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UAV-Based Phenotyping: A Non-Destructive Approach to Studying Wheat Growth Patterns for Crop Improvement and Breeding Programs

Sabahat Zahra [1,2,*], Henry Ruiz [3], Jinha Jung [4] and Tyler Adams [1]

[1] Molecular & Environmental Plant Sciences, Texas A&M University, College Station, TX 77843, USA
[2] Department of Soil and Crop Sciences, Texas A&M University, College Station, TX 77843, USA
[3] Texas A&M AgriLife Research and Extension Center, Weslaco, TX 78596, USA
[4] Lyles School of Civil and Construction Engineering, Purdue University, West Lafayette, IN 47907, USA
* Correspondence: zahra@tamu.edu

Abstract: Rising food demands require new techniques to achieve higher genetic gains for crop production, especially in regions where climate can negatively affect agriculture. Wheat is a staple crop that often encounters this challenge, and ideotype breeding with optimized canopy traits for grain yield, such as determinate tillering, synchronized flowering, and stay-green (SG), can potentially improve yield under terminal drought conditions. Among these traits, SG has emerged as a key factor for improving grain quality and yield by prolonging photosynthetic activity during reproductive stages. This study aims to highlight the importance of growth dynamics in a wheat mapping population by using multispectral images obtained from uncrewed aerial vehicles as a high-throughput phenotyping technique to assess the effectiveness of using such images for determining correlations between vegetation indices and grain yield, particularly regarding the SG trait. Results show that the determinate group exhibited a positive correlation between NDVI and grain yield, indicating the effectiveness of these traits in yield improvement. In contrast, the indeterminate group, characterized by excessive vegetative growth, showed no significant NDVI–grain yield relationship, suggesting that NDVI values in this group were influenced by sterile tillers rather than contributing to yield. These findings provide valuable insights for crop breeders by offering a non-destructive approach to enhancing genetic gains through the improved selection of resilient wheat genotypes.

Keywords: remote sensing; UAV-based phenotyping; multispectral imagery; wheat morphology; stay-green; VI data analytics; modern wheat model

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1. Introduction

Modern agriculture faces substantial productivity threats due to climate change, land and water availability, and—most importantly—increasing demand [1]. The recent pandemic has highlighted the vulnerability of developing nations to these problems, as inadequate global planning has led to further strains on production in regions already suffering from heatwaves and droughts [2]. Despite numerous advances in recent years, there persists a need to optimize crop production technologies and genotypic selection to achieve maximum genetic gain in these growing environments [3]. Thorough, targeted initiatives and innovative approaches are necessary to achieve greater food security in these regions. This means utilizing the modern strengths of research and development (R&D) institutions to improve the selection, adoption, and evaluation of advanced technologies addressing crop performance.

High-throughput remote sensing, employing platforms such as unmanned aerial vehicles (UAVs) and satellite imagery, has become increasingly adopted for a wide range of vegetation-related applications, including the study of crop phenology, analysis of biophysical characteristics, and non-destructive examination of root systems and their connection to the surrounding environment [4,5]. One of the most popular tools, LiDAR (light detection and ranging), facilitates the laser scanning of trees and crop plants to create highly accurate 3D structural models [6]. This advanced technology swiftly assesses the above-ground plant structure, revealing crucial information such as plant height and physiological arrangement, as well as metrics related to volume and density [7]. These parameters directly reflect various agronomic characteristics (particularly those related to crop yield and biomass), offering valuable insights into the interplay between light and vegetative resources, especially concerning plant tillering and branching patterns [8]. UAVs equipped with high temporal and spatial resolution multispectral or hyperspectral imaging capabilities can assess crop health and track growth stages throughout the entire growth period [9]. Similarly, the ground-penetrating radar (GPR) scanning system provides a non-destructive method for analyzing below-ground plant systems, offering measurements of root biomass, length, and density [10].

Bread wheat (*Triticum aestivum*) displays various forms of morphological traits under different environmental and natural selection processes [11], with the optimum crop performance being determined by the collective effects of the morphological, physiological, and genetic features of a plant [12]. The earlier model wheat plant (ideotype) was defined by features such as determinate and synchronized growth habit, short and strong stem, high leaf area index, and harvest index [13], with periodic shifts in climatic conditions also showing additional shifts in plant characteristics, mainly led by thermal requirements for phenological stages [14]. By contrast, the modern concept of wheat ideotype addresses avoidance and tolerance in response to abiotic stresses, with flexibility for phenology, improved photosynthesis efficiency, and delayed senescence [15]. Thus, the concept of the wheat plant model is continuously evolving.

Environmental conditions play a major role in regulating canopy structure development, affecting light harvesting potential, flowering synchronicity, and seed setting, which ultimately determines a plant's reproductive success [16]. In wheat, synchronized tiller growth ensures uniform development and maturation, a crucial element for optimizing resource use and enhancing grain production. This process is influenced both by genetic factors and environmental conditions, such as temperature and photoperiod [17,18], with this synchronization simplifying the harvesting process and reducing yield losses. Although a synchronized growth pattern offers significant advantages, it is essential to consider the potential trade-offs. For instance, although this trait promotes uniformity, its correlation with improved grain yield and quality needs further investigation. Thus, additional desirable traits to achieve synchrony before the onset of reproductive stages, such as the early termination of vegetative growth, need to be integrated with prolonged photosynthetic activity and delayed leaf senescence to maintain grain yield.

To effectively identify high-yield plants suitable for specific environments, connecting genotype (genetic makeup) and phenotype (observable traits) is crucial [19]. The structural and physiological characteristics of plants have been observed to directly influence their ability to capture resources in short-duration cereals and other species [20]. Alterations to these traits have demonstrated enhanced light penetration, carbon assimilation, and significant effects on overall crop yield [21]; however, our understanding of the genetics influencing growth, yield, and stress adaptation has been limited by the absence of advanced phenotyping tools—methods that enable high-throughput, precise, and non-invasive assessments of plant traits across multiple environmental conditions. Traditional methods, reliant on visual assessments, introduce biases and inaccuracies that hinder a comprehensive analysis of these traits [22]. Although advanced phenotyping techniques, such as the use of multispectral images captured by UAVs, provide a remote, non-destructive means to measure plant systems with a high degree of accuracy and resolution across varying environmental conditions, they still face limitations, particularly regarding temporal resolution. Such limitations have proven especially challenging for studying traits such as stay-green (SG), which is critical for improving drought resilience. Despite its significance, the inability to monitor phenotypic traits throughout all growth stages has hindered a full understanding and optimization of SG's impact on crop performance.

Given the power of robust and efficient phenotyping techniques, a determinate-tillered genotype with the SG trait holds great promise as a valuable selection target in crop improvement programs, especially in the context of environmental stresses like drought, as a longer photosynthesis duration during reproductive stages offers higher grain yield due to more photosynthetic tissue availability for further assimilation. Under terminal drought conditions, the SG genotypes have shown improved grain yield compared to non-SG types [23]. Even so, while research on drought in wheat has been extensive, understanding the SG type has progressed slowly. In previous studies, quantitative trait loci (QTLs) for plant architectural traits such as plant height and root number were found to be correlated with QTLs for SG traits [24]. Various studies have also identified differing numbers of genetic markers linked to SG traits in wheat, with the discrepancies being linked to inefficient phenotyping techniques [25]. Consequently, the challenge of comparing genetic maps in SG lines has persistently hindered this research [26].

The objective of this case study is to employ multispectral imagery acquired through UAVs to monitor vegetation index (VI) patterns throughout the entire growth season, with a particular focus on reproductive stages. This method provides non-destructive, high-resolution phenotyping for monitoring key traits like photosynthetic duration in SG genotypes, which have shown higher grain yield under drought conditions due to extended photosynthetic activity during reproductive stages. By applying this approach, we expect the VIs obtained from this imagery to effectively identify plants in a mapping population that have extended photosynthesis activity during the flowering and post-flowering stages, thereby providing a viable, precise, and scalable method of identifying SG traits in wheat, further bridging the existing gaps in genetic–phenotypic linkage studies.

2. Materials and Methods

2.1. Plant Material and Study Site

The study was conducted in 2016 at the Texas A&M AgriLife Research and Extension Center in Nueces County, Texas, on the border of the Gulf Coast and coastal saline prairies (at an elevation of approximately 16 m) (Figure 1). The region is humid subtropical (Cfa)—receiving, on average, 34–38 inches of rainfall annually (NOAA)—with soil composition consisting primarily of Victoria (VcA) clay (43.8%), with Orelia (Of) fine sandy loam (4.7%), Raymondville (CcA) complex (4.5%), and Galveston/Mustang (Gm) fine sands (3%) also being notable components (USDA-NRCS). The experiment was carried out on a field containing a wheat mapping population consisting of 180 recombinant inbred lines (RILS) developed from a cross between the heat-tolerant 'Halberd' and the moderately heat-susceptible 'Len' cultivars, planted in two replications across an alpha lattice layout, creating a total of 364 individual plots. Figure 2 illustrates the climatic conditions at the study site, highlighting a pattern of progressively increasing precipitation throughout the growing period.

Figure 1. Site location at the Texas A&M AgriLife Research and extension center, near Corpus Christi in Nueces County, Texas (27.780642, −97.562110).

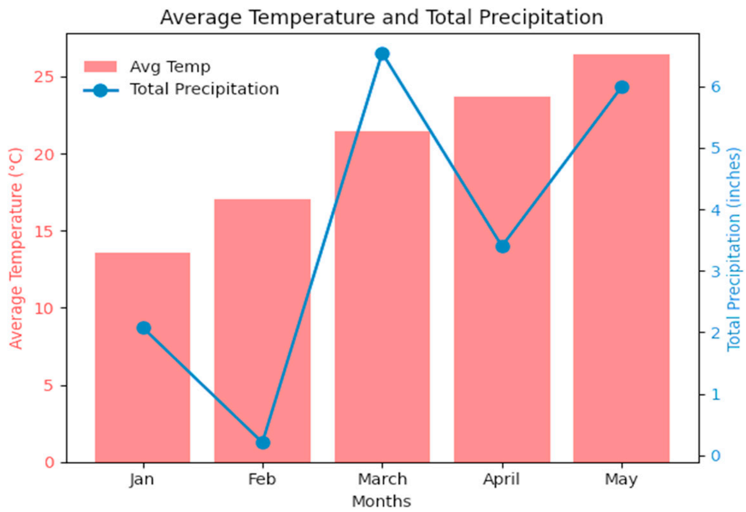

Figure 2. Temperature and precipitation pattern throughout the growing period.

2.2. Field Trait Measurements

Phenological stage: To define the phenological stage, the number of days to heading (50% of plants exhibiting heading out), flowering (50% exhibiting pollinated spikes), and physiological maturity (50% of spikes in a plot showing diminished greenness) were recorded using the method described by Zadocks et al. (1974) [27,28].

Tillering and flowering patterns: To monitor plant growth, data were recorded for tiller height within the plant as well as for the phase of tiller formation relevant to the vegetative and reproductive stage. The tiller length distribution for each RIL within a specific area was compared following the method used by Jia et al., (2015) [29]. Utilizing visual scoring, plants were categorized into two groups based on their vegetative and reproductive growth completion. Determinate plants displayed consistent and synchronized flowering and tillering. In contrast, indeterminate plants exhibited non-uniform tillering and flowering (Figures 3A and 4). In our study, SG types were only compared with non-SG within the determinate group. This was the crucial step, as these indeterminate plants, although exhibiting prolonged high NDVI values due to extensive vegetative growth, do not contribute to increased yield due to their lack of photosynthetic competence compared to determinate types (Figure 3B).

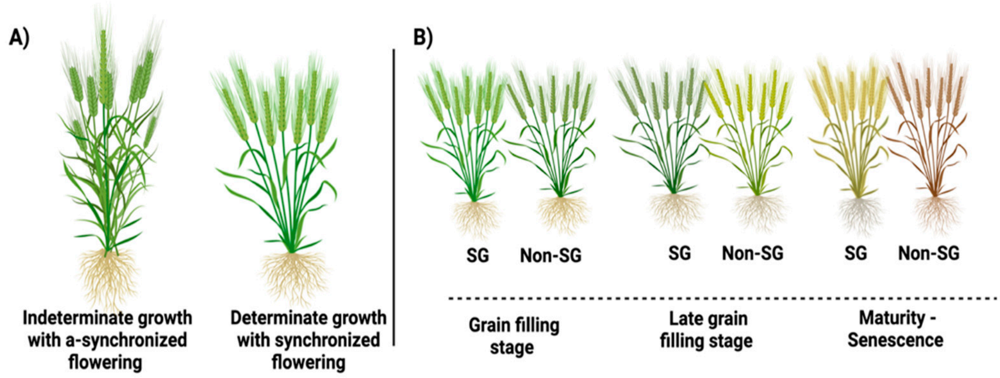

Figure 3. (**A**). Indeterminate plants display non-uniform tillers and asynchronized flowering, whereas determinate plants show uniform tillers and flowering. (**B**). Stay-green (SG) plants have a longer grain-filling period and delayed senescence compared to Non-SG.

Figure 4. Closeup UAV RGB images showing non-uniform growth patterns among 9 plots.

Stay-green phenotype: Among the determinate group, SG lines were identified based on their flowering time, rate and duration of leaf senescence, and physiological maturity. These lines demonstrated a delayed or slower onset of leaf senescence, resulting in a greener appearance and prolonged photosynthetic activity (validated through higher grain yield) compared to non-SG plants (Figure 3B).

2.3. Image Acquisition and Processing

Multispectral fine spatial resolution RGB and NIR images were acquired throughout the growing period using a UAV flying at an altitude of 30 m (Figure 5). In total, eight separate images of the entire study area were captured, one for each period beginning with early vegetation and ending at maturity. For the RGB data collection, the Canon S110 camera was integrated with the 3DR Iris + UAV platform. For multispectral data collection, the TetraCam ADC Snap sensor (Tetracam Inc. Chatsworth, CA, USA) was integrated into the 3DR X8 + UAV platform. We used Mission Planner software to design autonomous flights. The multispectral sensor used in the study ensured motion blur-free image capture, as the sensor has an electronic global snap shutter. Sensor specifications can be found in Table 1. The multispectral sensor captured false-color images in the green, red, and NIR regions equivalent to Landsat Thematic Mapper bands TM2 (green), TM3 (red), and TM4 (NIR), respectively. Additionally, color images were obtained using bands in the red, green, and blue regions of the visible spectrum. We further processed raw images collected by RGB and multispectral sensors using Agisoft Metashape 1.3 (https://agisoft.com) to generate geospatial data products such as orthomosaic images and digital surface models (DSMs). During the structure-from-motion (SfM) process, we utilized five ground control points (GCPs) to ensure good geometric alignments among multi-temporal flights. The GCPs were surveyed using a survey-grade GPS.

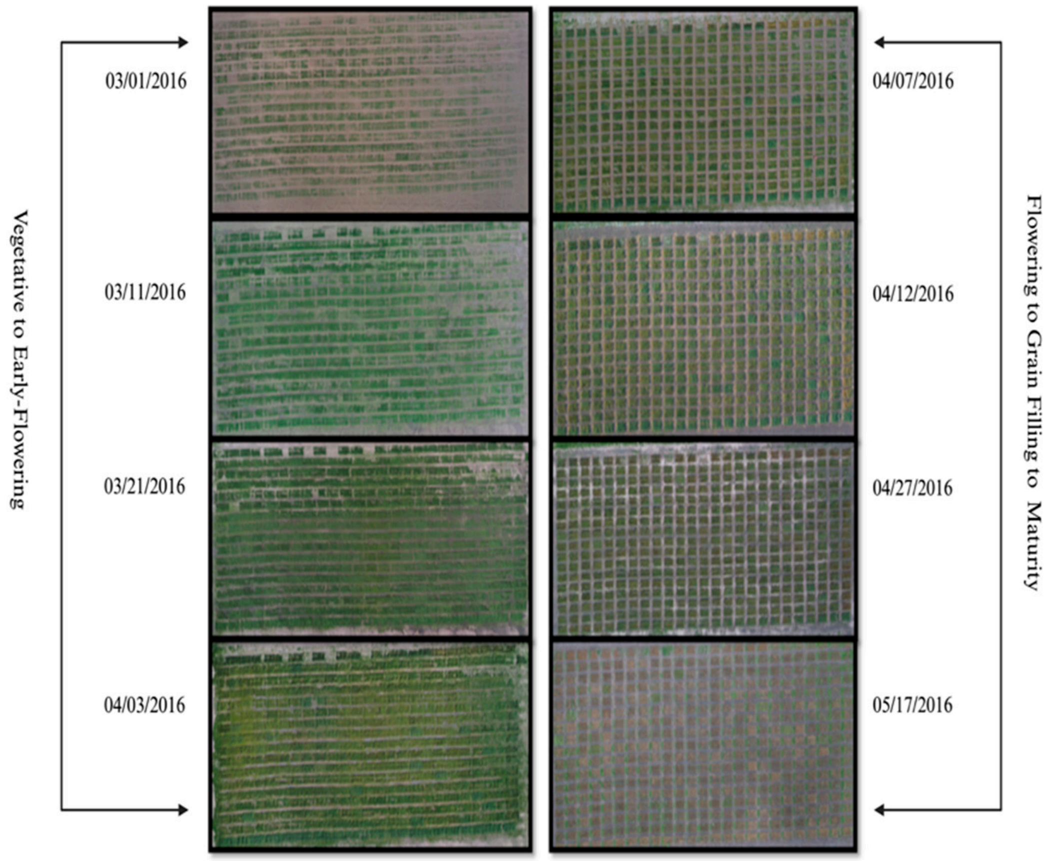

Figure 5. RGB images taken from vegetative to post-flowering stages.

Table 1. Ground resolution and view of field for images gathered at various altitudes above ground (**a**), sensor and lens parameters (**b**).

	Object Distance (Altitude above Ground Level)	Grand Resolution (mm per Pixel)
(a)	122 m	72.36
	213.4 m	126.54
	365.8 m	216.91
(b)	Sensor Dimention	6.59 × 4.9 mm
	Pixel Size	5 micron
	Camera Lens Focal Length	8.43 mm

A radiometric correction process was performed to convert the recorded digital numbers (DNs) of the orthomosaic images into reflectance values. In this case, four calibration targets with known reflectivity (3, 12, 33, and 56%) were placed within the flight path of a UAV platform. During image acquisition, a laboratory spectrophotometer (Perkin-Elmer Lambda 1050) was used to calculate the reflectance of the calibration targets and selected vegetation and soil samples. The ASD field spectrophotometer was calibrated using a Spectralon reflectance standard.

Radiometric calibration was performed using ENVI 5.3. software to extract reflectance values from the field plots, enabling the derivation of biophysical vegetation parameters (NDVI and GNDVI). The broadband spectral reflectance data from the UAV images were utilized to calculate vegetation indices for each plot, representing individual RILs (Figure 6).

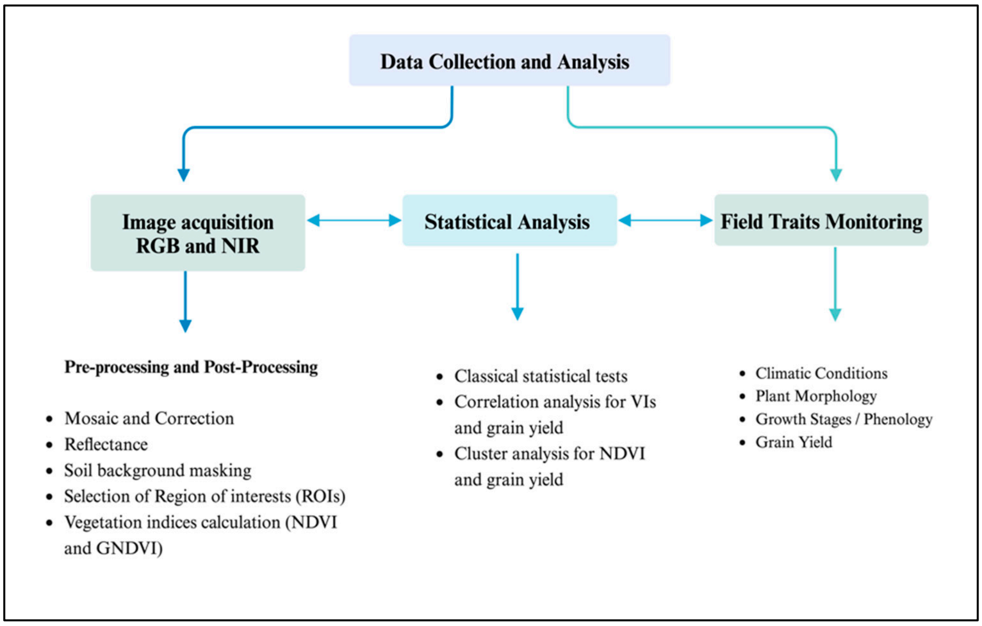

Figure 6. Summarized research protocol for data acquisition, processing, and analysis.

3. Results and Analysis

3.1. Growth and Flowering Characteristics—Field Observations

Table 2 presents the distribution of RILs categorized as determinate or indeterminate based on tiller length range and illustrates the proportion of vegetative and reproductive phases. Determinate lines exhibited synchronized flowering time and consistent tiller distribution, while indeterminate lines displayed greater variation in both features. Based on the refined selection criteria for SG types mentioned in the Methods Section and consideration for plant ideotype and the timing of greenness loss in the post-flowering stage, 14 plots were identified as SG types.

Table 2. Distribution of RILs by flowering time (50% head emergence at anthesis after planting) and tiller distribution (cm).

	No of RILS	Flowering Time (Days)	Tiller Length (cm)
Determinate	88	65–70	12–15
Indeterminate	94	70–75	25–35

The tillering pattern and SG trait in wheat are important determinants of yield, particularly under stress conditions, which significantly affect the plant's overall biomass and root-to-shoot ratio. The *tin gene* involved in tillering inhibition reduces the number of tillers but promotes root growth and enhanced water uptake. This genotype exhibits traits like slow water use, cool canopy temperature, and sustained green leaf area during the grain-filling stage. Reduced tillering has been found to provide a yield advantage in water-limited environments by optimizing resource allocation, reducing competition among tillers, and increasing both the harvest index and grain yield [30].

In the current study, despite the unfavorable weather conditions at the late reproductive stage, the SG lines were highly tolerant of environmental effects; in particular, lodging resistance was seen under heavy rainfall conditions. Previous studies have reported that cereal plant height is positively linked to lodging [31], whereas increased root-to-shoot ratio, root biomass, root depth, and early stem elongation were reported to be associated with the *tin gene* containing near-isogenic lines [32]. Comprehensive studies on the relationship between above-ground and below-ground plant systems in SG lines for overall plant performance in different environmental conditions need to be conducted by employing high-throughput phenotyping techniques.

Flowering synchrony is a crucial trait for yield optimization and efficient harvesting. Flowering synchronization is regulated by three major genetics systems in wheat—vernalization, photoperiodism, and earliness offer wheat's genetic potential to be fine-tuned by their exploitation [33]. Moreover, this flowering uniformity is particularly important under abiotic stress conditions where crops mature during increasing temperatures following an avoidance mechanism [34]. This strategy helps plants maximize yield by preventing the detrimental effects of frost and heat on reproductive developmental stages. Genetic studies have shown that earlier headings and delayed physiological maturity with prolonged grain-filling periods (SG traits) result in higher grain protein content, while overall grain yield can vary depending on environmental conditions [35]. Flowering synchrony and an extended grain-filling period could be important selection targets in crop breeding programs for improving grain yield and quality.

3.2. Association among Morphological Features Agronomic Traits and Spectral Reflectance

The observed patterns in vegetation indices among different plant groups, categorized by determinate versus indeterminate growth types and SG versus non-SG attributes at specific growth stages (Figure 7), can be linked to the underlying physiological and morphological inherent differences in these groups. During the flowering-to-booting period, the field exhibited the highest overall NDVI values, particularly in determinate plants. The elevation in NDVI values during this stage could be linked to the increased photosynthetic activity and canopy development characteristic of determinate plants during their reproductive phase. Interestingly, the divergence in NDVI patterns between determinate and indeterminate groups was initially subtle at the leaf sheath and flag leaf stages, with determinate types displaying slightly higher values. However, as the growth stages progressed, the distinctions became more pronounced, especially during the heading to flowering stages.

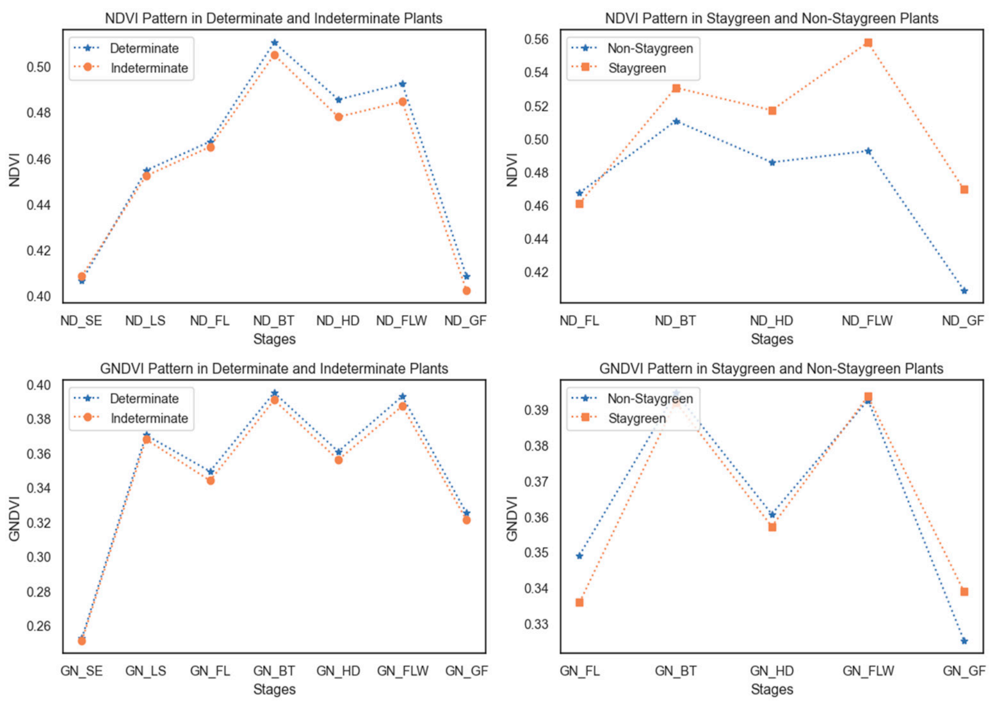

Figure 7. Trends in NDVI and GNDVI within wheat plants exhibiting different growth patterns at growing stages: stem elongation (SE), leaf sheath (LS), flag leaf (FL), booting (BT), heading (HD), flowering (FLW), and grain filling (GF).

These variations likely reflect differences in growth dynamics, canopy structure, and physiological processes between determinate and indeterminate plants. A notable distinction was seen during the early- and late-stage clustering of NDVI and GNDVI for grain yield in both determinate and indeterminate categories (Figure 8). This finding suggests that these indices effectively capture the dynamics associated with senescence and canopy greenness during the critical phase of the plant's life cycle.

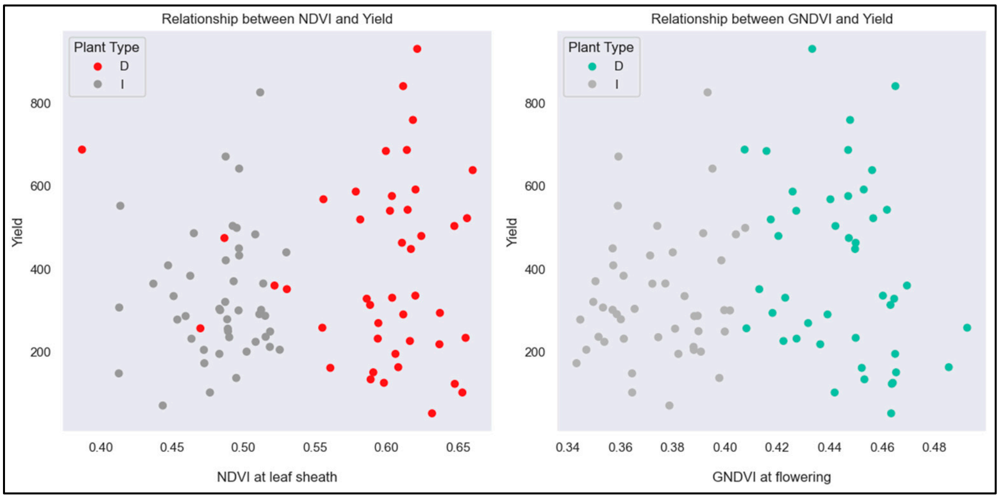

Figure 8. Cluster analysis of NDVI and GNDVI at different growth stages, and their relationship with grain yield (kg/acre) for determinate (D) and indeterminate (I) growth patterns in the overall RILs mapping population.

The violin plot (Figure 9) compares grain yield distributions between determinate and indeterminate plant types. The determinate group shows a wider spread and higher peak densities of around 400–600 kg/acre, suggesting a tendency for higher yields, with the median yield higher than that of the indeterminate group. In contrast, the indeterminate group has a more concentrated distribution, with values centered around 300–500 kg/acre, indicating lower overall yield. The interquartile ranges and medians further illustrate that determinate plants generally outperform indeterminate plants in grain yield.

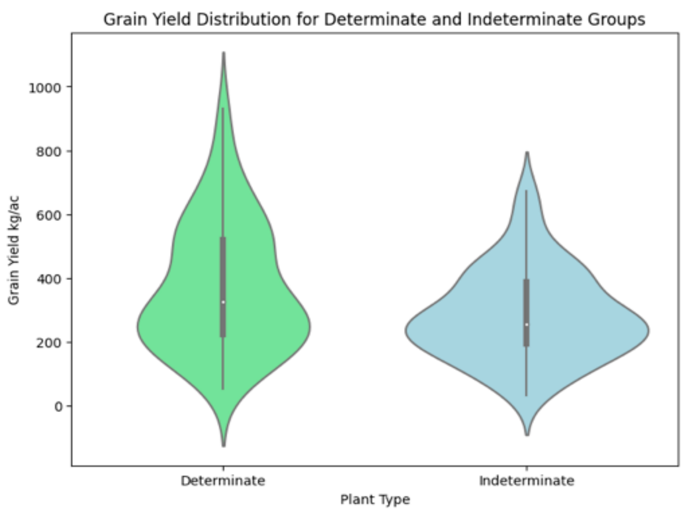

Figure 9. Distribution of grain yield (kg/acre)—Determinate plants with higher grain yield but greater variability and major clustering between 200 and 600 kg/acre; indeterminate plants with major clustering between 200 and 500 kg/acre.

In dense canopies, the red to far-red light (R:FR) ratio has been reported to be lower mainly because of the absorption of R light by leaves and the reflection of FR. This response to light signifies the competition for resources [36]. Consequently, this competition for resources caused by the excessiveness of vegetative growth in major cereal crops could reduce yield, as most tillers fail to contribute to the final yield. Research on the tiller-numbering trait in cereal crops has recently made significant progress. Yet, developing crop varieties with an optimal number of tillers to increase yield for a specific environment needs a holistic approach that studies plant physiology, genetics, and temporal dynamics in vegetative and reproductive phases.

3.3. How NDVI Changes during Different Growth Stages

NDVI is an important metric for monitoring crop health and development, particularly during the flowering stage, where NDVI values reach their peak, reflecting the highest photosynthetic activity and dense canopy cover. During the growth cycle, the NDVI values follow a low–high–low curve, peaking during the jointing to booting stages, including the flowering period. This trend is consistent across different wheat cultivars and is influenced by management practices and environmental factors [37]. Machine learning algorithms, such as support vector machines and random forest, have developed NDVI-based yield prediction with moderate-to-high performance during reproductive stages [38,39]. However, bidirectional reflectance factors and viewing angles also affect NDVI measurements, with forward-direction NDVI values being higher due to reduced shadow effects [40].

3.4. Association between Grain Yield, Vegetation Indices, and Growth Pattern

Initial statistical tests, including the *t*-test, one-way ANOVA, and regression analysis, on the mapping population revealed no significant results for overall grain yield or vegetation indices (Figure 10). Similar results were found when examining individual groups. The indeterminate group exhibited no correlation; however, significant differences in grain yield were found for the determinate group upon further analysis of subsets within the determinate and indeterminate groups across the minimum-to-maximum grain yield (average) range (Figure 11). Subsequent correlation analysis for the combined subset (both determinate and indeterminate) indicated a positive relationship between these traits, especially at late growth stages (Figure 12). The T-statistic was 2.735, with a corresponding p-value of 0.0072, indicating statistical significance. In contrast, for the SG and non-SG groups, the statistical tests for vegetation indices were nonsignificant regarding the relationship to grain yield.

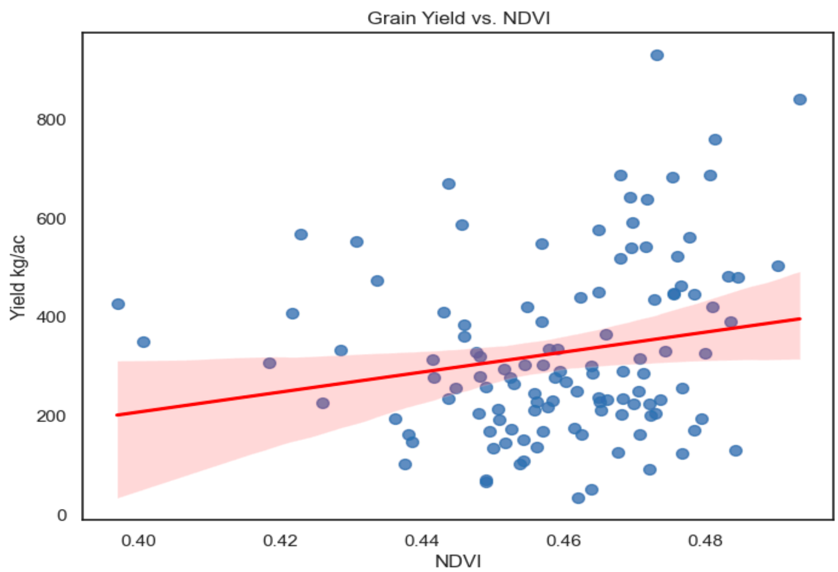

Figure 10. Association plot—No correlation was seen between NDVI for the overall mapping population and grain yield.

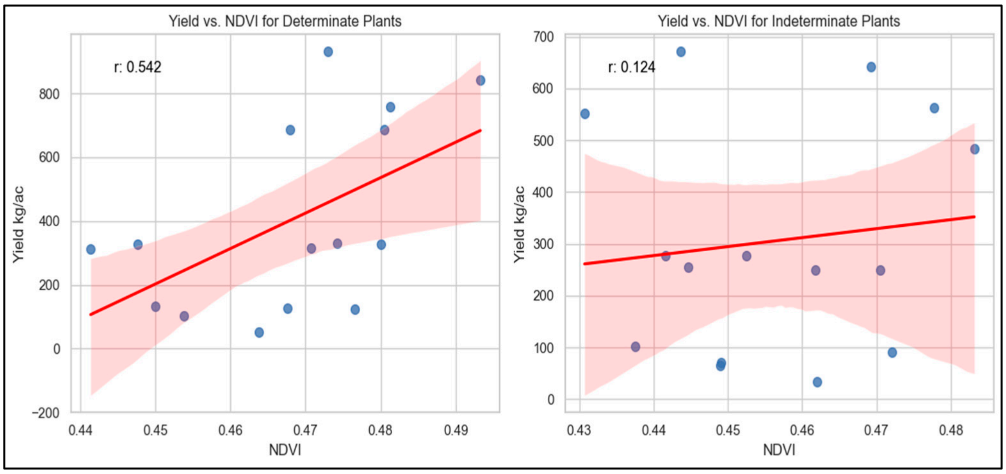

Figure 11. Correlation analysis within the subset for grain yield and NDVI in determinate (**left**) and indeterminate (**right**) groups.

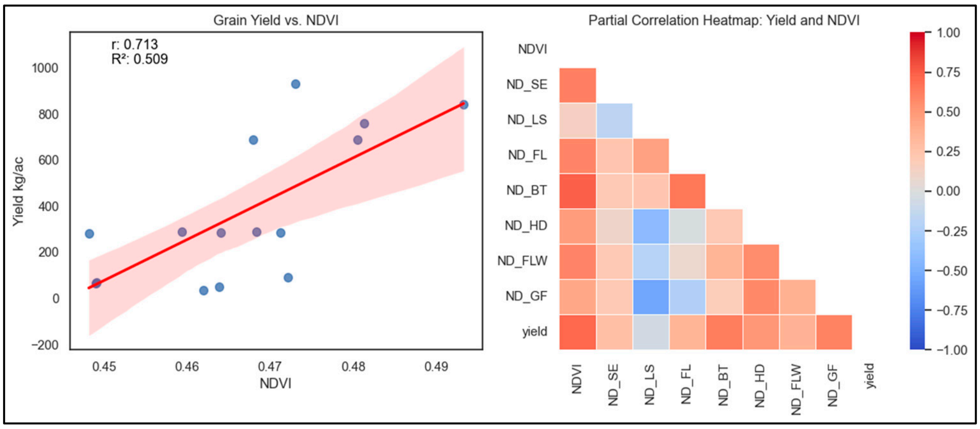

Figure 12. Plants with yield subgroups such as low, medium, and high show a positive correlation between overall NDVI and overall grain yield (**left**). Heat map showing a strong relationship between NDVI grain yield in subcategorized plants at BT, HD, and GF stages (**right**).

The inherent features of the canopy, such as the geometry and orientation of leaves during image capture, introduce biases that affect the precision of metric estimation [41]. In remote sensing studies, it has been observed that during periods of vegetation growth, especially in dense vegetation canopies, NDVI tends to saturate, resulting in the underestimation of other parameters such as the leaf area index (LAI), crop productivity, and overall crop performance [42]. Additionally, while there is an association between leaf chlorophyll content and NDVI, broad band-derived vegetation indices prove more adept at discerning broad differences than offering detailed information about canopy biophysiological features such as chlorophyll content and photosynthesis efficiency [43].

This study observed a positive correlation between overall NDVI and grain yield. However, no correlation was found between grain yield and NDVI during early growth stages. Notably, positive correlations emerged during the booting, heading, and grain-filling stages, emphasizing the dynamic nature of the relationship between NDVI and grain yield at different growth phases (Figure 12). The determinate group performed better for grain yield as compared to the indeterminate group. Further studies and an improved understanding of these plant groups' specific traits and physiological mechanisms can provide additional insights into the observed variations in NDVI distribution.

4. Conclusions and Future Directions

The implementation of modern technology into agriculture has been steadily increasing, not only in the realm of general plant genetics but also in exploring the specifics of plant phenomics. Over the past few decades, remote sensing technology has surged in prominence within plant phenotyping, providing an effective means of dissecting intricate relationships among genotypes, environments, and cultivation techniques. These methods are of pivotal importance for precision agriculture, digital farming, and the screening of the germplasm programs of the future. NDVI and GNDVI, functioning as remote sensing indices for assessing vegetation health, are important in monitoring phenology, canopy greenness, senescence, and SG dynamics. The interplay of canopy architecture and cover significantly influences light distribution and reflectance, serving as the basis for various vegetation indices. Of these indices, those derived from RGB multispectral images hold great potential for monitoring phenological stages among plots exhibiting diverse growth patterns. Specifically, the initiation of senescence within a population highlights the effectiveness of these indices in capturing subtle changes in plant health and development. Integrating uncrewed aircraft systems (UASs) with advanced remote sensing technologies, such as LiDAR, offers a robust alternative to capture accurate and detailed information on plant structure and morphology, which can overcome the limitations and biases associated with NDVI-based methods in diverse canopy patterns. The non-destructive and high-throughput nature of LiDAR makes it particularly beneficial for assessing canopy density and crop biophysical properties like height and leaf area index, as it can monitor both green and non-green plant elements, unlike NDVI, which primarily responds to chlorophyll content.

The research findings indicate that the determinate group in wheat showed a positive correlation between NDVI and grain yield, while the indeterminate group lacked a significant relationship. This suggests that NDVI values in the indeterminate group did not contribute to grain yield due to sterile tillers. Positive correlations between NDVI and grain yield were observed during the booting, heading, and grain-filling stages, highlighting the dynamic nature of this relationship at different growth phases. UAV-based phenotyping proved effective in studying wheat growth patterns, particularly in identifying SG. These lines exhibited delayed leaf senescence and prolonged photosynthetic activity, leading to higher grain yield compared to non-SG plants among the determinate group.

This study highlights the potential that SG trait phenotyping holds for using non-destructive remote sensing methods for advancing crop improvement and breeding programs. While the SG trait offers significant advantages in terms of grain yield and environmental stress resistance, it is essential to consider the need for its incorporation with other features such as optimum morphology, including uniform tillers and synchronized flowering. The development of high-yielding and stress-tolerant cultivars should balance multiple desirable traits to ensure overall crop performance and adaptability.

Results show that these techniques can provide detailed insights into wheat growth patterns, which are essential for enhancing the genetic basis of current breeding strategies. The ability to non-destructively monitor key traits like SG throughout various growth stages allows for a more accurate and comprehensive evaluation of genetic material, further allowing breeders to optimize the selection process. This, in turn, facilitates the development of wheat genotypes with improved resilience to environmental stresses and increased grain yield and quality. By integrating these methods into breeding programs, researchers and breeders can better understand the interactions between above-ground plant architecture and subterranean root systems, allowing for the cultivation of wheat varieties that meet the growing demands of the global food market.

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visualization, S.Z. and T.A.; supervision, J.J.; project administration, J.J.; funding acquisition, S.Z. and J.J. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: Data available on request due to restrictions, e.g., privacy or ethical. The data presented in this study are available on request from the corresponding author.

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