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Hyper Spectral Measurements as a Method for Potato Crop Characterization

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Abstract The main objectives of this research is to determine the optimal hyperspectral range and waveband/s in the spectral range of (400–2500 nm) to discriminate between four different varieties of Potato crop (Diamond, Everest, Mondial and Rosetta) that are cultivated in old and newly cultivated lands of Egypt and to propose detailed spectral reflectance characterization for these four varieties which will enable more accurate surveying of these varieties through satellite imagery. Hyperspectral ground measurements of ASD field Spec3 spectroradiometer was used to monitor the spectral reflectance profile during the period of the maximum growth stage of the crop. An average of thirty measurements for each variety was considered in the process. After accounting for atmospheric windows and/or areas of significant noise, a total of 2150 narrow bands in 400–2500 nm were used in the analysis. Spectral reflectance was divided into six spectral zones: blue, green, red, near-infrared, shortwave infrared-I and shortwave infrared-II. One Way ANOVA and Tukey's HSD analysis was used to choose the optimal spectral zone that could be used to differentiate between the four varieties. Then, linear discrimination analysis (LDA) was used to identify the specific optimal wavebands in the spectral zones in which each variety could be spectrally identified. The results of Tukey's HSD showed that NIR is the best spectral zone for the discrimination between the four varieties. The other five spectral zones showed close spectral characterizations between at least two varieties. The results of (LDA) showed the optimal waveband to identify each variety. These results will be used in machine learning process to improve the performance of the existing remote sensing software's to estimate potato crop acreage. The study was carried out in AlBuhayrah governorate of Egypt.
Keywords *Hyper Spectral Data, Potato Discrimination*

1. Introduction

Potato is Egypt's most important export vegetable crop and the second most important (after tomatoes) vegetable crop in economic value (El Tobgy, 1974). Out of an annual production of about 1.2 million tons, over one million are retained for domestic consumption. Average annual per capita consumption of potatoes is about (20-25 kg) (Geddes and Monninkhof, 1984). Therefore, there is a high need for a regular, costly and timely affective process for potato crop acreage estimation and yield prediction which could be achieved using remotely sensed data. Spectral data from the current generation of Earth orbiting satellites carrying broad-waveband sensors such as Landsat Thematic Mapper (TM), Le Syste me pour l'observation de la terre (SPOT) High Resolution Visible (HRV), and the Indian Remote Sensing (IRS) Linear Imaging Self-Scanning (LISS) have limitations in providing accurate estimates of biophysical characteristics of agricultural crops and vegetation cover (Fassnacht et al., 1997; Weigand et al., 1991; Weigand and Richardson, 1990). These limitations are mainly the low spectral and spatial resolution that makes it difficult to isolate potato crop from the other crop covers in the intensive cultivated lands and of course it is almost impossible to classify the different potato varieties on the national scale. This is in which hyperspectral remote sensing technology could be used to increase the potentiality of the existing satellite image processing software's in classifying potato crops. Also, assessment of potato biophysical and biochemical parameters through hyperspectral remote sensing could be a part of precision agriculture system that will enable more effective potato management process. Hyperspectral sensors measure reflectance in a large number of narrow wavebands, generally with band widths of less than 10 nm. With these narrow bands; reflectance and absorption features related to specific crop physical and chemical characteristics can be detected. Many researches have indicated good relationships between biochemical composition, physical structure, water content, and plant ecophysiological status (Gamon, Pen˜uelas, and Field 1992; Pen˜uelas and Filella, 1998). Spectral determinations have provided an automatic, quick, and non-destructive method of assessing physiological parameters and nutrient levels in crop plants (Hinzman et al., 1986; McMurtrey et al., 1994; Casanova et al., 1998; Diker and Bausch, 2003; Hansen and Schjoerring, 2003). Different hyperspectral remote sensors were used for precision agriculture applications, such as airborne visible infrared imaging spectrometer (AVIRIS), compact airborne spectrographic imager (CASI), multispectral infrared and visible imaging spectrometer (MIVIS), and hyperspectral mapping (HyMapTM) system. These sensors can provide quality images with high spatial and spectral resolutions (Taranik et al., 1993; Fraser, 1998; Treitz and Howarth, 1999; Nolin and Dozier, 2000).

The main objective of the current study is using field hyperspectral measurements to identify the spectral reflectance pattern for four potato varieties. These varieties are quite important for the national export of Potato as well as for the local markets. The final objective is to propose a new method of the assessment of potato biophysical and biochemical parameters that could be a part of precision farming system and finally to propose spectral reflectance pattern that could be used in machine learning process to improve the performance and the accuracy of satellite image processing software's in the estimation of potato acreage and potato yield estimation.

2. Study Area

The study was carried out in the newly reclaimed area of El-Behirah governorate (Nubaria area). The study area is irrigated by center pivot system using underground water. This water is characterized by EC equal 1.5 dSm^{-1}. The climate in this area is arid Mediterranean type with an average annual precipitation of about 10.3 mm and temperature is 25.8 C^{o}. Generally the soil is a slightly saline where the EC value is about 1.85 dS/m and pH values is about 7.8 and soil texture is sandy.

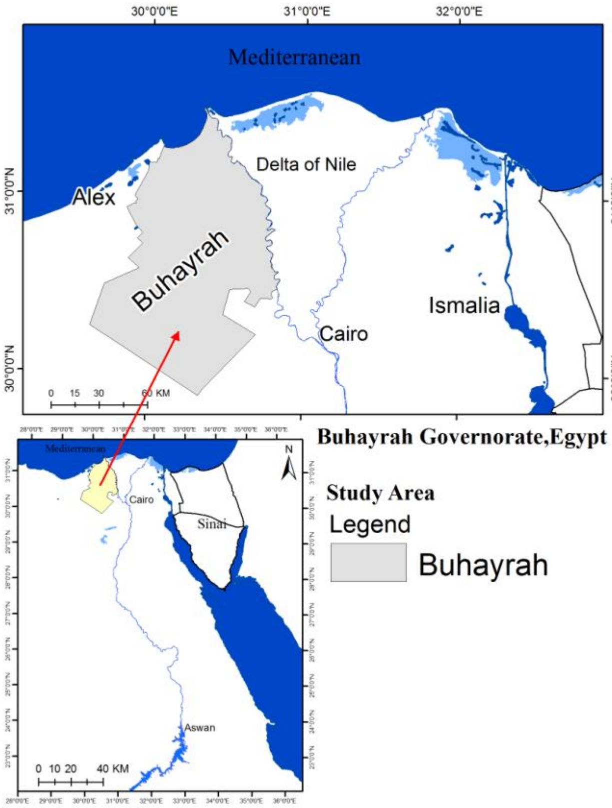

Figure 1: *Location Map of Al Buhayrah Governorate*

3. Field Hyper Spectral Measurements

The methodology of this work focused on field hyperspectral measurements and statistical analysis for the output measurements in order to choose the optimal spectral zone and wavebands to isolate each variety. As the final objective of this work is presenting information that could be used to increase the accuracy and performance of the existing remote sensing software's in classifying the different varieties in the intensive cultivated lands of the Nile delta. Analytical field spectroradiometer (ASD Field Spec) was used to measure the reflection of the four potato varieties under investigation. The average of thirty points distributed along the study area for each variety was calculated to be used in the study. Measurements were carried out in a full optical spectral range (Visible – Near Infrared – Short Wave Infrared) starting from 350 nm to 2500 nm with 1 nm interval output data. The sampling interval is 1.4 nm at the spectral range (350-1050 nm) while it is 2 nm at the spectral range (1000-2500 nm). These are the intervals which the device is capturing the reflectance. The device automatically performs an interpolation for the data and gives the final data output with (1 nm) interval for the all spectrum range (350-2500 nm). The spectrum characteristics of the device are shown in Table 1. The protocol used for the collection of spectral data is based on measuring radiance from a Spectralon® panel. A designed probe was attached to the instrument's fiber-optic cable to be used to ensure standardized environmental conditions for reflectance measurement. The fiber-optic cable provides the flexibility to adapt the instrument to a wide range of applications. Bare foreoptic 25 degrees used for outdoor measurements resulting circular field of view with 3 cm diameter as measurements were taken at 3 cm height in nadir position (90 degrees) over the measured plants. In the current study, the measurements were performed by holding the pistol grip by hand. As recommended in the instructions of using the device, the Spectralon® was tilted directly towards the sun during optimization.

Table 1: *The ASD Field Spec 3 Specifications*

Spectral Range	350-2500 nm
Spectral Resolution	3 nm : 700 nm 8.5 nm : 1400 nm 6.5 nm : 2100 nm
Sampling Interval	1.4 nm : 350-1050 nm 2 nm : 1000-2500 nm

4. Spectral Reflectance Pattern

Spectral reflectance pattern for the four potato varieties is shown in Figure 2. Reflectance pattern showed the same trend for the four varieties; however, reflectance of Evreast and Diamond was higher than reflectance of Rosetta and Mondial along the whole spectrum. Comparing the reflectance in the different spectral zones for the four varieties showed that the highest spectral reflectance was in infrared spectral zone (700–1300 nm), relatively low reflectance in the spectral zone (1450–1800 nm) while the lowest reflectance was found in the spectral zone (1950-2300 nm). It is noticeable that there is a big similarity in the spectral reflectance pattern between Evreast and Diamond. The reason of this might be the close structure and characterization of the two varieties.

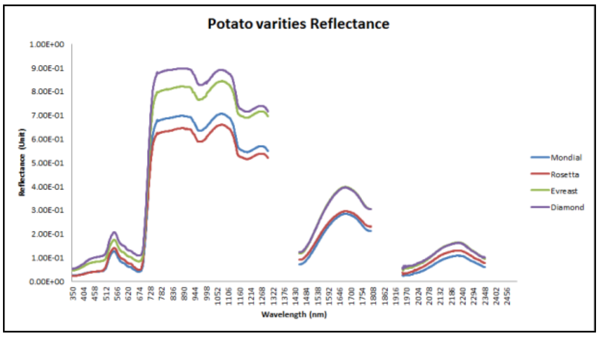

Figure 2: *The Spectral Reflectance Pattern for the Different Crops*

Spectral zones that represent the atmospheric windows (portions of the electromagnetic reflectance that include data noise because of the relative air humidity) were removed. Spectral pattern of each measured sample was identified. Generally, spectral reflectance could be divided into six different spectral portions as follows: blue (350 - 440 nm), green (450 - 540 nm), red (550 - 750 nm), NIR (760 - 1000 nm), SWIR I (1010–1775 nm) and SWIR II (2055–2315 nm).

5. Comparing Standard Deviations from Several Populations

Analysis of variance (ANOVA) methods are presented for comparing means from several populations or processes. While similar methods are occasionally used for comparing several standard deviations, often using the natural logarithm of sample variances as the response variable. There are also a number of alternative procedures that are not based on ANOVA methods that can be used to compare standard deviations. Two of these are described below. Both are highly sensitive to departures from the assumption of normality; consequently, they should be used only after verification that the assumption of normally distributed errors is reasonable. When using ANOVA models with data from designed experiments, a valuable assessment of the assumption of constant standard deviations across (k) factor-level combinations is given by the F-max test The F-max test is used to test the hypotheses (Mason 2003) **(**Equation 1).

$$F_{Max} = \left(\frac{\max(s_i)}{\min(s_i)}\right)^2 \qquad (1)$$

The *F*-statistics in an ANOVA table provide the primary source of information on statistically significant factor effects. However, after an *F*-test in an ANOVA table has shown significance, an experiment usually desires to conduct further analyses to determine which pairs or groups of means are significantly different from one another (Mason, 2003)**.** Tukey's procedure controls the experiment wise error rate for multiple comparisons when all averages are based on the same number of observations. The stated experiment wise error rate is very close to the correct value even when the sample sizes are not equal. The technique is similar to Fisher's LSD procedure. It differs in that the critical value used in the TSD formula is the upper 100α% point for the difference between the largest and smallest of *k* averages. This difference is the range of the *k* averages, and the critical point is obtained from the distribution of the range statistic, not from the *t*-distribution **(**Equation 2).

Two averages $\bar{y}_i$ and $\bar{y}_j$, based on n_i and $n_j$observations respectively, are significantly different if:

$$|\bar{y}_i - \bar{y}_j| > TSD$$

Where

$$TSD = q(\alpha; k, v)\left(MS_E \frac{n_i^{-1} + n_j^{-1}}{2}\right)^{\frac{1}{2}} \qquad (2)$$

The results of Tukey's HSD test (Figure 3) showed the significancy of the spectral difference between the different varieties along the six spectral zones attached with the general mean of the reflectance for the four varieties, the mean of the reflectance for each variety, the maximum and minmum reflectance values for each variety. Generally, as shown in Figure 3, NIR spectral zone was the best to differetiate between the four varieties with the highest significant difference while red spectral zone was inadequate to differentiate between the four varieties. Only the two spectral zones (NIR) and (SWIR II) showed significant difference between the two varietes (Rosetta and Modial) while three spectral zones (blue, green, NIR) showed significant difference between Diamond and Evreast. In the spectral zones (SWIR I) and (SWIR II), no significant difference was found between Diamond and Evreast while significant difference in these spectral zones was found between these two varieties and the other two varieties.

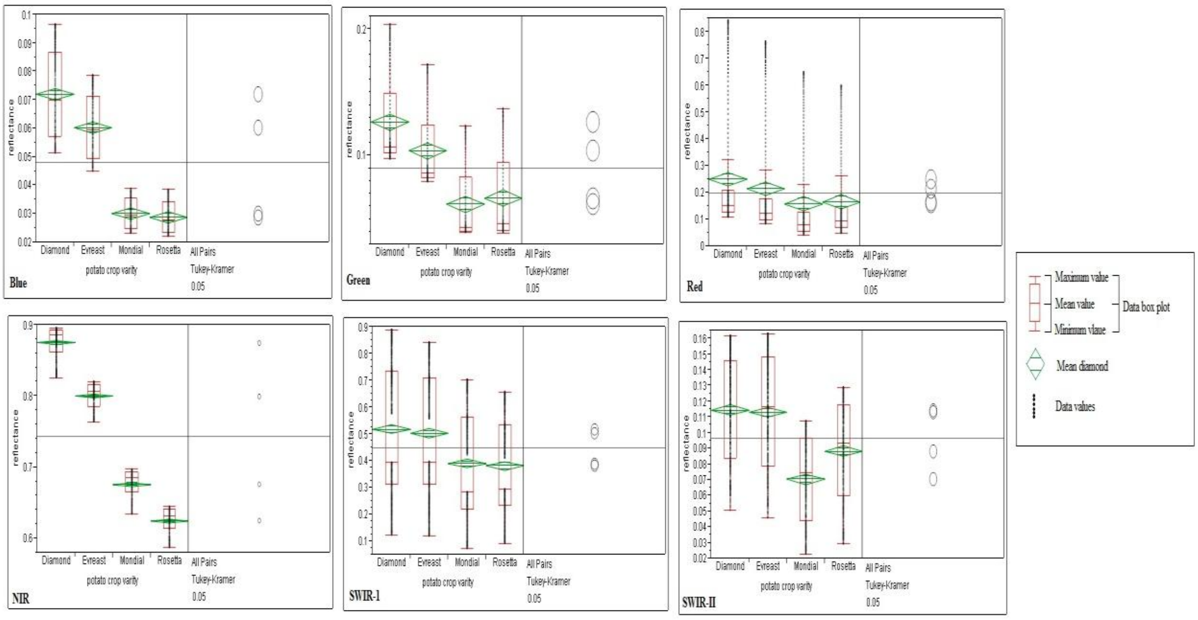

Figure 3: *ANOVA and Tukey's HSD Analysis to Differentiate between the Four Potato Varieties*

6. Linear Discriminate Analysis

Linear Discriminate Analysis (LDA) is a method to discriminate between two or more groups of samples. The groups to be discriminated can be defined either naturally by the problem under investigation, or by some preceding analysis, such as a cluster analysis. The number of groups is not restricted to two, although the discrimination between two groups is the most common approach. Linear Discrimination Analysis (LDA) is a commonly used technique for data classification. LDA approach is explained by Axler 1995. It easily handles the case where the within-class frequencies are unequal and their performance has been examined on randomly generated test data. This method maximizes the ratio of between-class variance to the within-class variance in any particular data set thereby guaranteeing maximal separability. LDA doesn't change the location but only tries to provide more class separability and draw a decision region between the given classes. This method also helps to better understand the distribution of the feature data. In the current study, class-independent transformation type of LDA was performed. This approach involves maximizing the ratio of overall variance to within class variance. It uses only one optimizing criterion to transform the data sets and hence all data points irrespective of their class identity are transformed using this transform. In this type of LDA, each class is considered as a separate class against other classes. In LDA, within-class and between-class scatter are used to formulate criteria for class separability. Within-class scatter is the expected covariance of each of the classes. The scatter measures are computed using equations 3 and 4.

$$Sw = \sum_j Pj \times (\mathrm{cov}_j) \quad (3)$$

Therefore, for the two-class problem,

$$Sw = 0.5 \times \mathrm{cov}_1 + 0.5 \times \mathrm{cov}_2 \quad (4)$$

All the covariance matrices are symmetric. Let and be the covariance of set 1 and set 2 respectively. Covariance matrix is computed using the following equation (5).

$$\mathrm{cov}\, j = (x_j - \mu_j)(x_j - \mu_j)^T \quad (5)$$

Then, the between-class scatter is computes using the following equation (6).

$$Sb = \sum_j (\mu_j - \mu_3) \times (\mu_j - \mu_3)^T \quad (6)$$

Sb can be thought of as the covariance of data set whose members are the mean vectors of each class. As defined earlier, the optimizing criterion in LDA is the ratio of between-class scatter to the within-class scatter. The solution obtained by maximizing this criterion defines the axes of the transformed space. As LDA is a class independent type in this study, the optimizing criterion is computed as equation (7)

$$criterion = inv(sw) \times Sb \quad (7)$$

Finally, transforming the entire data set to one axis provides definite boundaries to classify the data. The decision region in the transformed space is a solid line separating the transformed data sets thus equation (8)

$$transforme\_set = transform\_spec^T \times data\_set^T \quad (8)$$

This analysis was carried out to discriminate between the four Potato varieties (Diamond, Everest, Mondial and Rosetta) in order to identify the spectral reflectance pattern of each variety, the optimal waveband to isolate each variety and finally the specific wavelengths that could be used to isolate each variety. Linear discrminant analysis showed the optimal wavebands that could be used to identify each variety. As shown in Table 2, very narrow waveband (714 – 717 nm) was the best to identify Mondial variety while relatively wide spectral range could be used to identify the other three varieties.

Table 2: *The Optimal Waveband to Differentiate between the Four Potato Varieties*

Variety	Optimal Wavelength Zones (nm)
Everest	712:715/ 1596:1699/ 1700:1754
Diamond	713:1349/1656:1691
Rosetta	350:712/1421:1656/1799:2349
Mondial	714:717

7. Conclusion

Field hyper spectral measurements were used to discriminate between four potato varieties (Everest, Diamond, Rosetta, Mondial). Output measurements were analyzed through two statistical tests to show the best spectral zone and the optimal wavebands to discriminate between the four varieties. Tukey's HSD test indicated that NIR spectral zone was the optimal to differetiate between the four varieties while red spectral zone was inadequate to differentiate between the four varieties. Two spectral zones (NIR) and (SWIR II) showed significant difference between the two varietes (Rosetta and Modial) while three spectral zones (blue, green, NIR) showed significant difference between Diamond and Everest. Linear discrminant analysis showed the unique waveband/s that could be used to isolate each variety. The result of this work is a step forward for better potato crop acreage estimation. The result could be icluded through a machine learning process in the existing image processing softwares to improve crop classification results.

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