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# Effects of irrigation and rainfed practices on Normalized Difference Vegetative Index of Wheat (*Triticum aestivum* L.) and its Implications on Grain Yield in Northern China

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## Abstract

Five (5) winter wheat genotypes were evaluated based on the Normalized Difference Vegetative Index (NDVI) under irrigation and rainfed conditions. A randomized complete block design in a split-plot arrangement was used with 30 treatment combinations during the two consecutive cropping seasons, from 2017 to 2019. The NDVI was used to evaluate the differences in wheat genotypes growth from the effects of irrigation and rainfed. The results indicated that NDVI values varied at all vegetative stages and that there were significant differences ($p < 0.05$) in NDVI indices among genotypes throughout the growth period, especially at the booting and grain-filling stages from the end of March to mid-May. However the indices started to decrease immediately after physiological maturity. In the entire study, the maximum NDVI was 0.82 for the *Zhongmai-36* genotype, corresponding to a grain yield of 8.05 mg ha$^{-1}$ and was obtained in irrigation group. The maximum NDVI in rainfed group was 0.78 from *Zhongmai-36* and corresponded to the grain yield of 7.28 mg ha$^{-1}$. This study suggests that among the other four genotypes, *Zhongmai-36* could be prioritized under limited irrigation without compromising grain yield (GY). Since the NDVI, leaf area index (LAI) and GY related positively during the entire growth period therefore, can be used for the real time monitoring of wheat growth seasonal water requirements and grain yield simulation. This information could be used by agricultural stakeholders and decision-makers in early warning of food security concerning wheat productivity.

**Keywords** Optimum irrigation, NDVI, Drought adaptability, Genotypes differentiation, Efficient resource utilization, Handheld sensor

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## Background

Light interception measurements for crop growth and productivity evaluation are an important research concerns according to Babar et al. (2006a, b). According to (Zhang et al. 2019b), in semiarid areas, wheat is considerably affected by the unavailability of supplementary irrigation because it's deficiency creates stress, decreases the chlorophyll content in the leaves, and decreases yield. In recent years China has been able to raise its wheat production though at the cost of escalating environmental effects like increase of greenhouse gases emission due to overuse of nitrogenous fertilizers by the farmers, contamination of water resources and lowering of underground water table due to uncontrolled irrigation (Li et al. 2013). To combat these effects, a holistic approach is needed to improve or maintain a higher grain yield in order to feed the ever growing population (Bonanomi 2019). Improving and maintaining higher grain yield in wheat production remains a challenge because of the effects of physical (climate variability, limited land, soil depreciation) and biotic (slow formation of organic matter) factors (Curtis and Halford 2014). The North China Plain (NCP) region in particular, has 400–500 mm mean annual precipitation of which about 30% comes during the winter wheat season. This amount of rain is much less than the wheat requirements (He 1955; Lan et al. 2012; Lv et al. 2013a), leading to almost total dependence on irrigation water for wheat production. In Hebei Province, one of the areas in the NCP region, approximately 70% of groundwater pumped was used for irrigation, thus the ground table in the Piedmont Plain has been decreasing by approximately 1 $\mathrm{myr}^{-1}$ for the last 20 years (Zheng et al. 2010; Lv et al. 2013b; Yang et al. 2015, 2020). In order to attain sustainable winter wheat production in the region, it is essential and urgent to develop an optimal policy that avoids further over or improper utilization of water resources by using efficient irrigation methods and drought-adaptable wheat genotypes.

Wheat genotypes that are more drought adaptable and tolerant to the wider environmental effects like soil salinity and soil fertility depreciation, are becoming more desirable now than ever (Bapela et al. 2022; Pandey et al. 2022). Efforts to determine more tolerant genotypes through human manual destructive methods have offered reliable results. However, when large samples are involved the methods are tedious and impractical (Elliott and Regan 1993). Due to these reasons, and errors which cause difficulty in genotypes differentiation, as well as reduction of plot area for final biomass and yield estimation, the destructive methods are considered unsustainable (Mauya et al. 2015). Studies by several researchers (Reynolds et al. 2001; Paulsen 2002; Huang et al. 2014) proposed that productivity canopy reflectance indices can be used to differentiate wheat and other crop genotypes in various climatic conditions. Thus, using spectral reflectance indices in the determination of total aboveground biomass and total N in crop tissue can be done nondestructively, hence selecting superior genotypes of wheat for early vigor (Goodwin et al. 2018; Vian et al. 2018; Naser et al. 2020; Walsh et al. 2020). However, differentiation of plant tissue using spectral reflectance indices like NDVI is based on the identification of biochemical concentrations through infrared reflectance and has shown some difficulty in precision because of the overlapping spectral absorption bands of several biochemical processes in plant canopy tissues (Gómez et al. 2019; Evett et al. 2020). Hence, in addition to NDVI, Leaf Area Index (LAI) could be used to increase the precision of determining wheat genotypes growth differences.

Through normalizing the ratio of the difference between near-infrared NIR (correlated to leaf structure) and Red (correlated to chlorophyll content) the NDVI can be calculated. The NIR is the light reflectance in the near-infrared wavelength ranging from 720 to 1300 nm and Red is the light reflectance in the red wavelength ranging from 600 to 720 nm. The amount of reflectance in the NIR and Red is determined by the optical properties of the leaf tissues, their cellular structure and the air-cell wall protoplasm-chloroplast interfaces (Kumar and Silva 1973). The NDVI uses a wide range of light intensity to estimate fractional ground cover (Huang et al. 2014). According to Sultana et al. (2014), it varies from $-1$ (usually do represent water) to $+1$ (represent strongest vegetative growth), in more specific Ambika et al. (2016) reported that the maximum attainable considered for cropped area is normally ranges between 0.1 and 0.8. The disparities could be explained in terms of differences in leaf thickness and composition, the water content of leaves, and chloroplast number per unit area of the leaf. The higher NDVI values can be directly related to greater leaf area index, green plant biomass and higher N content (Shaver et al. 2011). According to Shaver et al. (2011), different crop cultivars, N and water rates can lead to different LAI values, which in turn influences NDVI and grain yield (GY). Several studies like Wang et al. (2015), Qiang et al. (2019), Zhang et al. (2019a) have concluded that increases in Red reflectance are related to the decreases in chlorophyll content resulting from lower N supply, while decreases in NIR reflectance mostly correspond to a reduction in LAI and green biomass. The LAI is related to the amount of leaves and stalks per unit area of land receiving light.

According to El-hendawy et al. (2019) and Xie et al. (2020), limited number of studies have compared the spectral reflectance indices accuracy from different sensors for real-time monitoring and multivariate methods in estimating agronomic parameters measured in combinations of multiple agronomic practices. These studies found variations in that aspects due the difference in sensor resolutions. The study by Song et al. (2021), indicated that, key requirements to obtain high-spatial-resolution satellite images are yet to be attained, despite the rapid advancement in satellite remote sensing technology, The accuracy in spectral reflectance estimation using satellite multi and hyper-spectral sensors varies based on the spatial-resolution (Janssen and van der Wel 1994; White et al. 2016; Wang et al. 2020). Another main challenge when dealing with multi and hyper-spectral reflectance measuring tools is their high cost and complexity from the operational point of view (Caturegli et al. 2020). In this study, spectral reflectance indices (NDVI and LAI) acquired by a ground-based handheld sensors has been used for real-time monitoring of winter wheat genotypes throughout the growth period. Field experiments were performed on drought-adaptable winter wheat genotypes treated with limited water application under irrigation or rainfed conditions. The aim of this study was to; (i) Analyze the response of winter wheat canopy NDVI on limited water treatments under irrigation or rainfed conditions, their relationships with LAI and implications on water consumption and grain yield (GY); (ii) Determine the most drought-adaptable genotype such as the optimal grain yield among the five winter wheat genotypes.

## Materials and methods

### Study site

The experiment was conducted at the experimental base of the Institute of Environment and Sustainable Development in Agriculture (IEDA), Chinese Academy of Agricultural Sciences (CAAS), which is located in Shunyi District, Beijing, China (40.13° N, 116.65° E) for two seasons, namely September 2017 to June 2018 (Season 1) and September 2018 to June 2019 (Season 2). Winter wheat is the major cereal crop in this region, comprising more than 30% of arable land, characterized by the subtropical and sub-humid monsoon climate, with an annual mean temperature of 15.2 °C. According to Kamphuis et al. (2012), the annual mean precipitation is 1230 mm, although less than 40% of rainfall occurs in the winter wheat-growing season (Table 1). The mean monthly precipitation and temperature patterns for this study for two seasons are presented below (Fig. 1).

According to study by Zhao (2004), the years 2017–2018 and 2018–2019 were identified as wet and normal years respectively.

### Design and treatments

The design used for the experiment was the Random Complete Block Design (RCBD) in split-plot arrangement with three replicates. The main plots consisted of two irrigation practices, and the sub-plots consisted of five wheat genotypes. A total of 30 treatments combinations of (2) irrigation practices x (5) wheat genotypes x (3) replications were randomly arranged in an experiment unit. Each plot was 7 m × 6.2 min size, with a 0.5

**Table 1** Agro-climatic description of the location where wheat genotypes NDVI were evaluated for limited water conditions in North China during 2017–2018 and 2018–2019. Modified from (Kamphuis et al. 2004)

| Characteristic | Description |
|---|---|
| Irrigation water source | More than 20 rivers run across Shunyi, all belonging to the North Canal, Chaobai River and Ji Canal water systems. The total length of the rivers equals 232 km, and the total flow rate reaches 170 Million Cubic Metres |
| Water resources status | The usable surface water in normal years is 43 Million Cubic Metres, and the underground that can be exploited is 400 Million Cubic Metres. Of this, 200 Million Cubic Metres of drinking water is supplied to Beijing. However the last few years` of rainfall have been far below average and the rivers have (almost) dried up |
| Temperature (Min/Max) | The mean temperature in the NCP region was 15.2 °C,with the lowest and highest temperatures in January and July at – 19.1 °Cand 40.5 °C respectively, However, in Shunyi the average annual temperature was 11.5 °C, with January recording the lowest at 4.9 °C, and July the highest at 25.7 °C |
| Rainfall | Sub-tropical and sub-humid monsoon climates, with the most rainfall duration from July to September of each year. The frost-free period lasts around 195 days |
| Sunshine/Humidity | Annual sunshine duration is 2750 h, and average annual relative humidity is about 50% |
| Mean rainfall (mm) | The overall annual mean precipitation in the NCP is 1230 mm, whereby less than 40% occurs in the winter wheat-growing season. However in Shunyi the average annual precipitation was about 625 mm, of which 75% falls in summer. Thus only about 25% occurs in the winter wheat-growing season |
| Latitude | 40° 00′–40° 18′ N |
| Longitude | 116° 28′–116° 58′ E |
| Altitude (m.a.s.l) | 45 m |
| Vegetation | Fertile soil, ranging from Sandy to Loamy soils |

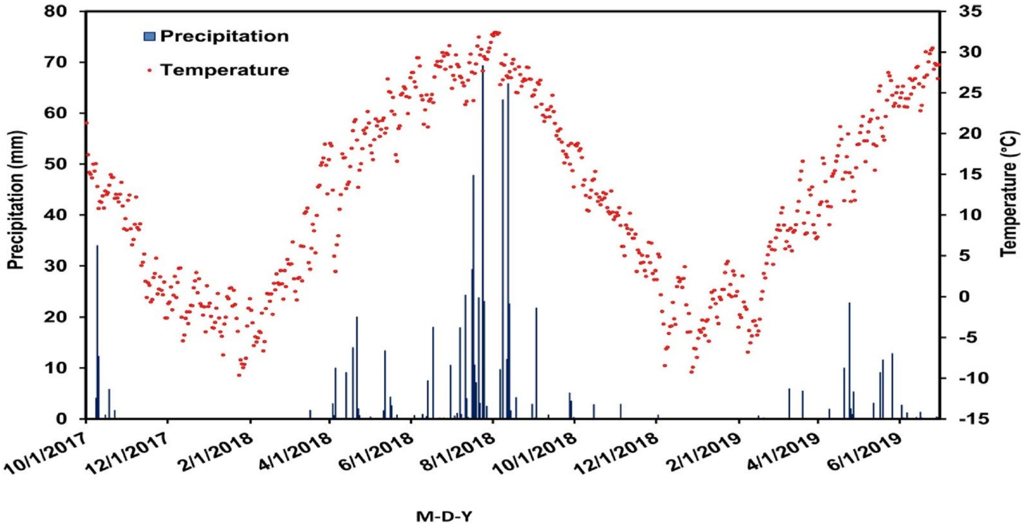


**Fig. 1** Daily average precipitation and air temperature during the winter wheat growing seasons 2017–2018 and 2018–2019

mbuffer zone between any given two adjacent plots. The two irrigation practices were one irrigation ($I_1$) and rain fed ($I_0$) which was deployed based on the soil moisture of the field and wheat water requirement at critical stages. The water supply in the irrigation practice was controlled to provide the required amount of water. Such that on $I_1$, 40 mmwere applied and on $I_0$ no irrigation was applied except for 2018–2019 season, which was dry during the planting stage. Only 10 mmof irrigation water was applied equalled to the amount of rain fall from the previous year at the same stage. The five wheat genotypes were *"Chang 6878 (Vr1), Zhongmai 36 (Vr2), Jinmai 47 (Vr3), Lunxuan 169 (Vr4), Jingdong 8 (Vr5)"* which are known for drought adaptability characterization (Table 2). The wheat genotypes were sown at an average distance of 20 cmbetween two adjacent rows, width oriented in N–S direction at a seed rate of 300 kg ha$^{-1}$ on 10th October during the 2017–18 and 2018–19 seasons. Treatments were laid out in an augmented design with a control experiment (CK).

### Agricultural inputs, cropping pattern and soil properties

The wheat genotypes were obtained from the Institute of Crop Sciences of CAAS, representing lines selected for drought-adaptable and relatively high yield potentials under limited water conditions. The presided planted crops on the plots before the commencements

**Table 2** Applied irrigation water and nitrogen

| Treatments | Irrigation frequency | Irrigation amount (mm) | Nitrogen (N kg ha$^{-1}$) | Date |
|---|---|---|---|---|
| T1 | 1 | 40 | 157.5 | 17–18/04/2018 |
| T2 | 1 | 40 | 157.5 | 17–18/04/2018 |
| T3 | 1 | 40 | 157.5 | 17–18/04/2018 |
| T4 | 1 | 40 | 157.5 | 17–18/04/2018 |
| T5 | 1 | 40 | 157.5 | 17–18/04/2018 |
| $T_{CK}$ | 3 | 120 | 315 | 07/12/2017, 17–18/04/2018, 16/05/2018 |
| $T_{CK}$ | 3 | 120 | 315 | 07/12/2017, 17–18/04/2018, 16/05/2018 |
| T6 | 0 | 0 | 157.5 | – |
| T7 | 0 | 0 | 157.5 | – |
| T8 | 0 | 0 | 157.5 | – |
| T9 | 0 | 0 | 157.5 | – |
| T10 | 0 | 0 | 157.5 | – |

of the experiments were summer maize and high-yielding winter wheat. The soil physiochemical properties from previous experiments in the same experiment field revealed that; the soil texture was sandy loam with a bulk density of 1.52 g $cm^{-3}$. The average contents of available soil nutrients; including nitrogen (N), phosphorous (P), and potassium (K) in 0–20 cm soil layer were 11.0 mg $kg^{-1}$, 24.5 mg $kg^{-1}$, 10.6 mg $kg^{-1}$ respectively, while the pH was 7.7. In the next soil layer of 20–40 cm, the soil nutrients were; 7.0 mg $kg^{-1}$ (N), 12.2 mg $kg^{-1}$ (P), 88.9 mg $kg^{-1}$ (K), and pH was 8.0. The soil organic matter content were 144.0 and 95.0 mg $kg^{-1}$ in two soil layers consecutively. The average moisture content at field capacity was 24.52%v/v.

### Fertilization, tillage and irrigation

In accordance with the local farming practices ammonium nitrate ($NH_4NO_3$), triple supper phosphate Ca ($H_2PO_4$), and sulphate of potash ($K_2SO_4$) were used as sources of N, P, and K nutrients respectively, with 108 N kg $ha^{-1}$ of 315 N kg $ha^{-1}$ applied as basal nitrogen and the remaining 207 N kg $ha^{-1}$ as top dressing at wheat re-greening stage. All fertilizers were spread by hand prior to sowing, at the re-greening stage followed by tillage (incorporated into the soil by ploughing before sowing) and irrigation events. To complete the NPK ratio, the basal nitrogen was equally mixed with phosphate, P: 90 kg $ha^{-1}$, and potash fertilizers, K: 30 kg $ha^{-1}$ according to Gao et al. (2014). Nitrogen fertilizer application was reduced to half of the local farmer's practical amount. Overall, the reduced amount of N, and the full amount of P and K nutrients were applied equally in all treatments according to conventional practice. For land preparation, a tractor-drawn rotary cultivator was utilized to a depth of 20 cm; such that the cultivator was used to break the larger soil clods levelling the seedbed. Sowing was done with the help of a tractor drawn seed drill.

The irrigation plots were irrigated with a sprinkler system using underground water with the help of a pump connected to the pressure regulators and pipeline near the experimental plots. Cultural practices such as weeding and pesticide were kept uniform for all the experimental treatments.

### Data collection

#### *Normalized Difference Vegetative Index*

The NDVI values were obtained by a spectro-radiometer, GreenSeeker Hand Held optical sensor unit, model 875; NTech Industries, Inc., Ukiah, CA, USA (Fig. 2) above the canopy at 50 cm height during re-greening winter wheat 160 days after sowing (DAS) to physiological maturity (242 DAS). The measurements were taken in the central rows of all plots and sometime by quick zigzag walk in a different location within the plot to maximize representative plant numbers, twice a week between 160 to 242 DAS in 2017–18 and 2018–19. The NDVI measurements were taken at 900 to 1200 h, hereafter referred to as early morning to midday according to (Padilla et al. 2019).

#### *Leaf Area Index*

The Leaf Area Index (LAI) values were obtained nondestructively with the SS1 SunScan Canopy Analysis System, Delta-T devices. In order to eliminate the effect of variation in wheat growth within the plot on LAI estimates, these measurements were conducted at the same position (around 0.4 $m^2$) in each plot. The measurements were made around 1100 h as indicated by Hirooka et al. (2017), whose studies involved a sequence of readings, one above and four below the wheat canopy taken

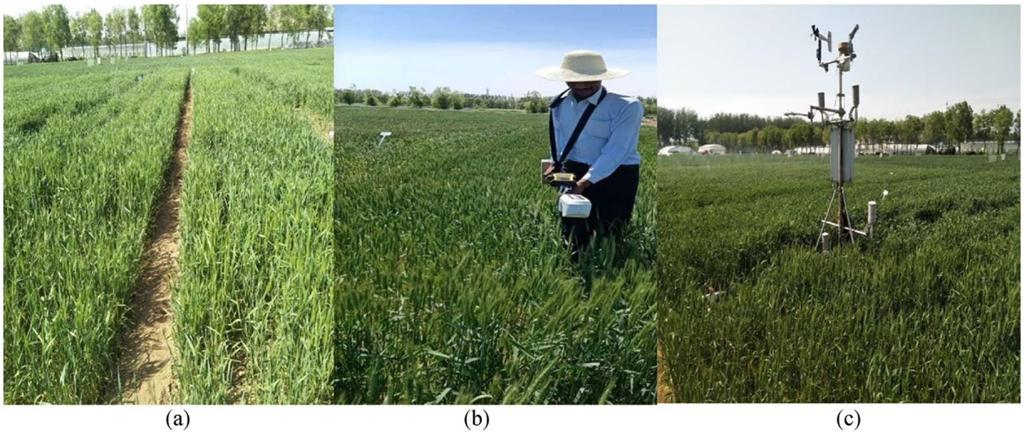

(a) (b) (c)

**Fig. 2** Plots buffer zone, delineated using 50 cm bunds (**a**), A handheld-GreenSeeker optical sensor (**b**) and Bowen ratio units (**c**) used to for measurements of NDVI values from crop canopy and weather data respectively three times in each plot. However, only three readings below the canopy were taken at different rows and considered enough for the scope of this study. The shadow was avoided on a beam fraction sensor which was used to monitor the light incidence on the canopy while measurements by the sensor were made beneath it. The averages of all below-canopy readings were used as the LAI estimate of each plot. Measurements of LAI were carried out, generally on bright days.

#### *Plant height and other pertinent agronomic parameters*

Plant height and other pertinent agronomic parameters were determined non-destructively in each plot one time after two weeks bases. Harvesting was done in mid-June of the following year and the final grain yield was determined at maturity by hand-harvesting two $1 \times 1$ $m^2$ areas near the center of each plot. Grains were winnowed manually and solar-dried up to a 12% wet moisture level basis according to Gao et al. (2014), and weighted using a precise digital balance.

All sampling was done at least two border rows away from the edge of the plot so that those areas did not influence the reliability measurements of the sensors due to the effects from neighboring treatments. The period of taking measurements was mainly from the re-greening of the winter wheat stage to physiological maturity. On average, the measurements were done twice a week and every day when there were fertilization and irrigation or rainfall events.

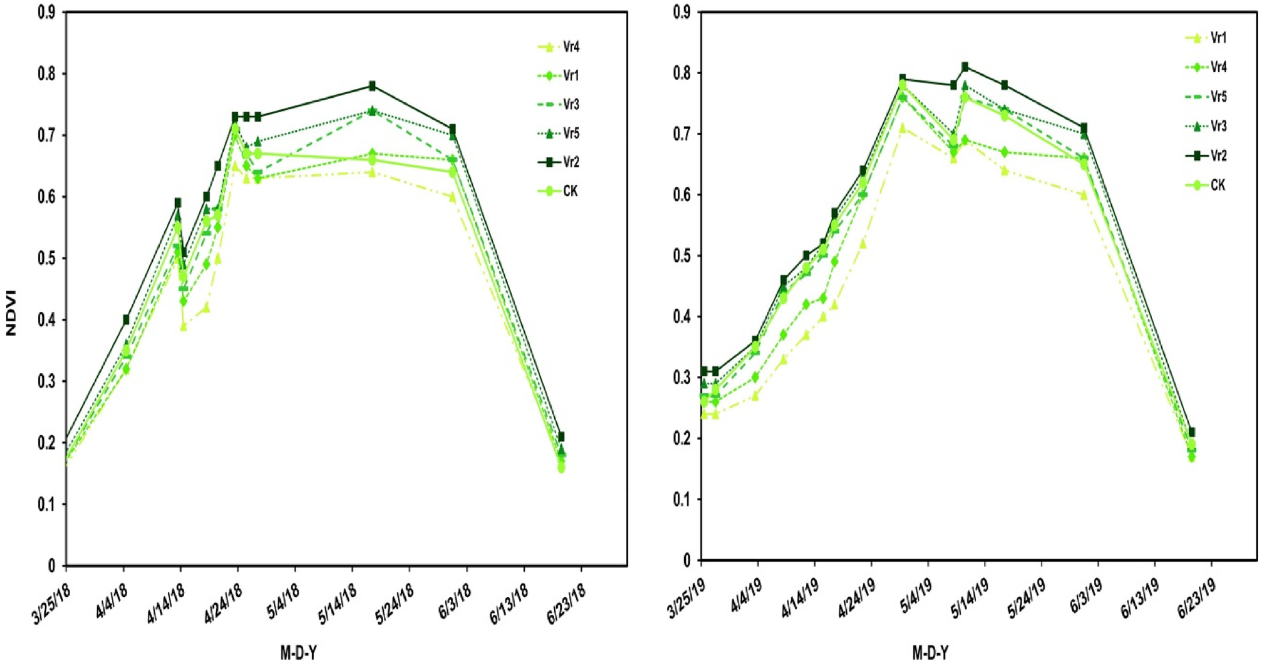
### Data analysis

Analysis of variance (ANOVA) was conducted for the NDVI data using SPSS 21.0 (SPSS Inc., Chicago, III, USA) software package with a repeated-measures option for the irrigation, rainfed and wheat genotypes. Thus the differences in NDVI as affected by irrigation and rainfed and their interaction with wheat genotypes were examined using two-way and three way-ANOVA, Duncan's Multiple New Range Test ($p < 0.05$). Linear regression analyses on LAI, NDVI and water consumed were conducted using a two-way ANOVA, Pearson's product-moment correlation coefficient (r) at $p < 0.05$ in order to examine their correlation. All results are shown as the mean ± SE, $n = 10$ (Appendices; Tables 5 and 6) and all graphs were plotted using Microsoft Excel 2010.

## Results

### The effects of irrigation on NDVI

In the 2017–2018 season the NDVI for irrigated and rainfed genotypes ranged from 0.14 to 0.82 and 0.13 to 0.78



(a) (b)

**Fig. 3** The NDVI trends from re-greening to physiological maturity in 2017–2018 (**a**) and 2018–2019 (**b**)

**Table 3** Mean NDVI values from re-greening to physiological maturity and grain yield of the five winter wheat genotypes under irrigation and rain-fed conditions

| | **2017–2018** | | | | | | | | | | | | **2018–2019** | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **Irrigated** | | | | | | **Rain-fed** | | | | | | **Irrigated** | | | | | | **Rain-fed** | | | | | |
| | **NDVI** | | | | | **GY (mg ha$^{-1}$)** | **NDVI** | | | | | **GY (mg ha$^{-1}$)** | **NDVI** | | | | | **GY (mg ha$^{-1}$)** | **NDVI** | | | | | **GY (mg ha$^{-1}$)** |
| **Wheat Genotype** | **R** | **B** | **A** | **G** | **M** | | **R** | **B** | **A** | **G** | **M** | | **R** | **B** | **A** | **G** | **M** | | **R** | **B** | **A** | **G** | **M** | |
| Vr1 | 0.14 | 0.69 | 0.78 | 0.80 | 0.67 | 6.19 | 0.13 | 0.69 | 0.72 | 0.76 | 0.58 | 7.08 | 0.21 | 0.58 | 0.63 | 0.74 | 0.70 | 6.26 | 0.15 | 0.65 | 0.69 | 0.80 | 0.76 | 6.47 |
| Vr2 | 0.15 | 0.67 | 0.82 | 0.78 | 0.65 | 7.48$^{*}$ | 0.16 | 0.77 | 0.74 | 0.78 | 0.72 | 7.28$^{*}$ | 0.19 | 0.78 | 0.82 | 0.81 | 0.73 | 8.05$^{*}$ | 0.18 | 0.67 | 0.76 | 0.76 | 0.68 | 7.18 |
| Vr3 | 0.19 | 0.71 | 0.73 | 0.80 | 0.69 | 6.38 | 0.21 | 0.75 | 0.75 | 0.77 | 0.74 | 6.05 | 0.18 | 0.69 | 0.73 | 0.77 | 0.69 | 7.64 | 0.13 | 0.70 | 0.66 | 0.72 | 0.63 | 6.89 |
| Vr4 | 0.14 | 0.67 | 0.70 | 0.75 | 0.62 | 6.05 | 0.15 | 0.61 | 0.69 | 0.68 | 0.50 | 5.96 | 0.17 | 0.70 | 0.68 | 0.68 | 0.60 | 6.18 | 0.16 | 0.68 | 0.68 | 0.65 | 0.61 | 5.78$^{**}$ |
| Vr5 | 0.15 | 0.67 | 0.70 | 0.75 | 0.65 | 5.63$^{**}$ | 0.16 | 0.73 | 0.59 | 0.75 | 0.70 | 5.44 | 0.19 | 0.65 | 0.62 | 0.70 | 0.66 | 6.26 | 0.19 | 0.69 | 0.67 | 0.48 | 0.65 | 6.35 |
| CK | 0.18 | 0.73 | 0.77 | 0.79 | 0.66 | 5.72 | 0.14 | 0.64 | 0.63 | 0.54 | 0.49 | 6.24 | 0.16 | 0.74 | 0.71 | 0.72 | 0.70 | 6.39 | 0.19 | 0.70 | 0.65 | 0.67 | 0.64 | 5.96 |

R: re-greening growth stage (160 DAS), B: booting growth stage (200 DAS), A: anthesis growth stage (210 DAS), G: grain filling growth stage (220 DAS), M: physiological maturity growth stage (242 DAS). $^{*}$ and $^{**}$ indicate maximum and minimum values, within the same column, respectively

respectively, across the different growth stages. However, these results were, not statistically different from those obtained in the 2018–2019 season, which ranged from 0.16 to 0.82 and 0.13 to 0.80, respectively. The highest NDVIs occurred the in irrigated group in both seasons. The NDVI magnitude varied throughout the growing period, as observed from data obtained starting at the re-greening stage, especially from the end of March to mid-May. The NDVI data collected at this period were used in the evaluation of the wheat genotypes growth differences. In both seasons, the NDVI value reached the maximum around the 14th to 24th of May, declining afterwards, in all wheat genotypes (Fig. 3a, b), a period that could be linked to physiological maturity. Variations were experienced among the genotypes, with some of the growth stages (booting and grain-filling) differing significantly (Table 4).

Overall, *Vr2, Vr5* and *Vr3* had the highest average NDVI, while *Vr1* and *Vr4* had the least in both 2017–2018 and 2018–2019 (Fig. 3). On average, all the wheat genotypes reached tillering; stem elongation, booting, anthesis, grain filling and physiological maturity at 190,200,210, 220 and 242 DAS, respectively (Table 3).

A three-way ANOVA was performed to analyze the effect of irrigation and wheat genotypes on NDVI for the 2017–18 season. It was revealed that there was no statistically significant interaction between the effects of irrigation and wheat genotypes ($I_r \; x \; G_e$), (F (12,130) = 1.46, p = 0.15). Simple main effects analysis showed that irrigation had an effect on NDVI ($p < 0.001$). The three-way interaction between irrigation, rainfed and wheat genotypes ($I_1 \; x \; I_0 \; x \; G_e$), was not statistically significant F (4, 1) = 0.99, p = 0.63. Similarly, in the 2018–19 season, a three-way ANOVA analysis did not reveal a significant statistical interaction between the effects of irrigation and wheat genotypes ($I_r \; x \; G_e$), (F (15,160) = 0.35, p = 0.99). Moreover, irrigation had an effect on NDVI ($p < 0.001$). However there was a statistically significant three-way interaction between irrigation, rainfed and wheat genotypes ($I_1 \; x \; I_0 \; x \; G_e$), F (4, 1) = 1214, p = 0.02.

### The NDVI and LAI relationship

The LAI increased as wheat grew. The exhibited numerical differences were exhibited between irrigation practices and the wheat genotypes in both seasons. The highest mean LAI value was reported for *Vr2* while Vr4 had the lowest (Fig. 4). The highest NDVI was realized at the maximum LAI value. Peak LAIs were attained in the last week of April to mid-May in all wheat genotypes (Fig. 4). Therefore, LAI as function of light interception on plant biomass, correlated positively to water consumption in both the irrigated (r = 0.66, 0.55) and rainfed (r = 0.68, 0.50) groups respectively. A positive correlation between LAI and NDVI was also exhibited in both seasons, such that 2017–18 reported an r = 0.72, (p = 0.63), while 2018–19 had an r = 0.64, (p = 0.58).

### Correlation between NDVI, GY and its components

The differences in crop height were mostly dependent on genotypic differences and were maximum at the physiological maturity stage. Generally, the tallest genotypes also achieved the highest LAI values but not necessarily the greatest NDVI and grain yield. In both seasons, maximum height was recorded in *Vr5, Vr2* and *Vr3* (Fig. 6a, b). Similarly, the minimum height was recorded in *Vr1* and *Vr4*. The wheat genotypes with the highest NDVI achieved the greatest grain yield (Fig. 5). During the 2017–2018 season, all genotypes performed well, with *Vr2* yielding the highest (Fig. 6a), followed by *Vr5* and *Vr3, Vr1 Vr4* performing the lowest. In the year 2017–2018 the NDVI (and their respective average grain yields) for irrigated crops ranged from 0.15 to 0.82 (grain yield = 7.48 mg ha$^{-1}$), rainfed ranged from 0.16 to 0.78 (7.28 mg ha$^{-1}$). Meanwhile in 2018–2019 NDVI from irrigation ranged from 0.19 to 0.82 (grain yield = 8.05 mg ha$^{-1}$), while rainfed from 0.18 to 0.76 (7.62 mg ha$^{-1}$).

The NDVI patterns (Fig. 3a, b) demonstrated that genotypes' growth trends and variability which existed as the crop cycle progressed until 100% ground cover. The significant NDVI differences were during the booting and grain filling stages when temperature rose substantially (Table 4). There was a positive correlation between NDVI to GY (r = 0.57, 0.28) and (r = 0.88*, 0.32) in 2017–18 and 2018–19 for irrigation and rainfed treatments respectively. These correlations were strong in irrigation than rainfed genotypes in both seasons. Overall, all vegetative indices had mutual associations directly or indirectly.

## Discussion

### The effects of irrigation on NDVI

The wheat NDVI values exhibited a similar tendency during the entire growth period, and both irrigated and rainfed groups achieved maximum values at the booting stage. This was in agreement with previous and recent studies like (Nguy-Robertson et al. 2013; Tao et al. 2020; Liu et al. 2022; Rose et al. 2022) which showed that, the spectral reflectance indices could be used to monitor crops' main growth stages. For example, the study by Sultana et al. (2014) reported a decrease in NDVI value at grain filling stage due to decreased ability to absorb PAR under stress conditions. However, in our study a

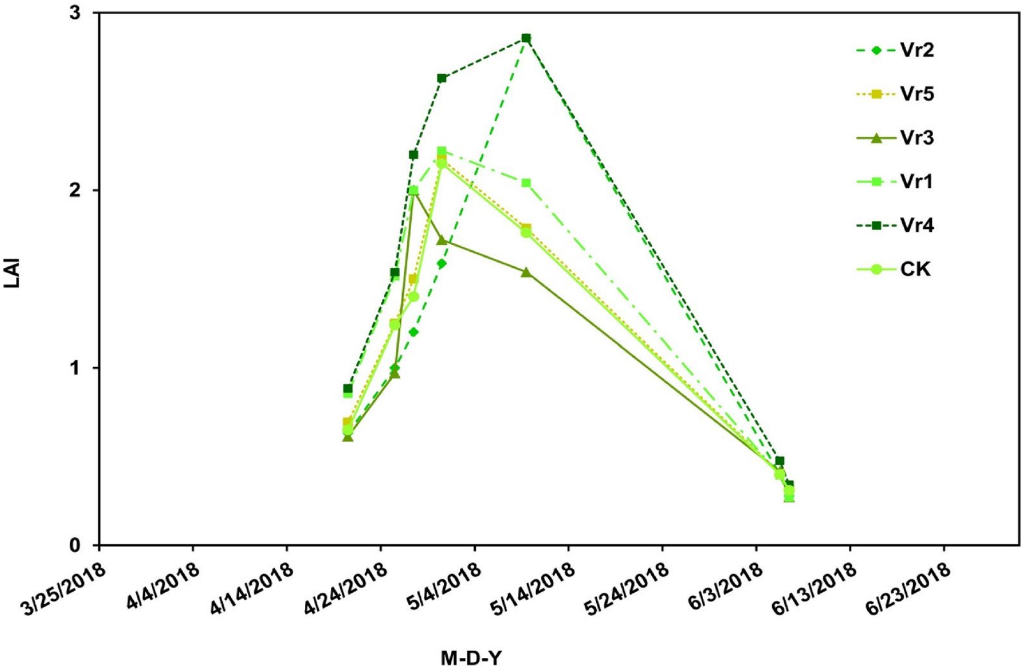


**Fig. 4** The LAI pattern from re-greening to physiological maturity in 2017–2018

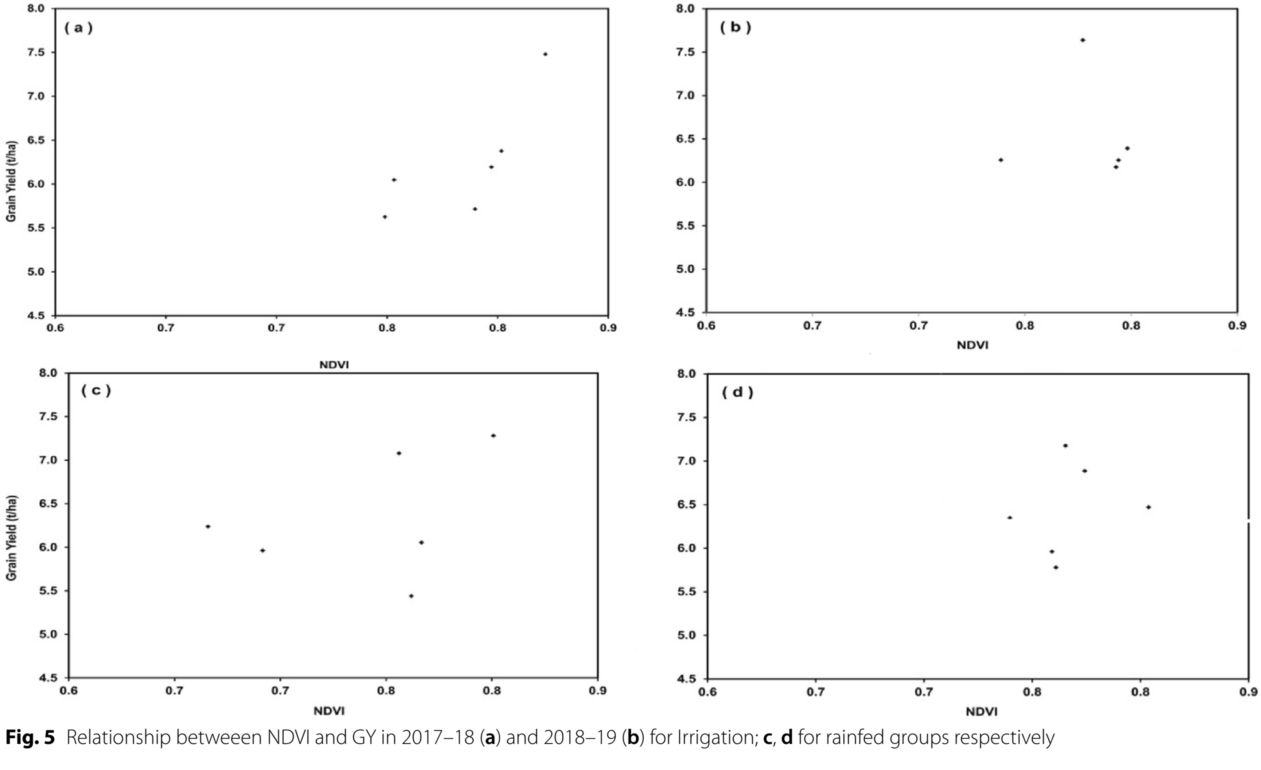


**Fig. 5** Relationship betweeen NDVI and GY in 2017–18 (**a**) and 2018–19 (**b**) for Irrigation; **c**, **d** for rainfed groups respectively

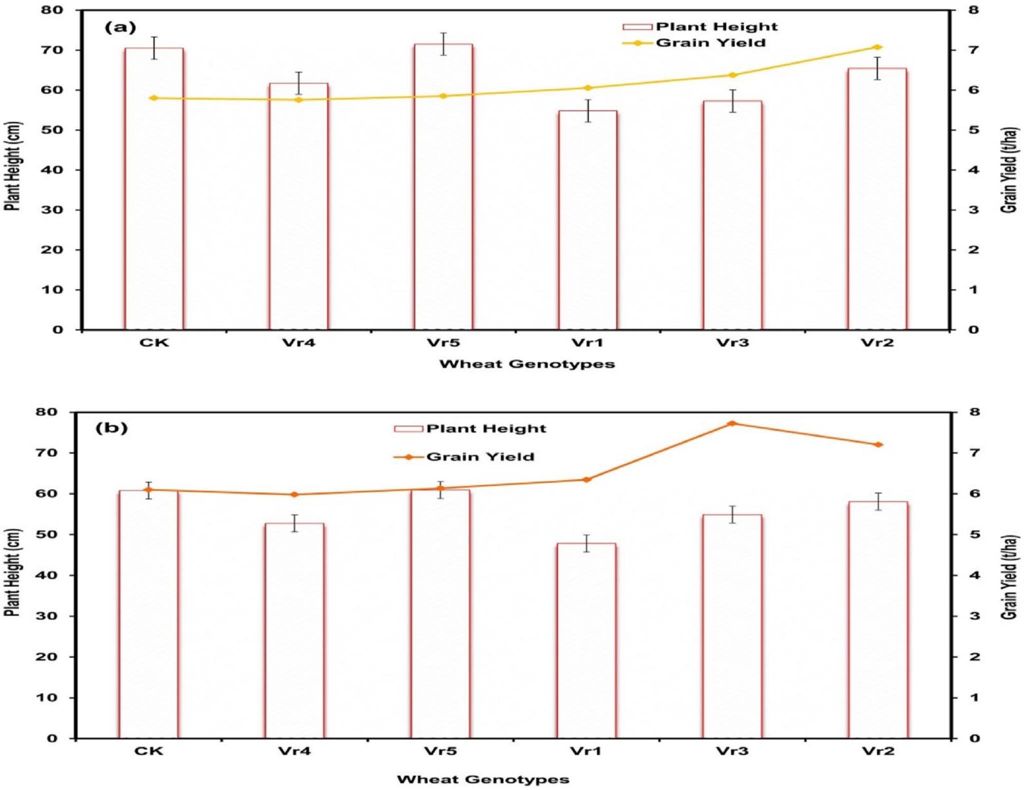


**Fig. 6** The relationship between the wheat genotypes for height and grain yield during the 2017–18 (**a**) and 2018–19 (**b**) seasons

slight decrease in NDVI value was observed at the grain filling stage, the value being slightly higher than that reported in the work of Ozyavuz et al. (2015), this effect probably induced the weak correlation between NDVI and grain yield in rainfed group. On the other hand, though precipitation was favorable in both experimental seasons, it was not sufficient to provide all the winter wheat water requirements. This was reflected in the differences in NDVI values and grain yield between the irrigated and rainfed groups in both seasons. The study by Abuzar et al. (2019) demonstrated that combination of satellite derived evapotranspiration (ET), NDVI and daily step soil water balance can be used to investigate the performance of crop water use during the peak irrigation demand period (summer). Moreover according to Ambika et al. (2016) NDVI can be used as an indicator for irrigated area as well as representation of the amount of green biomass with index values varying in response to changes in vegetation conditions.

## The NDVI and LAI relationship

The relationship obtained in this study, was also evident in the study by Sultana et al. (2014). Mostly importantly, NDVI saturation occurred when LAI reached a certain value (Misra 2016). Our results showed NDVI saturated when the LAI exceeded a critical value of 3.0. The LAI—induced NDVI saturation depended on genotype differences attributed to the genotypes` ability to intercept light. It has been argued that as LAI increases so does light interception, causing an increase in net photosynthesis up to a critical LAI value (Pearce et al. 1965; Liu et al. 2021; Romero et al. 2022). Several factors can affect LAI in plants such as weather and site conditions, leaf arrangement, age and shape. For example, the shape of the wheat plant might affect the pattern by which light is intercepted and reflected in the different genotypes stands. Thus abrupt increase in LAI in our study could be attributed to stem elongation and a decrease in shrinkage of post-maturity leaves. On the other hand, at the heading and grain filling stages, a decrease in LAI among the genotypes might have reflected the difference in spike size and/or morphology. However, we did not measure spike size and morphology but we recommend further research to confirm our speculations. Apart from stem elongation and wheat genotypes morphological changes, optimum LAI was also observed from the end of April to mid-May when light intensities were greater. Hence geographic location and diurnal fluctuations might also affect the optimum LAI extensively.

**Table 4** The effects of water and wheat genotypes on NDVI of 2017–2018 and 2018–2019

| **Treatments** | **NDVI 2017–18** | | | | | | | | | | **NDVI 2018–19** | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Date** | **29-Mar** | **09-Apr** | **10-Apr** | **14-Apr** | **16-Apr** | **21-Apr** | **23-Apr** | **26-Apr** | **5-May** | **10-May** | **Mar-28** | **2-Apr** | **6-Apr** | **9-Apr** | **16-Apr** | **23-Apr** | **4-May** |
| **DAS** | **174** | **185** | **186** | **190** | **192** | **197** | **199** | **202** | **211** | **216** | **173** | **178** | **182** | **185** | **192** | **199** | **210** |
| Irrigation practices | | | | | | | | | | | | | | | | | |
| Rainfed | $0.27^{b}$ | $0.39^{c}$ | $0.28^{c}$ | $0.31^{c}$ | $0.40^{c}$ | $0.61^{b}$ | $0.49^{b}$ | $0.49^{b}$ | $0.63^{b}$ | $0.54^{c}$ | $0.31^{b}$ | $0.39^{b}$ | $0.46^{b}$ | $0.49^{b}$ | $0.58^{b}$ | $0.74^{b}$ | $0.69^{b}$ |
| Irrigation | $0.35^{ab}$ | $0.52^{b}$ | $0.45^{b}$ | $0.49^{b}$ | $0.56^{b}$ | $0.67^{ab}$ | $0.67^{a}$ | $0.65^{a}$ | $0.71^{a}$ | $0.73^{b}$ | $0.32^{ab}$ | $0.40^{b}$ | $0.47^{ab}$ | $0.51^{b}$ | $0.59^{b}$ | $0.75^{ab}$ | $0.74^{ab}$ |
| CK | $0.39^{a}$ | $0.65^{a}$ | $0.61^{a}$ | $0.65^{a}$ | $0.70^{a}$ | $0.72^{a}$ | $0.69^{a}$ | $0.66^{a}$ | $0.77^{a}$ | $0.79^{a}$ | $0.36^{a}$ | $0.46^{a}$ | $0.53^{a}$ | $0.57^{a}$ | $0.68^{a}$ | $0.80^{a}$ | $0.77^{a}$ |
| Genotypes | | | | | | | | | | | | | | | | | |
| Vr1 | $0.32^{b}$ | $0.50^{c}$ | $0.39^{c}$ | $0.42^{c}$ | $0.50^{b}$ | $0.63^{b}$ | $0.63^{b}$ | $0.56^{c}$ | $0.67^{c}$ | $0.71^{d}$ | $0.27^{c}$ | $0.33^{b}$ | $0.37^{c}$ | $0.40^{b}$ | $0.52^{b}$ | $0.71^{b}$ | $0.69^{b}$ |
| Vr4 | $0.32^{b}$ | $0.51^{bc}$ | $0.43^{bc}$ | $0.49^{b}$ | $0.55^{b}$ | $0.65^{b}$ | $0.63^{b}$ | $0.63^{b}$ | $0.70^{bc}$ | $0.72^{cd}$ | $0.34^{ab}$ | $0.44^{a}$ | $0.47^{ab}$ | $0.50^{a}$ | $0.60^{a}$ | $0.76^{a}$ | $0.76^{a}$ |
| Vr3 | $0.34^{b}$ | $0.52^{bc}$ | $0.45^{abc}$ | $0.54^{ab}$ | $0.58^{ab}$ | $0.67^{ab}$ | $0.64^{b}$ | $0.63^{b}$ | $0.73^{ab}$ | $0.75^{bc}$ | $0.30^{bc}$ | $0.37^{b}$ | $0.42^{b}$ | $0.43^{b}$ | $0.60^{a}$ | $0.76^{a}$ | $0.69^{b}$ |
| Vr5 | $0.36^{ab}$ | $0.57^{ab}$ | $0.49^{ab}$ | $0.58^{a}$ | $0.58^{ab}$ | $0.68^{ab}$ | $0.69^{ab}$ | $0.68^{ab}$ | $0.74^{ab}$ | $0.76^{ab}$ | $0.35^{ab}$ | $0.45^{a}$ | $0.48^{a}$ | $0.52^{a}$ | $0.63^{a}$ | $0.78^{a}$ | $0.78^{a}$ |
| CK | $0.39^{a}$ | $0.65^{a}$ | $0.61^{a}$ | $0.65^{a}$ | $0.70^{a}$ | $0.72^{a}$ | $0.69^{a}$ | $0.67^{a}$ | $0.77^{a}$ | $0.79^{a}$ | $0.36^{a}$ | $0.46^{a}$ | $0.47^{a}$ | $0.53^{a}$ | $0.68^{a}$ | $0.80^{a}$ | $0.78^{a}$ |
| Vr2 | $0.40^{a}$ | $0.59^{a}$ | $0.51^{a}$ | $0.60^{a}$ | $0.65^{a}$ | $0.73^{a}$ | $0.73^{a}$ | $0.71^{a}$ | $0.78^{a}$ | $0.78^{a}$ | $0.36^{a}$ | $0.46^{a}$ | $0.50^{a}$ | $0.52^{a}$ | $0.64^{a}$ | $0.79^{a}$ | $0.81^{a}$ |

Mean followed by the same letter within the same column are not significant different at ($p < 0.05$)

According to Bajocco et al. (2022), the existing correlation relationship of NDVI and LAI is not directly proportional relationship. The relationship varies according to types of vegetation such as from broadleaf evergreens versus needle leaf evergreens and also soil types exhibit different relationship between the two parameters. Nevertheless the LAI is a direct indicator of vegetation activity, and its relationship with the NDVI has been investigated in several research studies like (Misra 2016; Nasa Earth Observatory 2020). In our study, wheat growth prior to heading was regarded as the development of foliar tissue, i.e., leaves and culms that intercept solar radiation and then convert the atmospheric carbon to biomass.

### Correlation between NDVI, GY and its components

In this study, we used NDVI in conjunction with grain yield and other growth parameters to study five wheat genotypes, aiming to prioritize at least one genotype. A linear relationship between NDVI and grain yield has been indicated in some studies like (Goodwin et al. 2018; Chandel et al. 2019; Zhang et al. 2019a), concerning the use of a portable active sensor to monitor growth parameters. In mature plants, some studies such as that of Sultana et al. (2014) have obtained positive correlation between NDVI and GY. Studies by Babar et al. (2006a) and Sultana et al. (2013), also showed that there was a relationship between biomass and NDVI. However, no study has attempted to explore the use of NDVI in drought wheat genotypes under irrigation and rainfed conditions, especially in the NCP. In our study, NDVI values increased until the onset of grain filling, with the highest value of NDVI recorded within milky-grain stages before dropping during the physiological maturity stage. Milky-grain to onset of grain-filling stages might the critical stages for the spectral reflectance indices estimation on plant biomass.

In addition all genotypes at booting to milking stages had quick changes in NDVI and LAI reflectance spectral indices accompanied by morphological changes. These observations indicated that the sensitivity of these stages could have easily caused much reduction in grain yield due to irreversible and rapid changes at these stages. In agreement, Royo et al. (2003), indicated that milky-grain stages were the best depictive for recording NDVI as they correlated directly to yield compared to the earlier measurements. Our findings could be applicable universally when factors related to the site condition are considered and adjusted accordingly (Sinica 2007). This study was limited to a single location, where eco-sites conditions were relatively homogeneous. More studies under different environmental and management perspectives should be conducted since vegetative indices are also influenced by the environment (Araus and Kefauver 2018; Chawade et al. 2019). Future studies should explore these genotypes in more stressful environmental conditions, in order to ascertain the NDVI dynamic implication on the limited water supply to drought-adaptable wheat genotypes. Alternatively, studies involving other, more efficient systems for controlling water supply need to be explored. In addition, more relationships between various factors such as biomass production, LAI, N accumulation, unit tiller number, and grain per head should be included in the models utilized to evaluate the different wheat genotypes accurately. Furthermore, labor saving techniques are needed to acquire information.

Our results helped us group or rank the genotypes based on their grain yield relative to NDVI values. However, several limitations were realized in this study. Firstly, due to the overlapping of the spectral band canopy tissue, it was not easy to differentiate the genotypes, as they displayed intermediate behavior. Secondly, we observed a weaker positive correlation between NDVI and LAI in rainfed groups than in irrigation groups. This effect could be linked to the water stress, early during sensitive stages when affecting the wheat genotypes chlorophyll synthesis ability when almost fully grown. However, apart from providing irrigation water management strategies, this study has provided scrutiny of phenotypes of five wheat genotypes. It was possible to identify *Zhongmai-36* as the most drought-adaptable genotype among the other four genotypes which need to be considered for further studies under serious water stress conditions.

## Conclusion

This study demonstrated that wheat genotypes with higher NDVI, LAI spectral reflectance indices and grain yield, are the most adaptable genotypes to the limited irrigation water and had optimal grain yield. The NDVI in this study reflected the differences in water consumption behavior at different growth stages for the genotypes under study. Hence, these results provide a basis for farmers and producers to monitor real-time crop performance and efficient agricultural water management. Therefore, improvement and awareness should be done on utilizing NDVI, LAI and other spectral reflectance indices for managing crop water, growth and for quick drought adaptability screening of wheat genotypes.

## Appendix

See Tables 5, 6.

**Table 5** Mean NDVI and their standard error measured at different growth stages of winter wheat genotypes in 2017–18

| Factors | Trt | 9-Mar | 23-Mar | 4-Apr | 13-Apr | 14-Apr | 18-Apr | 20-Apr | 23-Apr | 25-Apr | 27-Apr | 30-Apr | 9-May | 14-May |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Irrigation | T1 | 0.14 ± 0.0029 | 0.16 ± 0.0048 | 0.4 ± 0.0081 | 0.5 ± 0.0056 | 0.48 ± 0.0124 | 0.64 ± 0.0199 | 0.65 ± 0.0262 | 0.7 ± 0.0189 | 0.69 ± 0.026 | 0.73 ± 0.0183 | 0.67 ± 0.0050 | 0.78 ± 0.0216 | 0.8 ± 0.0173 |
| | T2 | 0.15 ± 0.0082 | 0.17 ± 0.0098 | 0.41 ± 0.0193 | 0.62 ± 0.0280 | 0.55 ± 0.0409 | 0.71 ± 0.0306 | 0.54 ± 0.0359 | 0.69 ± 0.0185 | 0.65 ± 0.0278 | 0.67 ± 0.0190 | 0.65 ± 0.0157 | 0.82 ± 0.0369 | 0.78 ± 0.0199 |
| | T3 | 0.19 ± 0.0015 | 0.16 ± 0.0052 | 0.31 ± 0.0137 | 0.6 ± 0.0365 | 0.48 ± 0.0418 | 0.7 ± 0.0420 | 0.7 ± 0.0414 | 0.71 ± 0.0369 | 0.71 ± 0.0568 | 0.73 ± 0.0424 | 0.69 ± 0.0199 | 0.73 ± 0.0053 | 0.8 ± 0.0105 |
| | T4 | 0.14 ± 0.0139 | 0.15 ± 0.0086 | 0.33 ± 0.0102 | 0.52 ± 0.0365 | 0.38 ± 0.0229 | 0.42 ± 0.0189 | 0.58 ± 0.0532 | 0.64 ± 0.0287 | 0.7 ± 0.0361 | 0.69 ± 0.0352 | 0.62 ± 0.0272 | 0.7 ± 0.0248 | 0.75 ± 0.0124 |
| | T5 | 0.15 ± 0.0069 | 0.15 ± 0.0067 | 0.38 ± 0.0364 | 0.47 ± 0.0358 | 0.5 ± 0.0404 | 0.5 ± 0.0367 | 0.62 ± 0.0307 | 0.67 ± 0.0236 | 0.67 ± 0.0394 | 0.68 ± 0.0282 | 0.65 ± 0.0292 | 0.7 ± 0.0325 | 0.75 ± 0.0271 |
| | $T_{CK}$ | 0.17 ± 0.0094 | 0.16 ± 0.0071 | 0.38 ± 0.0498 | 0.6 ± 0.0141 | 0.51 ± 0.0508 | 0.58 ± 0.0500 | 0.65 ± 0.0388 | 0.75 ± 0.0285 | 0.71 ± 0.0460 | 0.7 ± 0.0444 | 0.68 ± 0.0404 | 0.68 ± 0.0131 | 0.77 ± 0.0101 |
| Rainfed | $T_{CK}$ | 0.13 ± 0.0065 | 0.14 ± 0.0047 | 0.31 ± 0.0561 | 0.58 ± 0.0508 | 0.52 ± 0.0443 | 0.44 ± 0.0375 | 0.57 ± 0.0338 | 0.75 ± 0.0199 | 0.62 ± 0.0321 | 0.6 ± 0.0431 | 0.58 ± 0.0189 | 0.72 ± 0.0186 | 0.76 ± 0.0090 |
| | T6 | 0.16 ± 0.0114 | 0.16 ± 0.0057 | 0.43 ± 0.0079 | 0.6 ± 0.0194 | 0.57 ± 0.0336 | 0.6 ± 0.0139 | 0.59 ± 0.0179 | 0.8 ± 0.0584 | 0.74 ± 0.0413 | 0.72 ± 0.0457 | 0.72 ± 0.0201 | 0.74 ± 0.0038 | 0.78 ± 0.0199 |
| | T7 | 0.21 ± 0.0199 | 0.2 ± 0.0106 | 0.32 ± 0.0049 | 0.57 ± 0.0453 | 0.49 ± 0.0515 | 0.47 ± 0.0367 | 0.6 ± 0.0402 | 0.76 ± 0.0305 | 0.74 ± 0.0372 | 0.74 ± 0.0447 | 0.74 ± 0.0375 | 0.75 ± 0.0690 | 0.77 ± 0.0177 |
| | T8 | 0.15 ± 0.0039 | 0.15 ± 0.0049 | 0.31 ± 0.0144 | 0.48 ± 0.0073 | 0.4 ± 0.0052 | 0.42 ± 0.0099 | 0.42 ± 0.0060 | 0.66 ± 0.0307 | 0.56 ± 0.0224 | 0.57 ± 0.0092 | 0.5 ± 0.0100 | 0.69 ± 0.0170 | 0.68 ± 0.0119 |
| | T9 | 0.14 ± 0.0151 | 0.13 ± 0.0160 | 0.27 ± 0.0533 | 0.39 ± 0.0218 | 0.28 ± 0.0668 | 0.31 ± 0.0464 | 0.4 ± 0.0582 | 0.67 ± 0.0260 | 0.61 ± 0.0185 | 0.49 ± 0.0534 | 0.49 ± 0.0369 | 0.63 ± 0.0165 | 0.54 ± 0.0149 |
| | T10 | 0.17 ± 0.0021 | 0.16 ± 0.0114 | 0.38 ± 0.0383 | 0.6 ± 0.0389 | 0.51 ± 0.0463 | 0.58 ± 0.0418 | 0.65 ± 0.0232 | 0.75 ± 0.0115 | 0.71 ± 0.0217 | 0.7 ± 0.0298 | 0.68 ± 0.0091 | 0.68 ± 0.0190 | 0.77 ± 0.0219 |

**Table 6** Mean NDVI and their standard error measured at different growth stages of winter wheat genotypes in 2018–19

| Factors | Trt | 1-Mar | 8-Mar | 25-Mar | 27-Mar | 3-Apr | 8-Apr | 12-Apr | 15-Apr | 17-Apr | 22-Apr | 29-Apr | 8-May | 10-May | 17-May | 31-May | 19-Jun |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Rainfed | T1 | 0.15 ± 0.025 | 0.15 ± 0.029 | 0.23 ± 0.013 | 0.22 ± 0.019 | 0.30 ± 0.018 | 0.33 ± 0.027 | 0.40 ± 0.016 | 0.47 ± 0.031 | 0.48 ± 0.034 | 0.57 ± 0.038 | 0.74 ± 0.047 | 0.68 ± 0.019 | 0.80 ± 0.028 | 0.80 ± 0.005 | 0.76 ± 0.023 | 0.21 ± 0.014 |
| | T2 | 0.17 ± 0.016 | 0.18 ± 0.021 | 0.23 ± 0.008 | 0.26 ± 0.028 | 0.29 ± 0.011 | 0.38 ± 0.013 | 0.40 ± 0.029 | 0.44 ± 0.028 | 0.52 ± 0.029 | 0.57 ± 0.029 | 0.76 ± 0.016 | 0.76 ± 0.007 | 0.77 ± 0.009 | 0.76 ± 0.009 | 0.68 ± 0.013 | 0.19 ± 0.002 |
| | T3 | 0.15 ± 0.019 | 0.13 ± 0.027 | 0.31 ± 0.007 | 0.33 ± 0.007 | 0.37 ± 0.009 | 0.46 ± 0.017 | 0.49 ± 0.021 | 0.51 ± 0.021 | 0.56 ± 0.004 | 0.65 ± 0.017 | 0.74 ± 0.012 | 0.66 ± 0.005 | 0.77 ± 0.008 | 0.72 ± 0.005 | 0.63 ± 0.013 | 0.18 ± 0.013 |
| | T4 | 0.14 ± 0.017 | 0.16 ± 0.028 | 0.25 ± 0.008 | 0.25 ± 0.014 | 0.29 ± 0.008 | 0.35 ± 0.028 | 0.43 ± 0.038 | 0.44 ± 0.017 | 0.50 ± 0.016 | 0.61 ± 0.034 | 0.76 ± 0.003 | 0.68 ± 0.007 | 0.70 ± 0.067 | 0.65 ± 0.010 | 0.61 ± 0.010 | 0.18 ± 0.003 |
| | T5 | 0.16 ± 0.015 | 0.20 ± 0.027 | 0.31 ± 0.009 | 0.28 ± 0.022 | 0.33 ± 0.021 | 0.39 ± 0.017 | 0.47 ± 0.025 | 0.46 ± 0.027 | 0.55 ± 0.012 | 0.63 ± 0.054 | 0.74 ± 0.006 | 0.67 ± 0.024 | 0.68 ± 0.011 | 0.48 ± 0.012 | 0.65 ± 0.009 | 0.17 ± 0.007 |
| | $T_{CK}$ | 0.15 ± 0.004 | 0.17 ± 0.009 | 0.29 ± 0.012 | 0.31 ± 0.021 | 0.38 ± 0.047 | 0.47 ± 0.063 | 0.51 ± 0.032 | 0.54 ± 0.026 | 0.56 ± 0.043 | 0.66 ± 0.023 | 0.78 ± 0.010 | 0.68 ± 0.014 | 0.68 ± 0.013 | 0.69 ± 0.008 | 0.67 ± 0.007 | 0.17 ± 0.012 |
| Irrigation | $T_{CK}$ | 0.19 ± 0.011 | 0.21 ± 0.025 | 0.21 ± 0.039 | 0.22 ± 0.030 | 0.23 ± 0.026 | 0.32 ± 0.008 | 0.35 ± 0.034 | 0.35 ± 0.039 | 0.39 ± 0.037 | 0.47 ± 0.038 | 0.69 ± 0.007 | 0.63 ± 0.013 | 0.79 ± 0.020 | 0.74 ± 0.023 | 0.76 ± 0.016 | 0.23 ± 0.006 |
| | T6 | 0.16 ± 0.032 | 0.18 ± 0.033 | 0.30 ± 0.022 | 0.26 ± 0.028 | 0.36 ± 0.015 | 0.46 ± 0.027 | 0.55 ± 0.033 | 0.54 ± 0.034 | 0.60 ± 0.017 | 0.64 ± 0.026 | 0.79 ± 0.008 | 0.80 ± 0.014 | 0.81 ± 0.013 | 0.79 ± 0.154 | 0.68 ± 0.011 | 0.18 ± 0.003 |
| | T7 | 0.16 ± 0.015 | 0.18 ± 0.016 | 0.31 ± 0.022 | 0.29 ± 0.019 | 0.36 ± 0.025 | 0.46 ± 0.035 | 0.46 ± 0.022 | 0.52 ± 0.021 | 0.56 ± 0.023 | 0.61 ± 0.035 | 0.77 ± 0.020 | 0.73 ± 0.027 | 0.78 ± 0.018 | 0.77 ± 0.030 | 0.63 ± 0.011 | 0.17 ± 0.001 |
| | T8 | 0.15 ± 0.014 | 0.17 ± 0.003 | 0.27 ± 0.020 | 0.27 ± 0.021 | 0.31 ± 0.006 | 0.39 ± 0.011 | 0.42 ± 0.017 | 0.43 ± 0.032 | 0.49 ± 0.009 | 0.60 ± 0.029 | 0.79 ± 0.008 | 0.68 ± 0.033 | 0.69 ± 0.003 | 0.68 ± 0.030 | 0.61 ± 0.029 | 0.16 ± 0.011 |
| | T9 | 0.16 ± 0.019 | 0.19 ± 0.013 | 0.28 ± 0.013 | 0.27 ± 0.014 | 0.30 ± 0.012 | 0.41 ± 0.015 | 0.44 ± 0.012 | 0.45 ± 0.028 | 0.48 ± 0.015 | 0.55 ± 0.021 | 0.74 ± 0.018 | 0.62 ± 0.008 | 0.72 ± 0.017 | 0.69 ± 0.015 | 0.65 ± 0.002 | 0.18 ± 0.001 |
| | T10 | 0.15 ± 0.003 | 0.17 ± 0.007 | 0.29 ± 0.011 | 0.31 ± 0.013 | 0.38 ± 0.009 | 0.47 ± 0.005 | 0.51 ± 0.014 | 0.54 ± 0.005 | 0.56 ± 0.020 | 0.66 ± 0.012 | 0.78 ± 0.004 | 0.68 ± 0.012 | 00.68 ± 0.013 | 0.69 ± 0.017 | 0.67 ± 0.004 | 0.17 ± 0.008 |

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**Author contributions**

TERM: Investigation, data correction and curation, analysis, preparation of figures and main manuscript text preparation. ZG: Data collection assistance. XL: Experiment conceptualization, methodology and procedures validation. YL, YW and CG: Edited the manuscript. All authors read and approved the final manuscript.

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**Availability of data and materials**

The data that support the finding of this study are available upon request.

## Declarations

**Ethics approval and consent to participate**

Not applicable.

**Consent for publication**

We have agreed to submit for Environmental Systems Research journal and approved the manuscript for submission.

**Competing interests**

The authors declare no competing interests.

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