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ORIGINAL RESEARCH ARTICLE

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Wheat yield and protein estimation with handheld- and UAV-based reflectance measurements

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Abstract

Precision agriculture provides efficient means of obtaining real-time data to guide nitrogen (N) management based on predicted crop profitability. This study was conducted to assess the efficacy of using in-season measurements (plant height, biomass weight, biomass N, soil plant analysis development [SPAD], GreenSeeker [GS] normalized difference vegetative index [NDVI], and unmanned aerial vehicle [UAV] NDVI) at Feekes 5 (tillering) and Feekes 10 (anthesis) to estimate wheat (*Triticum aestivum* L.) yield and protein. The secondary aim was to determine whether the accuracy of yield and protein prediction varies by wheat class and cultivar. Six cultivars—hard red spring (HRS) wheat 'Jefferson' and 'SY Basalt', hard white spring (HWS) wheat 'Dayn' and 'UI Platinum', and soft white spring (SWS) wheat 'Seahawk' and 'UI Stone'—were planted at two locations in Idaho in 2018–2020. Plots were arranged in a randomized complete block design with four replications with each cultivar evaluated at seven N rates (0, 50, 100, 150, 200, 250, and 300 kg N ha^{-1}). The determination of the Pearson correlation coefficients revealed that all parameters were linearly correlated with yield except for SPAD at Feekes 5 and biomass weight at Feekes 10. Although estimation of in-season grain protein remains a challenge, NDVI was strongly correlated with yield especially at Feekes 5. The accuracy of yield prediction was similar for all wheat classes. Comparable accuracy of yield estimation was achieved with GS NDVI and UAV NDVI. Both hand-held and aerial-based spectral measurements could be used to prescribe N rates to be applied during tiller formation when wheat yield can be optimized.

1 | INTRODUCTION

Nitrogen (N) is one of the most limiting nutrients in many cropping systems, and its proper management is important for both economic and environmental sustainability of crop production (Fageria & Baligar, 2005). The supply of

Abbreviations: GS, GreenSeeker; HRS, hard red spring; HWS, hard white spring; NDVI, normalized difference vegetative index; NIR, near-infrared; SPAD, soil plant analysis development; SWS, soft white spring; UAV, unmanned aerial vehicle.

plant-available N and the rate of N losses from the plant–soil system ultimately define the sustainability of crop production. Available soil N and crop yield potential determine the crop's need for additional N, and both are necessary to quantify optimum N fertilizer application rates (Walsh & Belmont, 2015).

As prices of N fertilizers continue to rise (Dehlinger, 2021), better management options need to be put in place to avoid losses. Omara et al. (2019) documented N use efficiency at only 35% worldwide. Precision nutrient management is one of the techniques that have been highlighted for optimizing fertilizer inputs by considering both spatial and temporal variability of crop N demand and supply (Diacono et al., 2013; Miao et al., 2007).

Results from three comprehensive experiments reported on by Raun et al. (2017) that included wheat (*Triticum aestivum* L.) grown in a wide range of environments indicated that using historical yields (yield goal approach) is not an appropriate strategy for prescribing N fertilizer rates. These findings highlight the importance of using better methods to predict yield potential (to replace yield goal), which is achievable using mid-season active crop sensor data. According to Cao et al. (2015), adopting precision agriculture depends on development of efficient technologies for real-time diagnosis of the in-season crop N status. Real-time evaluations provide data to guide fertilizer management based on predicted crop profitability.

Biomass weight, N content, chlorophyll concentration, plant height, and various vegetative spectral indices, such as normalized difference vegetative index (NDVI), can be used to evaluate the in-season crop status. These parameters can be measured directly by physical and chemical analysis of harvested plants or estimated using remote sensors. Accurate estimation of crop N status is useful for developing effective fertilizer-N recommendations (Walsh et al., 2018). Sensor-based spectral indices can be used to generate field maps to show spatial variability of crop condition. These indices have also been integrated into various algorithms for crop N content estimation, to make N fertilizer recommendations based on crop need for N, and to boost economic return for growers (Bushong et al., 2016).

The examples of handheld sensors include the GreenSeeker (GS) optical sensor (Trimble Agriculture Division) for estimating NDVI and the soil plant analysis development (SPAD) meter (Konica Minolta Sensing) for estimating chlorophyll content. Unmanned aerial vehicles (UAVs) can be used to collect spectral imagery using various sensors and cameras.

Several authors reported a high correlation between plant height and yield (Katsvairo et al., 2003; Machado et al., 2002; Mallarino et al., 1999). However, plant height has not been often used for yield prediction because of the need to be coupled with other parameters that account for spatial variability of plants (Girma et al., 2006).

Core Ideas

- GreenSeeker (GS) and UAV NDVI at Feekes 5 shows the most potential for in-season wheat yield estimation.
- Comparable accuracy of yield estimation was achieved with GS NDVI and UAV NDVI.
- The accuracy of yield estimation was comparable for all wheat classes and cultivars.
- Estimation of in-season wheat protein content remains a challenge.

Biomass has also been used for mid-season prediction of yield. Agegnehu et al. (2014) reported that wheat yield was significantly positively correlated with biomass (R^2 = .80). On the other hand, Serrano et al. (2000) found aboveground wheat biomass weight was poorly correlated with yield. Simple ratio (SR) (calculated using narrow-band reflectance values as follows: SR = R_{900}/R_{680}, where R indicates reflectance, and the subindex indicates the wavelength [nm]) was a better predictor of yield. They hypothesized that the simple ratio–yield relationship was strong because of simple ration closely tracking the duration and intensity of the wheat canopy photolytic capacity.

Chlorophyll content of plants estimated with a SPAD meter can be used to assess the N nutrition (Reussi Calvo et al., 2015). A strong relationship between SPAD readings and leaf N concentration has been documented in several studies since the 1990s (Schepers et al., 1992; Waskom et al., 1996). Mehrabi and Sepaskhah (2022) reported that strong linear relationship of SPAD values with N concentration in wheat leaves may aid in more accurate yield estimation. Bavec and Bavec (2001) and Yildirim et al. (2010) found a significant correlations between SPAD values at Feekes 10 and wheat yield. However, work by Monostori et al. (2016) observed that SPAD values were cultivar specific, suggesting that SPAD values may need to be calibrated by cultivar to make more accurate yield prediction.

The NDVI is one of the most used indices in crop sensing. The NDVI is calculated as follows: NDVI = $(\rho_{NIR} - \rho_{Red})/(\rho_{NIR} + \rho_{Red})$, where ρ_{NIR} and ρ_{Red} are the fractions of reflected near-infrared (NIR) and red radiation, respectively, returned from the sensed area. Early work showed that the NDVI could be used to accurately estimate green biomass (Tucker, 1979). The NDVI values range from 0 to 1, with bare soil or unhealthy plants ranging between 0.2 and 0.4 and vibrant, green, vigorous, healthy plants ranging between 0.5

and 0.9 (Walsh, 2015). Advances in remote sensing have led to the development of ground-based active optical sensors that measure a portion of the radiation reflected from the plant canopy expressed as NDVI (Holland et al., 2012).

Freeman et al. (2003) reported a strong correlation between NDVI and yield, grain N uptake, straw N uptake, and total N uptake of wheat at Feekes 9 (flag leaf emergence) and 10.5 (anthesis). The NDVI was strongly correlated with plant biomass, N concentration, and N uptake for several wheat varieties (Osborne, 2007). Teal et al. (2006) found a strong relationship between crop biomass weight and yield.

In recent years, UAVs have become increasingly common in many agricultural applications. High-resolution images obtained with UAVs are valuable for various agriculture-related purposes. Installed on the UAVs, sensors and cameras enable time efficient inspection of large fields to evaluate crop parameters contributing to yield and quality in varied growing environments.

Zeng et al. (2021) reported high correlation between UAV-based spectral indices with wheat yield at Feekes 5–9 (stem elongation), Feekes 10.5, and Feekes 11 (early maturity) (R^2 = .76–.93), with the highest prediction power (R^2 = .88–.93) at Feekes 10.5. Zhou et al. (2021) observed a correlation between predicted grain protein values obtained with UAV-based multispectral imagery collected at Feekes 5 and Feekes 11 (R^2 = .55–.66) and grain protein content of wheat measured at harvest. Veverka et al. (2021) were able to predict wheat grain protein content at Feekes 3 to Feekes 6 (R^2 = .60) with UAV-based red edge normalized difference vegetation index.

Based on reports in literature, additional work must be conducted on utilization of spectral indices for yield and grain protein estimation (Tian et al., 2011). One of the most frequent questions asked by wheat producers is how to manage N fertilizer depending on what cultivar they choose to grow. The hard wheat cultivars have a higher protein, in general, and gluten, specifically, content than soft wheat (Master Class, 2020). The hard red spring (HRS) wheat cultivars are typically used to produce high-volume pan and crusty breads requiring high protein content and strong gluten; they are excellent for artisan and 'designer' wheat-containing foods like baguettes, croissants, bagels, and pizza crust (The Idaho Wheat Commission, 2022). The HRS wheat flour is also blended with other flours to improve baking parameters (Carson & Edwards, 2009; The Idaho Wheat Commission, 2022). The HRS wheat cultivars are characterized by high concentration of vitamins such as thiamin, niacin, and folate (Asp, 2004). The hard white spring (HWS) wheat flour has naturally milder, sweeter flavor and is suitable for whole wheat breads, Asian-style noodles, bagels, hard rolls, and high-extraction applications (flour is sifted to partially remove bran) (The Idaho Wheat Commission, 2022). The soft white spring (SWS) wheat flour is characterized by low moisture and high extraction rates, providing a whiter, brighter product for cakes, pastries, cookies, crackers, Asian-style noodles, and flat breads (The Idaho Wheat Commission, 2022).

Different cereal ideotypes have been identified, with a major emphasis on shoot architecture attributes. Plant height, tillering, leaf size, morphology, and arrangement are fundamental for light interception, photosynthetic efficiency, and, ultimately, plant performance: biomass and yield production (Shaaf et al., 2019). Indeed, wheat cultivars differ in growth parameters, such as height, tillering pattern, plant architecture, leaf size and angle, and produced biomass volume and color, which may affect their spectral characteristics. Work by Sultana et al. (2014) revealed significant differences in NDVI values for all growth stages (from tillering to maturity) associated with wheat cultivars. However, nonsignificant differences in NDVI values were observed between five evaluated wheat genotypes (Sembiring et al., 1998). Similarly, Karande et al. (2014) found no statistically significant differences in NDVI and other spectral indices for wheat of different cultivars for any growth stage.

The objectives of this study were to (a) assess the efficacy of irrigated spring wheat yield and grain protein prediction using in-season measurements (SPAD, GS NDVI, plant height, biomass weight, biomass N, and UAV NDVI) and (b) determine whether the accuracy of yield and protein prediction varies by wheat class and cultivar.

We hypothesized that (a) NDVI measured at Feekes 5 should provide the most accurate in-season yield estimation; (b) UAV NDVI-based yield estimation accuracy should be comparable with that of GS NDVI; and (c) the wheat class and cultivar should not affect the accuracy of NDVI-based yield prediction.

2 | MATERIALS AND METHODS

2.1 | Experimental locations

Field trials were conducted at two locations in southern Idaho at Aberdeen and Parma during 2018, 2019 (Parma only), and 2020 growing seasons resulting in a total of five site-years. Both sites are characterized by the semi-arid climate with long, cold, moderately snowy winters and hot dry summers. Latitude and longitude, planting dates, soil type, and preplant soil characteristics (top 60 cm) and total precipitation and average air temperature from planting to harvest for five site-years in Idaho are reported in Table 1. Overall, Aberdeen site was characterized with lower soil organic matter and higher soil K and S than at Parma. Also, Aberdeen had lower average temperature and lower total precipitation than Parma (except for 2018). In general, for both sites, the 2018 season was drier and warmer, whereas 2020 was wetter and cooler. Temperature and precipitation at Parma in 2019 were wetter and cooler

TABLE 1 Latitude and longitude, planting date, soil type, preplant soil characteristics[a] (top 60 cm), total precipitation, and average air temperature from planting to harvest for five site-years in Idaho

Location	Site-year	Latitude and longitude	Planting date	Soil type	pH	OM	Soil residual N	P	K	SO_4^{2-}–S	Total precip.	Avg. temp.
						%	kg ha^{-1}	———mg kg^{-1}———			mm	°C
Parma, ID	2018	43°80′54.22″ N, 116°95′64.17″ W	10 Apr.	Greenleaf–Owyhee silt loams, 0–1% slopes	6.8	2.5	193	26	256	16	50.8	18.5
	2019	43°80′61.28″ N, 116°95′54.84″ W	3 Apr.		8.2	1.8	125	45	178	20	114.8	17.4
	2020	43°80′07.94″ N, 116°93′76.81″ W	7 Apr.		7.9	1.7	119	38	215	11	182.9	17.1
Aberdeen, ID	2018	42°57′22.29″ N, 112°49′28.84″ W	9 Apr.	DeA Declo loam, 0–2% slopes	8.1	0.9	170	25	260	44	58.4	15.1
	2020	42°57′24.58″ N, 112°49′27.12″ W	9 Apr.		7.8	0.9	250	26	365	78	88.9	14.1

Note. Detailed methods for soil laboratory analysis described in Yang et al. (2018); OM, organic matter. Sources: Marshall et al. (2018, 2020), Bureau of Reclamation, and Walsh (unpublished data, 2021).

than 2018 but drier and warmer than in 2020 growing season (Table 1).

2.2 | Wheat classes and cultivars

Six spring wheat cultivars—Jefferson and SY Basalt (HRS), Dayn and UI Platinum (HWS), and SWS Seahawk and UI Stone (SWS)—were evaluated in this study.

Jefferson HRS wheat was released in 1998 by the Idaho Agricultural Experiment Station in cooperation with the Oregon and Washington Agricultural Experiment Stations and the USDA–ARS. Jefferson is a semi-dwarf wheat with excellent yield and milling quality (Souza et al., 1999). The cultivar SY Basalt is a HRS wheat developed by Syngenta Seeds, Inc. and was SY Basalt was selected for high yield performance, height, and absence of stripe rust (Washington State Wheat Improvement Association, 2015).

Cultivar Dayn is a HWS wheat bred by the Washington State University with an excellent yield potential and very good protein, straw strength, and stripe rust tolerance (Washington State University, 2017). Cultivar UI Platinum was developed by the Idaho Agricultural Experiment Stations; this HWS wheat has excellent yield potential, good end-use quality, and strip rust resistance (Chen et al., 2016).

Cultivar UI Stone SWS wheat was developed by the Idaho Agricultural Experiment Station for high yield, desirable end-use quality, and resistance to Fusarium head blight (Chen et al., 2013). Cultivar Seahawk SWS wheat was developed by the Washington State University; it has outstanding disease defense traits and very good yield potential (Washington State University, 2018).

2.3 | Treatment establishment

Wheat was planted at Parma using H&N Equipment small plot drill and at Aberdeen using a Hege 500 series drill. Plant density was ∼3.9 million seed ha^{-1}(106.5 kg seeds ha^{-1}). Row spacing was set at 17.78 cm using double-disk openers. The plots were 1.52 m wide by 4.27 m long and then cut to 3.05 m using glyphosate herbicide application and rototiller. Each wheat cultivar was evaluated under seven N rates (0, 50, 100, 150, 200, 250, and 300 kg N ha^{-1}) applied as granular urea (46-0-0) and incorporated into the soil prior to seeding using tillage. Each treatment was replicated four times in a randomized complete block design, resulting in a total of 168 plots for each site-year. Research plots were irrigated every 7 to 10 d using sprinkle irrigation system.

2.4 | In-field sampling and measurements

At Feekes 5 (tillering) and Feekes 10 (anthesis) growth stages, the wheat vegetative parameters were assessed by measuring (a) plant height, (b) aboveground biomass weight and N content, (c) chlorophyll content estimate, and (d) biomass volume and greenness estimate.

The wheat plant height was determined by measuring height of 10 randomly selected plants per plot. The biomass samples were collected by hand cutting all wheat plants near the soil surface within the 0.2 m^2 area in the middle of each plot. Plant samples were dried in the oven for 72 h at 80 °C and transferred to the lab for total N content analysis. Samples' N content analysis was performed using the Association of Official Analytical Chemists (AOAC) method 990.3 at Brookside

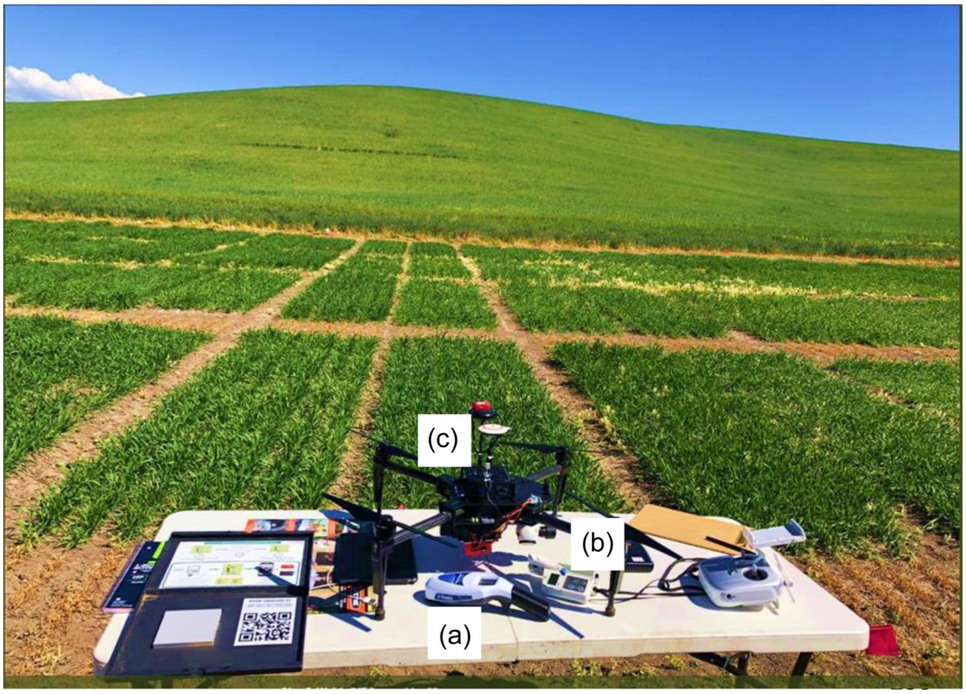

FIGURE 1 (a) GreenSeeker handheld optical sensor (Trimble Agriculture Division), (b) soil plant analysis development (SPAD) chlorophyll meter (Konica Minolta Sensing), and (c) the Matrice 100 (DJI) unmanned aerial vehicle used to collect the in-season crop reflectance data, Aberdeen, ID, 2020

Laboratories, Inc (New Bremen, OH, USA) with extended uncertainty of ± 5%.

Chlorophyll content was estimated using the SPAD chlorophyll meter (Konica Minolta Sensing) (Figure 1). The SPAD meter quantifies the difference between the transmittance of a red (650 nm) and an infrared (940 nm) light through the plant leaf, producing a three-digit SPAD value (Uddling et al., 2007). The top-most, fully unfolded leaves from 10 plants randomly selected within each plot were analyzed. Data was collected on the same day from all experimental plots to make sure the values for each plot are comparable.

Biomass volume and greenness was estimated as NDVI using GS handheld optical sensor (Trimble Agriculture Division) (Figure 1) by sensing the two middle rows of wheat plants within each row at 70 cm above the canopy. Spectral reflectance data was collected at a rate of 70 readings m^{-2} by walking at a speed of 5 km h^{-1}. The GS sensor employs a patented technology that emits light and measures the crop reflectance at 660 and 770 nm and calculates NDVI (Raun et al., 2001; Tremblay et al., 2009).

Wheat was harvested at maturity and analyzed for end-use quality (grain test weight, grain protein content, and baking quality). These postharvest data will be reported in a separate manuscript. The current paper is specifically focused on the vegetative and spectral measurements of various wheat classes for in-season yield and protein estimation.

Multispectral RedEdge M (MicaSense) camera mounted on a UAV Matrice 100 (DJI) (Figures 1 and 2) was used to collect the aerial imagery from each plot at Feekes 5 and Feekes 10 growth stages at each site-year. Images were collected at 100 m above the ground level within 2 h of solar noon.

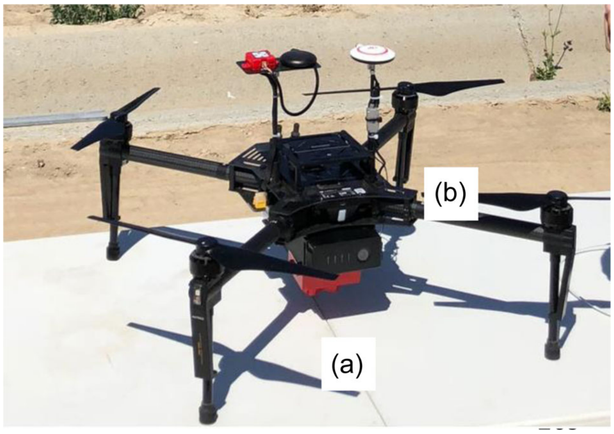

FIGURE 2 (a) Multispectral RedEdge M (MicaSense) camera mounted on (b) an unmanned aerial vehicle Matrice 100 (DJI) (Figure 1) used to collect the aerial imagery

The RedEdge M camera enables to simultaneously capture images of ultra-high spatial resolution within five spectral ranges: blue (530–570 nm), green (530–570 nm), red (640–680 nm), red-edge (730–740 nm), and NIR (770–810 nm) (Mamaghani & Salvaggio, 2019).

TABLE 2 Analysis of variance for five site-years. The table shows the sources of variation and probability values for the *F* tests of each main effect (N rate, wheat class, and location) and interactions (N rate × wheat class, location × N rate, location × wheat class, and location × N rate × wheat class)

Effect	df	*F* value	Pr > *F*
N rate (N)	5	10.80	<.0001
Wheat class (C)	2	33.28	<.0001
Location (L)	1	1,626.86	<.0001
N×C	10	0.31	.9797
L×N	5	5.19	.0001
L×C	2	2.38	.0930
L×N×C	10	0.53	.8689

TABLE 3 Analysis of variance for five site-years. The table shows the sources of variation and probability values for the *F* tests of each main effect (N rate, wheat variety, location) and interactions (N rate × wheat variety, location × N rate, location × wheat variety, and location × N rate × wheat variety)

Effect	df	*F* value	Pr > *F*
N rate (N)	5	10.87	<.0001
Wheat variety (V)	5	14.56	<.0001
Location (L)	1	1637.46	<.0001
N×V	25	0.45	.9908
L×N	5	5.22	.0001
L×V	5	3.73	.0025
L×N×V	25	0.72	.8355

The UAV images were processed using Micasense Atlas software (MicaSense, Inc) and Pix4Dmapper software (v4.3.33) (Pix4D SA) as described in detail in Walsh et al. (2018).

2.5 | Statistical analysis

Data were analyzed using SAS v9.4 (Littell et al., 2006). Proc CORR was used to determine the Pearson correlation coefficients between yield and grain protein with the other measured parameters. Data were also analyzed using the GLIMMIX procedure to compare the least-square means, main effects, and assess interactions of the experimental factors. Year (Y) was treated as a random effect to determine the N rate (N) × class of wheat (C), N × C ×location (L), N × variety of wheat (V), and N × V × L association. Figures and linear regressions were generated using Excel (Microsoft Corp.).

3 | RESULTS AND DISCUSSION

This paper is summarizing the results relevant to in-season prediction of wheat yield and grain protein using ground-based data and UAV-based crop sensors. Tables 2 and 3 detail that N rate, wheat class and cultivar, and location were significant sources of variation in wheat yield. In the absence of the N×C×L or N×V×L (Tables 2 and 3), the data were combined for further analysis. This approach enables us to make generalized conclusions regarding use and accuracy of GS NDVI and UAV NDVI data for wheat yield and protein estimation across wheat classes and cultivars and locations. Because of wheat class and cultivar being significant (Tables 2 and 3), we chose to expand the GS NDVI and yield relationship by wheat class discussion as well.

Results showing the relationship between parameters measured at Feekes 5 and 10 and wheat yield and grain protein are reported in Table 4. At all site-years (except Aberdeen, 2018), most ground-based parameters at both sampling times (tillering and anthesis) were correlated with yield. These parameters were correlated with grain protein, to the lesser extent, compared with yield.

3.1 | Yield vs. in-season measured parameters

There was a positive linear relationship between plant height and biomass weight (measured at Feekes 10 only, except Aberdeen in 2020) with yield at three of four site-years. Although the correlation with yield was strong for plant height measured at Feekes 10 (*r* values ranged from 0.43 to 0.68), the relationship was moderate to strong for biomass weight (*r* values from 0.31 to 0.60) (Table 4).

Biomass N content was positively linearly correlated with yield at two of five site-years at Feekes 5 and three of five site-years at Feekes 10. The relationship was moderate to strong, with *r* values ranging from 0.38 to 0.64 at Feekes 5 and from 0.35 to 0.58 at Feekes 10 (Table 4).

The SPAD meter readings were also linearly correlated with yield at two site-years at Feekes 5 and Feekes 10. The relationship was positive and moderate to strong, with *r* values ranging from 0.31 to 0.78 at Feekes 5 and from 0.36 to 0.58 at Feekes 10 (Table 4).

GreenSeeker NDVI values were linearly, positively, strongly correlated with yield at all but one site-year (Aberdeen, 2018). The *r* values were between 0.58 and 0.71 at Feekes 5 and between 0.45 and 0.72 at Feekes 10 (Table 4). GreenSeeker NDVI better predicted yield at Feekes 5 (R^2 = .79) compared with Feekes 10 (R^2 = .58) (Figure 3a,b).

When site-years were combined, yield was linearly, strongly, positively correlated with all measured parameters except for SPAD at Feekes 5, biomass weight at Feekes 10, and plant height at Feekes 10. Overall, the strongest relationship observed for yield was with GS NDVI at Feekes 5

TABLE 4 Pearson correlation coefficients between plant height, biomass weight, biomass N, soil plant analysis development (SPAD), GreenSeeker (GS) normalized difference vegetative index (NDVI), and unmanned aerial vehicle (UAV) NDVI with wheat yield and grain protein content for Parma and Aberdeen, ID, in 2018, 2019, 2020, and combined site-years

		Feekes 5				Feekes 10					
Site and year	Parameter	Biomass N	SPAD	GS NDVI	UAV NDVI	Plant height	Biomass weight	Biomass N	SPAD	GS NDVI	UAV NDVI
Parma, ID											
2018	Yield	−0.04ns[†]	0.12ns	0.72	0.79	0.68	0.45	0.08ns	0.36	0.55	0.66
	Grain protein	−0.07ns	0.08ns	−0.04ns	−0.01ns	−0.08ns	00.05ns	−0.07ns	−0.01ns	0.02ns	0.04ns
2019	Yield	0.23ns	0.31	0.58	0.54	0.23ns	0.31	0.40	0.29ns	0.45	0.43
	Grain protein	0.03ns	0.14ns	0.02ns	0.17	0.11ns	0.11ns	−0.05ns	0.16ns	−0.02ns	0.13ns
2020	Yield	0.64	0.78	0.56	0.44	0.67	0.60	0.58	0.58	0.72	0.72
	Grain protein	0.30	0.33	0.43	0.25ns	0.05ns	0.11ns	0.38	−0.03ns	0.32	−0.05ns
Aberdeen, ID											
2018	Yield	−0.18ns	0.03ns	0.02ns	0.10ns	−0.12ns	−0.12ns	0.15ns	0.09ns	−0.11ns	0.08ns
	Grain protein	−0.18ns	0.01ns	0.02ns	0.25ns	−0.13ns	−0.10ns	−0.10ns	0.13ns	0.16ns	0.55
2020	Yield	0.38	0.23ns	0.71	0.64	0.43	–	0.35	0.18ns	0.57	0.54
	Grain protein	0.33	0.36	0.21ns	0.06ns	0.01ns	–	0.41	0.25ns	0.32	0.07ns
Combined											
	Yield	0.46	0.23ns	0.76	0.63	−0.36	0.21ns	0.40	0.42	0.64	0.60
	Grain protein	0.37	0.01ns	0.24ns	0.23ns	−0.37	0.05ns	0.17ns	0.10ns	0.44	0.35

[†]ns, nonsignificant at the .05 probability level.

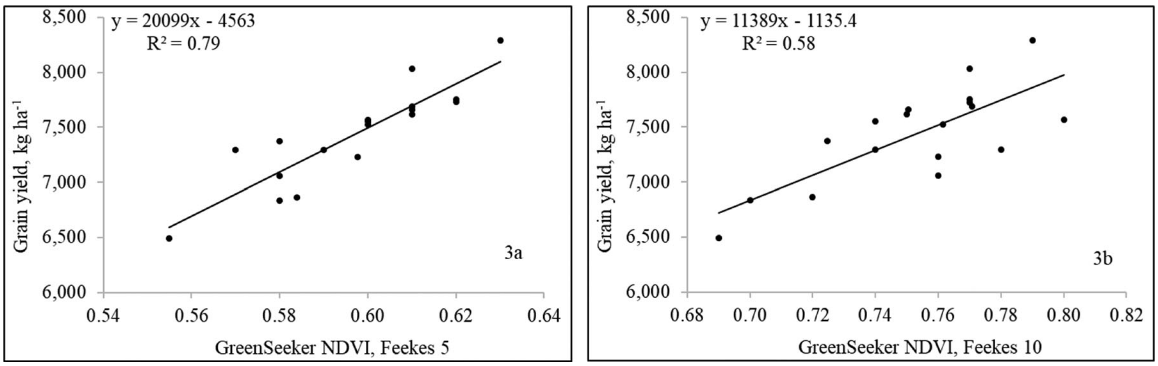

FIGURE 3 Relationship between yield and GreenSeeker normalized difference vegetative index (NDVI) at (a) Feekes 5 and at (b) Feekes 10. Each data point represents a NDVI value averaged for each experimental plot replicated four times at each location across 14 site-years

(Table 4). Walsh et al. (2020) reported that SPAD and NDVI values at Feekes 10 explained 80 and 84% of the variation in wheat yield, respectively.

Wheat plant anthesis is initiated at Feekes 10 closely followed by pollination and grain filling and ripening (Freije & Wise, 2015). In this study, GS NDVI was more correlated with yield at Feekes 5 than Feekes 10. Several authors have also found similar results (Moges et al., 2005; Walsh, personal communication, 2022). Gupta (2006) reported that the relationships of in-season estimate of yield defined as NDVI per day with grain yield was stronger at Feekes 5, compared with later in-season NDVI vs. yield relationship. Freeman et al. (2007) observed a stronger relationship between yield and GS NDVI at early growth stages. Feekes 4–5 is an optimal time for top dress N fertilizer applications for wheat. Determining wheat yield potential at Feekes 5 using crop sensors, therefore, is practical for determining N fertilizer rates. Our findings agree with results by Freeman et al. (2007) in that the NDVI at Feekes 5 was most closely correlated with wheat yield. This is significant considering that yield-targeted N fertilization should occur near Feekes 5 growth stage. In cereals, including wheat, yield is driven by tiller development. As wheat plants

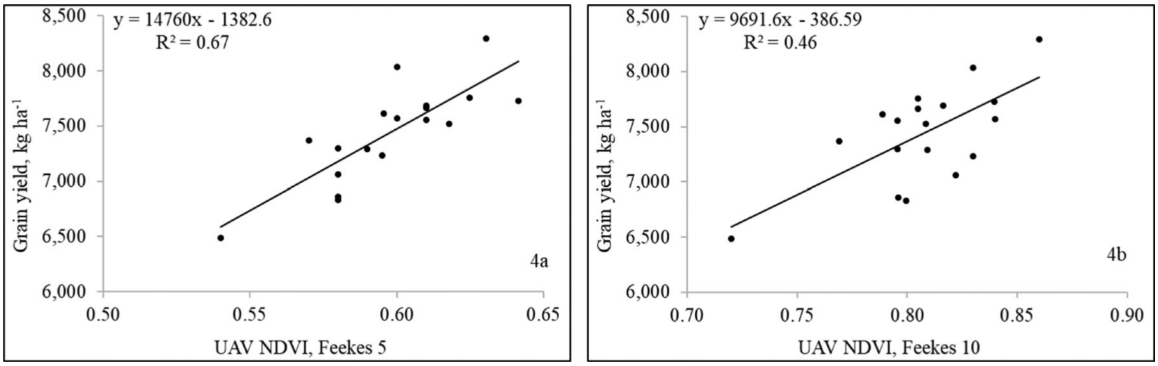

FIGURE 4 Relationship between yield and unmanned aerial vehicle (UAV) normalized difference vegetative index (NDVI) at (a) Feekes 5 and at (b) Feekes 10. Each data point represents an NDVI value averaged for each experimental plot replicated four times at each location across 14 site-years

form tillers (Feekes 2 to Feekes 8), the grain spike size is set, and tillers added after Feekes 5 typically to contribute little to yield (Wise et al., 2011).

In our study, UAV NDVI explained significant variations in yield (Table 4, Figure 4). As with GS NDVI, the accuracy of yield estimation with UAV NDVI was higher at Feekes 5 (R^2 = .67) compared with Feekes 10 (R^2 = .46).

Hassan et al. (2019) also reported that UAV NDVI measurements were highly consistent with ground data captured by the handheld GS sensor from Feekes 6 to Feekes 10. The UAV NDVI explained significant variation in wheat yield (R^2 = .83–.89), and results were consistent with GS NDVI. They concluded that UAV NDVI at Feekes 10 can be used to select high-yielding wheat genotypes. Their results also indicated that the UAV platform had s lightly higher accuracy in predicting wheat yield than that of the GS sensor.

Lower of accuracy of GS NDVI and UAV NDVI for yield estimation later in the season (Feekes 10) could partially be due to saturation of NDVI values at higher biomass volume. The NDVI represents the overall vegetative status rather than the N status of the crop. The NDVI saturation issue is well documented at denser vegetation levels observed as wheat plants mature and canopy closure occurs (Wang et al., 2016). Our results revealed that GS NDVI and UAV NDVI were comparable in accuracy of detecting differences in yield. Since GS and UAV NDVI were strongly correlated, especially at Feekes 5, we suggest that both hand-held and aerial-based spectral measurements could be used for crop monitoring depending on grower priorities and equipment availability as well as field size and weather conditions. This agrees with Walsh (O. S. Walsh, personal communication, 2022) and Benincasa et al. (2017), who suggested that both GS NDVI and UAV NDVI can be used interchangeably to estimate wheat N status and yield especially early in the season (Feekes 5) when the wheat crop can be fertilized to optimize yields.

3.2 | Grain protein vs. in-season measured parameters

There were no statistically significant relationships between biomass weight with grain protein. When site-years were combined, plant height at Feekes 10 was negatively moderately correlated with grain protein (r = −0.37) (Table 4).

Biomass N content was moderately correlated with grain protein at two of five site-years; r values varied from 0.30 to 0.33 at Feekes 5 and from 0.38 to 0.41 at Feekes 10 (Table 4).

A moderate positive correlation of SPAD meter readings with grain protein was observed for two of five site-years at Feekes 5 only. At the same two site-years, GS NDVI values were moderately correlated with grain protein (r values of 0.32). When site-years were combined, grain protein was positively moderately correlated with biomass N at Feekes 5 (r = 0.37) and GS NDVI at Feekes 10 (r = 0.44) (Table 4).

In this study, variation in GS NDVI and UAV NDVI values at Feekes 5 and Feekes 10 explained <1% of variation in grain protein, respectively (Figures 5a–d).

Walsh (O. S. Walsh, personal communication, 2022) reported that the relationship between GS and UAV NDVI with grain protein was weak and linear, explaining <1% of variation in protein values. Similarly, in a study by Walsh and Christiaens (2014), wheat grain protein content was moderately correlated with GS NDVI at only three of eight site-years, a trend commonly observed for NDVI vs. protein in cereal crops.

Macnack et al. (2014) found that GS NDVI at Feekes 7 (stem elongation) explained 45% of variation in grain protein. Rodrigues et al. (2018) and Fernandez et al. (2019) proposed that NDVI could be useful for in-season estimation of grain protein. Freeman et al. (2003) observed no relationship between NDVI and wheat grain N at any growth stage and concluded that wheat grain protein could not be accurately estimated using NDVI. On the other hand, Tan et al. (2011)

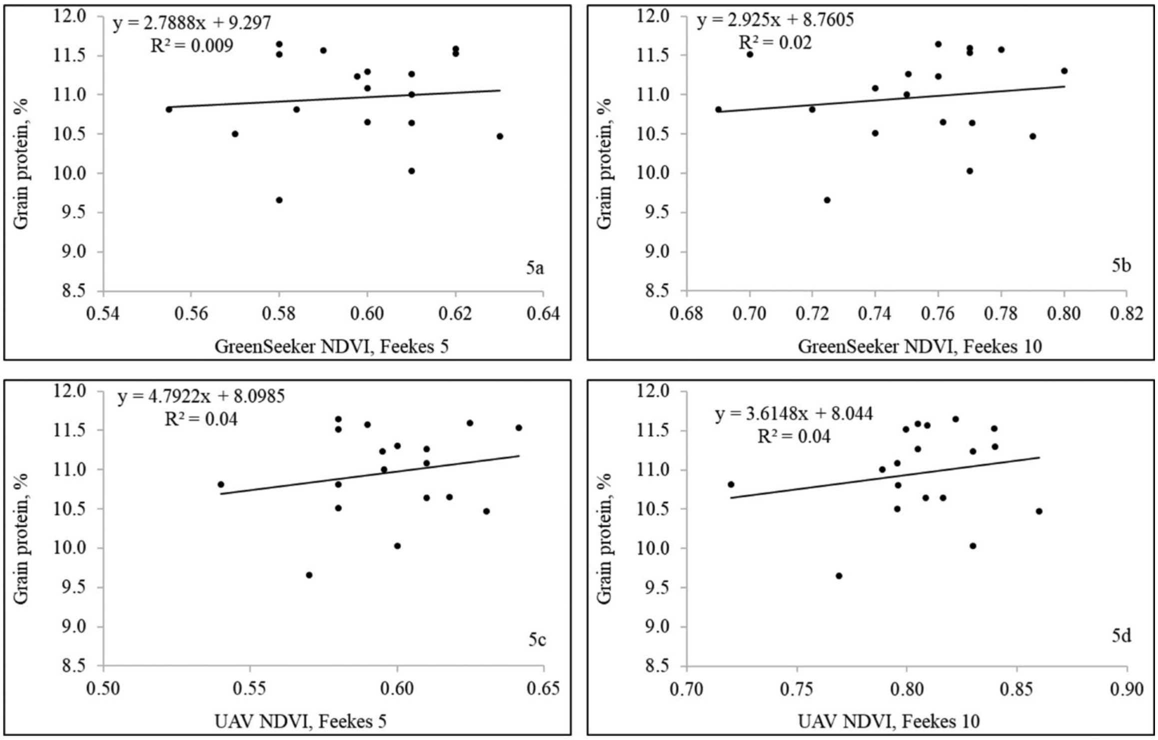

FIGURE 5 Relationship between grain protein and GreenSeeker normalized difference vegetative index (NDVI) at (a) Feekes 5 and at (b) Feekes 10 and unmanned aerial vehicle (UAV) NDVI at (c) Feekes 5 and at (d) Feekes 10. Each data point represents an NDVI value averaged for each experimental plot replicated four times at each location across 14 site-years

reported that NDVI values at Feekes 10 had potential for grain protein prediction. Walsh et al. (2020) reported that SPAD and NDVI values also explained 37 and 28% of variation in grain protein.

3.3 | GreenSeeker NDVI vs. UAV NDVI

The relationship between GS NDVI and UAV NDVI was strong, positive, and linear at both Feekes 5 and Feekes 10. The correlation was stronger at Feekes 5 (R^2 = 85%) compared with Feekes 10 (R^2 = 67%) (Figures 6a,b).

In a study by Walsh (O. S. Walsh, personal communication, 2022), a strong positive correlation was observed between GS NDVI and UAV NDVI at Feekes 5 (R^2 = .78) and Feekes 10 (R^2 = .70). In this study, as well as in other field trials, the overall accuracy of wheat yield estimation was higher at Feekes 5 than at Feekes 10 for both GS- and UAV-based NDVI. Similarly, the correlation between GS NDVI and UAV NDVI was stronger at the earlier growth stage. This may be associated with (a) lower fractional vegetation cover at Feekes 5 vs. more closed canopy at Feekes 10 or (b) NDVI values saturation at higher canopy volume later in the growing season.

On the other hand, Hassan et al. (2019) reported significant correlations between GS and UAV NDVI in wheat (R^2 ranging from .38 to .90) during Feekes 5–6 to Feekes 10 (Hassan et al., 2019). Similarly, in rice (*Oryza sativa* L.), Ya et al. (2019) recorded a strong correlation between GS and UAV NDVI with R^2 values of .58 to .80. In a study with Bermudagrass (*Cynodon dactylon* L.) and tall fescue (*Festuca arundinacea* L.), Caturegli et al. (2020) also observed a strong relationship between GS and UAV NDVI (R^2 of .96–.98). Ya et al. (2019) concluded that UAV-based reflectance measurements could be used by crop growers to monitor crop growth and nutrient status throughout the season in real time.

3.4 | GreenSeeker NDVI and yield by wheat class

Since in this study GS NDVI had the strongest correlation with wheat yield compared with other parameters measured at both Feekes 5 and Feekes 10, we chose to discuss the relationship in more detail by wheat class. Several authors have reported contradicting results regarding spectral reflectance of different crop cultivars. Sultana et al. (2014) documented changes in spectral measurements among wheat cultivars. Whereas Sembiring et al. (1998) did not find any significant differences in NDVI between five winter wheat cultivars at any growth stage. Jasper et al. (2006) suggested that wheat cultivars could affect NDVI values obtained later in the

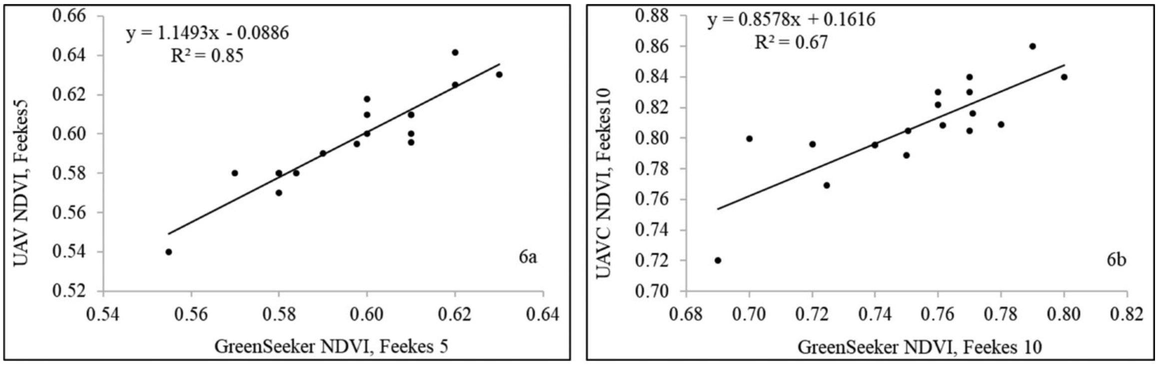

FIGURE 6 Relationship between GreenSeeker normalized difference vegetative index (NDVI) and unmanned aerial vehicle (UAV) NDVI at (a) Feekes 5 and at (b) Feekes 10. Each data point represents an NDVI value averaged for each experimental plot replicated four times at each location across 14 site-years

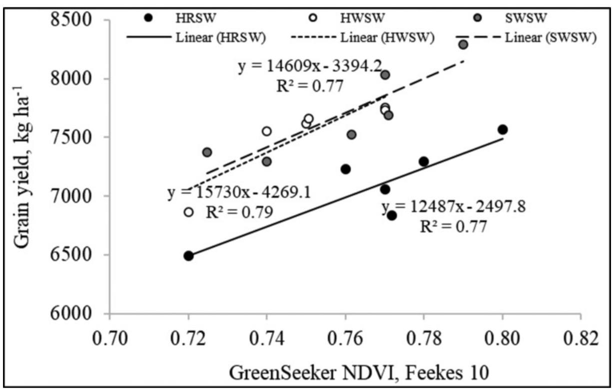

FIGURE 7 Relationship between yield of hard red spring wheat (HRSW), hard white spring wheat (HWSW), and soft white spring wheat (SWSW) and GreenSeeker normalized difference vegetative index (NDVI) at Feekes 5. Each data point represents an NDVI value averaged for each experimental plot replicated four times at each location across 14 site-years

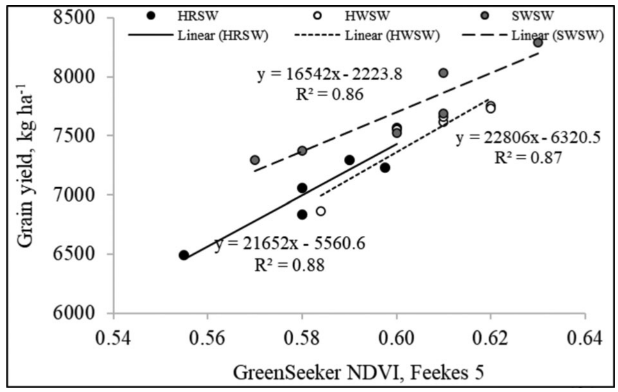

FIGURE 8 Relationship between yield of hard red spring wheat (HRSW), hard white spring wheat (HWSW), and soft white spring wheat (SWSW) and GreenSeeker normalized difference vegetative index (NDVI) at Feekes 10. Each data point represents an NDVI value averaged for each experimental plot replicated four times at each location across 14 site-years

growing season, whereas spectral measurements at Feekes 5–6 did not differ among wheat cultivars. Reusch (2003) and Jasper et al. (2006) reported that spectral measurements at Feekes 5–6 did not differ among wheat cultivars. Jasper et al. (2009) found NDVI to be unaffected by winter wheat varietal characteristics such as stem length, leaf orientation, and leaf color.

Although Mostaza-Colado et al. (2019) found no correlation between the GS NDVI and the camelina [*Camelina sativa* (L.) Crantz] seed yield, they observed differences in GS NDVI values among various camelina cultivars. Similarly, in a study conducted among different potato (*Solanum tuberosum* L.) cultivars, Yang et al. (2020) found significant effect on GS NDVI-based estimation of plant N concentration.

The relationship between GS NDVI at Feekes 5 and Feekes 10 with yield of various classes is illustrated in Figures 7 and 8, respectively.

At Feekes 5 GS NDVI explained 88, 87, and 86% of variation in yield of HRS, HWS, and SWS wheat, respectively (Figure 7). At Feekes 10, the accuracy of yield prediction was slightly lower: variation in GS NDVI explained 77% of variation in HRS and SWS wheat and 79% variation in yield of HWS wheat (Figure 8). Thus, the accuracy of yield estimation was comparable for all evaluated wheat classes. Notably, when data was separated by wheat class, the accuracy of yield estimation using GS NDVI has increased compared with when classes were combined. This suggests that, in some cases, it might make sense to develop sensor-based yield prediction algorithms for specific wheat classes rather than using a universal algorithm for all wheat grown in the state.

4 | CONCLUSIONS

This study examined the accuracy of prediction of primary wheat production parameters: yield and grain protein using in-season plant measurements including hand-held and UAV-based crop sensors. At Feekes 5, biomass N and SPAD measurements were correlated with wheat yield and grain protein at two of five site-years. At the same growth stage, both GS NDVI and UAV NDVI were correlated with wheat yield at four of five site-years. Grain protein content was correlated with Feekes 5 GS NDVI and UAV NDVI at only one of five site-years. At Feekes 10, plant height and biomass N were correlated with wheat yield at three of five site-years; biomass weight was correlated with yield at three of four site-years. At the same growth stage, while SPAD measurements were correlated with yield at only 2 of 5 site-years, GS NDVI and UAV NDVI were correlated with yield at four of five site-years. At Feekes 10, only biomass N and GS NDVI were correlated with grain protein at two of five site-years and UAV NDVI at only one of five site-years. GreenSeeker NDVI and UAV NDVI had the strongest relationship with wheat yield independent of sensing time. The accuracy of yield estimation, however, was stronger for Feekes 5 than for Feekes 10.

When site-years were combined, yield was linearly, strongly, positively correlated with all measured parameters except for SPAD at Feekes 5, biomass weight at Feekes 10, and plant height at Feekes 10. Grain protein was positively moderately correlated with biomass N (two site-years) at Feekes 5 and GS NDVI (two site-years) and UAV NDVI (one site year) at Feekes 10.

For all wheat classes, the relationship between GS NDVI and yield was positive and linear at both growth stages. At Feekes 5 and Feekes 10, GS NDVI explained 86–88 and 77–79%, respectively, of variation in wheat yield.

In conclusion, our results support our hypothesis: (a) GreenSeeker and UAV NDVI at Feekes 5 has shown the most potential for in-season wheat yield estimation, (b) comparable accuracy of yield estimation was achieved with GS NDVI and UAV NDVI, and (c) the accuracy of yield estimation was comparable for all wheat classes and cultivars.

Although the accuracy of yield prediction was comparable for all wheat classes, separating the dataset by wheat class produced a stronger correlation between NDVI and yield. Estimation of in-season grain protein remains a challenge. Further studies of how the spectral characteristics of wheat may differ by class or cultivar when grown at different irrigated and dryland locations throughout Idaho is of great value. Conducting large-scale experiments on commercial growers' fields is required to confirm the results of the small-plots research to improve the precision of yield and grain protein prediction.

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AUTHOR CONTRIBUTIONS

Olga S. Walsh: Conceptualization; Data curation; Formal analysis; Funding acquisition; Investigation; Methodology; Project administration; Resources; Software; Supervision; Validation; Visualization; Writing-original draft; Writing-review & editing. Juliet Marshall: Data curation; Funding acquisition; Investigation; Project administration; Resources; Supervision. Chad Jackson: Data curation; Investigation; Resources; Supervision. Sanaz Shafian: Data curation; Investigation; Methodology; Software. Jordan R. McClintick-Chess: Data curation; Investigation; Methodology; Resources; Supervision. Eva Nambi: Data curation; Formal analysis; Writing-original draft; Writing-review & editing. Emmanuella Owusu Ansah: Data curation; Writing-original draft. Ritika Lamichhane: Data curation; Writing-original draft.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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