Original article

Utilizing spectral vegetation indices for yield assessment of tomato genotypes grown in arid conditions

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ABSTRACT

Tomato is among important vegetable crops cultivated in different climates; however, heat stress can greatly affect fruit quality and overall yield. Crop reflectance measurements based on ground reflectance sensor data are reliable indicators of crop tolerance to abiotic stresses. Here, we report on using non-destructive spectral vegetation indices to monitor yield traits of 10 tomato genotypes transplanted on three different dates (Aug. 2, Sept. 3 and Oct. 1) during 2019 growing season in the Riyadh region. The ten genotypes comprised six commercial cultivars–(Pearson Improved, Strain B, Valentine, Marmande VF, Super Strain B, and Pearson early) ––and four local Saudi cultivars (Al-Ahsa, Al-Qatif, Hail and Najran). Spectral reflectance data were utilized using a FieldSpec 3 spectroradiometer in the range of 350–2500 nm to calculate nine vegetation indices (VIs): Normalized Water Band Index (NWBI), Difference Water Index (NDWI), Photochemical Reflectance Index (PRI), Normalized Difference Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Red Edge Normalized Difference Vegetation Index, Soil Adjusted Vegetation Index (SAVI), Red Edge Normalized Difference Vegetation Index (RENDVI), Renormalized Difference Vegetation Index (RDVI), and Normalized Difference Nitrogen Index (NDNI). VIs and yield parameters (total fruit yield, harvest index) revealed that second transplanting date was optimal for all the genotypes. Valentine showed the best growth performance followed by Najran, Hail, Super Strain B and finally Pearson early. For all the three transplanting dates, Valentine recorded the highest total fruit yield. Additionally, some genotypes had no significant differences in the VIs values or the total fruit yield between the second and third transplanting dates. This study indicated that yield parameters could be linked to rapid, non-destructive hyperspectral reflectance data to predict tomato production under heat stress.

1. Introduction

Heat waves and fluctuations in rainfall brought about by climate change are responsible for several types of abiotic stresses that are causing crop losses of about 50% (Atkinson and Urwin, 2012, Costa and Farrant, 2019). Therefore, evaluating and selecting crops with a high stress tolerance is a top priority (Newton et al., 2011; Abdelrahman et al., 2015; Mukhtar et al., 2020). Growth and development mainly depend on the interactions among genotypes, environment, and management, which can lead to significant variations in crop yield (Potgieter et al., 2021). Thus, to meet a steadily increasing food demand, an increase in productivity through the selection of good varieties and better managed agricultural practices is required. Heat stress negatively affect crop development, especially under open field conditions; hence, a reduction in yield is expected unless suitable strategies are implemented (Ayenan et al., 2019; Mukhtar et al., 2020). Berova et al., (2008) reported that the best way to increase plant tolerance for high temperature is to apply appropriate agricultural techniques and select good varieties.

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The tomato is one of the world's most important crops, and in 2019 total production was 180,766,329 tons (FAOSTAT, 2019). In Saudi Arabia, it was estimated at 332,608 tons. The tomato is considered to be sensitive to heat stress (HS) since an increase of a few degrees above the average daily temperature of 25 °C leads to a sharp drop or even a complete failure of fruit setting (Ayenan et al., 2019, Chaudhary et al, 2020, Alsamir et al., 2021).

Previous studies evaluated crop heat tolerance utilizing different criteria (Alsamir et al., 2021; Mukhtar et al., 2020). As an example, Berova et al., (2008) studied some physiological parameters including photosynthetic intensity, transpiration intensity, stomatal conductance, and chlorophyll content. Prashar and Jones (2014) reported that changes in canopy temperature is an indication of stomatal conductivity, which is related to many stress responses. In addition, Shaheen et al., (2016) identified various morphological traits (plant height, vegetative fresh and dry weight and leaf area) and physiological traits (photosynthesis and transpiration rates, water use efficiency and chlorophyll content) to investigate differences in heat tolerance among different genotypes.

Plant growth status can be continuously monitored using non-destructive sensing techniques, which can lead to higher crop yields and better management of available resources. Remote sensing has witnessed rapid developments in in recent decades. Therefore, it is possible to use hyperspectral sensors to obtain clear quality images with the spatial and spectral resolutions (Zhang et al., 2003), which have produced very detailed real-time information that supports good crop management strategies. Plant leaves differ in shape and chemical components, which leads to diverse plant reflection that can be used to understand the interaction between the microclimate and plant health (Katsoulas et al., 2016). In this aspect, spectradiometers are used to collect electromagnetic data, which means that additional information on plant characteristics can be obtained by generating new spectral vegetation indices (VIs), which contribute effectively to vegetation studies (Martínez, 2017). VIs are generated from geospatial remote sensing data (Duarte et al., 2021). For example, NDVI is commonly used in agriculture studies (Lan et al., 2010, Campos et al., 2019).

VIs calculated from multispectral data are effective for diagnosing biophysical traits that are used for quantitative and qualitative assessments of vegetation health or growth dynamics (Da Silva et al., 2020, Lima et al., 2020). In general, Khan et al, (2018) reported that healthy plants show red reflectance which results in a high index value while unhealthy, stressed or dead plants show low index values.

Although Saudi tomatoes are usually grown in open fields in September when the temperature is most suitable, introducing good heat-tolerant cultivars in additional periods to extend production season is also a consideration. This study aimed at evaluating crop growth dynamics of the 10 tomato genotypes, transplanted in three different dates, using non-destructive spectral vegetation indices and yield parameters.

2. Materials and methods

2.1. Tomato genotypes

The tomato genotypes used for this study (Table 1) comprised six commercially available cultivars in the local market (Pearson Improved, Strain B, Valentine, Marmande VF, Super Strain B, and Pearson early) and four local Saudi cultivars (Al-Ahsa, Al-Qatif, Hail, and Najran) from the National Plant Genetic Resources (NPGR) of the Ministry of Environment, Water and Agriculture (MEWA) in Riyadh, Saudi Arabia.

Four-weeks-old seedlings were transplanted on beds of 100 cm between rows and 50 cm between plants. They were transplanted on three different periods during the 2019 season: period 1 (August 2), period 2 (September 3) and period 3 (October 1). Experiments were conducted at the Research Farm of the Plant Production Department, College of Food and Agriculture Sciences, King Saud University, Riyadh, Saudi Arabia (Fig. 1). The soil of the experimental field is characterized as sandy loam with the physicochemical properties summarized in Table 2.

Split plot design with three replications was used. The main plots were the three transplanting dates and the sub plots were the 10 genotypes. Each replicate comprised 10 plots, each containing 10 plants of a single genotype.

2.2. Data collection

2.2.1. Spectral data

Hand-held ASD FieldSpec 3 Spectroradiometer (Analytical Spectral Devices Inc., Boulder, CO, USA) was used to measure canopy spectral reflectance (350–2500 nm). Canopy reflectance measurements were taken at 1.0 m above the canopy with a pistol grip of a 25° field of view on cloudless days between 11:00 and 14:00. Three measurements were collected from different locations in each plot. Spectral measurements were performed three times during the growth cycles for the three dates: 75, 107 and 139 days after transplanting (DAT). Continuous wavelength bands of the canopy reflectance were utilized for the calculation of 9 vegetation indices (VIs) shown in Table 3: the Normalized Difference Water Index (NDWI), Water Band Index (WBI), Photochemical Reflectance Index (PRI), Normalized Difference Vegetation Index (NDVI), Soil Adjusted Vegetation Index (SAVI), Normalized Difference Nitrogen Index (NDNI), Red Edge Normalized Difference Vegetation Index (RENDVI), Green Normalized Difference Vegetation Index (GNDVI), and Renormalized Difference Vegetation Index (RDVI).

2.2.2. Temperature and growing degree days

Temperatures were recorded from on-site weather station. In general, the maximum and minimum mean daily temperatures in Riyadh area were 42 °C (summer) and 12 °C (winter), respectively (Al-Gaadi et al., 2021). Growing degree day (GDD) equations

Table 1
Description of the 10 studied tomato genotypes.

No.	Genotype		Type	Source
1	V1	Pearson Improved	Commercial cultivar	American seed, USA
2	V2	Strain B	Commercial cultivar	American seed, USA
3	V3	Valentine	Commercial cultivar	May Seed, Turkey
4	V4	Marmande VF	Commercial cultivar	Petoseed, USA
5	V5	Super Strain B	Commercial cultivar	Bonanza, USA
6	V6	Pearson early	Commercial cultivar	Pacifica, USA
7	V7	Al-Ahsa −308	Local Saudi cultivar	NPGR, MEWA
8	V8	Al-Qatif − 365	Local Saudi cultivar	NPGR, MEWA
9	V9	Hail −548	Local Saudi cultivar	NPGR, MEWA
10	V10	Najran − 934	Local Saudi cultivar	NPGR, MEWA

NPGR: National Plant Genetic Resources of the Ministry of Environment, Water and Agriculture (MEWA) in Riyadh, Saudi Arabia.
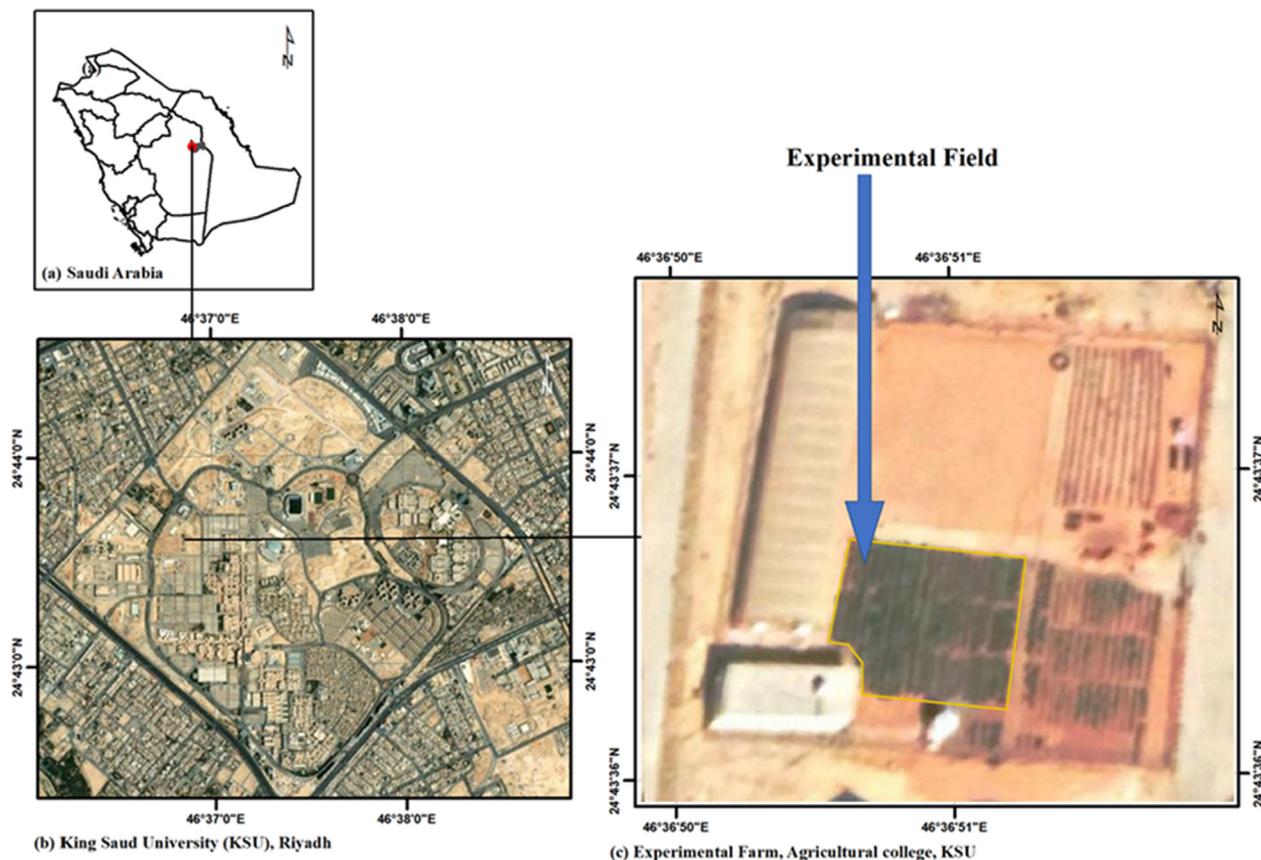
Fig. 1. Location map of the experimental site.

Table 2
Soil properties of the experimental field.

Soil Texture				pH	EC dS m^{-1}	Anions (mEq L^{-1})				Cations (mEq L^{-1})		
Clay (%)	Silt (%)	Sand (%)	Soil Type			Ca	Mg	K	Na	HCO$_3$	Cl	SO$_4$
8.45	7.83	83.72	Sandy Loam	7.8	1.98	10.50	4.50	1.32	6.97	2.30	2.65	18.34

Table 3
Selected vegetation indices (VIs), respective equations and references.

Vegetation Index (VIs)	Abbreviation	Equation	Reference
Normalized Difference Water Index	NDWI	$NDWI = \dfrac{NIR - SWIR}{NIR + SWIR}$	Jackson et al., (2004)
Water Band Index	WBI	$WBI = \dfrac{\rho_{970}}{\rho_{900}}$	Champagne et al, (2001)
Photochemical Reflectance Index	PRI	$PRI = \dfrac{\rho_{531} - \rho_{570}}{\rho_{531+}\rho_{570}}$	Gamon et al., (1997)
Normalized Difference Vegetation Index	NDVI	$NDVI = \dfrac{NIR - Red}{NIR + Red}$	Rouse et al., (1973)
Soil Adjusted Vegetation Index	SAVI	$SAVI = \dfrac{1.5 * (NIR - Red)}{(NIR + Red + 0.5)}$	(Huete, 1998)
Green Normalized Difference Vegetation Index	GNDVI	$GNDVI = \dfrac{(NIR - Green)}{(NIR + Green)}$	(Gitelson and Merzlyak, 1998)
Red Edge Normalized Difference Vegetation Index	RENDVI	$RENDVI = \dfrac{\rho_{750} - \rho_{705}}{\rho_{750+}\rho_{705}}$	(Sims and Gamon, 2002)
Renormalized Difference Vegetation Index	RDVI	$RDVI = \dfrac{(NIR - Red)}{(\sqrt{(NIR + Red)}}$	(Roujean and Breon, 1995)
Normalized Difference Nitrogen Index	NDNI	$NDNI = \dfrac{Log\left(\frac{1}{\rho_{1510}}\right) - Log\left(\frac{1}{\rho_{1680}}\right)}{Log\left(\frac{1}{\rho_{1510}}\right) + Log\left(\frac{1}{\rho_{1680}}\right)}$	Serrano et al., (2002)

can transfer climate data into useful agricultural applications that growers can use to make strategic decisions (Pathak and Stoddard, 2018). GDDs, were calculated during the tomato growing season using the GDD model in Equation (1) (Scholberg et al., 2000). The cumulative growing degree days (CGDD), however, were calculated by taking the sum of the GDDs as in Equation (2).

$$GDD = \frac{T_{max} + T_{min}}{2} - T_{base} \tag{1}$$

where, T_{max} and T_{min} are the maximum and minimum daily temperatures (°C); and T_{base} is the base temperature (10 °C for tomato).

$$CGDD = \sum_{j=1}^{n} GDD_j \qquad (2)$$

where, j is the indicated day; n is a specific day during the growth period; and GDD_j is the heat unit on the jth day (° Cd).

2.2.3. Yield parameters

Total fruit yield (t ha^{-1}) for each tomato genotype for the three transplanting dates was determined as the average cumulative weight of all fruit harvested during the entire period per unit area. In addition, the harvest index (HI) was calculated as: total fruit yield/ total biomass.

2.3. Statistical analysis

Combined statistical analysis (SAS for Windows v. 9.4, SAS Institute Inc., Cary, NC), was performed for the spectral vegetation indices and yield parameters to determine the interaction effects for the transplanting periods, tomato genotype and the crop growth stage. The least significant differences (LSDs) were calculated with a significance level at $p \leq 0.05$

3. Results

3.1. Temperature and growing degree days

The distribution of the daily mean air temperature and the cumulative growing degree days (CGDD) for the three periods are presented in Figs. 2 and 3, respectively. These indicate that the cultivated genotypes experienced different conditions during the three periods, with high values of both mean daily temperature and CGDD for the Period 1 followed by Period 2 and Period 3. The results of the CGDD or heat units (°Cd) on the three sampling times [75, 107 and 139 (DAT)] differed significantly among the three periods (Fig. 3). The highest value was for period 1 and the lowest value for period 3.

3.2. Vegetation indices

To study the patterns of the VIs at different developmental stages, comparisons were made between the results collected at 75, 107 and 139 DAT for all three periods. It was clear that the VIs measured at different crop growth stages showed significantly different trends among the periods and crop genotypes.

3.2.1. Comparison between the transplanting periods

At the first measurement (75 DAT), the significantly higher overall mean VI values in the third period indicated a better growth status compared with the other two, whereas the lowest values were recorded in the first period. This may have been attributable to different climatic conditions during the early growth stage (Figs. 2–3). The average minimum and maximum daily temperature in the first 75 days during the third period was 22 and 35 °C, whereas, for the second it was 23 and 37 °C, and for the first it was 27 and 41 °C. In addition, the third period showed the least CGDD (1107 °Cd) at this stage compared to the first (1846 °Cd) and second (1482 °Cd) periods. These results indicated that the crop during the third growing period was subjected to lower heat stress in the first growth stage compared to the others.

About a month after the date of the first measurements (107 DAT), significantly higher mean VI values were recorded for the crop of the second period with minimum and maximum temperatures of (14, 23 °C) compared to the first (20, 33 °C) and third (9, 21 °C). These results indicated that the crop of the second period experienced little or no heat stress (CGDD = 1771 °Cd) compared to the crop of the first, which experienced high heat stress (2306 °Cd), and that of the third period which experienced low heat stress (CGDD = 1269 °Cd). The third measurements (139 DAT) also indicated that the crop was healthier (i.e. had higher mean VI values) in the second period compared to the other two. However, no significant differences in the mean VI values were observed between the second (CGDD = 1933 °Cd) and first (CGDD = 2594 °Cd) periods, while significantly lower mean VI values were recorded in the third (CGDD = 1431 °Cd). Based on the overall results of the three measurement dates, the best tomato crop health status was observed during the second growing period (transplanting date: September 3, 2019). However, good results were also recorded for the third period (transplanting date: October 1, 2019), which meant that the optimal dates for transplanting the tomato crop were from the beginning to the end of September.
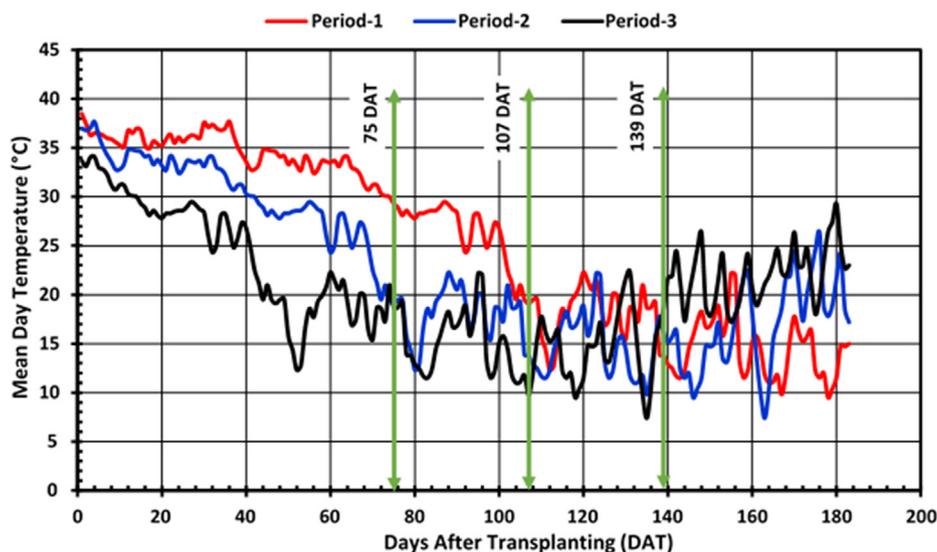

Fig. 2. Mean daily temperature during the three growing periods.

Table 4
Summary of the significant differences in the VIs among the 10 tomato genotypes (V1-V10).

Vegetation Index	Tomato Genotype									
	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10
NDNI-75	0.20 a	0.18b	0.21 a	0.21 a	0.20 a	0.20 a	0.19 ab	0.21 a	0.20 a	0.20 a
NDVI-75	0.76 a	0.72b	0.80 a	0.77 a	0.79 a	0.80 a	0.77 a	0.78 a	0.76 a	0.78 a
SAVI-75	0.54 acd	0.48b	0.57c	0.55 ac	0.58c	0.54 acd	0.50 bd	0.55 ac	0.51 abd	0.52 abcd
GNDVI-75	0.81 ad	0.78b	0.83c	0.81 bd	0.83c	0.83 ac	0.80 bd	0.81 acd	0.82 acd	0.82 acd
RENDVI-75	0.60 a	0.56b	0.63c	0.61 ac	0.61c	0.63c	0.60 ac	0.60 ac	0.57 ab	0.60 abc
RDVI-75	0.51 acd	0.46b	0.55c	0.53 ac	0.55c	0.52 acd	0.48 bd	0.53 ac	0.49 abd	0.51 abcd
NDNI-107	0.18 a	0.17b	0.18 ab	0.18 abc	0.17b	0.19 abc	0.21c	0.19 abc	0.21 ac	0.21 ac
NDVI-107	0.78 a	0.74b	0.81 ac	0.80 ac	0.80 ac	0.80 ac	0.79 a	0.78 a	0.82 cd	0.85 d
SAVI-107	0.53 a	0.51 a	0.55 ab	0.55 ab	0.53 a	0.55 ab	0.59 bc	0.55 ab	0.61c	0.59 bc
GNDVI-107	0.82 ade	0.79b	0.85 cef	0.83 ade	0.84 cde	0.83 ade	0.82 ad	0.81 ab	0.86 cf	0.87f
RENDVI-107	0.62 abc	0.57b	0.65 ad	0.65 ad	0.65 ad	0.62 acd	0.62 abc	0.60 bc	0.63 acd	0.66 d
RDVI-107	0.51 a	0.49 a	0.52 ac	0.52 ac	0.50 a	0.52 ac	0.56 bc	0.52 ac	0.57b	0.56 bc
NDNI-139	0.15 ab	0.13 a	0.15 ab	0.14 a	0.14 ab	0.17b	0.15 ab	0.13 a	0.15 ab	0.15 ab
NDVI-139	0.71 acd	0.62b	0.76c	0.67 bd	0.74 ac	0.70 ad	0.74 ac	0.66 bd	0.76c	0.73 ac
SAVI-139	0.48 ac	0.40b	0.50c	0.44 abc	0.45 abc	0.51c	0.46 abc	0.42 ab	0.50 ac	0.50 ac
GNDVI-139	0.79 ace	0.71b	0.82c	0.77 de	0.80 ace	0.78 ade	0.79 ace	0.75 d	0.82c	0.81 ac
RENDVI-139	0.50 ade	0.42b	0.56c	0.46 bd	0.55 ac	0.46 bd	0.55 ace	0.46 bd	0.53 ace	0.49 de
RDVI-139	0.46 ac	0.38b	0.48c	0.42 ab	0.44 ab	0.48c	0.45 abc	0.41 ab	0.48c	0.47 ac

* Means in the same row with the same letter are not significantly different according to LSD at $p \leq 0.05$.
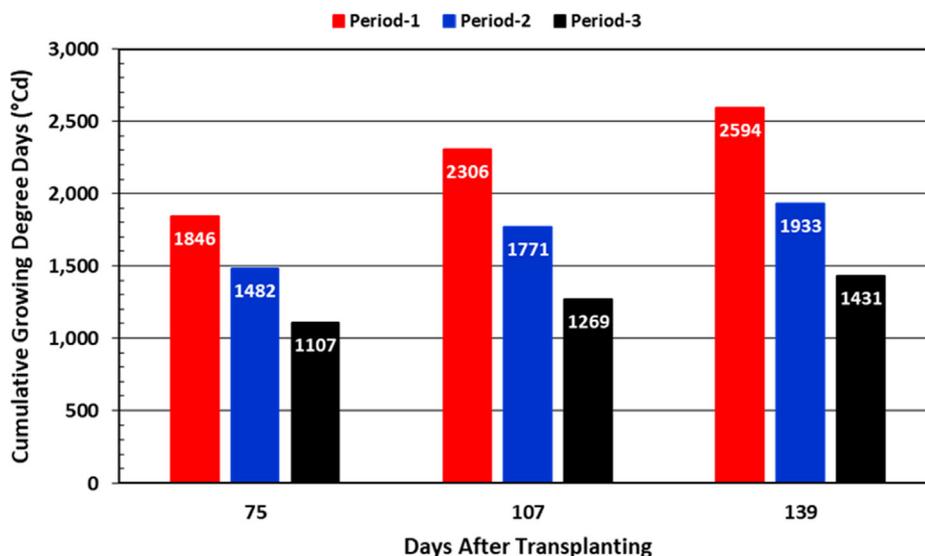

Fig. 3. Cumulative growing degree days on the three sampling dates for the three growing periods.

(ii) Comparison between tomato genotypes

Significant differences between the studied genotypes and the three sampling dates (Table 4) were only shown by six of the nine studied VIs. For more interpretation of these results, comparisons were made among the genotypes in each period, in addition to a comparison of the growth dynamics of each genotype during all three periods.

The results of the VI's and the corresponding statistical analysis was used to classify the 10 tomato genotypes based on the interaction among the mean VI values, growing period and crop age (Table 5). For the first period, V5 showed the highest overall mean VI's value and ranked as the healthiest genotype during this period, followed by V3, V6 and V9. During the second period, however, the best growth was recorded for V7 followed by V10, V3 and V6. During the third period, V9 ranked first followed by V3, V10 and V5. The classification results indicated that V2 showed the least mean VI values. The overall rankings (based on the overall VI means) indicated that V3 (Valentine) showed the best results followed by the V10 (Najran), V9 (Hail), V5 (Super Strain B) and V6 (Pearson early), while V2 (Strain B) showed the lowest VI results followed by V8 (Al-Qatif) and V4 (Marmande VF).

3.3. Yield parameters

The previously discussed VI results showed that there were significant differences in the growth performance among the three periods. For further analysis, however, yield parameters were evaluated to understand the response of the genotypes to different environmental conditions. Total fruit yield and harvest index were determined for all 10 genotypes, and the results are presented in Figs. 4–5 while, the statistical results of the studied yield parameters are summarized in Table 6. Overall, the classification of the tomato genotypes based on total fruit yield (Table 7) was in partial agreement with that made based on VIs (Table 5), where V3 (Valentine cultivar) showed the best VI results and the highest yield for all three periods.

4. Discussion

Heat stress is defined as the effect of a rise in temperature higher than a threshold level that has a permanent effect on plant growth and development (Alsamir et al., 2021). It can occur when

Table 5
Classification of the 10 tomato genotypes (V1–V10) based on interactions among the VIs, transplanting dates (period-1, period-2, and period-3) and days after transplanting.

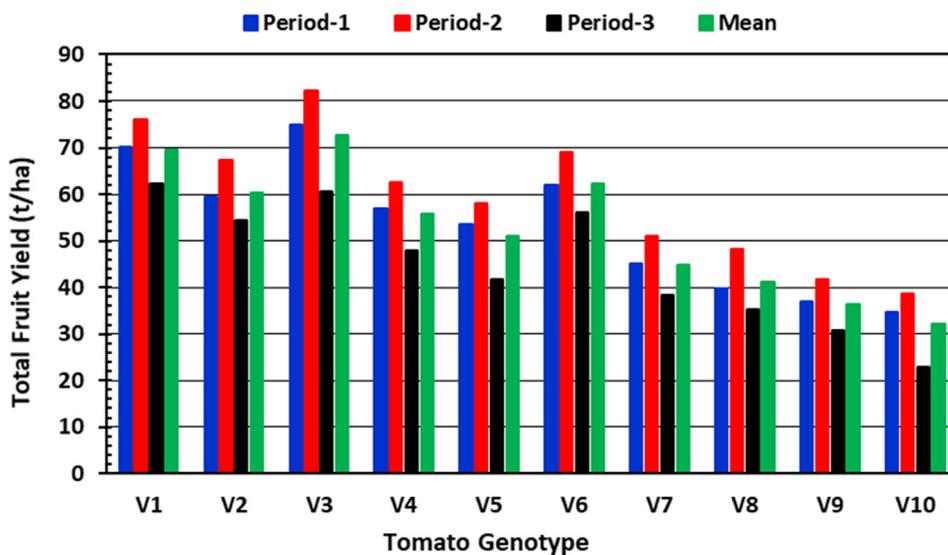| Rank Based on the VI* Growing Period			Rank Based on VI* After Transplanting			Overall Ranking
Period-1	Period-2	Period-3	75 Days	107 Days	139 Days	
V5	V7	V9	V3	V10	V3	**V3**
V3	V3	V10	V5	V9	V9	**V10**
V6	V10	V3	V6	V7	V10	**V9**
V9	V6	V5	V8	V3	V7	**V5**
V4	V8	V7	V4	V4	V5	**V6**
V1	V5	V1	V1	V6	V6	**V7**
V10	V1	V6	V10	V5	V1	**V1**
V7	V4	V4	V9	V8	V4	**V4**
V8	V9	V8	V7	V1	V8	**V8**
V2	V2	V2	V2	V2	V2	**V2**

Fig. 4. Total fruit yield of the tested tomato genotypes for the three periods.
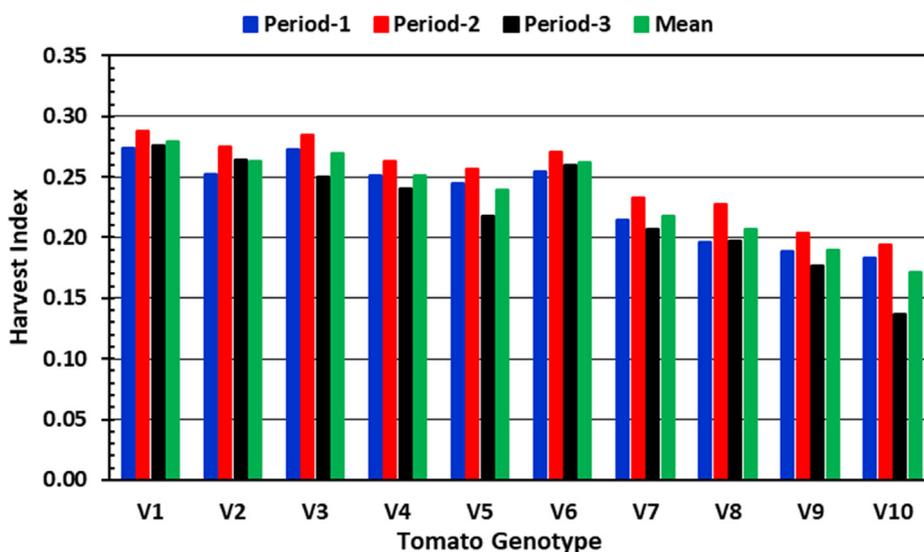

Fig. 5. Harvest index of the tested tomato genotypes for the three periods.

temperature exceeds optimum level by 10–15 °C (Wahid et al., 2007). The intensity of heat stress depends on the total period and the speed of the rise in temperature (Blum, 1988).

The differences in VIs among tomato genotypes and growth periods were mainly due to variation in the responses to changes in climate. These results agreed with (Berova et al., 2008), who

Table 6
Significant results of the total fruit yield and harvest index of the tested tomato genotypes.

Genotypes	Total fruit Yield (t ha^{-1})					Harvest Index				
	P-value	LSD	Period-1	Period-2	Period-3	P-value	LSD	Period-1	Period-2	Period-3
V1	0.0006	4.197	70.218b	76.087 a	62.250c	0.2634	0.020	0.274 a	0.288 a	0.276 a
V2	0.0037	5.626	59.426b	67.426c	54.357b	0.1910	0.026	0.252 a	0.275 a	0.264 a
V3	0.0000	2.754	75.022b	82.223 a	60.450c	0.0003	0.009	0.273b	0.285 a	0.250c
V4	0.0001	3.096	57.039b	62.548 a	47.902c	0.0462	0.017	0.251 ab	0.263 a	0.240b
V5	0.0007	5.194	53.400 a	58.044 a	41.702b	0.0245	0.025	0.245 a	0.256 a	0.218b
V6	0.0001	2.824	61.976b	69.079 a	56.062c	0.0205	0.010	0.254b	0.270 a	0.260 ab
V7	0.0005	3.732	45.147b	51.126 a	38.273c	0.0241	0.017	0.214b	0.233 a	0.206b
V8	0.0000	2.001	39.735b	48.221 a	35.332c	0.0009	0.012	0.196b	0.228b	0.197b
V9	0.0001	2.553	36.798b	41.709 a	30.688c	0.0063	0.013	0.188b	0.204 a	0.177b
V10	0.0000	1.102	34.680b	38.507 a	22.933c	0.0000	0.007	0.183b	0.194 a	0.137c

* Means in the same row for each parameter with the same letter are not significantly different according to LSD at p $\leq$ 0.05.

Table 7
Classification of the 10 tomato genotypes based on total fruit yield.

Rank	Period-1	Period-2	Period-3	Overall
1	V3	V3	V1	V3
2	V1	V1	V3	V1
3	V6	V6	V6	V6
4	V2	V2	V2	V2
5	V4	V4	V4	V4
6	V5	V5	V5	V5
7	V7	V7	V7	V7
8	V8	V8	V8	V8
9	V9	V9	V9	V9
10	V10	V10	V10	V10

reported that heat stress has a negative effect on tomato physiological status, depending on the genotype. In general, many environmental factors may play a crucial role in the variability of the VIs (Clay et al., 2006, Gianquinto et al., 2011). Furthermore, several factors may influence overall crop canopy reflectance such as light intensity, image angle of view, effects of diseases and nutritional disturbances (Jia et al., 2004).

All tomato genotypes showed significantly higher fruit yields and harvest indices during the second period when the crop was planted in the first week of September. Accordingly, the second period was considered to be the optimal period for tomato production. The first period showed a crop yield reduction of 8–18%, and for the third it was 18–40%. However, the total fruit yield in the first and third periods contrasted with the VIs, where overall growth was better in the third period compared to the first. Differences in tomato production can be attributed to variations in the degree of heat stress, which reduces the rate of flower pollination and thus fruit setting and yield (Alsamir et al., 2021). Abdul-Baki and Stommel (1995) evaluated fruit yield and seed numbers of tomato cultivars and wild species in a greenhouse under high-temperature conditions. Heat stress increased the abscission of flowers and decreased fruit set and yield. Tomato cultivars showed different responses to high-temperature stress: for each degree increase above the optimum temperature, yield losses may reach 10–15% (Kumar et al., 2011). The same has been reported by Driedonks (2018) that high temperature is associated with limited fruit yield. Overall, the classification of the tomato genotypes based on total fruit yield) was in partial agreement with that made based on the crop growth), where V3 (Valentine cultivar) showed the best VI results and highest yield for all three periods.

5. Conclusions

Non-destructive spectral vegetation indices were used to monitor the growth status of 10 tomato genotypes under arid conditions in the Riyadh region of Saudi Arabia during three periods in the 2019 growing season. The use of spectral vegetation indices allowed for effective monitoring and evaluation of the health status of the genotypes at different growth stages and changing environmental conditions. The results of both the vegetation indices and yield parameters indicated that the best performance was in the second period, which was considered ideal for tomato production. Among the studied genotypes, V3 (Valentine cultivar) showed the best growth and yield results. Although the second transplanting period showed the best crop growth and yield performances, the statistical results indicated no significant differences in the mean VI values between the second and third periods. This meant that the period from the beginning to the end of September could be considered optimal for transplanting tomatoes. Crop reflectance measurements based on ground reflectance sensor data were reliable indicators of crop tolerance to abiotic stresses. This study indicated that rapid, non-destructive hyperspectral reflectance data could predict tomato production under heat stress conditions.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

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