraction and features selection, like photographic data.

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