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THERMAL- AND RGB IMAGING AS POTENTIAL TOOLS FOR ASSESSING CHLOROPHYLL AND NUTRITIONAL PERFORMANCE OF PEPPER (*CAPSICUM ANNUM)*

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ABSTRACT

Nutrient management requires traditional soil and plant analysis, which is time-consuming, costly, and requires effort. Therefore, a lot of efforts have been directed toward developing novel approaches for estimating plants' status. Our objective was to evaluate the potential of thermal and RGB imaging to estimate Chlorophyll levels and some essential nutrients in the pepper plant *(capsicum annum*). Forty plants were randomly selected and marked for subsequent imaging. Thermal and RGB sensor cameras have been used for remotely sensed image acquisition of the studied plants. Chlorophyll was measured by SPAD then Plants were analyzed for determination chlorophyll, Nitrogen, Phosphorus, Potassium, and sulfur contents. The correlation between the measured/observed values and data of thermal and RGB images was calculated, as well as seven vegetation indices. The results showed that Chlorophyll b, and Chlorophyll measured by SPAD significantly correlated with the blue band of RGB images (r=0.625 and 0.709), respectively. To assess the Chlorophyll performance, excess blue, excess green, excess green-red, and excess red indices, and the Color Index of Vegetation (CIVE) were the best. In thermal imaging: band3 in capture 1 was the best to assess Chlorophyll. The more fitting band to assess Nitrogen, potassium and sulfur was band2 in capture2. The more detective indices to assess pepper nutrient content were excess blue, excess green, excess green red, and CIVE indices. The regression analysis revealed that a simple linear equation can be used to estimate the percentage of Nitrogen,

sulfur, and potassium in plants using the excess green index (r = 0.9159, 0.8942, 0.8715, and 0,9117, respectively) and the red-blue ratio index (RBRI) could be used to estimate the percentage of P (r = 0.9098). Thermal and RGB imaging can be used as a tool for assessing some nutrients and Chlorophyll content in pepper plants.

Keywords: Thermal images, RGB images, Non-destructive methods, Chlorophyll, Nutrients, Pepper.

INTRODUCTION

Climate change and population growth are the most important global challenges that need to be addressed by developing possible solutions such as precision agriculture (PA). Surplus or deficiency of plant nutrients causes severe damage and yield decrement. Therefore, accurate and fast detection of crop nutrient status is essential for PA which requires accurate determination. PA offers the advantage of better and prompt crop management to avoid yield losses and environmental degradation. Moreover, PA could lead to the optimal application of fertilizers, in terms of time and application rate. As a result, financial resources are reduced, and environmental problems are minimized. PA is used to determine the inputs for crop high production in a way that meets the needs of the plant such as fertilizers, seeds, and chemicals (Bongiovanni and Deboer., 2004). Furthermore, as a part of decision support and farm management tools, remote sensing tools for nutrient monitoring became available and could be useful for farmers, especially those who do not have access to professional assistance.

Fertilizers are important factors to increase crop production, but their excessive use causes serious damage to the environment, so it is necessary to develop an accurate nutrient management system. Several approaches were used for nutrient management including soil and plant samples analysis (Singh *et al.*, 2016). However, such analyses are costly and time-consuming, therefore, could affect the timely fertilization management (Beede *et al.*, 2005; Dezordi *et al.*, 2016; Cunha *et al.*, 2016). Therefore, the farmers visually (the most traditional method) determine plant nutrient status, using plant color guides. However, this method does not allow for quantitatively rigorous evaluations (Graeff *et al.*, 2008), leading to inaccurate fertilization management. Some nutrients have indirect measurement alternatives, such as the chlorophyll meter (SPAD) for nitrogen forecasts (Balasubramaniam and Ananthi, 2016), although this is a time-consuming process (Jia *et al.*, 2004), and estimations are not always precise (Nauš *et al.*, 2010). As a result, a lot of efforts have been directed to develop novel approaches for detecting and estimating plant's chlorophyll (chl) content and nutritional deficits (Muñoz-Huerta *et al.*, 2013; Ali *et al.*, 2017). The non-destructive methods (NDM) are very important in evaluating and obtaining quantitative and qualitative data with high accuracy and efficiency, especially in the field of food and agriculture, without causing damage to products or plants. One of the NDM methods is imaging systems such as the machine vision technique (El-Mesery *et al.*, 2019).

Thermal imaging measures the temperature of a certain object; these thermal data are used for direct or indirect applications, i.e., surveillance, human emotions, agriculture, and medicine (Rai *et al.*, 2017). This technology is characterized by its low cost and simplicity. Thermal imaging is used in agriculture in field nurseries, greenhouses monitoring, irrigation scheduling, identifying the level of soil salinity, pre-harvest operations, yield forecasting, bruise detection of fruits and vegetables, and the detection of disease and pathogen, and foreign substances in food and wood drying (Ishimwe *et al.*, 2014; Manickavasagan *et al.*, 2005; Ishimwe *et al.*, 2014).

RGB images are one of the most useful tools for estimating and monitoring the health and status of plants. Moreover, RGB images have been used in agriculture in several other applications such as determining grain quality, fruit inspection and grading, weed detection, and plant disease detection (Jayapal *et al.*, 2022; Gupta *et al.*, 2014). The uses of RGB images have been extended to the estimation of leaf water status (Han *et al.*,2014; Gupta *et al.*, 2014), chl and nitrogen status, pigment contents, shoot length of regenerated rice callus (Gupta *et al.*, 2014), soil salinity (Abdelaty and Aboukila., 2017), water quality evaluation (Abdelaty, 2018), and change detection (Rabia *et al.*, 2021).

The prime goal of the current study is to evaluate the potential of using thermal- and RGB imaging to estimate the level of some nutrients and chl content in pepper plants cultivated under open field conditions. Moreover, to study the relationship between chl and some essential nutrients in plants and data of thermal and RGB images. The results of this study could provide a non-destructive, fast, accurate, and cost-effective tool for better/faster fertilization management as a main principle of PA.

MATERIALS AND METHODS

Crop selection

This study was conducted on pepper plants (*Capsicum annum*) because they have large leaves to monitor the morphological variations using the images. The imaging was conducted at the age of one month (at the beginning of flowering), to avoid the overlaying of the fruits over (the leaves "the targeted object" cannot be covered by the fruits). Pepper was planted on 1st June 2019 under the furrow irrigation system. The soil of the experimental field site is clay and located in Kafr Eldawar, Elbeheira Governorate, Egypt (31.0971, 30.132400). Forty plants were randomly selected and marked to be representative of the cultivated area (350 m^2) for subsequent imaging and chemical analysis. Thermal and RGB sensor cameras have been used for remotely sensed image acquisition. Leave samples were collected and stored for chemical analysis of NPK and S, while SAPD measurements were conducted under field conditions.

Thermal and RGB imaging cameras

Thermal images were acquired for the forty plants by thermal imaging camera (HT-02D). The camera has 32 × 32 IR image pixels. It is combining the function of surface temperature measurement and real-time thermal imaging. The range of temperature measurement is -20˚c to +300˚c, and spectral resolution (range of wavelength) is 8-14 µm. Under the field conditions, images were taken for each growing and active plant (with expanded leaves) separately at approximately 55 cm height above the surface (the most suitable height to take a good image of the plant in our experiment). RGB images (0.4-0.7 µm) of the plants were taken at the same height above the surface by a 13 megapixels digital camera.

Chlorophyll measurement by SPAD

Chlorophyll was measured by SPAD-502 chlorophyll meter (Konica Minolta, Europe); 35 days after planting.

Laboratory chemical analysis of leaves

Plants that were selected were collected for the chl and N, P, K, and S contents content.

Chlorophyll measurement by spectrophotometer

Chlorophyll a (Chl-a) and chlorophyll b (Chl-b) were measured by spectrophotometer according to Arnon, (1967) By using 200 mg of fresh leaf tissue and gradually grinded using 20 ml of 80% acetone extract Chl into the acetone solution. The final volume of the solution was then brought up to 20 ml using 80% acetone. The solution was centrifuged at 400 rpm for 10 min and the optical absorption of the supernatant was then read at 645, and 663 nm. Chl-a and Chl-b were estimated using the following equations.

Chl *a (mg/g fresh weight of leaf)* = (19.3×A663-0.86×A645) V/100W

Chl *b (mg/g fresh weight of leaf)* = (19.3×A645-3.6×A663) V/100W

Where:

A663 = solution absorption at 663 nm wavelength.

A645= solution absorption at 645 nm wavelength.

W = leaf fresh weight, and

V = volume of extract (mL).

Total chlorophyll is the sum of chl a and b

Determination of plant nutrients content

Fresh Plant samples were dried at 65-70˚C for 48 hr, grained, and sieved to determine nitrogen, phosphorus, potassium, and sulfur.

Plant total nitrogen content

The total nitrogen content in leaves was determined following the modified Kjeldahl method (AOAC., 1995). Plant samples were oven dried at 65-70˚C for 48 hr to be wet-digested by a mixture of concentrated sulfuric acid and salysililc acid and catalyst mixture of (K_2SO_4), ($FeSO_4$) and ($CuSO_4$). Then digestion samples were distilled with NaOH (40%) in a distillation unit and titrated with sulfuric acid (0.1 N) until the color changed from green to red.

Plant phosphorus content

One g of dry plant for all samples was digested by a digestion mixture of nitric acid. Perchloric acid then ammonium molybdate and ammonium vanadate were added to filtered digested sample solutions to make color solutions and read the transmittance at 420 nm wavelength by spectrophotometer (Koenig and Johnson., 1942).

Plant potassium content

One g of dry plant samples was digested by a digestion mixture of nitric acid and perchloric acid and potassium in the plant was determined using a flame photometer (Yash,1998).

Plant sulfur content

One g of dry plant samples was digested by a digestion mixture of nitric acid and perchloric acid. Sulfur in plants was determined by spectrophotometer using the barium sulfate turbidity method (Thakur *et al.*, 2012; Tabatabai and Bremne, 1970).

Images processing and data analysis

Images were acquired at interval times 4:00 pm and 6:00 pm (25˚C) in four image types. One of these types was the color image (RGB) which was taken by a digital camera and the other three types were thermal images which were taken by the thermal camera. The thermal camera can take 4 different captures of the same scene, and images were taken in only the first three captures. All images were processed using ArcGIS software (Version 10.5; Esri, 2017). Ten points were selected randomly in all images to extract pixel values of the plant canopy. Red, green, and blue bands were obtained for RGB images, then seven vegetation indices (Table 1) were calculated for each RGB image using raster calculate module in ArcGIS software (Figure 1 and 2). In addition, three bands were generated for each capture of thermal images (band 1 – band 2 – band 3) (Figure3).

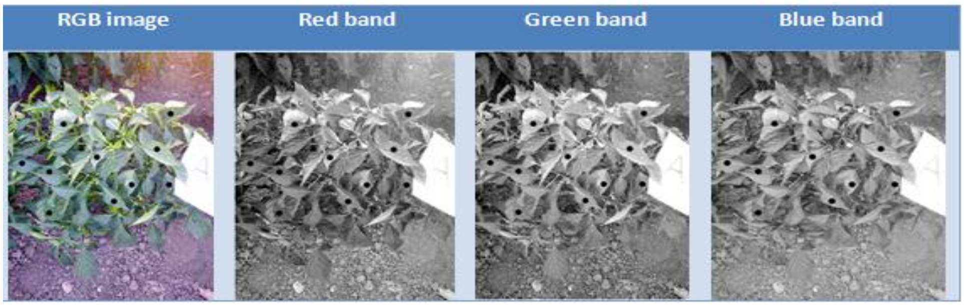

Figure 1: RGB image; red (0.6-0.7 µm), green (0.5-0.6 µm), and blue (0.4-0.5 µm) bands.

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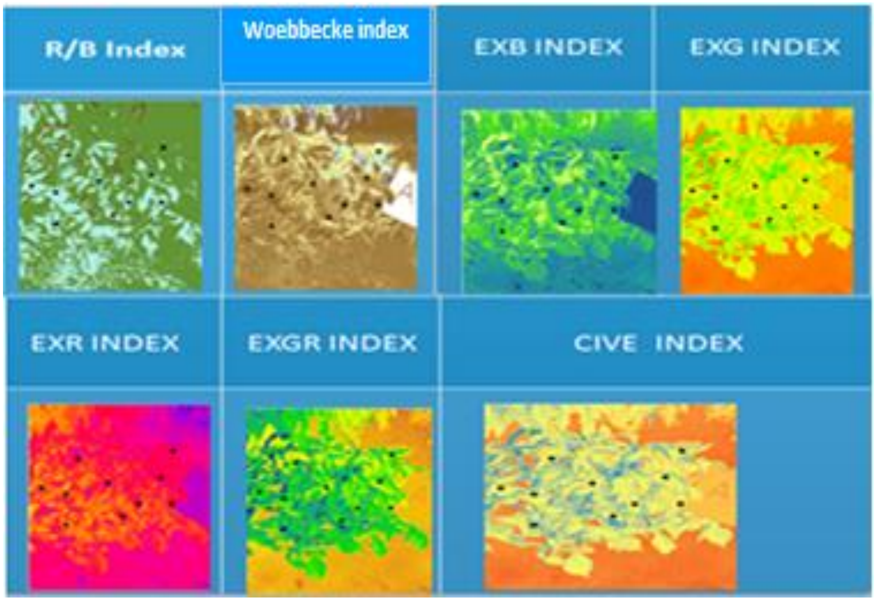

Figure 2: Vegetation indices of RGB (red, green and blue) image.

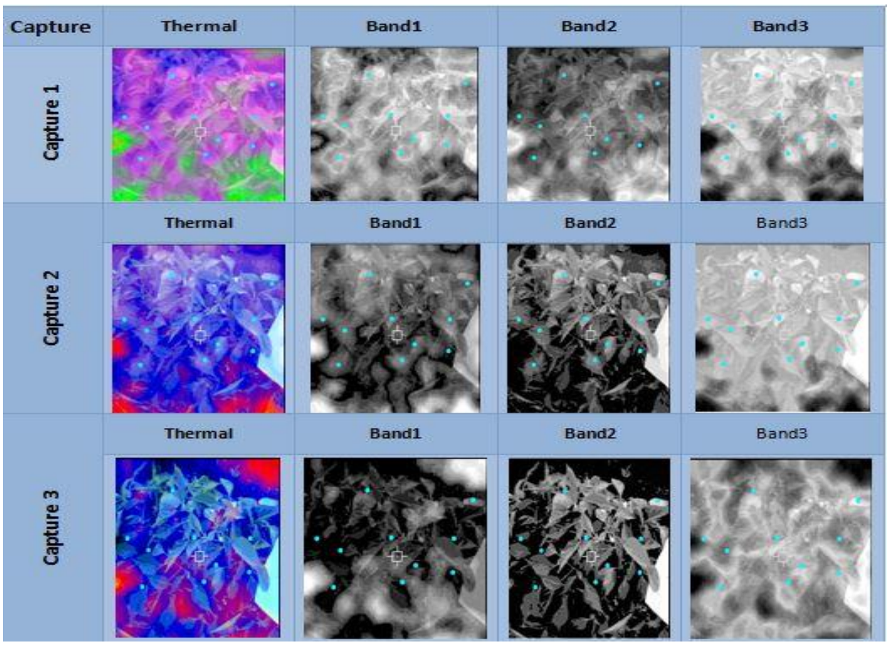

Figure 3: Bands of three captures of thermal images.

Table 1: The selected seven vegetation indices (derived from RGB images)

Vegetation Index	Formula
Red-Blue Ratio Index (RBRI), Everitt *et al.*, 1987	$\frac{R}{B}$
Woebbecke Index (WI), Woebbecke *et al.*, 1995	$\frac{(g - b)}{(r - g)}$
Excess Blue Index (EXB), Mao *et al.*, 2003	1.4b – g
Excess Green Index (EXG), Woebbecke *et al.*, 1995	2g - r – b
Excess Red Index (EXR), Meyer *et al.*, 2008	1.4r – g
Excess Green-Red Index (EXGR), Neto *et al.*, 2004	3g-2.4r-b
Color Index of Vegetation (CIVE), Kataoka *et al.*, 2003	0.441R-0.811G+ 0.385B+18.78745

In this study, the correlation between chl and nutrients measurements and the pixel values of RGB and thermal images was elaborated to assess the performance of RGB and thermal images in predicting the chl content of pepper plants.

RESULTS AND DISCUSSION

Assessing chlorophyll performance

Results showed that there is a non-significant correlation between chl a and red and green bands of RGB images, but it was significantly correlated with the blue band (Table 2). As for chl b, total chl, and data of SPAD, a significant correlation with bands of RGB images has been observed (Table 2).

The correlation coefficients were highest in the case of Chl (SPAD) with the value of 0.709** (blue band). In addition, this correlation was also marked between Chl-b and the blue band, where the correlation coefficients had the value of 0.625** (Table 2).

The results illustrated in table (3) show the correlation coefficients between chl contents and vegetation indices of RGB bands. The RBRI had a non-significant correlation with chl a and total chlorophyll but significantly correlated with chl b and SPAD-chl (r =-0.487 and -0.508), respectively. Woebbecke index had a non-significant correlation with chl a, chl b, total chlorophyll, and by SPAD-chl. Excess

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blue index, excess green index, excess green-red index, and CIVE index had non-significant correlation with chl a and significantly correlated with chl b, total chlorophyll, and SPAD-chl. The excess red index significantly correlated with chl a, chl b, total chlorophyll, and SPAD-chl (r=0.325, 0.415, 0.392, and 0.537), respectively.

Data in table 4 showed the Correlation coefficients between chl contents and bands of thermal images in pepper. Band 1 in capture 1 had non-significantly correlated with chl a, chl b, total chlorophyll, and SPAD-chl. However, band 2 had a non-significant correlation with chl b, and SPAD-chl, but had a significant correlation with chl a, and total chlorophyll (r=0.528). There was a significant correlation between band 3 and chl a, total chlorophyll, and SPAD-chl (r=0,787, 0.742, and 0.321), respectively, but had a non-significant correlation with chl b. In capture 2; chl a and total chlorophyll had a non-significant correlation with bands. Chl b, and SPAD-chl non-significantly correlated with band 1 and band 3, but significantly correlated with band 2. Bands of Capture 3 had a non-significant correlation with chl a, chl b, total chlorophyll, and SPAD-chlorophyll. Previous studies investigated the analysis of rice leaves images which were taken at 12:00-13:00 on a sunny day and citrus leaves images which were taken at daylight from 9:00 am and 11:00 am showed that blue color values (blue band) have a non-significant correlation with Chl-a, Chl-b, and total chlorophyll. Also, a high correlation between green color value (green band) and Chl-a, Chl-b, total chlorophyll more than the correlation between red color (red band) and Chl-a, Chl-b, total chlorophyll (Hu *et al.*, 2013; EL-Azazy, 2018).

Table 2: The correlation coefficients between pepper chlorophyll contents and red, green, and blue bands of RGB images.

Chlorophyll Type	Bands of RGB images		
	Red Band	Green Band	Blue Band
Chl-a	0.307	0.299	0.330*
Chl-b	0.371*	0.327*	0.625**
Total chlorophyll	0.364*	0.347*	0.448*
SPAD-Chl	0.462**	0.389*	0.709**

* Significant at 95% and ** significant at 99%.

Table 3: The correlation coefficients between pepper chlorophyll contents and vegetation indices of RGB bands.

Chlorophyll Type	Indices of RGB Images						
	RBRI	WI	EXB	EXG	EXR	EXGR	CIVE
Chl-a	-0.027	0.001	0.309	-0.290	0.325*	-0.268	0.263
Chl-b	-0.487**	0.156	0.784**	-0.835**	0.415**	-0.642**	0.760**
Total chl	-0.145	0.037	0.469**	-0.464**	0.392*	-0.397*	0.422**
SPAD-Chl	-0.508**	0.164	0.8382**	-0.957**	0.537**	-0.767**	0.863**

* Significant at 95% and ** significant at 99%.

Table 4: The correlation coefficients between pepper chlorophyll contents and bands of thermal images.

Captures of Thermal Camera	Bands of Thermal Camera	Chlorophyll Types			
		Chl-a	Chl-b	Total chl	SPAD-Chl
Capture -1	**Band 1**	0.155	0.165	0.179	0.172
	Band 2	0.528**	0.241	0.528**	0.123
	Band 3	0.787**	0.178	0.742**	0.321*
Capture - 2	**Band 1**	0.169	-0.179	0.109	-0.279
	Band 2	-0.208	0.426*	-0.085	0.459**
	Band 3	0.263	-0.264	0.173	-0.312
Capture – 3	**Band 1**	-0.160	0.098	-0.117	0.207
	Band 2	0.067	-0.165	0.018	0.022
	Band 3	-0.006	-0.081	-0.025	0.010

* Significant at 95% and ** significant at 99%.

The Regression analysis between chl types with all bands of RGB camera, spectral indices, and thermal camera bands was computed. It was noticed that the linear regression analysis gave the highest R^2 (0.9159) between SPAD-chl and the EXG. Therefore, the EXG could be used in the linear equation to find chl in plants (Figure 4).

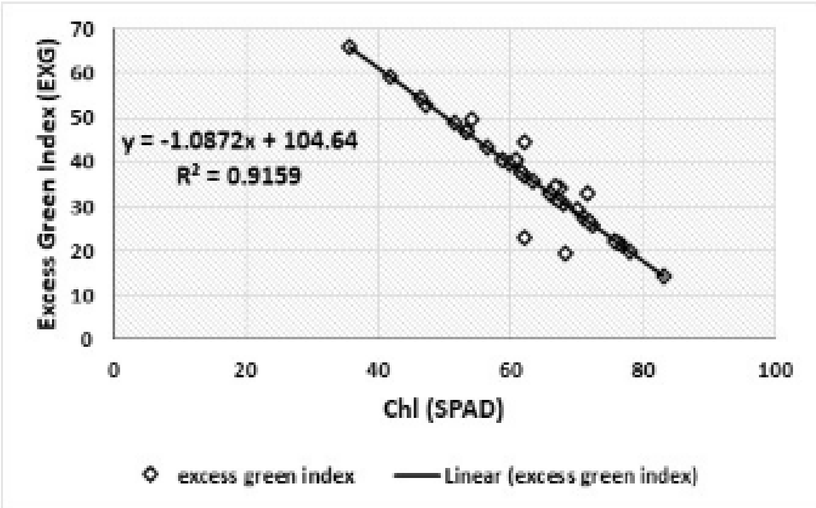

Figure 4: The linear regression analysis between SPAD-chlorophyll and excess green index (EXG).

Assessing nutrients performance

Table 5 shows the correlation coefficients between nutrient contents and bands of RGB images. N, K, and S were significantly correlated with red, green, and blue bands. However, P non-significantly correlated with red and green bands but had a significant correlation with the blue band (r=0.372).

Table 5: Correlation coefficients between nutrient content in pepper leaves and bands of RGB images.

Nutrients concentration (% of the dry weight)	RGB Bands		
	Red Band	Green Band	Blue Band
N	0.470**	0.393*	0.703**
P	-0.020	0.0340	0.372*
S	0.449**	0.375*	0.689**
K	0.456**	0.382*	0.703**

* Significant at 95% and ** significant at 99%.

The Correlation coefficients **(**Table 6) show that the RBRI, excess blue, excess green, and CIVE indices significantly correlated with N content (r=-0.46, 0.823,-0.945, 0.853) respectively, P (r=-0.953, 0.627, -0.514,0.518) respectively, S (r=-0.470, 0.814, -0.933, 0.839) respectively, and K (r=-0.489, 0.833, -0.954, 0.861) respectively, but woebbecke index had non-significant correlation with all measured nutrients. Excess red and excess green, red indices had significant correlation with N (r=0.549 and -0.764) respectively, S (r=0.525 and -0.742), respectively, and K (r=0.533 and -0.763), respectively, however, a non-significant correlation with phosphorus has been observed.

Table 7 shows the correlation coefficients between nutrient content in leaves and the bands of thermal pepper images. In capture 1, band1 and band2 non-significantly correlated with all tested nutrients (N, P, K, and S). However, Band 3 significantly correlated with N, K, and S (r=0.337, 0.331, and 0.317) respectively, but non-significantly correlated with P. In capture 2: band1 and band3 had a non-significant correlation with all nutrients, while band 2 significantly correlated with N, K, and S (r=0.445, 0.430, and 0.410), respectively, and non-significant correlation with P. All bands of capture 3 showed a non-significant correlation with all tested nutrients.

Table 6: Correlation coefficients between pepper nutrient content and some indices of RGB images.

Nutrients concentration (% of the dry weight)	Indices of RGB Images.						
	RBRI	WI	EXB	EXG	EXR	EXGR	CIVE
N%	-0.46**	0.15	0.823**	-0.945**	0.549**	-0.764**	0.853**
P%	-0.953**	0.161	0.627**	-0.514**	-0.127	-0.233	0.518**
S%	-0.470**	0.137	0.814**	-0.933**	0.525**	-0.742**	0.839**
K%	-0.489**	0.146	0.833**	-0.954**	0.533**	-0.763**	0.861**

* significant at 95% and ** significant at 99%.

Our results agree with several previous studies in which there is a significant correlation between N content and red and green band on apple trees, tomatoes, and pepper (Treder *et al.*, 2016; Mercado-Luna *et al.*, 2010; Yuzhu., 2011). Moreover, EL-Azazy., (2018) found a significant correlation between blue color (blue band) and N content in citrus leaves. Another study on corn leaves showed that N content was significantly correlated with EXR, EXGR, and CIVE indexes, and non-significantly with woebbecke index (Aderson *et al.*, 2021).

Table 7: Correlation coefficients between pepper nutrients content and bands of thermal images.

Captures of Thermal Camera	Bands of Thermal Camera	Nutrients concentration (% of the dry weight)			
		N	P	K	S
Capture -1	Band 1	0.193	-0.263	0.190	0.200
	Band 2	0.156	-0.215	0.141	0.130
	Band 3	0.337*	0.092	0.331*	0.317*
Capture -2	Band 1	-0.283	0.011	-0.250	-0.236
	Band 2	0.445*	0.184	0.430*	0.410*
	Band 3	-0.318	-0.010	-0.283	-0.263
Capture -3	Band 1	0.227	0.071	0.184	0.157
	Band 2	0.017	0.170	-0.022	-0.038
	Band 3	-0.016	0.263	-0.024	-0.035

* significant at 95% and ** significant at 99%.

In contrast, K content was non-significantly correlated with all indexes (EXR, EXR, EXGR, CIVE, and woebbecke indexes). The inconsistency among results could be attributed to the variation in the cultivated crop, plant growth stage at which the imaging and sampling have been done, imaging time (during the day), and the type of the used camera (pixel and wavelength).

Phosphorus requirements of the crop may be estimated on the basis of morphological characteristics like leaf color and dimensions because it is easy to collect data for the color of the leaf or dimensions (Ali *et al.*, 2015). In this study, there were no deficiency symptoms of phosphorus or potassium on the pepper plant, so there were no color effects whether in thermal or RGB images.

Nitrogen is in the composition of proteins, free amino acids, and chl or bonds with other elements. So, N and pigments can be analyzed by remote sensing since there is a distinct absorption spectrum, and spectral changes in the visible, NIR, and short waves infrared portion of the electromagnetic spectrum. Similarly, other elements such as S and P can be analyzed by the same methods. On the other hand, K is found in plants as a cation that does not have any chemical bonds. Therefore, there is not any absorption feature, but its absence has noticeable effects on plant tissues which can be detected using remote sensing methods. Noon has been found to be the best time of the day to capture remotely sensed data of the physiological attributes of plants when the solar radiation is strongest and it is the best for performing remote spectral data acquisition or direct observation of plants (Weksler et al ., 2021). The thermal camera which is used in this study has a wavelength of 8-12 µm, this wavelength is a long infrared wavelength (Rai *et al.*, 2017). This camera is known as an uncooled thermal camera that is used for applications of mid-range in cooler climates, its performance is better than Mid-wavelength IR (MWIR) cameras in fog, low-cost, and cold climates (https://silentsentinel.com).

Regression analysis between the nutrients (N, P, S, and K) with all bands of RGB camera, spectral indices, and thermal camera bands were computed. It was noticed that the linear regression analysis gave the highest R^2 between N, S, and K (0.8942, 0.8715, and 0. 9117, respectively) and EXG. In this way, a simple linear equation could be used to estimate/calculate the percentage of N, S, and K in plants using the EXG index (Figure 5). The linear regression analysis gave the highest R^2 between P (0.9098) and RBRI. Therefore, the RBRI could be used in the linear equation to estimate the percentage P in the plant (Figure 5).

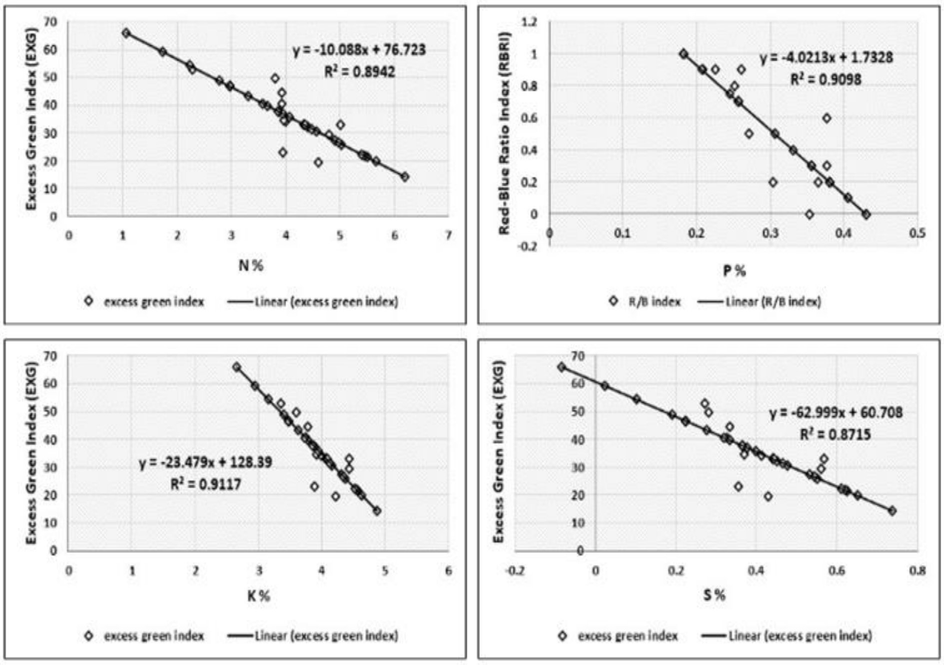

Figure 5: The linear regression analysis between nutrients with excess green index (EXG) and red-blue ratio index (RBRI).

CONCLUSION

Thermal and RGB imaging may be considered effective methods to assess plant contents of chl elements and nutrients in plants. They have the advantages of being non-destructive, cheap, easy to use, and time-saving. This study showed that EXG index can be used for estimating chl in plants like pepper. Also, EXG index can be used to estimate/calculate the percentage of N, S, and K in plants. On the other hand, the RBRI index can give better performance in estimating the percentage of P in the plant. Finally, more work needs to be done to evaluate and calibrate the use of RGB and thermal sensors for accurate nutrient management in different plants at different growth stages.

REFERENCES

Abdelaty, E. F and E. F. Aboukila (2017). Detection of soil salinity for bare and cultivated lands using Landsat ETM+ Imagery Data: A case study from El-Beheira Governorate, Egypt. Alexandria Science Exchange Journal, 38(3). Doi: 10.21608/asejaiqjsae.2017.4055

Abdelaty, E. F (2018). Monitoring of water quality for agriculture purposes using high resolution images (ASTER): A case study from Egypt. Alexandria Science Exchange Journal, Vol. 39, No.3. July- September. Doi: 10.21608/asejaiqjsae.2018.15336

Ali, M., A. Al-Ani., D. Eamus and D. K. Tan. (2017). Leaf nitrogen determination using non-destructive techniques–A review. Journal of Plant Nutrition 40, 928-953.

Ali, M.M., A. Al-Ani, D. Eamus, and D. K. Y. Tan. (2015). Image-based (RGB) technique for estimating phosphorus leaves of crops . International Journal Of Agricultural And Biosystems Engineering, 1125-1128.

AOAC,(1995).Official Methods Of Analysis 16th Edn . Association Of Official Analytical Chemists, Washington, DC.

Arnon, A. N (1967). Method of extraction of chlorophyll in the plants. Agronomy Journal 23:112-121.

Balasubramaniam, P., and V. Ananthi, (2016). Segmentation of nutrient deficiency in incomplete crop images using intuitionistic fuzzy C-means clustering algorithm. Nonlinear Dynamics 83, 849-866.

Beede , R. H., P. H. Brown, C. Kallsen and S. A. Weinbaum (2005). Diagnosing And Correcting Nutrient Deficiencies. https://www.researchgate.net/publication/242204193.

Bongiovanni, R., and J. l. Deboer (2004). Precision Agriculture and Sustainability 788 Precision Agriculture. 5: 359–387.

Cunha, M. L. P., L. A. Aquino, R. F. Novais, J. M. Clemente and P. M. de Aquino (2016). Diagnosis of the nutritional status of garlic crops. Revista Brasileira de Ciência do Solo 40.

Dezordi, L. R., L. A. d. Aquino, R. F. B. d. A. Aquino, J. M. Clemente and N. S. Assunção (2016). Diagnostic methods to assess the nutritional status of the carrot crop. Revista Brasileira de Ciência do Solo 40.

EL-Azazy, A. M. (2018). Inspect the potential of using leaf image analysis procedure in estimating nitrogen. Middle East Journal of Agriculture Research. 1059-1071.

El-Mesery, H. S., H. Mao , and A. Abomohra (2019). applications of non-destructive technologies for agricultural and food products qualityinspection. Sensors. 1:23.

Esri (2017). ArcGIS 10.5, ArcGIS Pro 1.4, and ArcGIS Earth 1.4 Enterprise Deployment. ESRI. 1:113.

Everitt, J. H., R. Villarreal (1987). Detecting huisache (Acacia farnesiana) and Mexican palo-verde (Parkinsonia aculeata) by aerial photography. Weed Sci. 427–432.

Graeff, S., J. Pfenning, W. Claupein and H. P. Liebig, (2008). Evaluation of image analysis to determine the N-fertilizer demand of broccoli plants (*Brassica oleracea* convar. botrytis var. italica). Advances in optical technologies; 1:9.

Gupta , S. D., and Y. ibaraki (2014). Plant image analysis fundamental and applications, "chapter3." .CRC.41:55.

Han ,W., S. Yu., X. Tengfei and C. Xiangei (2014). Detecting maize leaf water status by using digital RGB images. International Journal Of Agricultural and Biological Engineering, 45-53.

Hu, H., J. Zhang, X. Sun and X. Zhang, (2013). Estimation of leaf chlorophyll content of rice using image color analysis, Can. J. Remote Sens., 39, 185–190. https://silentsentinel.com july,2022

Ishimwe, Roselyne, K. Abutaleb and F. Ahmed. (2014). Applications of thermal imaging in agriculture. Advances in Remote Sensing, 128-140.

Jayapal, P. K., E. Park, M. A. Faqeerzada, Y. Kim, H. Kim, I. Baek, M.Kim, Domnic, Sandanam and B. Cho. (2022). Analysis of RGB plant images to identify root rot disease in Korean ginseng plants using deep learning. Applied Sciences, 1-16.

Jia, L., X. Chen, F. Zhang, A. Buerkert and V. Römheld, (2004). Use of digital camera to assess nitrogen status of winter wheat in the northern china plain. Journal of Plant Nutrition 27, 441-450.

Junior ,A. S. A., F. B. Melo,E. A. Bastos and m. J. Cardoso (2021). Evaluation of the nutritional status of corn by vegetation indices via aerial images. Ciencia Rural, 2021: 1-13.

Kataoka, T., T. Kaneko, H .Okamoto and S. Hata,(2003). Crop growth estimation system using machine vision. Proceedings 2003 IEEE/ASME International Conference on Advanced Intelligent Mechatronics (AIM 2003). pp. b1079-b1083 vol.2.

Koenig, R. A., and C.R. Johnson, (1942). Colorimetric determination of biological materials Ind. Eng. Chem. Analyst. End.14:155-156.

Manickavasagan ,A., D. S. Jayas, N. D. G. White and J. Paliwal. (2005). Applications of thermal imaging in agriculture. The Canadian society for engineering in agricultural, Food, and biological system, Paper No. 05-002; 1-11.

Mao,W., Y. Wang, Y. Wang, (2003). Real-time detection of between-row weeds using machine vision. In Proceedings of the 2003 ASAE Annual Meeting; American Society of Agricultural and Biological Engineers, Las Vegas,NV, USA, 27–30 .

Mercado, L. A., G. E. Rico, H. A. Lara, Z. G. Soto, V. R. Ocampo, G. R. Guevara, R. G. Herrera and P. I. Torres, (2010). Nitrogen determination on tomato (Lycopersicon esculentum Mill.) seedlings by color image analysis (RGB). African Journal of Biotechnology, 9: 5326–5332

Meyer, G. E., and J. C. Neto, (2008). Verification of color vegetation indices for automated crop imaging applications. Comput. Electron. Agric. 63, 282–293.

Muñoz-Huerta, R. F., R. G. Guevara-Gonzalez, L. M. Contreras-Medina, I. Torres-Pacheco and J. Prado-Olivarez (2013). A review of methods for sensing the nitrogen status in plants: advantages, disadvantages and recent advances. Sensors 13, 10823-10843.

Nauš, J., J. Prokopová, J. Řebíček and M. Špundová, (2010). SPAD chlorophyll meter reading can be pronouncedly affected by chloroplast movement. Photosynthesis Research 105, 265-271.

Neto, J. C. (2004). A combined statistical-soft computing approach for classification and mapping weed species in minimum -tillage systems. Ph.D. Thesis, University of Nebraska – Lincoln, Lincoln, NE, USA, August.

Rabia, A.H., Abdelaty, E.F., Elsayed, M.L., Mohamed, A., Wassar, F., Fiorillo, E., Di Vecchia, A. and Tarchiani, V., (2021). Change Detection of Olive Trees Distribution using Semi-Automated

Object Based Image Classification. Alexandria Science Exchange Journal, 42(4), pp.857-869.

Rai, M., T. Maity and R. K. Yadav, (2017). Thermal imaging system and its real time applications. Engineering Technology, 290-303.

Singh ,V., R. Kaur, B. Singh, B. Sing, and A. Kaur,(2016). Precision nutrient management, Indian Journal of Fertilisers, p. 15.

Tabatabai, M. A., and J. M. Bremner, (1970). Factors affecting soil arylsulfatase activity. Soil Science Society of America Journal, 34, 427-429.

Thakur, R. K., S. S. Baghell,G. D. Sharma,R. K. Sahu, and P. C. Amule (2012). Training programme on advances in agro-technologies for improving soil, plant and atmosphere system. Center of Advanced Faculty Training, Department of Soil Science and Agricultural Chemistry, 25-26.

Treder, W., K. Klamkowski, W. Kowalczyk, D. Sas and K. Wójcik, (2016). Zemdirbyste Agriculture, 103(3): 319-326.

Weksler ,S., O. Roenstein, N. Haish, M. Moshelion, R. Wallach and E. Ben-Dor, (2021). Detection of potassium deficiency and momentary transpiration rate estimation at early growth stages using proximal hyperspectral imaging and extreme gradient boosting . Sensors, 1-19.

Woebbecke, D. M., G. E. Meyer ., K. Von Bargen and D. A. Mortensen, (1995). Color indices for weed identification under various soil, residue, and lighting conditions. Trans ASAE, 38, 259–269. www.perfect-prime .com

Yash P. K. (1998). Reference methods for plant analysis. Boca Boston London New York Washington,D.C.: Taylor&Francis Group, LLC.

Yuzhu, H., W. Xiaomei and S. Shuyao, (2011). Nitrogen determination in pepper (Capsicum frutescens L.) plants by color image analysis (RGB). Afr. J. Biotechnol., 10(77).

الملخص العربي

التصوير الحراري والملون كأدوات محتملة لتقييم الكلوروفيل والأداء الغذائي لنبات الفلفل

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تتطلب إدارة المغذيات التحليلات التقليدية للتربة والنبات ، وهو أمر مكلف ويستغرق وقتًا طويلاً ويتطلب جهدًا. لذلك ، تم توجيه الكثير من الجهود نحو تطوير مناهج جديدة لتقدير حالة النباتات. الهدف من الدراسة هو تقييم إمكانات التصوير الحراري والتصويرالملون (RGB) لتقدير مستويات الكلوروفيل وبعض العناصر الغذائية الأساسية في نبات الفلفل (*capsicum annum*). تم اختيار أربعين نباتًا بشكل عشوائي وتمييزها للتصوير. تم استخدام الكاميرات الحرارية وكاميرات استشعار RGB للحصول على صور الاستشعار عن بعد للنباتات المدروسة. تم قياس الكلوروفيل بواسطة SPAD ثم تم تحليل النباتات لتقدير محتوى الكلوروفيل والنيتروجين والفوسفور والبوتاسيوم والكبريت. تم حساب الارتباط بين القيم المقاسة وبيانات الصور الحرارية والصورالملونة (RGB) ، بالإضافة إلى سبعة مؤشرات للنباتات. أظهرت النتائج أن الكلوروفيل ب والكلوروفيل المقاس بواسطة SPAD يرتبطان بشكل كبير مع النطاق الأزرق للصورالملونة(RGB)ومعامل الارتباط يساوي (0.625) و (0.709) على التوالي. لتقييم أداء الكلوروفيل ، كانت مؤشرات اللون الأزرق الزائدة والأخضر الزائد والأخضر والأحمر الزائد والأحمر الزائد ومؤشر لون الغطاء النباتي (CIVE) هي الأفضل. في التصوير الحراري: كان النطاق 3 في اللقطة 1 هو الأفضل لتقييم الكلوروفيل. كان النطاق الأكثر ملاءمة لتقييم النيتروجين والبوتاسيوم والكبريت هو النطاق 2 في اللقطة 2. كانت المؤشرات الأكثر تحريًا لتقييم المحتوى الغذائي للفلفل هي مؤشرات اللون الأزرق الزائد والأخضر الزائد والأخضر والأحمر الزائد ومؤشرات CIVE. أظهر تحليل الانحدار أنه يمكن استخدام معادلة خطية بسيطة لتقدير النسبة المئوية للنيتروجين والكبريت والبوتاسيوم في النباتات باستخدام المؤشر الأخضر والأحمر الزائد ومعامل الارتباط يساوي (0.9159 و 0.8942 و 0.8715 و 0.9117) على التوالي . يمكن استخدام مؤشر النسبة بين النطاق الاحمروالازرق (RBRI) لتقدير النسبة المئوية للفوسفور ومعامل الارتباط يساوي (0.9098) . يمكن استخدام التصوير الحراري والملون (RGB) كأداة لتقييم بعض العناصر الغذائية ومحتوى الكلوروفيل في نباتات الفلفل.