J. Agr. Sci. Tech. (2011) Vol. 13: 1223-1232

RESEARCH NOTES

Vegetation Species Determination Using Spectral Characteristics and Artificial Neural Network (SCANN)

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ABSTRACT

Classification of vegetation according to their species composition is one of the most important tasks in the application of remote sensing in precision agriculture. To prepare an algorithm for such a mandate, there is a need for ground truth. Field operation is very costly and time consuming. Therefore, some other method must be developed, such as extracting information from the satellite images, which is comparatively cheaper and faster. In this study, we first introduced a simple method for Determination of the Vegetation Specie in full cover pixels (DVS) using their laboratory measured spectral reflectance curves. Then, based on these pixels, a hybrid method for vegetation field classification, which we call SCANN (Spectral Characteristics and Artificial Neural Network), is introduced. In this method, different vegetation spectral reflectance characteristics at the three extremes of green, red, and near-infrared along with an artificial neural network method were used. Comparing the results of DVS with those of field collected data showed near 100% accuracy. Based on the results of DVS, the results of SCANN showed an overall accuracy of more than 94%. This method is suggested for unsupervised classification using Hyperspectral images.

Keywords: Image classification, Neural networks; Spectral characteristics, Vegetation.

INTRODUCTION

The use of satellite remote sensing in monitoring changes in biospheric processes such as vegetation cover, phenology, primary production, crop yield, evapotranspiration, and many other physiological and climatological parameters requires frequent repeated observations (Javadnia *et al*., 2009; Mobasheri *et al*., 2008).

In remote sensing, among different methods of image classification, Artificial Neural Network (ANN) classification method has shown higher accuracy (Jayas and Paliwal., 2000). This is due to the fact that in ANN there is no pre-assumption regarding data distribution. Consequently, the method is a valuable tool for image classification and its development has gained lots of attention by researchers in recent years, particularly in precision farming (Irmak *et al*., 2006; Subramaniana *et al*., 1997). This is due to the fact that remote sensing technology is increasingly being used in measuring agricultural parameters necessary for precision farming and also in forest monitoring (Mobasheri *et al*., 2007; Pan *et al*., 2004).

A lot of information has so far been extracted from broad-band sensor products

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[DOR: 20.1001.1.16807073.2011.13.7.10.5]

such as TM, ETM, Spot and LISS-III. Although the data collected through broad-band sensors proved to be useful in some applications, they have their own limitations mostly due to the limited number of bands and wide spectral width.

. Different surface materials produce different signals in different parts of the electromagnetic spectrum where this makes them detectable. These signals may only be present in a very narrow region of the spectrum. Consequently, determination and detection of these signals can only be done by the sensors operating in narrow bands such as Hyperspectral sensors. These sensors are imaging in almost continuous spectra and are powerful tools for determination and precise detection of vegetation dominant species, surface and environmental parameters (Mobasheri *et al*., 2007).

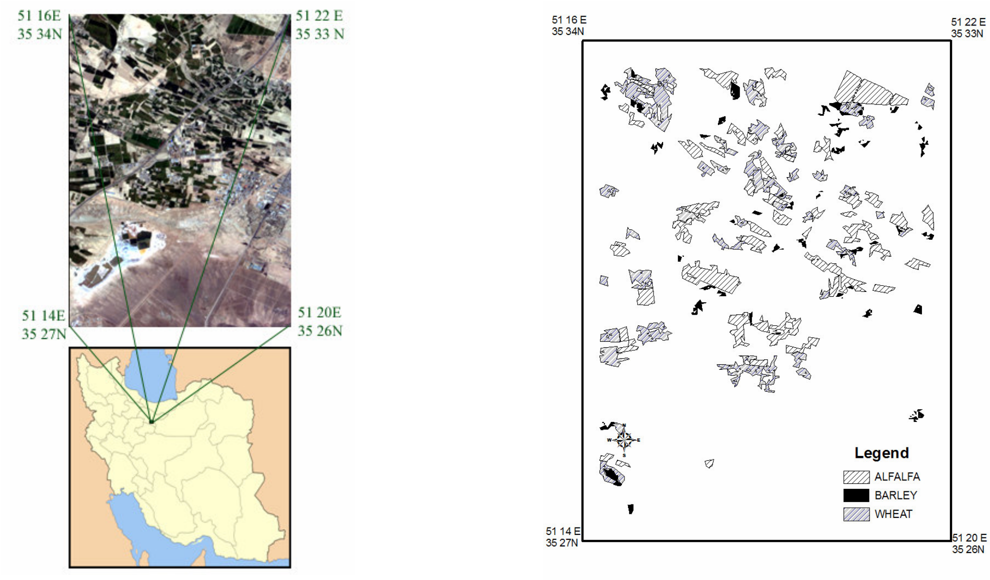
On the other hand, by using Hyperspectral sensors, it is possible to extract more useful information from surface materials. However, although increasing the number of bands might be useful in some aspects, it may cause some problems in selecting the best spectral band for monitoring specific features. In many researches, a combination of bands has been used for detection of particular minerals and vegetation species (Zhouyu *et al*., 2006; Cho *et al*., 2008). These bands may vary from one vegetation species to another. This is also true for inter-species as well as in one species at different stages of growth and/or under different stress conditions.

MATERIALS AND METHODS

In this research, it is tried to classify different species of vegetation using Hyperion sensor image products. This sensor is onboard of EO-1 platform and has 224 bands in 400 to 2500 nm spectral region. The spatial resolution is about 30m with a swath width of 7.5km. The region of study is located at the south of Tehran (Figure 1) and the acquisition date is May 21, 2002. To prepare the images for this study, the following preprocessing stages were carried out.

Image Pre-processing

Post-level 1B1 data processing operations for preparation of the Hyperion data for classification were performed. This included



(a) (b)

Figure 1. (a) Image of the region of interest RGB (86, 67 and 50) and (b) Land cover map of the region of interest.

[DOR: 20.1001.1.16807073.2011.13.7.10.5]

band selection, correction for bad lines, correction for striping and smile effects, co-alignment and a pixel-based atmospheric correction using FLAASH software.

The calibrated channels were bands 8-57 in the Visible and Near-Infra-Red (VNIR) and bands 77-224 in Short-Wave Infra-Red (SWIR). One of the problems we encountered in VNIR and SWIR was one pixel displacement from array 128 onward (Stanez *et al*., 2002). This was corrected at this stage. Then, conversion of *DN* to radiance was carried out using the following conversion equations (Beck R., 2003):

$$L_{VNIR} = Digital\ number/400 \qquad (1)$$
$$L_{SWIR} = Digital\ number/800$$

Bad lines in Hyperion level 1B1 data appear as dark vertical lines. The pixels on these lines have lower *DN* values as compared to their neighboring pixels. These pixels were corrected by replacing their *DN* values with the average *DN* values of their immediate left and right neighboring pixels (Han *et al*., 2002; Ashoori *et al*., 2008).

Vertical stripes are caused by differences in gain and offset of different detectors in pushbroom-based sensors. This could be detected through the statistics of the detector arrays by calculating mean, variance, minimum, and maximum data for each pixel in each band in the image. It is assumed that such gains and offsets are relatively stable throughout one image collection but not necessarily between different collections (Beck *et al*., 2003).

A general approach for removing vertical stripes with these characteristics is similar to methods used in balancing horizontal stripes in mirror scanner images through histogram equalization (Beck *et al*., 2003). This means that the histogram moments, such as the means and variances of the columns in each band, are used to balance the statistics of the arrays to those of a reference histogram. In this research, global balancing method was used (Beck *et al*., 2003).

Smile effect that exists in all Hyperion datasets refers to an across-track wavelength shift from the center wavelength. This is due to the change of dispersion angle with field position. According to the Hyperion spectral calibration (Goodenough, *et al*., 2003; Ashoori *et al*., 2008), the shifts are depending on the pixel position in the across-track direction. For VNIR bands, the shifts range between 2.6–3.5 nanometers. For SWIR bands, the shifts are less than 1nm and are not significant for agricultural applications (Goodenough, *et al*., 2003). Considering the high spectral resolution of the Hyperion data, the 2.6–3.6-nm shifts of VNIR bands cannot be ignored. In this case, the pixel spectrum may cause a reduction in the accuracy of classification. To correct the smile effect in this research, the Column Mean Adjustment in Radiance Space method was used (Goodenough, *et al*., 2003).

Then, the image was corrected for the effects of the atmosphere using FLAASH software based on MODTRAN algorithm (FLAASH Module User guide, ENVI FLAASH Version 4.2 August, 2005 Edition; Ashoori *et al*., 2008). The input parameter was horizontal visibility that was supplied by the nearby weather station.

In the next step, to find and dismiss the noisy bands, the Minimum Noise Fraction (MNF) was applied to the image. It is worth noting that the use of the MNF transforms is for determination of the inherent dimensionality of image data to segregate noise in the data and to reduce the computation requirements for subsequent processing (Boardman and Kruse, 1994). These operations led to a final image with 157 bands.

The methodology consisted of two stages. In the first stage, we tried to find a way for Determination of the Vegetation Specie (DVS) in few full covered pixels and, in the second stage, based on the findings of the first stage, a method for determination of the vegetation specie in each field was developed.

Stage1: Determination of Vegetation Species of a Pixel (DVS)

It is not always possible to have ground truth activities and location at the same time when satellites overpass. Therefore, it would be useful to find a way to detect surface covers

[DOR: 20.1001.1.16807073.2011.13.7.10.5]

with a higher degree of accuracy. This was the main objective of the first stage in this work.

A method for detecting vegetation specie in few full covered pixels is explained here that uses laboratory measured spectral reflectance curves for species present in this scene i.e. alfalfa, barley, and wheat. Of course, these curves are different from those sensed by the space-borne sensors due to the effects of the mixed pixels and the intervening atmosphere. However, it is almost always possible to find a fully vegetated pixel having spectral behavior similar to those measured in the laboratory and this was the case in our study.

We used the Laboratory Measured Vegetation spectral Reflectance curves (LMVR) produced by NASA (David *et al*., 1985) and USGS Spectral Library. A precise comparison of different LMVRs shows that each species at particular biological and environmental condition has usually its own spectral behavior different from the others (David *et al*., 1985). These differences are in the position and values of the maxima and minima in the reflectance curve. For instance, Figure 2 shows that alfalfa has a local maximum at 550 nm, a local minimum at 670 nm, and again, a local maximum at 1,062 nm. These values for wheat are at 580, 640 and 1,080 nm, respectively. To this, we might add the difference in the reflectance values of these extremes. Our investigation showed that almost no two vegetation LMVRs could be found having exactly similar spectral behaviors in detail. This uniqueness of spectral behavior could be the basis for the detection of the vegetation species, particularly for the fully homogenously covered healthy vegetation pixels from which we intended to determine the field vegetation specie.

The main focus of this study was on the three crop plants whose presence was confirmed by field surveillance, namely, alfalfa, barley, and wheat. The reflectance values of these three species at green, red and NIR extremes i.e. Maximum Reflectance at Green (MRG), Minimum Reflectance at Red (MRR) and Maximum Reflectance at NIR (MRNIR) and their differences were extracted from the relevant LMVRs and are shown in Table 1.

The bands selected in this way are well away from the strong water vapor absorption bands and, consequently, are less affected by the atmospheric water vapor content. Of course, the other atmospheric constituents may affect the pixels reflectance.

On the other hand, after relative atmospheric correction, the remaining effects of the atmosphere, to an acceptable degree, may be

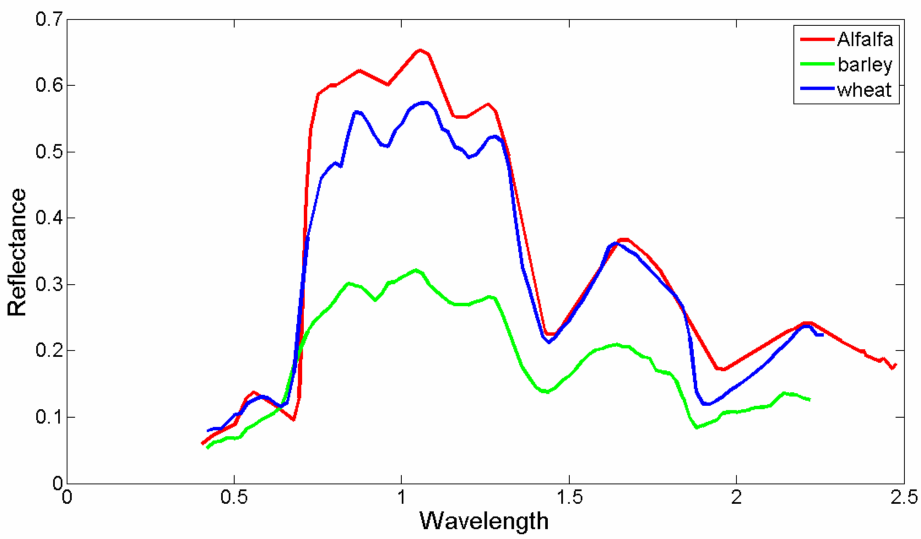


Figure 2. Spectral curve for three vegetation species: alfalfa, barley and wheat (David *et al*., 1985; USGS. 2007).

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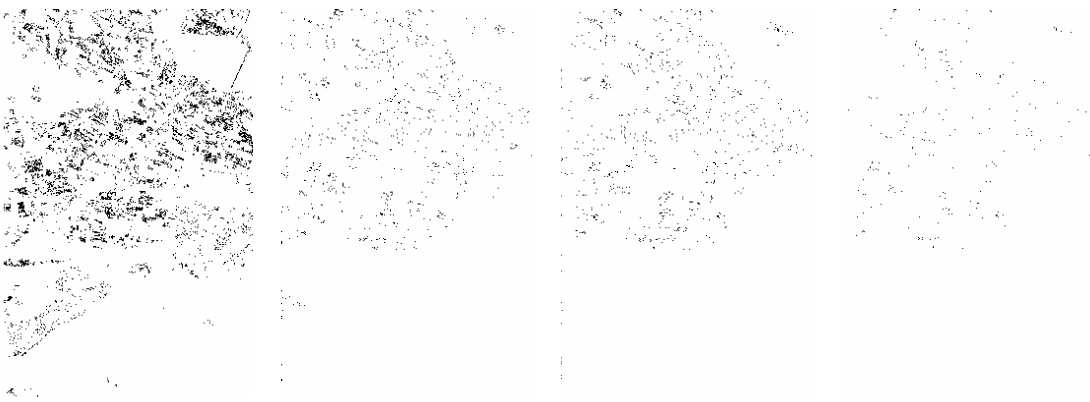
Table 1. Wavelength and reflectance in the extremes of Green, Red and NIR for three species of crop plants, namely, alfalfa, barley and wheat.

Vegetation	Alfalfa	Barley	Wheat
Wavelength of MRG	0.55	0.58	0.58
Reflectance In Green	0.137	0.095	0.13
Wavelength of MRR	0.67	0.6	0.64
Reflectance in Red	0.095	0.1	0.115
Wavelength of MRNIR	1.06	1.04	1.08
Reflectance in NIR	0.652	0.321	0.574
NIR-Green	0.515	0.226	0.444
NIR-Red	0.557	0.221	0.459
Green-Red	0.042	-0.005	0.015

considered the same for the three adjacent bands of green, red, and NIR. Based on this assumption, the difference between reflectance in these adjacent bands may be considered almost independent of the atmospheric effects. So it can be assumed that the difference between the reflectance of the two neighboring bands extracted from full covered pixels and those extracted from LMVR for the same vegetation specie is roughly the same. Although the absolute atmospheric correction may improve the results, for this method, a relative correction for the atmospheric effects would suffice.

By using bands corresponding to each of the vegetation reflectance extremes (Table 1), the image of the reflectance differences for each of the aforementioned species were produced (Figures 3, 4 and 5).

What we had as ground truth to evaluate the results was a land cover map collected through field surveying (Figure 1). As can be seen, the number of pixels meeting the criteria is small. This is mainly due to the presence of the mixed soil-vegetation pixels. To this, we may add the effect of shadow and lack of proper BRDF. By composing images 4-d, 5-d and 6-d one can produce an RGB image showing distribution of wheat, barley and alfalfa (Figure 6). Although the shapes of the field boundaries for none of these species is clear, a comparison with the land cover map in Figure 1 shows that the methodology works 100% accurate. Therefore, this method is accurate enough to be used for producing a reliable pixel specie cover map whenever the



(a) (b) (c) (d)

Figure 3. Alfalfa cover detection: (a) Pixels whose reflectance difference in bands 0.55 μm and 0.67 μm is 0.042; (b) Pixels whose reflectance difference in bands 1.06 μm and 0.67 μm is 0.557; (c) Pixels whose reflectance difference in bands 1.06μm and 0.55μm is 0.51, (d) Pixels having all conditions set in a, b and c.

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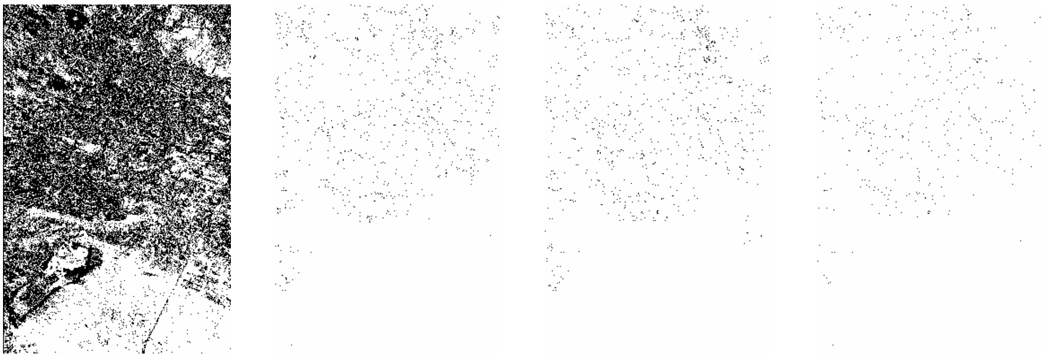
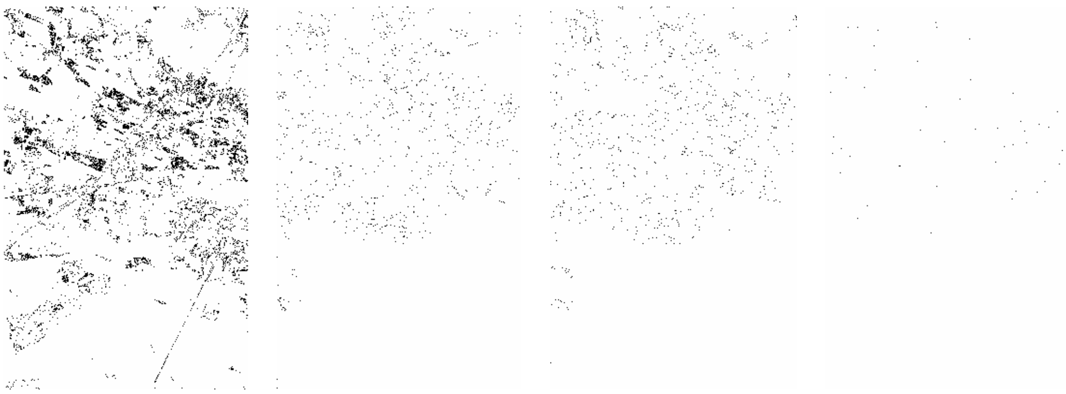


(a) (b) (c) (d)

Figure 4. Barley cover detection: (a) Pixels whose reflectance difference in bands0.58 μm and 0.60 μm is -0.005; (b) Pixels whose reflectance difference in bands 1.040 μm and 0.60 μm is 0.221; (c) Pixels whose reflectance difference in bands 1.040 μm and 0.58 μm is 0.226, (d) Pixels having all conditions set in a, b and c.



(a) (b) (c) (d)

Figure 5. Wheat cover detection: (a) Pixels whose reflectance difference in bands0.58 μm and 0.64 μm is 0.015; (b) Pixels whose reflectance difference in bands 1.080 μm and 0.64 μm is 0.459; (c) Pixels whose reflectance difference in bands 1.080μm and 0.40μm is 0.444, (d) Pixels having all conditions set in a, b and c.

need arises. In what follows, these pixel specie cover maps will be the basis of the whole field specie detection and classification by Artificial Neural Network (ANN) method.

Stage 2: Spectral Characteristics and Artificial Neural Network (SCANN)

Artificial Neural Networks (ANN) is a non-linear model that acts similar to a human neural system. Each ANN consists of a series of nodes and weighted connections between them (Carvajal *et al*., 2006).

One of the privileges of ANN method in comparison to traditional statistical methods is that the networks are free in distribution i.e. the training and recalling are dependent on the linear combination between data patterns and are independent of input data (Jayas and Paliwal *et al*., 2006; Civco and Waug , 1994). However, the reasons for the success of ANN in classification can be summarized as: (1) there is no need for pre-assumption in data distribution, (2) it permits the user to make use of the initial knowledge regarding classes and possible limitation, (3) the method allows management of the spatial data from multiple

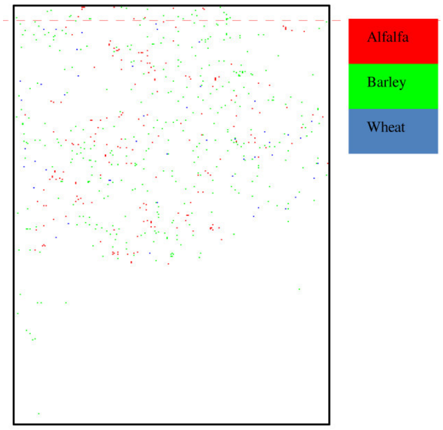


Figure 6. Map of three plant species, namely, wheat, barley and alfalfa produced by applying DVS criteria.

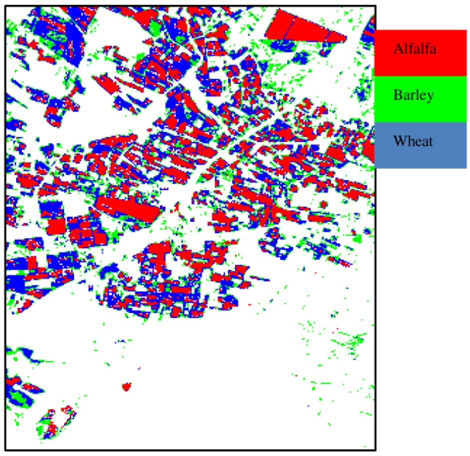


Figure 7. Classified image produced by ANN method for alfalfa, barley, and wheat.

sources and can achieve their classification results equally (Carvajal *et al*., 2006).

To determine the proper ANN for the present work, different numbers of hidden layers with different number of nodes were tested (Table 2), out of which a one layer system with 10 nodes was found suitable.

The input layer consists of 3 nodes to which three differences between reflectance in three extremes i.e. (RG-RR), (RN-RR) and (RN-RG), are assigned.

Out of 826 detected pixels in the previous stage, 124 were used as training data and the rest were left for algorithm evaluation. Thus, the classification algorithm was run once for each of the three species (barley, alfalfa, and wheat). At the end, the output images were composed in a RGB image to produce the classified image of the sub scene (Figure 7).

RESULTS AND DISCUSSION

To evaluate the accuracy of the method, 702 pixels were used and a confusion matrix was prepared (Table 3).

As can be seen in Table 3, the overall accuracy of 94.16% and a Kappa value of 0.90 were achieved through this method. This is a little different for that of the

Table 2. Results of the investigation regarding the determination of proper number of layers and nodes in ANN.

Number of hidden layer	Number of nodes in hidden layer1	Number of nodes in hidden layer2	RMSE	Execution time	Number of iterations	Overall accuracy	Kappa coefficient
1	5	0	0.00093	55s	500	94.01	0.9037
1	10	0	0.00078	44s	500	9416	0.9064
2	5	5	0.00044	48s	500	90.59	0.8496
2	10	10	0.00036	73s	500	93.30	0.892
2	20	20	0.00033	463s	500	91.73	0.8666

Table 3. Confusion Matrix for image classification by SCANN method.

Overall accuracy	94.16%			
Kappa coefficient	0.9064			
		Ground Truth pixel		
Class	Alfalfa (Test)	Barley (Test)	Wheat (Test)	Total
Unclassified	0	0	0	0
Alfalfa	302	6	1	309
Barley	2	255	2	259
Wheat	12	18	104	134
Total	316	279	107	702
Class	Commission (%)	Omission (%)	Prod. ACC. (%)	User. Acc. (%)
Alfalfa	2.27	4.43	95.57	97.73
Barley	1.54	8.60	91.40	98.46
Wheat	22.39	2.80	97.20	77.61

individual species i.e. the overall accuracy for alfalfa, barley and wheat are 95.57%, 91.39% and 97.20%, respectively. This shows that the method works acceptably well for these three plant species. The wheat commission error shows that 22.39% of barley and alfalfa are labeled in wheat class. The other parameters that can be used for classification accuracy assessment are the User Accuracy (UA) and Producer Accuracy (PA). As can be seen in Table 3, while the *PA* is greater than 90% for all three species, the *UA* for wheat is much lower compared to the other two species. This might be due to the high similarity between the spectral reflectance of barley and wheat. Since the method is pixel based, the improper choice of spatial resolution might be another source of error. This, for the present study, is 30 m and, consequently, the presence of mixed pixels is inevitable.

To compare the SCANN method with other traditional methods, it was decided to compare the results with the results of well known classification methods such as Maximum Likelihood (ML) (Paola and Schowengerdt, 1995, Alavi Panah, 2001). The result of classification by ML method is shown in Figure 8 and its confusion matrix is shown in Table 4.

As can be seen in Table 4, all parameters such as overall accuracy, Kappa coefficient, PA, and UA decreased dramatically compared to SCANN method. Also, the commission error for wheat is 44.6% compared to 22.39% in SCANN method.

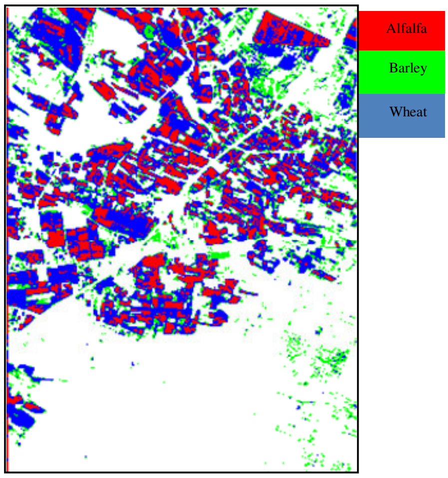


Figure 8. Classified image produced by ML method for alfalfa, barley and wheat.

CONCLUSIONS

It was found that a method based on SCANN was successful in differentiating between barley, alfalfa and wheat. In this method, useful information present in the spectrum of vegetation was used in building up the SCANN algorithm. This information consists of the reflectance and reflectance differences of each of the vegetation species in some particular wavelengths. These wavelengths are extremes in green, red, and NIR. Investigation of the vegetation spectral

[DOR: 20.1001.1.16807073.2011.13.7.10.5]

Table 4. Confusion Matrix for ML classification method.

Overall Accuracy	79.91%			
Kappa coefficient	0.6920			
		Ground Truth pixel		
Class	Alfalfa (Test)	Barley (Test)	Wheat (Test)	Total
Unclassified	3	21	2	26
Alfalfa	301	27	0	328
Barley	3	157	2	162
Wheat	9	74	103	186
Total	316	279	103	702
Class	Commission (%)	Omission (%)	Prod. ACC (%)	User. Acc. (%)
Alfalfa	8.23	4.75	95.25	91.77
Barley	3.09	43.73	56.27	96.91
Wheat	44.62	3.74	96.26	55.38

reflectance showed that the wavelength at which these extremes occur, are different for different vegetation species as well as inter-species. Also, the differences between the reflectance of these extremes differ from one species to the other. This was the basis for detection of the three plant species studied, namely, wheat, barley and alfalfa.

Comparing the results with the field collected data, it was found that SCANN method was able to classify the pixels with an accuracy of more than 94%. The SCANN method was compared with ML method where the differences were noticeable. To improve the applicability of this method, the following data is needed (i) a rich library of the spectral reflectance for different vegetation species at their different growing stages, (ii) hyperspectral image, preferably airborne, and (iii) a complete set of weather parameters for absolute atmospheric corrections.

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تعیین گونه گیاهان با استفاده از خصوصیات طیفی و شبکه عصبی مصنوعی (SCANN)

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چکیده

طبقه بندی گیاهان برحسب گونه آنها یکی از مهمترین اهداف سنجش‌ازدور در کشاورزی دقیق است. برای تهیه آلگوریتمی که بتواند این مهم را انجام دهد، نیاز به داده‌های زمینی است. از طرفی عملیات میدانی بسیار زمان‌بر و هزینه‌بردار است. بنابراین نیازمند تهیه راهکاری برای استخراج اطلاعاتی قابل اعتماد زمینی از خود تصاویر هستیم. در این تحقیق با استفاده از منحنی‌های طیفی آزمایشگاهی گیاهان روشی آسان (DVS) برای شناسائی پیکسل‌های با پوشش کامل گیاهی معرفی می‌شود. سپس با استفاده از این پیکسل‌ها روشی هیبریدی برای طبقه‌بندی برابی گیاهان با نام SCANN معرفی می گردد. در این روش از مقادیر بازتابندگی گیاهان مختلف در سه مقدار بیشینه سبز، کمینه قرمز و بیشینه فروسرخ نزدیک بهمراه روش شبکه عصبی مصنوعی استفاده می‌شود. مقایسه نتایج روش DVS با داده‌های جمع‌آوری شده میدانی صحت طبقه‌بندی نزدیک ۱۰۰ درصد را نشان می‌دهد. با استفاده از این داده‌ها با نتایج حاصل از روش پیشنهادی SCANN صحت کلی ۹۴ درصد را نشان می‌دهد. این روش برای طبقه‌بندی نظارت نشده گیاهان با استفاده از تصاویر ابرطیفی پیشنهاد می‌شود.

[DOR: 20.1001.1.16807073.2011.13.7.10.5]