COMPARISON OF NDVI VALUES AT DIFFERENT PHENOLOGICAL STAGES OF WINTER WHEAT (TRITICUM AESTIVUM L.)

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Abstract.

Winter wheat (Triticum aestivum L.) is one of the most important crops in the world. Due to the changing climate conditions, winter wheat yield becomes more hectic. The goal of this study is to compare and analyze the Normalized Difference Vegetation Index (NDVI) values derived from the GreenSeeker handheld crop sensor and MicaSense RedEdge-MX Dual Camera System data at six different measurement times and to examine the relationship between NDVI values and yield over the 2021-22 and 2022-23 seasons. The research field was located in Mosonmagyaróvár, in the north-western region of Hungary, part of the European Union. The small-scale field trial included four treatments (Environmental: N-135.3, P_2O_5-77.5, K_2O-0; Balance: N-135.1, P_2O_5-91, K_2O-0; Genesis: N-135, P_2O_5-75, K_2O-45; and Control: N, P, K 0 kg/ha) and four replications with a randomized block design in winter wheat. The measurements were conducted from mid-April (5 Feekes growth stages) to harvesting (11 Feekes growth stages). The aim was to determine the strongest positive correlation between the yield of winter wheat and NDVI values derived from two sensors. The results showed a significant difference ($p \leq 0.05$) between the Control and the other treatments (Environmental, Balance, Genesis) in the NDVI values obtained from GreenSeeker measurements at all times in both years. Similar findings were observed regarding NDVI values calculated from the MicaSense camera data.

However, May 12 could not demonstrate a significant difference ($p \geq 0.05$) between the treatments in the 2021-22 and 2022-23 seasons. Yield estimation based on NDVI values showed that the expected yield could be most accurately determined on the 226th day after sowing. These results support selecting suitable sensors and determining the optimal yield estimation time to achieve more reliable in-season prediction outcomes. Moreover, using the portable GreenSeeker allows for better monitoring of growth parameters and predictive grain yield of winter wheat compared to NDVI values calculated from MicaSense camera data.

Keywords.
NDVI, MicaSense RedEdge-MX Dual Camera System, GreenSeeker HCS-250, winter wheat, yield prediction

Introduction

Winter wheat (Triticum aestivum L.) plays a key role in global food security (Shiferaw et al., 2013). It is one of the most important cultivated plants in Hungary (Bognár et al., 2017); therefore, monitoring the vitality of crops during the whole growing season is crucial to increasing yield and reducing inputs and costs (Brisco et al., 1998). Vegetation indices, derived from the values of different wavelength spectra reflected by plants, provide good opportunities for monitoring plant development in the vegetation period (Wang et al., 2010).

The Normalized Difference Vegetation Index (NDVI) is one of the most popular and frequently used vegetation indices, known for its versatility. NDVI values could be used to estimate the expected yield (Lofton et al., 2012; Aranguren et al., 2020; Walsh et al., 2022) and protein content (Walsh et al., 2022). Furthermore, NDVI is also suitable for monitoring foliage disease (Bhandari et al., 2020), assessing plant development (Duan et al., 2017), assessing chlorophyll content (Khadka et al., 2021), or developing nitrogen management strategies and evaluating nitrogen use efficiency (Bijay-Singh et al., 2011; Jiang et al., 2021). The NDVI values could be calculated from reflectance at near-infrared (NIR) and red band (Tucker, 1979).

Low-cost active sensors have been developed for small-scale plot experiments. One of the most reliable devices is the GreenSeeker handheld sensor, which can monitor vegetation development and examine biomass changes by NDVI values (Ali et al., 2014; Lake et al., 2016).

Many studies have been conducted using this portable sensor in alfalfa (Tang et al., 2022), where the GreenSeeker demonstrated significant potential in distinguishing inoculation treatments in the field. Additionally, there have been studies also in cabbage (Ji et al., 2017), maize (Verhulst et al., 2011), ryegrass (Wang et al., 2019), rice (Ali et al., 2014), wheat (Bijay-Singh et al., 2011; Duan et al., 2017; Aranguren et al., 2020) and sugarcane (Lofton et al., 2012). Despite numerous studies conducted on plant monitoring, a notable disadvantage of the GreenSeeker handheld sensor is its limited temporal and spatial resolution. Data collection with this device is time-consuming and prone to subjective measurement errors (Schirrmann et al., 2016).

The development and adaptation of unmanned aircraft systems (UAS) provide new opportunities for non-destructive data collection, offering an alternative to time-consuming manual ground-based methods (Shi et al., 2016). Drones with various cameras can survey extensive areas and capture superior spatial and temporal resolution images. Additionally, unmanned aircraft systems offer significant advantages in terms of time efficiency and flexibility in flight planning (Walsh et al., 2018). However, selecting the camera according to the user's requirements is essential during data acquisition (Lu et al., 2020),

Nowadays, multispectral cameras are widely utilized in various research applications, including studies on soybean (Maimaitijiang et al., 2020), spring wheat (Shafiee et al., 2021; Veverka et al., 2021), durum wheat (Kyratzis et al., 2017), and winter wheat (Hassan et al., 2019). These multispectral cameras enable the examination of different crop parameters in time-series analyses, contributing to the prediction of yield and quality (Walsh et al., 2018; Maimaitijiang et al., 2020; Shafiee et al., 2021).

The objectives of this study were: (1) comparison of NDVI values derived from the GreenSeeker and the MicaSense camera data in winter wheat during the 2021-22 and 2022-23 period; (2) to predict the expected yield in different phenological stages for two sensors under different fertilizer application rates.

Materials and Methods

Site description

The research field (Figure 1) was located in Mosonmagyaróvár (N 47°8′67.89″ E 17°26′9.94″), in the northwestern region of Hungary in Europe, at an elevation of 119 meters above sea level. The two-year small-scale field trial was examined from April to the end of June in the 2021–2022 and 2022–2023 growing seasons.

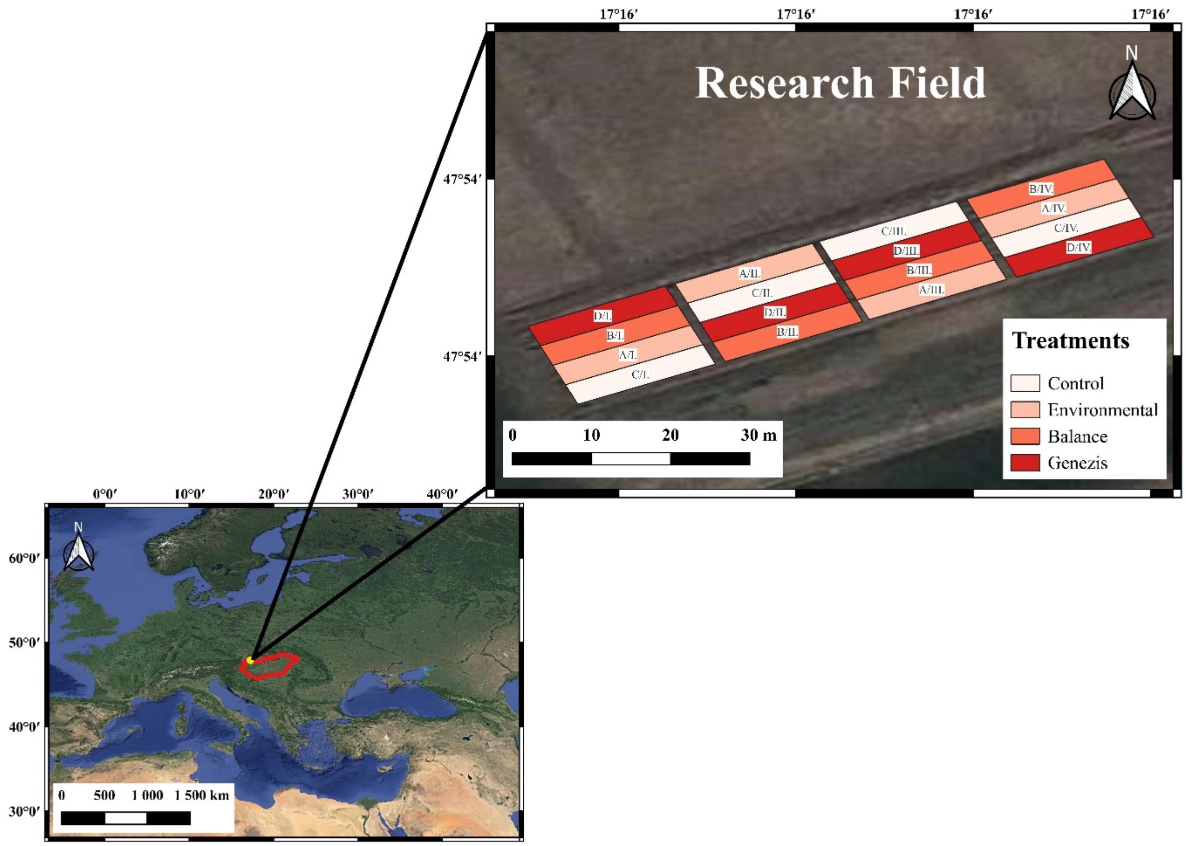

Figure 1. Location and arrangement of the experiment plots in the northwestern part of Hungary, Europe. The small-scale field trial included four treatments (Control, Environmental, Balance and Genezis) and four replications of each treatment.

The field experiment was conducted in a randomized block design with four replicates and four treatment levels, each differing fertilizer application rate (Figure 1). The size of the experimental plot was 4.2 × 22.0 m. The plots were sown with winter wheat, and the green crop was rapeseed (Brassica napus L.).

Winter wheat was sown on October 25 in both years. The seeds were sown in rows with a space of 12cm. The seeding rate was set at 4.5 million seeds per hectare. Fertilization was carried out in two parts, with sowing on October 25 for 2021 and 2022 and again on March 1 for 2022 and 2023. The applied active nitrogen substance was consistent at 135 kg/ha in different treatments (Environmental-135.3 kg/ha, Balance-135.1 kg/ha, Genezis-135 kg/ha). The active phosphorus substance was in Environmental 77.5 kg/ha, Balance 91 kg/ha, and Genezis 75 kg/ha. In the Genezis treatment, 45 kg/ha potassium was too. The harvesting was meticulously executed, involving the separate harvesting of the yield from a designated section of each plot, measuring 2.4 meters by 22.0 meters, using a Sampo SR2010 plot combine, a reliable and widely used combine harvester in agricultural research.

Data collection

Image acquisition were on six different dates from April to the end of June 2022 and 2023, aligning with Feekes growth stages from 5 to 11 (Large et al., 1954). Data collection employed two platforms: the GreenSeeker (NTech Industries, Trimble, Sunnyvale, California, USA) and the MicaSense RedEdge-MX Dual Camera System (MicaSense Inc., Seattle, Washington, USA) mounted on a DJI Matrice 210 V2 drone (Da-Jing Innovation, Nanshan, Shenzhen, China).

Ground-level measurements were conducted using the GreenSeeker Model HCS-250, a manual active optical sensor. The Normalized Difference Vegetation Index (NDVI) readings from the GreenSeeker were collected at three predefined GPS coordinates for each plot. According to Zhitao et al. (2014) study, the sensor was held at approximately 60 cm above the canopy to accurately represent NDVI values for a 0.5 m² area. According to the methodology by Wang et al. (2019), these measurements were performed three times per plot, with each instance comprising an average of ten NDVI readings.

The image acquisition were April 12, April 28, May 12, May 24, June 7, and June 21 in 2022. The exact schedule was maintained for 2023, although starting from the third session, there was one- or two-days derogation between measurements date due to the rainy weather conditions. Each drone flight lasted between 2 and 3 minutes, the images captured consistently between 11:30 and 12:00 to maintain uniform environmental conditions according to Zhitao et al. (2014). The flight altitude was set on 40 meters, with 2.9 cm per pixel ground resolution.

The flight paths were planned with a 70% overlap both frontally and laterally. During each session, 48 triggers in ten spectral bands were activated, resulting in 480 multispectral images per flight. A calibration panel was photographed before and after each flight session to control for lighting variations at different times of the day (An et al., 2016).

Before the first mission, four ground control points (GCPs) were established on the experimental site to support precise geo-referencing. The coordinates of these GCPs were determined using a South S660N GPS RTK Receiver (South Surveying & Mapping Instrument Co., Ltd., Beijing, China).

Data and statistical analysis

The raw images underwent a meticulous process in Agisoft Metashape Professional (version 2.0.1) to create ortho-mosaic images. This software's standard workflow, with minor adjustments in quality settings, was meticulously followed. The resulting ortho-mosaic images, saved in *.tiff format using the WGS84 coordinate system, boasted a defined pixel size of 2 × 2 cm, ensuring precision in our data analysis.

QuantumGIS (version 3.22), an open-source GIS software, was used for further data analysis. The first step is calculating NDVI values by the red and near-infrared (NIR) bands according to the following equation (1):

$$NDVI=\frac{(NIR-Red)}{(NIR+Red)} \quad (1)$$

where:

NIR = near-infrared wavelength

Red = red wavelength

The statistical analyses were conducted with utmost thoroughness using R statistical software, with a specific focus on the 'rcompanion' package (RCore, 2020). This comprehensive approach ensured the robustness and reliability of our results, instilling confidence in the validity of our findings.

In the first step (1), descriptive statistics were used to analyse the NDVI values derived from the data of two sensors concerning treatments and six measuring times.

In the second step (2), NDVI values derived from the MicaSense multispectral camera and GreenSeeker data were compared using a two-sample t-test, assuming equal or unequal variances determined by the results of Levene's test. Meanwhile, regression analysis was performed to reveal the relationship between two sensors on different treatments.

In the third step (3), Tukey's Honestly Significant Difference (HSD) test for two-way analysis of variance (ANOVA) was employed to identify differences in NDVI values between treatments as measured by the sensors. All statistical analyses were conducted at a significance level of $p \leq 0.05$.
In the fourth step (4), based on Pearson correlation analysis was determined the correlations (at significance levels of $p \leq 0.05$, $p \leq 0.01$, and $p \leq 0.001$) between NDVI values produced from GreenSeeker (GS) and MicaSense (MS) data and winter wheat yield across different sowing dates. This analysis aimed to identify the most suitable date for yield predictions.
Finally (5), the coefficient of determination (R^2) was calculated to assess the relationship between NDVI values obtained from GreenSeeker measurements and MicaSense camera data and winter wheat yield. This analysis used linear, exponential, and quadratic equations at significance levels of $p \leq 0.05$, $p \leq 0.01$, and $p \leq 0.001$.

Results

Comparative analysis of treatments based on NDVI

Figure 2 shows the mean NDVI values calculated from GreenSeeker and MicaSense data. Measurements were conducted six times during the 2021-22 (Figure 2a,b) and 2022-23 (Figure 2c,d) periods for all four treatments, with the average NDVI value (n=12) of each treatment. Based on the results of all four treatments, the NDVI values measured with the GreenSeeker were consistently lower than those obtained from the multispectral camera data at all measurement times for both years. Notably, a significant difference was observed between the Control and the other treatments (Environmental, Balance, and Genesis) in the NDVI values measured by the GreenSeeker in both years. This pattern was also proper for the NDVI values derived from the MicaSense camera data, except for May 12, where no significant differences were found between the Control and the Environmental, Balance, and Genesis treatments for 2021-22 and 2022-23.

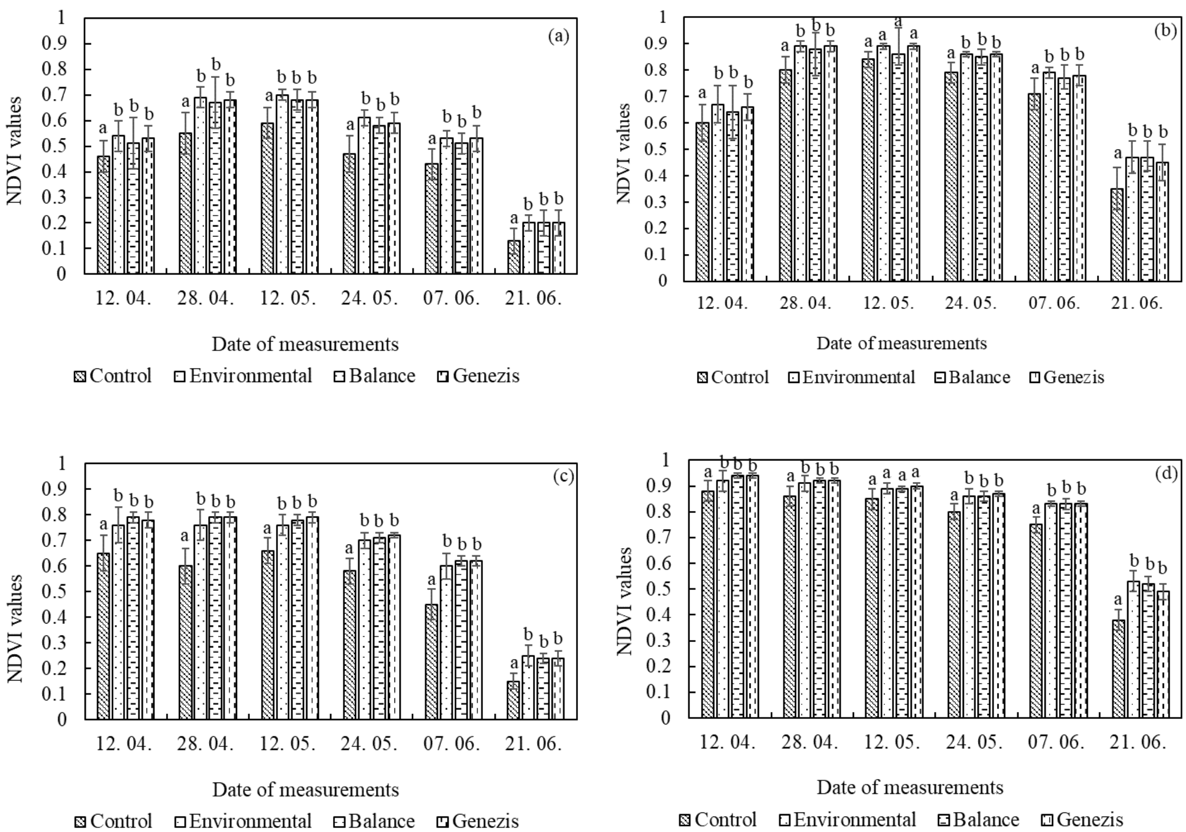

Figure 2. NDVI values were calculated from GreenSeeker and MicaSense camera data for the 2021-22 and 2022-23 periods. The average NDVI values for the four treatments (Control, Environmental, Balance, and Genesis) are depicted at six different measurement times. (a) GreenSeeker in 2021-22; (b) MicaSense in 2021-22; (c) GreenSeeker in 2022-23; (d) MicaSense in 2023-23. Within each year and sensor, treatments that differ significantly at p ≤ 0.05 are indicated with a different letter.

Comparison of different treatment of yields

According to the yield of winter wheat depicted in Figure 3a, the yield obtained from the Control parcel showed a significant difference (p≤0.05) compared to the yields of other treatments (Environmental, Balance, and Genesis) during both growing seasons. However, comparing the Environmental, Balance, and Genesis treatments, no significant differences were observed either in the 2021-22 and 2022-23 seasons. A significant difference (p≤0.05) was observed between the yields of 2021-22 and 2022-23 in all treatments, as shown in Figure 3b. More favourable weather conditions were experienced in 2022-23, contributing to the higher yields of winter wheat.

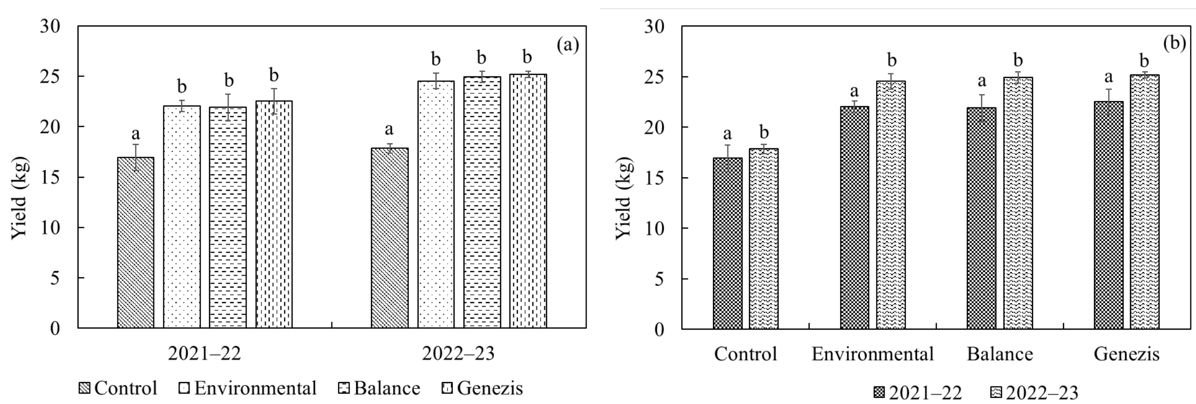

Figure 3. The mean yield of winter wheat per treatment in 2021-22 and 2022-23. (a) A year-by-year comparison of the yields for each treatment (Control, Environmental, Balance, Genesis), (b) the yields for the four treatments (Control, Environmental, Balance, Genesis) were compared between the 2021-22 and 2022-23 growing seasons. a–significant difference (p≤0.05), b–no significant difference (p≥0.05)

Relationships between NDVI measurements and winter wheat yields

Table 1 demonstrated the Pearson correlation analysis outcomes between NDVI values derived from the GreenSeeker handheld sensor and MicaSense multispectral cameras and winter wheat yield. As seen for the GreenSeeker NDVI values, a significant correlation could be found between the NDVI values and the yield for all treatments except the Control treatment. In this case, the range of Pearson correlation coefficients was “weak positive” or “moderately positive” (212 DAS), except for 240 DAS. The correlation coefficients ranged from “strong positive” to “very strong positive” for the Environmental, Balance, and Genesis treatments. Regarding the MicaSense camera data, a declining correlation trend was observed between the NDVI values and yield from 170 DAS to 200 DAS. However, the Genesis treatment reached a “very strong positive” correlation at 186 DAS. “Very weak negative” correlation values were found at 200 DAS for the MicaSense data. Each treatment's most vital "Pearson r" values occurred on various dates. However, the strongest correlations between NDVI values and yield showed at 170 DAS and 226 DAS for both sensors. The NDVI values derived from the MicaSense camera data are insufficiently (“very weak negative”) predictive of winter wheat yield in the case of Environmental treatment. Based on Table 1, the GreenSeeker sensor allows for much more accurate and reliable yield prediction at different measurement times.

Table 1. The range of Pearson Correlation coefficients - based on NDVI values calculated from data obtained using the MicaSense (MS) multispectral camera and GreenSeeker (GS) - is illustrated using different colours to indicate the strength of the correlation. The correlation coefficients were calculated at each sampling date (n = 8) at every sampling time.

Significance level: * p ≤ 0.05, ** p ≤ 0.01, *** p ≤ 0.001.

	Days After Sowing (DAS)					
Treatments	**170**	**186**	**200**	**212**	**226**	**240**
Control (GS)						**
Control (MS)						***
Environmental (GS)	**	*	**	**	**	
Environmental (MS)	**				**	
Balance (GS)	*		**	**	***	*
Balance (MS)	**				**	**
Genezis (GS)	**	*	**	**	**	*
Genezis (MS)	**	***			*	

0.80 to 1.00	Very strong positive
0.60 to 0.79	Strong positive
0.40 to 0.59	Moderate positive
0.20 to 0.39	Weak positive
0.00 to 0.19	Very weak positive
-0.19 to -0.01	Very weak negative

To evaluate the relationship between NDVI values and winter wheat yield, three different equations ((exponential (E), linear (L), and quadratic (Q)) were used from 170 DAS to 240 DAS, as shown in Table 2. The results of analyses included the coefficients of determination and ANOVA F-test. The regression analyses revealed no significant differences among the three equations for GreenSeeker and MicaSense cameras. The highest coefficient of determination (R^2) between NDVI values and winter wheat yield was determined in the Control treatment at 240 DAS for both sensors. On the contrary, based on Table 2, the highest R^2 values showed the Environmental, Balance, and Genesis treatments at 170 DAS and 226 DAS. The NDVI values calculated from multispectral camera data reached the lowest R^2 values between 200 DAS and 212 DAS. The most accurate predictions were obtained in treated plots using the GreenSeeker at 226 DAS (R^2 = 0.76–0.91). Similarly, the MicaSense camera provided accurate predictions in treated plots at 226 DAS (R^2 = 0.69–0.86). However, the MicaSense camera's R^2 values were more variable, with the highest values found at 186 DAS (R^2 = 0.88) and 240 DAS (R^2 = 0.89–0.90).

Comparative analysis of data from the two sensors indicates that GreenSeeker measurements demonstrated higher reliability and relevance for yield prediction for all treatments, from stem extension to ripening. As presented in Table 2, the minimal differences between the various equations suggest that all three models are equally effective for predicting wheat yield at 226 DAS for both sensors.

Table 2. The coefficient of determination (R^2) between NDVI values derived from GreenSeeker measurements and calculations of MicaSense camera data and winter wheat yield for the Control, Environmental, Balance, and Genesis treatments was assessed using three distinct models (exponential (E), linear (L), quadratic(Q)).

		DAS	170	186	200	212	226	240
GreenSeeker	**Control**	**E[1]**	0.09	0.06	0.12	0.25	0.13	0.70**
		L[2]	0.09	0.05	0.11	0.23	0.11	0.70**
		Q[3]	0.09	0.09	0.16	0.47	0.61	0.86**
	Environmental	**E[1]**	0.72**	0.52*	0.78**	0.81**	0.76**	0.44
		L[2]	0.73**	0.53*	0.89**	0.80**	0.77**	0.43
		Q[3]	0.74*	0.78*	0.82*	0.81*	0.82*	0.45
	Balance	**E[1]**	0.81*	0.42	0.68*	0.74**	0.90***	0.68*
		L[2]	0.70**	0.44	0.70**	0.77**	0.91***	0.66**
		Q[3]	0.68*	0.75*	0.73*	0.77*	0.91**	0.84**
	Genezis	**E[1]**	0.74**	0.67*	0.77**	0.78**	0.78**	0.53*
		L[2]	0.75**	0.80*	0.78**	0.79**	0.79**	0.53*
		Q[3]	0.76*	0.68	0.85**	0.80*	0.79*	0.57
MicaSense	**Control**	**E[1]**	0.13	0.32	0.00	0.07	0.50	0.90***
		L[2]	0.12	0.09	0.00	0.06	0.48	0.89***
		Q[3]	0.23	0.12	0.12	0.25	0.70	0.89**
	Environmental	**E[1]**	0.74**	0.19	0.08	0.04	0.79**	0.37
		L[2]	0.75**	0.20	0.01	0.04	0.79**	0.35
		Q[3]	0.82*	0.21	0.01	0.30	0.86**	0.38
	Balance	**E[1]**	0.71**	0.28	0.07	0.28	0.79**	0.71**
		L[2]	0.72**	0.29	0.08	0.28	0.78**	0.87*
		Q[3]	0.80*	0.88**	0.20	0.28	0.79**	0.69
	Genezis	**E[1]**	0.78*	0.88***	0.15	0.37	0.69*	0.47
		L[2]	0.79**	0.88***	0.15	0.37	0,69*	0.47
		Q[3]	0.86**	0.88***	0.15	0.37	0.69*	0.48

[1] Represented the exponential equation, and formula $y_{yield} = a \times e^{b \times xNDVI}$ was used; [2] represented the linear equation, and formula $y_{yield} = a \times x_{NDVI} + b$ was used; [3] represented the quadratic equation, and formula $y_{yield} = a \times x_{NDVI}^2 + b \times x_{NDVI} + c$ was used, a and b are regression parameters in each equation. * Significance level at the $p \leq 0.05$ level, ** significance level at the $p \leq 0.01$ level, *** significance level at the $p \leq 0.001$ level.

Discussion

This study examined the NDVI values derived from two sensors: the GreenSeeker handheld crop sensor and the MicaSense multispectral camera. These values were compared to different phenological stages of winter wheat in the 2021-22 and 2022-23 growing seasons. The study's findings demonstrated through two-year small-scale field trials revealed that NDVI readings could be effectively used to predict the in-season yield of winter wheat.

Based on our result (Figure 2), measurements by GreenSeeker had much lower NDVI values than the MicaSense camera data, regardless of the year or time of the measurements. These findings were confirmed also in other experiments on wheat in Australia (Duan et al., 2017) or in paddy rice in China (Jiang et al., 2020; Nakano et al., 2023).

The NDVI values calculated from the GreenSeeker and MicaSense camera data showed a significant difference (Figure 2) between the Control and other treatments (Environmental, Balance, Genezis) at different measurement times. However, no significant differences were observed between the Environmental, Balance, and Genesis treatments over the period considered because all treatments received the same amount of nitrogen except for the Control treatment. Numerous studies have shown that nitrogen could affect the NDVI values of wheat (Li et al., 2009; Bijay-Singh et al., 2011; Kizilgeci et al., 2021).

Table 1 summarizes Pearson's correlation coefficients as a measure of the strength of the association between NDVI values measured by GreenSeeker (GS) and calculated from the MicaSense (MS) camera data. Based on our result, 170 DAS (Feekes 5) and 226 DAS (Feekes 10.5) were the highest relationship between GS NDVI and MS NDVI and winter wheat yield. Higher values were observed for the GS NDVI in both measurements compared to the two sensors. Based on Walsh et al. (2023) study, UAV NDVI values showed a higher correlation coefficient with yield in spring wheat at Feekes 5 and 10, with r=0.66 and r=0.52 than GS NDVI

r=0.56 and r=0.34, respectively. Hassan et al. (2019) and Duan et al. (2017) found high correlation coefficients between GreenSeeker and UAV NDVI. Goodwin et al. (2018) and Kiran et al. (2015) reported a good correlation between flowering and the mid-grain filling period based on NDVI. In addition to wheat, the correlation between NDVI values obtained from GreenSeeker or multispectral camera data has also been examined for crops such as cabbage (Ji et al., 2017) or rice (Perros et al., 2021; Nakano et al., 2023).
To determine the relationship between the yield of winter wheat and NDVI values more effectively in-season, linear and non-linear regression analyses were used with three (exponential, linear and quadratic) equations. Based on Table 2, our study showed that the linear model could explain the relationship between the in-season yield of winter wheat and NDVI values. Similar findings were reported in wheat by Benedetti et al. (1993). Several studies confirmed that a linear model could be more suitable for predicting the yield of crops (Groten, 1993; Mkhabela et al., 2000; Mkhabela et al., 2005; Almeida-Ñauñay, 2023). According to Holzapfel et al. (2009), exponential and linear were suitable for predicting the excepted yield of canola in Canada, while Hayes et al. (1996) reported that the quadratic model could explain the relationship between the yield of maize and NDVI values. Similar in-season yield prediction examinations were also performed on cabbage by Ji et al. (2017), on rice by Son et al. (2014), and on millet by Rasmusen (1992).
Our results demonstrate the GreenSeeker handheld optical sensor's superiority in providing readily available, reliable, and relevant NDVI values at all measurement times. This reliability extends to the Pearson correlation result and the in-season yield prediction of winter wheat. In contrast, the MicaSense camera, as Bang et al. (2017) reveal, requires time-consuming calibration and image processing service to generate an orthomosaic NDVI map, necessitating additional data extraction expertise.

Conclusions

This research aimed to examine one of the most popular and frequently used vegetation indexes: NDVI. During the comparison of the GreenSeeker and MicaSense sensors based on NDVI values, it was demonstrated that more reliable results can be achieved with the GreenSeeker handheld crop sensor when examining winter wheat in the growing season. The differences in NDVI values could be due to the variations in the wavelengths used by the MicaSense and GreenSeeker sensors. In our two-year small-scale field trial, the Pearson correlation and regression analyses showed that the NDVI values calculated from MicaSense RedEdge-MX Dual Camera System data and GreenSeeker optical sensor at 226 DAS were significantly associated with the winter wheat yield. However, it is worth considering several more years of data to determine the appropriate in-season yield forecast model.

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