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ORIGINAL RESEARCH ARTICLE

Spectroradiometer and thermal imaging as tools from remote sensing used for early detection of spiny bollworm, *Earias insulana* (Boisd.) infestation

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Abstract

The spiny bollworm (SBW), *Earias insulana* (Boisd.), is from the most destructive cotton pests in Egypt. Larvae can reduce the yield about 40%. Monitoring and forecasting have become an integral aspect of the crop production system in developed countries to control pests. Recently, remote sensing has gained popularity in agriculture for pest monitoring, yield forecasting and early warning to crop growers for proper time in pest management with the least quantity of ground sampling possible. This work aims to measure the validity of using a new methodology for pest detection in cotton bolls without exposing the plant to any danger., This action could be conducted by making a spectroscopy check using spectroradiometer for every boll in field and compare this reading automatically with the spectral library that was built in earlier by measuring numbers of well-known bolls (healthy and infected measuring of some Vegetation Indices (MCARI, TCARI, NPCI, NDVI, NDWI, WBI) also done from reflectance values that carried out, in order to detect the best indices affected by pest infection. Thermal imaging also was done to differentiate between diseased and non-infected tissue. The results described the reflectance spectra of cotton bolls with known SBW infestations and healthy ones and could identify the certain narrow band that is sensitive to SBW damage, BLUE band has found to be the best for spectrally identifying infested bolls. Normalized Pigment Chlorophyll Index (NPCI) is the best index among vegetation indices used in this research. Complementally, to use remote sensing applications, thermal imaging was used to detect thermal patterns associated with insect infestation. The result of study indicate the validity of using spectral measurement and thermal imaging as a tools of remote sensing in detection of the presence of spiny boll worm without wasting and ruined the bolls in field, this method could be also effective in detection of other pests on other crops.

Keywords Remote sensing · Hyperspectral data · Spiny bollworm · Cotton · Monitoring · Predictions

Introduction

The most significant industrial crop in the world is cotton. Egypt remains one of the most interested countries in cotton growing because it's economic importance. As a result, the government worked hard to improve its ability to compete in international markets by manufacturing high-quality cotton (Abd-El Rahman et al. 2015).

Spiny bollworm (SBW) *Earias insulana,* is a serious cotton pest in Egypt and is a polyphagous pest (Moustafa 2020). Larvae are the most common stage attacking cotton or okra farms, it causes severe damage to cotton bolls as well as significant losses in both the quality and quantity of cotton output (Said 2020). In cotton yields larvae can destroy up to 3 squares and one cotton boll per 1-2 plants as observed by Durán et al. (2000). As Larvae attack and damage squares,

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flowers, and cotton bolls, devouring seeds and destroying them with faeces that provide as a perfect medium for secondary pests and fungi, larvae can destroy all of the cotton bolls in a field, resulting in yield losses, especially when the cotton plants are in their final stages of growth (Bennett 2015). SBW also can cause a reduction in the quantity and quality of lint and oil obtained from the crop (Abu-Hatab 2009). *Earias* spp. Can decrease the quality of cotton by approximately 50% and the yield by around 40% by staining lint (Ahmad and Arif 2009).Environmental factors, especially temperature, have a significant impact on the population dynamics of the spiny bollworm (El-Sayed 2014).

Plant diseases are a major source of economic and post-harvest losses in the agricultural production sector around the world (Mohd et al. 2019). Early detection of plant infection is critical for the agricultural sector's long-term viability. Non-destructive techniques are of the most effective and feasible ways of monitoring plant health for real-time applications in this regard.

Spraying pesticides is the most used method of pest control in cultivated crops. Crops are uniformly sprayed at various stages of the cultivation cycle and across fields; however, most insect infestations do not quietly spread across sprayed areas and occur only in patches. Pesticides can only be used in specific areas of the field. Thus, early recognition is essential to assist farmers in avoiding heavy pesticide sprays and to take precautions to limit severe insect infestations (Yones et al. 2012). It's critical to adjust the pest's generations and insecticidal application timing once appearance of the target stage. This parameter can be determined using remote sensing technologies to monitor larval population detection in bolls (Yones et al. 2019).

Large efforts have been undertaken over the past few years to improve stress detection in agriculture fields. As a result, plant phenotyping based on imaging techniques has become a crucial tool in agriculture. particularly leaf temperature is a useful indicator of the plant physiological condition with regard to how plants respond to biotic and abiotic stresses and also the use of thermography in the implementation of a more automated, precise, and sustainable agriculture is frequently integrated with other image sensors and data-mining techniques (Pineda et al. 2020).

Remote sensing technologies can detect and diagnose plant diseases. Theoretical foundation for remote sensing applications in crop disease assessment is that crop diseases cause physiological changes and considerable damage to plant tissues (Abdel Wahab et al. 2017). As a result, insect pest infection interferes with photosynthesis and the structure of the plant, affecting the intake of light energies and changing the reflectance function of the plant (Hatfield and Pinter 1993). Remote sensing data allows crop identification and area measurements, as well as assessment of crop stress, pest damage, and yield forecasts, with only a small amount of field sampling required. Increasing maximum yield potential while reducing pesticide usage is a critical feature for farmers. Detection of plant diseases and disease prevention are also essential activities. The use of spectroscopy to detect plant diseases is a very practical choice (Kshirsagar et al. 2019). With the aid of vegetation indices, we can detect plant illnesses. “A Vegetation Index is an indicator that reflects the health of vegetation,” (Brown 2018).

Thermal imaging can aid in the detection of pest infestation by detecting the pest evidence. it is a technology that visualizes an object's infrared radiation (IR) and displays it as temperature. Remote sensing of leaf temperature techniques can be used to identify changes in plant physiological condition and plant responses to biotic and abiotic conditions. Thermal imaging can also be used in agriculture to monitor plant stress reactions, such as water stress (Khorsandi et al. 2018), temperature disorder (Poirier-Pocovi et al. 2020), nutrient disturbance (Christensen et al. 2005) and crop maintenance (Wang et al. 2019).

Insect pest forecasting in the agro-ecosystem allows farmers to be informed about potential outages, allowing them to be prepared and take appropriate action to use biocontrol agents, mechanical means, and pesticides, lowering production costs and serving as a tool in precision farming.

The main purpose of this research is to apply a new method for detecting SBW-infested cotton plants without causing boll losses. Also, to study out the characterization of reflectance spectra of cotton plants with known SBW infestations, with the aim of identifying healthy and infected cotton bolls with determination of the narrow wavelengths that are sensitive to SBW damage. Also using newly remote sensing technique, thermal imaging to observe and monitor the differentiation between healthy bolls temperature and infected one.

This work is considered of the new approaches in the diagnosis and detection of plant infections by insect pests. Those are all preliminary tests for further and broad field applications

Material and methods

For achieving the aim of this work, cotton bolls sample was collected of two group. The first group which is the well-known bolls (healthy and infected), as we take spectroradiometer measuring for this bolls then we checked them immediately to know the measuring related for every sample, in this case we built the library that will be used later in detecting the other unknown sample (infected or not). The second step is to measuring the second group of samples using spectroradiometer. Third step is to compare this reading with the library that measured previously and predict infected and the non infected samples. Fourth step is making a laboratory check for the second group of samples in order to validate the result and the predictions. Fifth step is to calculate some well-known vegetation indices aiming to select the best indices that can be used as a second method for detection infected and non infected cotton bolls using the spectroradimeter measuring in their calculation. The last step is the thermal imaging for cotton bolls samples, this was done before make any laboratory check for the cotton boll samples that was also to differentiate between diseased and non-infected tissue.

According to Mahlein (2016) Optical sensors have been used to investigate the following topics: the response of plants to pathogens, pests, and abiotic stressors; the identification of primary disease.

Spectroradiometer measurement

Samples was collected from Qaha, Qalyubia Governorate, during the growing season of the cotton plant in 2020, from March to September, and processed in the laboratory in 30 minutes. Under laboratory conditions, a High Resolution Spectroradiometer (ASD Field Spec 4 Hi-Res) was used to measure the reflectance of cotton bolls. Reflectance measurements were taken, for 27 boll samples which had been collected from a cotton field. Following the measurement, each boll was examined for the existence of SBW.

Cotton boll samples were measured using a spectral range of 350 nm to 2500 nm [visible – Near-infrared (NIR) – Short Wave infrared (SWIR)]. The sampling interval was 1.4 nm for the spectral range of 350 nm to 1050 nm. However, the spectral range from 1000 to 2500 nm has a sample interval of 2 nm. The instrument automatically performs an interpolation for every data, so the final data output is delivered with a 1 nm interval to the whole spectrum range.

Table 1 shows the High Resolution Spectroradiometer specifications and spectrum characteristics. The measuring methodology for collecting spectral data is based on the reflectance measurement from the white panel. For typical ambient conditions and reflectance measurements, a probe was attached to the instrument's fiber-optic cable. For outdoor measurements, a twenty-five-degree lens was employed with a circular field of view and a 3 cm diameter nadir(90 degrees) position above the measured object. (ASD, Boulder, CO, United States) (Pimstein et al. 2011).

Table 1 High Resolution Spectroradiometer Specifications and spectrum characteristics

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

The data was analyzed using spectral data measurements, and the JMP ver. 25 application was utilized to provide it.

Linear discriminant analysis (LSD) and Tukey's Honest Significant Difference (Tukey HSD) tests are used to confirm where the differences between groups occurred, as there is a statistically significant difference in group means (McDonald et al. 2014). They are also used to identify the best wave band, or specific wavelength, that could be used to spectrally separate healthy and infected samples.

Linear discriminant analysis (LSD) introduced 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.

Indices calculation

In order to analyse the field spec measurements the SIX vegetation indices were used which are Normalized Pigment Chlorophyll Index (NPCI), Modified chlorophyll absorption in reflectance index (MCARI), Normalized Difference Vegetation Index (NDVI), Transformed Chlorophyll Absorption Index (TCARI), Normalized Difference Water Index (NDWI) and Water Band Index (WBI).

Normalized Pigment Chlorophyll Index (NPCI)

Leaf reflectance in visible light is regulated by chlorophyll pigment. Plant nitrogen status has been estimated using information from reflectance spectra. The NPCI is calculated using the equation Peñuelas et al. 1994

$$NPCI = (R680 - R430)/(R680 + R430)$$

Modified Chlorophyll Absorption in Reflectance Index (MCARI)

MCARI is an indicator used to determine the amount of chlorophyll absorbed. It is extremely sensitive to changes in chlorophyll concentrations and Leaf Area Index (LAI). MCARI is used for decreasing the effect of the illumination conditions, background reflectance from soil, and other non-photosynthetic materials detected. MCARI vegetation index is calculated as follows (Daughtry et al. 2000):

MCARI = [(R700 – R670) – 0.2 (R700 – R550)] ∗ (R700/R670)

Normalized Difference Vegetation Index (NDVI)

The NDVI is a useful parameter for detecting leaves. To discriminate between infected and non-infected leaves, the NDVI is used. The NDVI is also used to determine green vegetation present and is useful for vegetation monitoring. The NDVI vegetation Index is calculated as follows (Rouse et al. 1973):

NDVI = (NIR − RED)/(NIR + RED)

where, NIR demonstrate reflectance in near infrared band (801 nm) and Red reflectance at the Red Band (670 nm). The values range is +1.0 to -1.0. High NDVI values are almost 0.6 to 0.9. (Daughtry et al. 2000)

Transformed Chlorophyll Absorption Reflectance Index (TCARI)

The TCARI is one of several CARI indices that show how much chlorophyll present in a given area. The underlying soil reflectance has an impact on it, especially in vegetation with a low LAI, TCARI can be defined by (Chaoyang et al. 2008):

TCARI = 3[(R700 – R670) – 0.2 (R700 – R550) (R700/R670)]

The canopy water content VIs gives an indication of how much water is in the leafy canopy. Higher water content suggests healthier plant that is more likely to develop faster and survive fire, Reflectance measurements in the near-infrared and shortwave infrared regions were utilized to determine canopy water content Vis. however to take advantage for recognition of water absorption properties and light penetrating depth in the near-infrared region to determine integrated measurements of the total column water content.

Normalized Difference Water Index (NDWI)

Reflectance of wavelength at 857 nm and 1241 nm have similar but slightly different liquid water absorption characteristics so this measurement is sensitive to variations in vegetation canopy water content. The weak liquid water absorption at 1241 nm is boosted by the scattering of light by vegetation canopies. Forest canopy stress study, leaf area index investigations in heavily foliated vegetation, plant productivity models, and fire susceptibility studies are just few applications. This index's value ranges from -1 to 1. Green vegetation has a usual range of -0.1 to 0.4 (Jackson et al. 2004; Gao 1996),

NDWI = (R857 − R1241)/(R857 + R1241)

Water Band Index (WBI)

This index measures reflectivity and is sensitive to variations in canopy water condition. The degree of absorption at 970 nm increases in comparison to 900 nm as the water content of vegetation canopies increases. Canopy stress study, production prediction and modeling, fire hazard condition analysis, cropland management, and ecosystem physiology studies are some of the applications. WBI= (R900/R970) (Peñuelas et al. 1997)

Thermal measurement

Thermal images were captured with Testo 890 Thermal Imaging Camera with a 0.1 mm 42° x 32° (Standard lens). The auto-focus of the Testo 890 Thermal Imaging Camera ensures the capability to obtain sharp photos. Such feature also makes it easy to use the camera with one hand. The minimum focus distance for the Testo 890 Thermal Imaging Camera is 10 cm. 307 200 measurement points are available with a thermal resolution of 640 × 480 px. The thermal resolution of the Testo 890 can be extended to 1280 x 960 px owing to the inclusion of Super Resolution technology. The Testo 890 Thermal Imaging Camera also features a thermal sensitivity of 40 mK, allowing it to detect and visualize minute temperature variations. The Testo 890 Thermal Imaging Camera's SD card can be used to save thermal photos as JPEGs. For the duration of the experiment, the camera's emissivity setting was kept constant at 0.95. The image camera was placed at a distance of 1.1 m from the plants. Both healthy and diseased bolls were checked in each experiment.

The following mode was used to measure bolls temperature data:

> Offline measurements. The data was recorded as radiometric pictures and analyzed by using Testo IR soft software. By selecting an oval, rectangle, or user-defined form, the software presents statistical data for each plant's leaf temperature distribution and can calculated maximum and lowest temperatures from any pre-defined oval regions of interest (ROI) (Martynenko et al. 2016). By the same program, Testo IR soft software Histogram adjustment can be created. Hence, leaf temperature can be used as an indicator of plant stress (Costa et al. 2013).

Statistical analysis

Using IBM SPSS Statistics 26 to calculate the Pearson's correlation coefficient which is a mathematical method for determining the strength of a relationship between two variables, healthy and diseased bolls VIs values. It is indicated by r and is used to examine the correlation between two quantitative variables. which assigns a value between -1 and 1, where 0 expresses no correlation, 1 denoting total positive correlation and -1 denoting total negative correlation. A positive correlation means that if variable A rises, then variable B will likewise increase, whereas a negative correlation means that if A increases, then B decreased (Nettleton 2014a, b).

Pearson's correlation coefficient also calculated between plant water content indices (NDWI and WBI) and maximum temperature of samples to improve the extent of the relationship between them to improve the importance of using thermal camera.

Results and discussion

As mentioned above the aim of this work is to find the validity of using spectroradiometer by measuring cotton boll samples in detection of infection by spiny boll worm and also using this measurement in calculation of some known indices that used for detection of plant healthiness to determine the best indices that must be used in the detection of the presence of the spiny boll worm also found the potency of utilization of thermal imaging in finding out the presence of infection by cotton boll worm

Spectral measurements

By using specroradiometer, it found that the spectral reflectance pattern for measurements of cotton bolls with varied levels of infestation compared to healthy bolls in the experiment was the same. However, the reflectance of healthy cotton bolls was higher than that of all other infected cotton bolls. Along the whole spectrum, the reflectance of moderately infected bolls is higher than the reflectance of severely infected bolls (Fig. 1). When the reflectance of healthy and infected cotton bolls were compared, they demonstrated that the maximum spectral reflectance, associated to healthy bolls, was at 850 nm which located in infrared spectral zone, comparatively low reflectance at 1650 nm and the minimum reflectance in

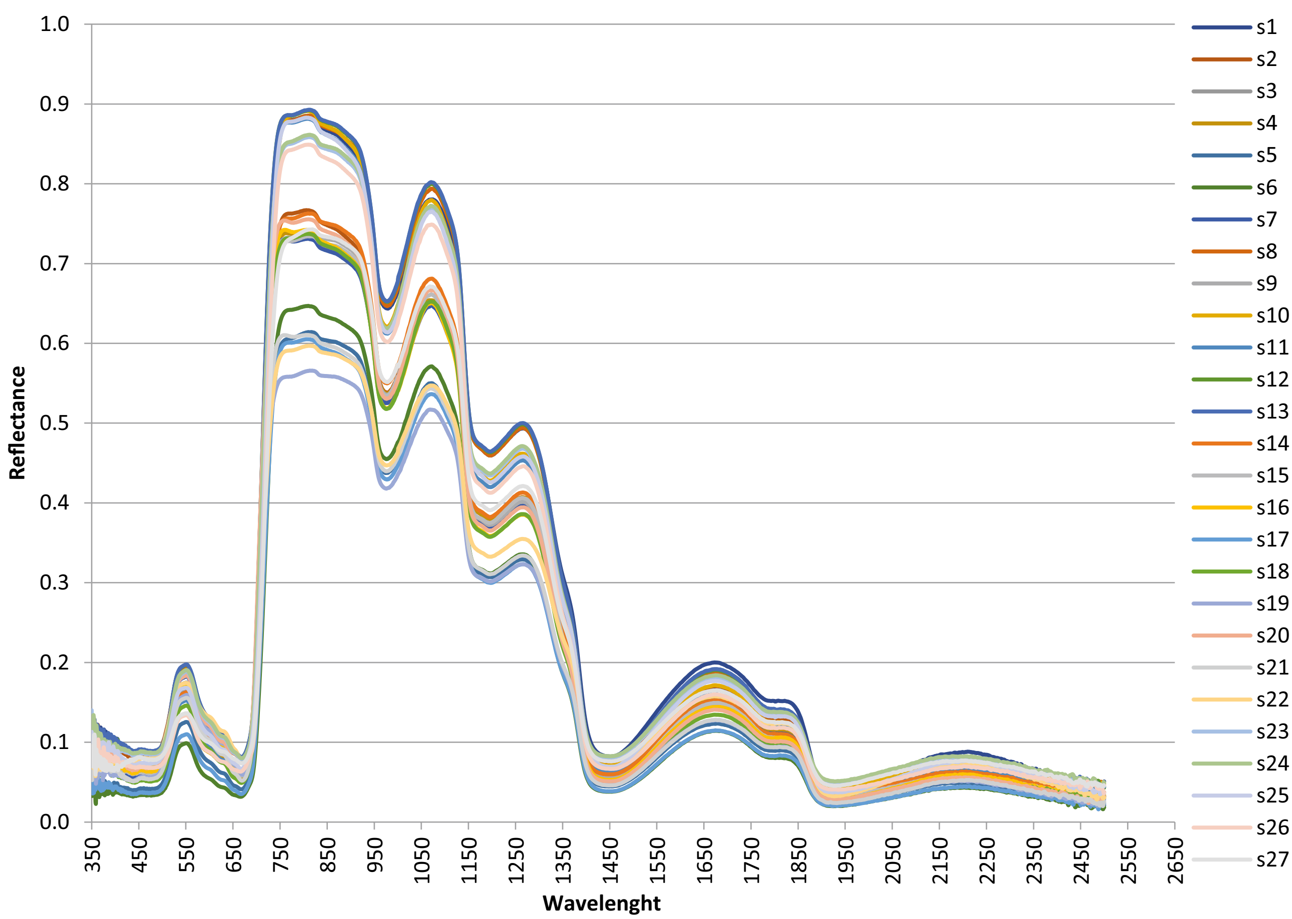


Fig. 1 The Spectral Reflectance Pattern for healthy and different level of infested cotton bolls by using Microsoft excel

the spectral zone at ~2200 nm, this reflectance decreased dramatically in infected ones.

Our results indicated that, the infected bolls displayed higher reflectance values in the visible area (400–780 nm) than healthy bolls, that was due to a decrease in chlorophyll (Chl) concentration in infected bolls. In the near-infrared band (780–1,000 nm), however, reflectance values of infected bolls were lower than those of healthy leaves, owing to the pest's internal structure damage. And this result agree with Broge and Leblanc (2000).

ANOVA and Tukey's HSD test revealed a significant difference between healthy and infected bolls for each of general mean of reflectance, max., and min. reflectance, and mean of reflectance across all spectral zones. Prominence difference between healthy bolls and cotton bolls with different degrees of infection showed in the (Fig. 2). Our results also revealed that the Blue spectral zone was found to be the best for spectrally identifying infection on cotton bolls i.e., distinguishing between healthy and infested bolls. Green, Red, NIR, SWIR-2 spectral zones are acceptable for discrimination, since they almost distinguish between healthy and infected bolls, but the SWIR-1 spectral zone show no significant difference. Some discriminant analysis applied on the spectral reflectance data, showed that the percent of misclassified samples at Blue band is the least (84.78%) compared to other bands and at Green, Red, NIR, SWIR-2 spectral zones are moderate, as the percent of misclassification at Green band

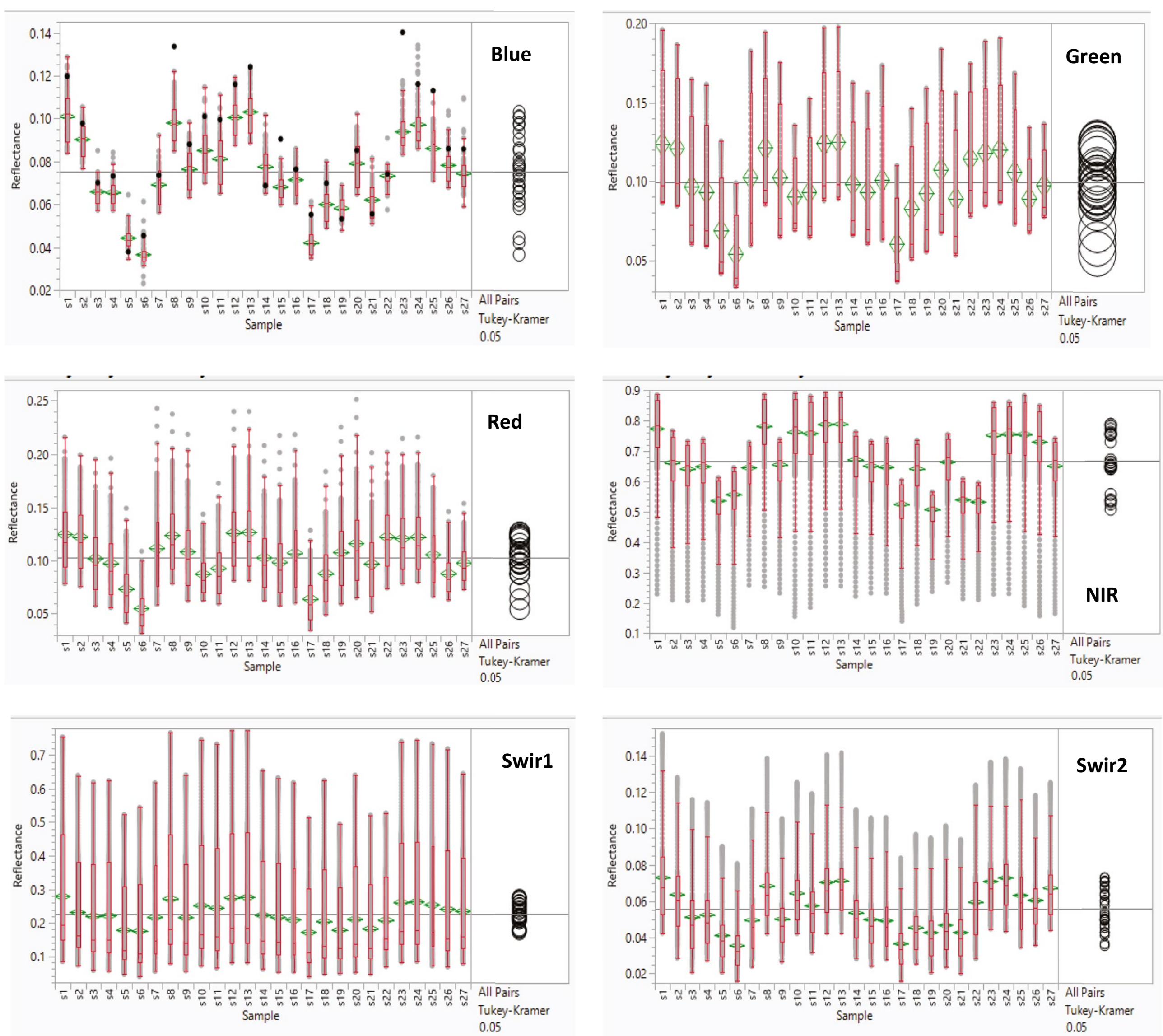


Fig. 2 ANOVA and Tukey's HSD analysis to differentiate between healthy and infected cotton bolls among different wavelengths visible – Near-infrared (NIR) – Short Wave infrared (SWIR)

(95.18%), at Red band (92.64%), at NIR band (91.39%) but at SWIR-2 spectral zone (93.58%) and percent misclassified at SWIR-1 zones is the heights (95.97%).

The blue band is the best band that have least correlation among them, have high information content and are able to discriminate between healthy and infected cotton bolls. This result is agreed with Yones et al. (2014) for assessment of the infection of red palm weevil and Yones et al. (2019), which demonstrate early detection of pink bollworm.

A healthy plant canopy appears green, and the reflectance curve in the red and blue region reveals low, because leaf pigments absorb blue and red light and reflect green light. Thus, increased near-infrared reflectance was more related to vegetation cover, biomass, leaf internal cell structure, leaf water content, and LAI, whereas the red region's boundary has strong absorption due to leaf chlorophyll, Nitrogen concentration, and reflection due to mesophyll cells in growing plants (Datt 1998). Plant infection resulted in a considerable decrease in blue and red spectrum since most of the red and blue spectrum is required for photosynthesis, according to Wang et al. (2016). The spectral reflectance profile is also affected by the visible and exterior symptoms of plant illnesses. With the formation of chlorotic and necrotic tissues, which manifested as symptoms of several plant illnesses, a large decrease in transpiration rate and a rise in temperature occurred, and these symptoms influenced spectral reflectance properties, particularly in the infrared spectrum (Oerke et al. 2006). As described by Calderón et al. (2015), changes in leaf pigments such as chlorophyll a, b and carotenoid as a result of leaf blotch could be examined utilizing visible bands of the spectrum.

Vegetation Indices calculation

Vegetation Indices produced from canopies based on remote sensing are simple and effective algorithms for assessing vegetation cover, vigor and growth dynamics, among other aspects (Xue and Su 2017). Remote sensing is a high-precision technology that can detect energy wavelengths and provide a variety of data, such as plant coverage vs. soil coverage, plant health, soil type, and so on. This information can be transformed into a vegetation index on an intra-field basis with resolution range from one to several meters to provide relative information on plant vigor. Plant response to different types of plant injuries, produced by diverse arthropod pest damage and other factors, can also be determined using the wavelengths utilized and reflectance detected.

Calculation of spectral vegetation indices (MCARI, TCARI, NPCI, NDVI, NDWI, WBI) from reflectance values carried out, in order to, detect the best indices affected by pest infection (Table 2).

The results showed that; there was a significant difference between “NPCI” values of healthy and different degree of infestation samples. The study found that in the visible region of the spectrum, infected cotton bolls reflected more energy than healthy ones; this result agreed with the finding of Broge and Leblanc (2000) who remarked that Infected leaves showed high reflectance values in the visible area (400–780 nm) than healthy leaves, which was due to a decrease in Chl concentration. So, it suggested that Chlorophyll content may be an effective short-term predictor of health in plant species because of its direct function in the photosynthesis process and because the chlorophyll concentration responds to pest presence. Plants lost chlorophyll as a result of insect pest damage. Our findings suggest that the infection by pest is linked to the loss of chlorophyll in cotton plants, decreasing amount of light absorption and increasing in NPCI readings. This finding agreed with Barry et al. (2009) who found that chlorophyll content is closely linked to plant photosynthetic performance, and this capability varies depending on environmental and phonological factors.

Table 2 Vegetation Indices of some healthy and infected samples used in the experiment

Healthy sample							Infected sample						
SAMPLES	NPCI	MCARI	NDVI	TCARI	NDWI	WBI	SAMPLES	NPCI	MCARI	NDVI	TCARI	NDWI	WBI
s1	0.0107	0.3664	0.8368	0.3789	0.2827	1.306	s5	0.1083	0.3721	0.8735	0.272	0.3022	1.3488
s8	0.0081	0.4467	0.8352	0.3963	0.2847	1.3082	s6	0.0982	0.2502	0.9046	0.2092	0.3153	1.3528
s10	-0.0084	0.1759	0.8662	0.2281	0.316	1.3613	s17	0.0887	0.3227	0.8891	0.2386	0.3022	1.3369
s11	0.0247	0.3069	0.8712	0.3012	0.3188	1.3617	s19	0.1176	0.5791	0.8094	0.3471	0.276	1.3109
s12	0.0066	0.4409	0.8323	0.3994	0.2838	1.3091	s21	0.0733	0.5426	0.8431	0.3419	0.2912	1.3221
s13	0.0032	0.4382	0.8318	0.3996	0.2831	1.3105	s22	0.0527	0.3299	0.7779	0.3374	0.2548	1.2835
s23	0.0045	0.3555	0.8316	0.3647	0.2952	1.3328	s7	0.087	0.7089	0.8507	0.4023	0.294	1.3267
s24	-0.0039	0.3518	0.8294	0.3661	0.2941	1.3341	s9	0.0567	0.5121	0.8435	0.3762	0.2999	1.3351
s25	0.0322	0.2951	0.8584	0.3195	0.3134	1.3544	s18	0.0689	0.4702	0.8742	0.3183	0.3122	1.3542
s26	0.0254	0.1808	0.8593	0.229	0.311	1.3401	s20	0.0734	0.6623	0.8406	0.4011	0.3132	1.3534

S Sample number

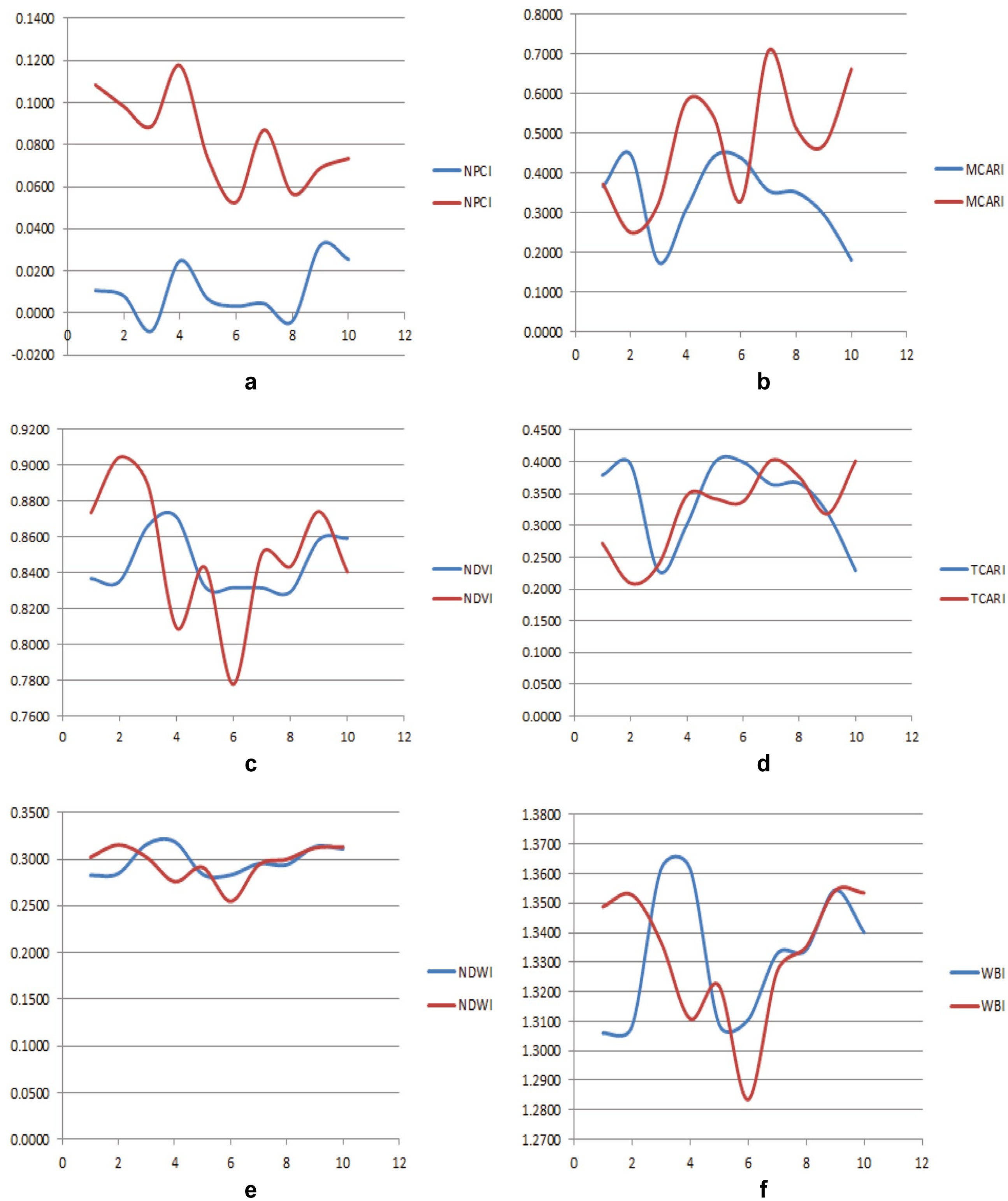


Fig. 3 Graphs of vegetation indics (**a**: NPCI- **b**: MCARI- **c**: NDVI- **d**: TCARI- **e**: NDWI—**f**: WBI) for some healthy (blue line) and infected (red line) samples in the experement by using Microsoft excel

Gitelson and Merzlyak (1994) stated that Chlorophyll content may be a good predictor of vegetal health since it plays a direct role in photosynthesis and is responsive to a variety of stressors. The intensity of chlorophyll pigment absorptions in the red are compared to the high reflectance of plant components in the NIR to determine vegetation indicators (Mirik et al. 2007).

Magare and Deshmukh (2016) concluded that the amount of chlorophyll in a plant is an excellent indication of its health. Gitelson et al. (2002) proved that the range of 450 nm to 750 nm is used to estimate the chlorophyll content of leaf. This result is agreed with Kshirsagar et al. (2019) who elucidated detection of infection from Chilly plant using Vegetation Indices.

Our results showed that values of the other calculated indices almost were the same, increased or decreased values and there is no significant difference between values of healthy samples and different degree of infestation.

The result after calculation of vegetation indices and comparing between them numerically (Table 2) Also, graphically (Fig. 3) and statistically (Table 3) by Using IBM SPSS Statistics 26 to calculate the Pearson correlation between healthy and infected bolls in six VIs utilized in the experiment which are NPCI, TCARI, MCARI, NDVI, NDWI and WBI, indicated that NPCI is the best vegetation index to differentiate between healthy and infected cotton bolls.

AL-Saddik et al. (2017) found that Spectral measurements are used in many precision agricultural applications, because of their capacity to monitor the health of the vegetation and detecting crop diseases. Spectral vegetation indices are one of the most utilized approaches in remote sensing, because they are linked to biophysical and biochemical agricultural factors. Spectral reflectance variations can be enhanced by using vegetation indices, which are mathematical modifications that evaluate the spectral contribution of vegetation to multispectral observations.

In recent years, researchers have been studying numerous spectral vegetation indices (SVIs) to detect various vegetation illnesses. The influence of the infection on a plant's pigments and structure, as well as changes in their spectrum sensitivities, allow spectroradiometry and remote sensing techniques to successfully identify plant infection (Zhang et al. 2012a, b). The leaf content constituents as chlorophyll, anthocyanin, and water can be detected and quantified using indices derived from reflectance values at various wavelengths (Gitelson et al. 2002).

Linking spectral reflectance features to plant infection is clearly an empirical inquiry confined to a number of elements, including field measurement parameters, phonological stage, biophysical and biochemical properties of the plant organ under investigation, and forms of symptoms. These factors have a big impact on spectroscopic parameters and spectrum reflectance characteristics. Remote sensing can produce relevant spectrum reflectance data, which can be used to monitor crop growth using a variety of biophysical, physiological, or biochemical parameters. Timely observation of plant biophysical properties and Ecophysiological status, such as leaf area, light use efficiency, chlorophyll, and nitrogen contents, has become critical for crop dynamic monitoring in order to improve nutrition and yield for universal food security and sustainable development (Zhao et al. 2013).

Thermal imaging

BY imaging the cotton bolls, abnormal warmth and wetness were observed; our results showed that the maximum temperature difference (MTD) between healthy bolls and bolls with different degree of infections was found in the range of 20.9 °C to 21.9 °C. Thermal imaging provides detailed information about the temperature distribution on the surface. The temperature difference between healthy and diseased cotton bolls was substantial and noticed that the temperature of diseased bolls was 1 °C higher than that of healthy bolls on average and those results were illustrated by Histogram adjustments (Figs. 4 and 5). Alternatively, the pest infection could affect the structure of the bolls. Thermal imaging looks to be a good way to differentiate between diseased and non-infected tissue. And it can provide high precision.

It was found that there was a correlation between the presence of moisture and the possibility for insect infestations presence. Temperature and moisture had a strong correlation with pest damage within the bolls. Statistically, Pearson correlation between water continent indices NDWI & WBI and max temp of each plant was -0.318 in NDWI and -0.081 in WBI index. So, there is strong correlation between them. Therefore, MTD may be used not only for the differentiation between infected and non-infected bolls, but also for disease quantification.

Thermal imaging played an important role in various fields of agriculture such as nursery monitoring and plants disease detection, yield estimation, maturity evaluation and bruise detection of fruits and vegetables. This technique gains the popularity in agriculture due to its higher temporal and spatial resolutions images. Thermal imaging is a simple

Table 3 Pearson correlation of healthy and infected samples for six vegetation indices applied in the experiment

VIs	Correlation coefficients
NPCI	0.203
MCARI	-0.280
NDVI	0.065
TCARI	-0.079
NDWI	0.194
WBI	0.116

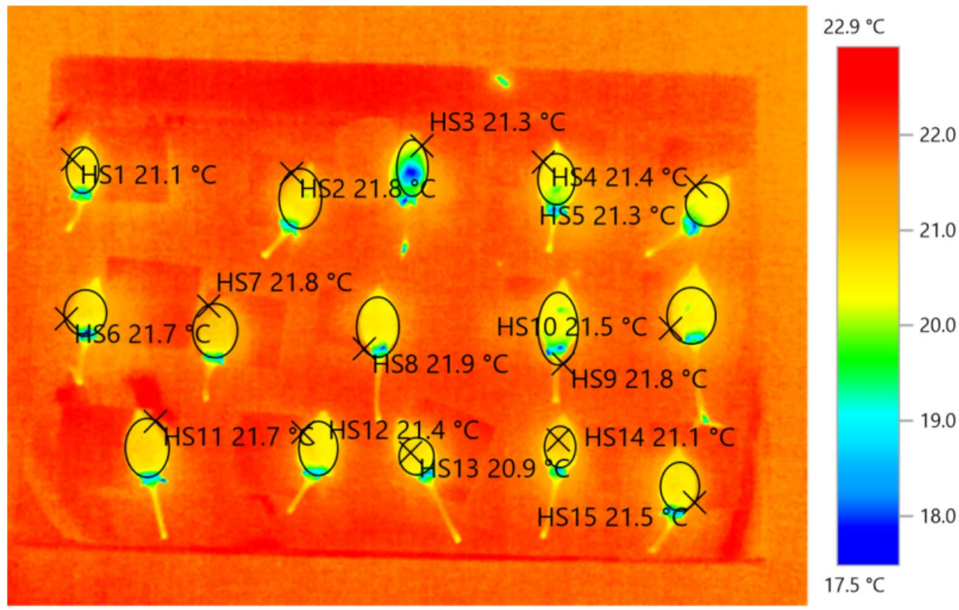
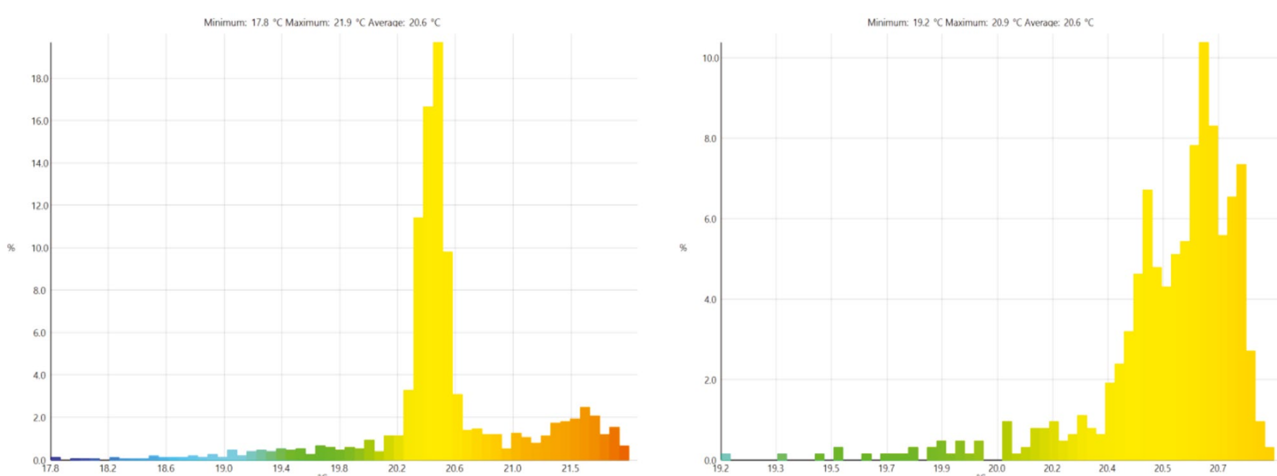


Fig. 4 Thermal image show MTD in healthy and infected cotton bolls created by Testo IR soft software

way to provide information for pre-symptomatic diagnosis of biotic stressors on leaves, by seeing and evaluating the temperature difference between infected and non-infected leaves. Digital infrared thermography has the potential to discover and quantify management zones in pest control and associated infections with high spatial resolution, because they are sensitive to physiological disorders occurs. In addition, any leaf infection often affected the plant transpiration. Moshou et al. (2004) were able to identify powdery mildew of barley, damaged cucumber leaves and yellow rust of wheat presented by Oerke et al. (2006).

Thermal imaging could identify early-stage physiological responses of cotton boll plants to water stress according to the initial assumption, the temperature was recorded to test this idea, in order to fully understand the difference between healthy and diseased plants in the identical conditions (Martynenko et al. 2016).

Visual and manual examinations have been used by pest management professionals for years to discover insect pest infestations. Fruits can sometimes mask the presence of pest infestations so locating pest problems has gotten more difficult as fruits have improved. Furthermore, fruits have contributed to the insect problem by providing a suitable



Histogram adjustment for Severe infected Sample (no. 8)   Histogram adjustment for Healthy Sample (no.13)

Fig. 5 Histogram adjustments illustrate the maximum temperature difference between healthy and infected boll samples by using Testo IR soft software food and nesting supply. The Insect Management Industry has just recently realized that IR thermography can help to detect pest infestations by detecting indications of latent moisture within structures. The use of thermal imaging to detect thermal patterns associated with insect infestation, data verification, and particular problems related with the inspection process are discussed by Grossman (2005).

Conclusion

Increasing maximum output capacity while reducing pesticides to reduce the environmental impact of hazards is a critical aim for this research. Detection of plant illnesses and disease prevention are equally significant tasks. And this study explains how spectroradiometer and thermal imaging as a tools from remote sensing works and how it can be used in agriculture, with a focus on pest management, Pest monitoring, yield forecasting and early warning to crop growers for prompt pest treatment have all become common uses of remote sensing in agriculture. As a result, costs are reduced and environmental standards are achieved.

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Declarations

Conflict of interest The authors certify that they have No funding was received to assist with the preparation of this manuscript, and NO affiliation with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangement), or non-financial interest such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

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