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Original Article

Spectral measurements for monitoring of sugar beet infestation and its relation with production

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Abstract
Identification of the best spectral zone and wavelength to be used for the discrimination of healthy and infected sugar beet plants and also to discriminate between the different infections of sugar beet plants is the goal achieved in this research. Field hyperspectral radiometer was used to measure spectral reflectance characteristics. By comparing spectral reflectance for the three infections of sugar beet plants (Cotton leaf worm, Aphid and Whiteflies), showed high pattern similarity. HSD Tukey's analysis showed that the NIR and Blue spectral zone are the best for the discrimination between healthy sugar beet plant and the different infections; on the other hand SWIR-1 and SWIR-2 was the worst but Red and Green spectral zones showed reasonable discrimination. Also, Spectral discrimination was clearer in case of old leaves than young ones. Hence a result of this study is significant, as remote sensing technologies can be used for early detection for plants infections, and thus can be used for integrated pest management system.

Keywords: Hyperspectral data, Sugar beet, White fly, Aphid, Cotton leaf worm

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Introduction

In Egypt there is only two master sugar producer one of them Sugar beet; *Beta vulgaris* L. The total sugar beet area in Egypt reached 362 thousands feddans representing 5.41% from the total winter crop area. Amount of sugar beet production was 74861 tons represented 5.03 % from the total production of winter crops in 2011 (Central Agency for Public Mobilization and Statistics, 2013). Sugar beet area harvested to increase by 10 percent or 20,000 ha, to reach 224,000 ha. with production, expected to reach 9.5 MMT, an increase of 3.4 percent or 313,000 MT. Beets are planted in August and September and harvested in March (Hamza, 2017).
In climatic condition of Egypt the crop production of *B. vulgaris* was attacked by many insect pests thought its growing phases, (Amin et al., 2008). At the same time, spraying pesticides is still the most widely applied choice in pest and disease control in cultivated crops. Uniform spraying of crops is carried out at different times of the cultivation cycle and all over fields; although most pest infestations are not quietly extended across sprayed areas but occur only in

patches. Pesticides should be applied only on targeted places in the field. Thus, to help farmers in avoiding heavy sprays of pesticides and taking the precautions to restrict serious insects' infestations, early diagnosis should take place (Yones et al., 2012). Remote sensing technology considers the most important instrument for pre-visual diagnosis of plant diseases. It can supply quick reaction in compare with usually booklet scout procedure for determination of the pest existence (Moran et al., 1997). Theoretical basis of remote sensing applications in assessment of crop diseases, that crop diseases cause some physiological changes and serious damages in plant tissues. Consequently, infection caused by insect pests intervenes with photosynthesis and the structure of plant so influences the intake of light energies; and modifies the reflectance feature of plant (Hatfield and Pinter, 1993).

These changes are represented in significant change in plant spectroscopic parameters. Therefore, as the first step, there is a high need to specify spectral reflectance characteristics in case of healthy and infected plants. Secondly, these characteristics will be used for pre-visual diagnosis for possible future infection. Many researchers observed the competence of remote sensing technologies in detection and diagnosis of plant diseases, Hillnhütter et al. (2011), Mahlein et al. (2010, 2012) and (Abdel Wahab et al., 2017). Spectral reflectance measurements could be used efficiently for disease and pest infestation detection and that depends on the determination of the highly correlated zone and wavelength to a particular infection. Basically, from 400 - 700 nm (visible region) is concerning with related to the composition of pigment (Blackburn & Steele, 1999; Gitelson et al., 2002) while leaf traits structure and water content almost influence from 700 - 1100 nm (NIR region) Jacquemoud & Baret (1990) and Yones et al., (2014). The improvements of sensor technology extremely increase the capacity for getting the hyperspectral data and potency of quantifying pigments of plant (Blackburn, 2007). Recently, the evolution in optical technology has enabled to differentiate between healthy and diseased crops, so the possibility of automatic detection of insect pests and crop diseases spatial distribution. Spectroscopy and imaging technologies can be combined with developed agricultural in that it can supply knowledge on spatial distribution of infection and early detection of diseases, thus notification on best time for specific place for application of pesticide (West et al., 2003).

Generally green plant leaves absorb most of red and blue spectrum to be used for photosynthesis process, at the same time most of green spectrum is reflected from plant leaves since only a small part of it is used for photosynthesis process. There is also strong reflectance between 0.7 and 1.0 µm (near IR) in the spongy mesophyll cells located in the interior of a leaf, within which light reflects mainly at cell wall/air space interfaces, much of which emerges as strong reflection rays. Water content is the main factor that affect spectral reflectance pattern in short wave infrared (SWIR). Higher water content in plant leaves appears in lower reflectance in SWIR.

Any changes in chlorophyll content or mesophyll cell as well as water content of plant leaves due to pest activities dramatic changes for spectral reflectance will occur. *S. littoralis* larvae prefer to feed on young leaves, Aphids usually feed on sap of phloem and xylem, Whiteflies feed by sucking phloem sap of plants, introducing toxic saliva and decreasing the plants' overall turgor pressure. And due to the variation in the feeding behavior of the different pests, a relative discrepancy of spectral reflectance pattern is expected.

The main objective of the present study is to determine as a first step the optimal spectral zone and as the second step the optimal waveband spectrally identify healthy and infected sugar beet leaves and to discriminate between different infections (cotton leaf worm, Aphid and Whiteflies).

Material and Methods

Study area

El-Minya governorate Located in Upper of Egypt is one of the most highly Agriculture area , it have the largest Reclaimed Land in Upper Egypt that extend from North to south in the West desert of Egypt, El Minya Governorate is an important agricultural and industrial area. The most important agricultural products are sugar-cane, cotton, beans, soya beans, garlic, onions, tomatoes, potatoes, watermelons, and grapes. The governorate is one of the most highly populated governorates of Upper Egypt. It contains nine cities; 3,375 villages; and 10,875 hamlets, within the following nine boroughs, from north to south (Abu Qurqas -El Idwa-Minya -Bani Mazar- Deir Mawas-Maghagha-Mallawi-Matai-Samalut). Figure 1 shows El-Minya governorate with the administrative boundaries of the different cities. The total sugar beet area at Menia which calculated by this study was reached 33570 feddans.

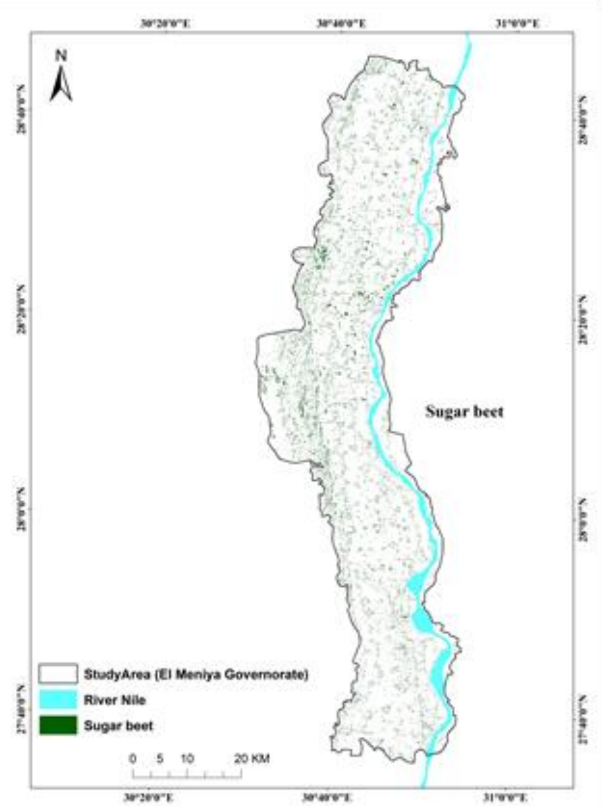

Figure 1. Location of the study area

Field spectral measurements

Field spectroradiometer (ASD Field Spec) were used for measuring the reflectance of sugar beet plants under different consideration (Temp., RH., etc.). Measurements carried out in sugar beet farms at Al-Minya governorate, middle of Egypt. Twenty samples for each age to the leaves (young, old) of sugar beet in the study area were measured to be used in this research (ten leaves for each infestation). Leaves are low to moderately infected in order to maximize the importance of this work. Measurements were measured on the spectral range (visible – NIR – SWIR) from (350 nm): (2500 nm). The spectral range (350-1050 nm) has the sampling interval 1.4 nm. While the sampling interval for spectral range (1000-2500 nm) was 2 nm. This instrument automatically executes an interpolation for all data and the final data output will gave with (1 nm) interval for the full spectral range (350-2500 nm). Table 1 was shown the spectrum characteristics of the instrument. The measurement protocol utilized for the collecting spectral data is relayed on measurement the reflectance from a white panel. A probe was attached to the instrument's fiber-optic cable to be used to ensure standardized environmental conditions reflectance measurement. Twenty-five degrees lens was used for outdoor measurements with circular field of view with 3 cm diameter (90 degrees) nadir position over the measured object (ASD, Boulder, CO, United States) (Pimstein et al., 2011).

Table 1: Specifications of ASD Field Spectroradiometer 4

Full Range	350 to 2500 nm
Spectral Resolution	700 nm (3 nm) 1400 nm (8.5 nm) 2100 nm (6.5 nm)
Sampling Interval	350 to 1050 nm (1.4 nm) 1000 to 2500 nm (2 nm)

Statistical Analysis

Linear discriminant analysis (LSD and Tukey HSD are run to confirm where the differences occurred between groups, as there is an overall statistically significant difference in group means (McDonald, 2014.) to identify the optimal waveband the specific wavelength that could be used to isolate healthy and infected samples spectrally.

Linear discriminant analysis (LSD) developed by Fisher, (Williams and Abdi, 2010)

Calculated by:

$$LSD = t \sqrt{2MSE / n^*}$$

Where; t is the critical, tabled value of the t-distribution with the df associated with MSE, the 2 denominator of the F statistic and n* is the number of scores used to calculate the means.

Tukey's test was developed in reaction to the LSD test; the formula for Tukey's is:

$$HSD = q \sqrt{MSE / n^*}$$

Where q = the relevant critical value of the studentized range statistic

Results and Discussion

In the recent process for producing crop, it's a tendency to minimize usage to pesticides, to eliminate hazards impact on environment. At the same time, increasing agricultural production is an urgent need for food security. Remote sensing tools could be used to recognize the areas under infection, this could help to rationalize the use of pesticides to be used in specific areas of infection, thus reducing cost and increasing compliance with environmental standards. Application of remote sensing requires principally identifying of spectral properties to healthy plants as well as plants under infection. Therefore, the main objective is to spectrally differentiate different infections (white fly, aphid, cotton leaf worm) on sugar beet leaves (young and old) using hand-held field spectro-radiometer. Spectral reflectance pattern was identified for all young and old leaves. The results showed that the blue and near infrared (NIR) were the optimal to spectrally identify the three infections on young leaves. The results propose possible use of remotely sensing technologies for pest detection, thus enabling successive regulation and application of site specific pest management.

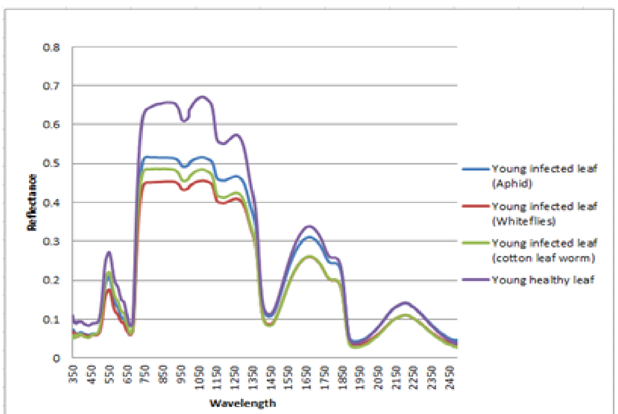

Figure 2: The Spectral Reflectance Pattern for young leaves of sugar beet plants with different kind of infestation (cotton leaf worm, Aphid and Whiteflies) with healthy plant.

In order to specify the spectral zone and optimal waveband for detecting sugar beet plants infected by different kinds of pest infestations (cotton leaf worm, Aphid and Whiteflies), some statistical procedures were used on spectral mensuration. The spectral reflectance pattern for young and old leaves of sugar beet plants with different kind of infestation (cotton leaf worm, Aphid and Whiteflies) with healthy plant are shown in figures (2 and 3) respectively. Spectral reflectance modality for the four sugar beet plants made the same manner; As though, healthy plant reflectance is higher, reflectance of all other infected plants was low. Whilst reflectance of sugar beet plant which infected by aphids is higher than the reflectance of sugar beet which destroyed by cotton leaf worm and the lowest reflectance was for sugar beet which infected by white flies along the entire spectrum.

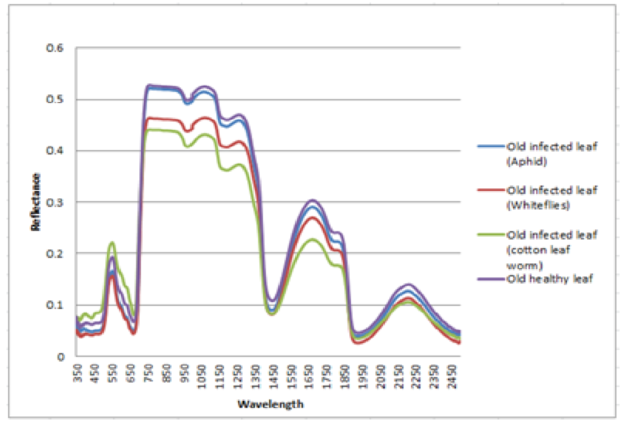

Figure 3: The Spectral Reflectance Pattern for old leaves of sugar beet plants with different kind of infestation (cotton leaf worm, Aphid and Whiteflies) with healthy plant.

In comparing the reflectance of the three infection of sugar beet plant demonstrate that the maximum spectral reflectance (1000 nm) located in infrared spectral zone, comparatively low reflectance (1650 nm) and the minimum reflectance in the spectral zone (2200 nm), Yones et al., 2014.

The reason probably owing to the action of insect infection on sugar beet plants which causes a significant loss to the fundamental components in the sugar beet leaves. Tukey's HSD test concluded prominence discrepancy among healthy and infected sugar beet plant over all spectral zones for each general mean of reflectance, max. and min. reflectance and mean of reflectance. Prominence discrepancy among healthy and different kinds of infection for sugar beet plant showed in figures. Tukey's HSD test concluded Blue and NIR spectral zones showed better result to discriminate between healthy and infected sugar beet plants. Also, these two spectral zones consider the best for discrimination between three kind of infection (cotton leaf worm, Aphid and Whiteflies). Red and Green spectral zones shows acceptable results, as they differentiate between healthy and infected sugar beet plant only but SWIR-1 as well as SWIR-2 zones did not show significant difference, this result is agreed with Yones et al. (2014) for assessment of the infection of red palm weevil .

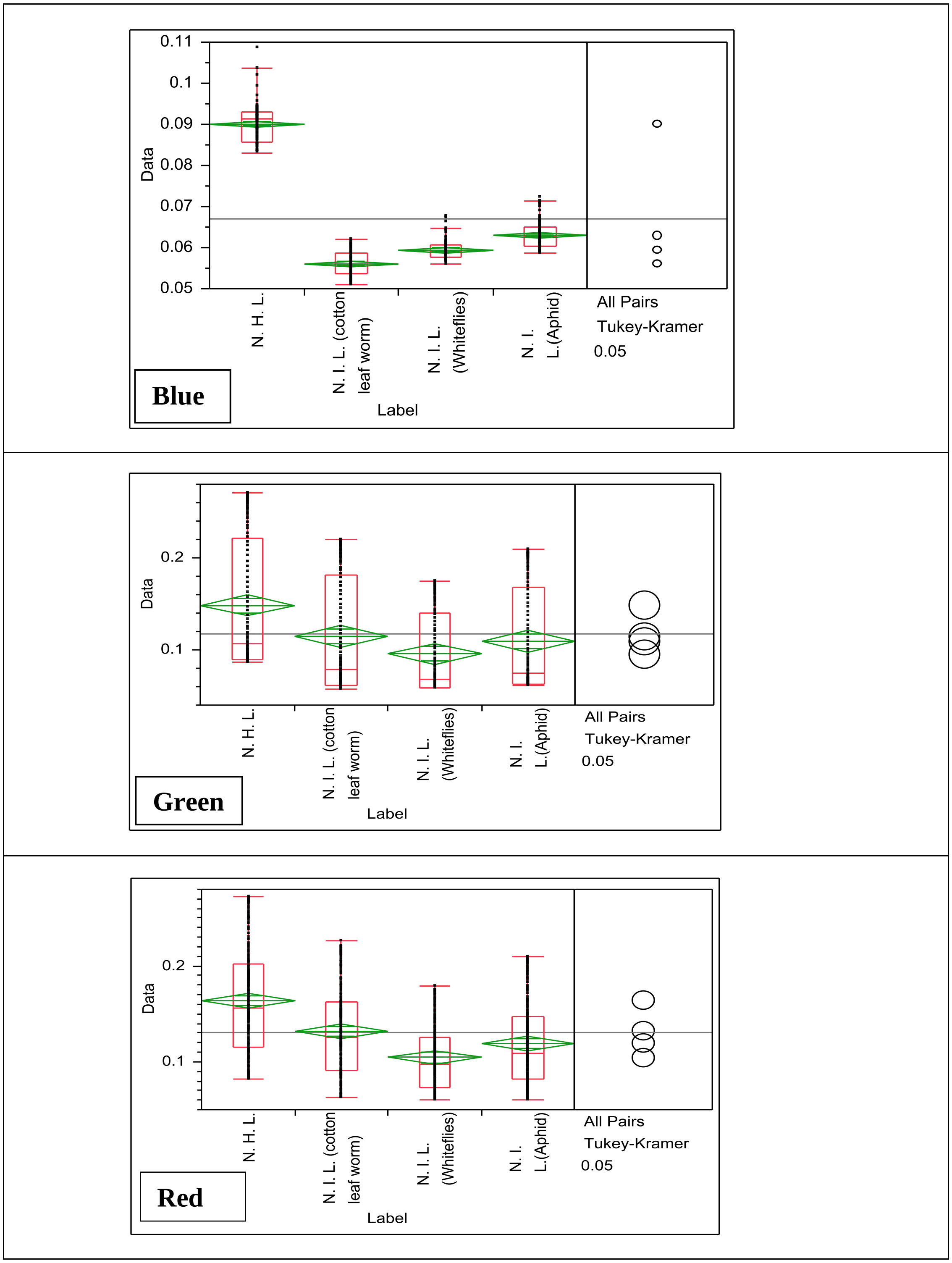

Figure 3: ANOVA and Tukey's HSD analysis to differentiate between sugar beet plants healthy, and infected (Cotton leaf worm, Aphid and White flies).

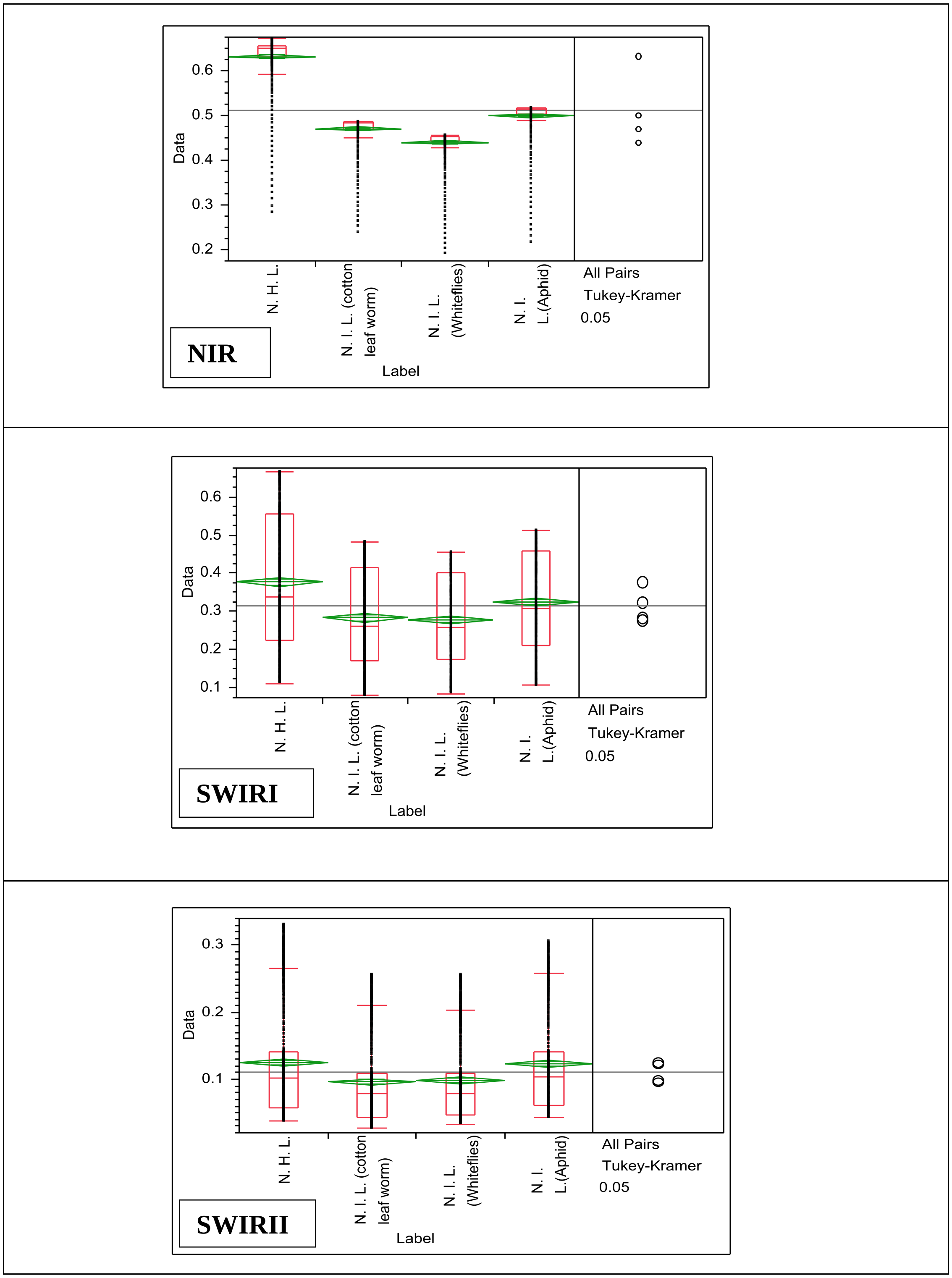

Figure 3 (Cont.): ANOVA and Tukey's HSD analysis to differentiate between sugar beet plants healthy, and infected (Cotton leaf worm, Aphid and White flies).

Table 2: Correlation coefficients for healthy and infected samples

Sample	Correlation coefficient (r^2) Blue (healthy) vs. Blue (infected)	Correlation coefficient (r^2) NIR (healthy) vs. NIR (infected)
Young leaves (Aphid)	0.822	0.981
Young leaves (Whiteflies)	0.822	0.988
Young leaves (Cotton leaf worms)	0.567	0.979
Old leaves (Aphid)	0.507	0.998
Old leaves (Whiteflies)	0.696	0.999
Old leaves (Cotton leaf worms)	0.240	0.983

As the two spectral bands (Blue and NIR) indicate the promising results for differentiation between healthy and the different kind of sugar beet plants infections, Correlation coefficient was then examined between blue and NIR spectral reflectance data of healthy samples and the same spectral reflectance datasets for infected samples and the results of this analysis is appeared in Table (2).

Table 3: **The specific wavelengths to identify the different infections**

Healthy Young leaves	(548 – 557 nm) /(701 – 1387 nm)
Healthy old leaves	(1574 -1597 nm) / (1749-1775 nm)
Infected young leaves (Cotton leaf warm)	(542 – 559 nm) / (1580 – 1592 nm) / (1751 – 1763 nm)
Infected old leaves (Cotton leaf warm)	(350 – 698 nm) /(1944 – 2500 nm)
Infected young leaves (Aphid)	(1563 – 1567 nm) / (1785 – 1833 nm)
Infected old leaves (Aphid)	(1569 – 1580 nm) /(1764 – 1781 nm)
Infected young leaves (Whiteflies)	(1575 – 1579 nm) / (1764 – 1769 nm)
Infected old leaves (Whiteflies)	(1782 – 1814 nm)

As most of red and blue spectrum is used for photosynthesis process, plant infection is resulted in significant decrease in blue and red spectrum, Wang et al., 2016. As shown from the results, blue spectral zone was much better than NIR in discrimination between healthy and infected samples. At the same time, comparing the results of blue spectral zone showed that infection of old leaves was clearly spectrally identified much well than young leaves. Blue spectral band showed a remarkable result to differentiate between healthy and Cotton leaf worms infection on old leaves as the correlation coefficient was (0.24) between healthy and infected old leaves.

Discrimination analysis results appeared in table (3), and indicated the best wavelength/s to spectrally identify healthy and infected samples. It was found that short wave infrared ranged from (1500 nm to 2000 nm) were the optimal to spectrally identify the three infections. In case of Cotton leaf warm infection, green spectral range can also be utilized to recognize the infection of Cotton leaf warm on young leaves when all visible spectral range (350 to 598 nm) were the optimal wavelengths to identify the same infection on old leaves.

Plant diseases decrease total crop production worldwide by about 10% as reported by (Christou and Twyman, 2004; Strange and Scott, 2005). Early diagnosis of plant diseases could significantly increases the efficiency of any control program. This will also decrease the cost of production and reduce the danger of toxic residue in agricultural products as the disease control could be performed within fields timely and locally. Timely spectral measurements within field is costly effective comparing to ground survey that requires high labor cost and results with low efficiency. The theoretical base of the effect of plant diseases on crop spectral reflectance characteristics that the stressed plants (induced by the disease) react with protection mechanisms that lead to suboptimal growth which show up as changes in biophysical and biochemical variables such as leaf area index (LAI),chlorophyll content, or surface temperature and thus, affect spectral signature of stressed plants that is different from the signature of healthy, unstressed plants (Martinelli et al., 2015). The critical point of using remote sensing tools for the early detection of plant diseases is to identify the appropriate remote sensing tools and the appropriate spectral wavebands and wavelength/s to handle a specific plant disease. The visual and external symptoms of plant diseases also affect the spectral reflectance signature. (Lindenthal et al., 2005 and Oerke et al., 2006) reported a significant decrease in the transpiration rate and a rise in temperature with the appearance of chlorotic and necrotic tissues which appeared as symptoms of some plant infections and these symptoms effected spectral reflectance characteristics especially in infrared spectrum. Changing in leaf pigments such chlorophyll a, b and carotenoid as the result of leaf blotch could be studied using visible bands of the spectrum as reported by (Calderón et., 2013).

This study was carried out to identify the significance of using spectroscopic parameters as a brief and early indicator for three types of infections on Sugar beet on old and new plant leaves. Investigation was carried out through spectral reflectance from (350 – 2500 nm). Identification of the optimal spectral zone and spectral wavelength for three types of infection was carried out. It is clear that linking spectral reflectance characteristics with plant infection is empirical investigation limited to many factors including: conditions of the field measurements, phonological stage; biophysical and biochemical parameters of plant organ under investigation and types of symptoms. These parameters significantly affect spectroscopic parameters and spectral reflectance characteristics. Also, according to our investigation through previous research works, it is not practical to compare spectral reflectance characteristics throughout the whole spectrum; it is more efficient to focus on the sensitive wavebands and wavelengths for each type of infection. Therefore, this work was necessary as the starting point of using hyperspectral tools for these infections on sugar beet. Further work will be carried out based on the result of this work to build up a timely spectral based early warning system for these infections based on the spectral zone and wavelengths that are proved to be effective during the current work.

Conclusion

This work was carried out to monitor spectral reflectance characteristics of sugar beet canopy (healthy and infected). Three common infections were observed in this study: Cotton leaf worm, Aphid and Whiteflies. The main objective was to identify the most sensitive spectral zone and wavelength/s to the three infections. Results of HSD Tukey's statistical analysis showed that NIR and Blue spectral zone were the optimal for the discrimination between healthy sugar beet plants and the different infections. SWIR-1 and SWIR-2 showed disability to discriminate between healthy and infected plants when red and Green spectral zones showed relatively reasonable ability for discrimination between healthy and infected plants. Linear discriminant analysis specifically identifies the optimal wavelength to identify the different infections. Generally, spectral discrimination was clearer in case of old leaves than young ones. Results of this work could be the basis for early warning system for the observed infections on sugar beet plants. The main approach of this system will be the regular field hyper spectral measurements during the growing season of sugar beet especially during the period of the maximum vegetative growth.

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Contribution of Authors

Yones MS: Conceived Idea, Designed Research Methodology, Literature Search, Data Interpretation, and Manuscript Writing

Aboelghar MA: Conceived Idea, Manuscript final reading and approval

Khdery GA: Data Collection, Statistical analysis

Ali AM: Designed Research Methodology, Data Interpretation

Salem NH: Data Collection, Data Interpretation, Literature Review

Farag E: Statistical analysis, Literature Review

Ma'mon AM Shireen: Manuscript writing, Literature Review, Literature Search

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