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Monitoring winter wheat growth at different heights using aerial imagery

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Abstract

Drones (unmanned aerial vehicles) provide another system to mount sensors for measuring plant characteristics. For winter wheat (*Triticum aestivum*) this can include evaluating stands and making nitrogen (N) recommendations. Timing these flights and adequate camera resolution (based on flying height), must be known before applying tasks. This study observed six winter wheat planting populations (222, 297, 371, 445, 494, and 544 seeds m^{-2}) at three different heights above ground level (30, 60, and 120 m) over three growing seasons. Plant populations could be separated at all growth stages and heights flown but were easier to separate right after emergence (GS11). In the spring, additional tillering caused the higher populations (371–544 seeds m^{-2}) to have similar normalized difference vegetative index (NDVI), much like the final yields. Comparing changes in NDVI between flights was also successful in separating high and low planting populations, with inverse relationships in the fall and spring. A random forest classification of tiller counts by NDVI measurements ranked change in NDVI between stages as the most important compared to single flights. As separation and classification was successful at the lowest camera resolution (120 m), it can be possible for scouts to collect whole field imagery for analyses prior to deciding on split N applications.

1 | INTRODUCTION

Winter wheat (*Triticum aestivum*) relies on tillers for yield, where additional tiller formation can be related to both seeding rate (plant population), row spacing, and nitrogen (N) additions (Aase & Siddoway, 1980; Tilley, Heiniger, & Crozier, 2019). When higher seeding rates are used, fall tillers contribute the most to yield, whereas lower rates rely on spring tiller growth for yield (Tilley et al., 2019). To increase spring tillers, N may be split applied, which requires labor intensive hand counts to measure stiller density (Phillips, Keahey, Warren, & Mullins, 2004; Tilley et al., 2019. The measurement of canopy reflectance has also successfully evaluated stands to make N applications (Aase & Siddoway, 1980; Phillips et al., 2004; Ruan et al., 2001).

Since the 1970s, satellite imagery has been used to measure vegetation characteristics (Mulla, 2013). Vegetation indexes, such as the normalized difference vegetation index (NDVI), were developed from satellite multispectral bands to measure crop biomass (Hatfield, Gitelson, Schepers, & Walthall, 2008; Mulla, 2013). The NDVI uses near infrared (NIR) and red bands to measure vegetative biomass and is commonly used in agronomic applications (Aase & Siddoway, 1980; Erdle, Mistele, & Schmidhalter, 2011; Phillips et al., 2004). Shortly

Abbreviations: AGL, above ground level; GS, growth stage; NDVI, normalized difference vegetation index.

Version of Record at: https://doi.org/10.1002/agj2.20539

after satellite imagery was used to measure vegetative characteristics, handheld radiometers were used to successfully examine NDVI for wheat at ground level (Aase & Siddoway, 1980; Aase & Siddoway, 1981). These proximal measurements were further refined for agricultural use by attaching sensors to tractors or other agricultural equipment and could be active or passive (Mulla, 2013).

Finding relationships between sensors, vegetation indexes, and wheat characteristics depends on the growth stage. Early wheat growth is mostly leafy vegetation, which is why leaf area index (LAI) correlates to total biomass and tillering (Aase, 1978; Aase & Siddoway, 1981). After jointing, wheat will accumulate more stem biomass and leaves eventually senesce, so the relationship of LAI to biomass diminishes (Aase, 1978; Phillips et al., 2004). This same relationship has been observed with NDVI and wheat growth stages, where LAI and leaf dry matter have linear relationships with NDVI until stem matter accumulates or LAI saturates NDVI (Aase & Siddoway, 1980; Aase & Siddoway, 1981; Aparacio, Villegas, Casadesus, Araus, & Royo, 2000). Saturation of NDVI occurs when LAI is above 2–3 (Erdle et al., 2011; Mulla, 2013), so that in higher tiller densities, NDVI and LAI will have an exponential relationship (Aparacio et al., 2000). The NDVI has a linear relationship with tillers until there are more than 1,000 tillers m^{-2}, therefore, tiller density can be predicted with more accuracy at earlier growth stages or less biomass (Erdle et al., 2011; Phillips et al., 2004). In a study of wheat planting rates, it was easier to discern the highest and lowest rates from each other than those in the middle range (Aase & Siddoway, 1980). Water stress can cause lower canopy density so that NDVI performs better in dryland wheat than irrigated fields (Aparacio et al., 2000), leading to better yield predictions (Thapa et al., 2019). Wheat yield prediction through NDVI also has strong relationships prior to joining, when LAI is less than 2.5 (Aparacio et al., 2000; Goodwin, Lindsey, Harrison, & Paul, 2018), and at the milk-grain (GS75) stage (Marti, Bort, Slafer, & Araus, 2007; Royo et al., 2003; Hassan et al., 2019; Prasad et al., 2007). For winter wheat growth, the highest NDVI is often at the heading stage, peaking between jointing and anthesis in the .8–.9 NDVI range (Hochheim & Barber, 1998; Thapa et al., 2019).

Earlier studies used Julian days to evaluate NDVI and wheat (Tucker, Holben, Elgin, & McMurtrey, 1980), but correlations were improved by using growing degree days (GDD), since growth stages will correlate better to heat units (Dhillon, Figueiredo, Eickhoff, & Raun, 2019; Hochheim & Barber, 1998). For winter wheat, this has been further refined into summing the number of GDD >0, with a range of 97 to 115 (GDD >0) predicting yield using NDVI (Dhillon et al., 2019).

While satellites, tractor mounted sensors, and handheld devices have aided past research efforts, recent advances in drone (unmanned aerial vehicles) technology have provided another sensor mounting option. The use of a drone still provides the resolution of a handheld device while allowing for faster acquisition of whole plot or field data. Satellite imagery works better at a regional level versus farm scale (Labus, Nielsen, Lawrence, Engel, & Long, 2002), where measuring crop biomass needs 1- to 3-m resolution, but variable rate application can be done at 5–10 m (Mulla, 2013). The resolution of drone imagery can be 2–3 cm (Duan, Chapman, Guo, & Zheng, 2017) higher than is necessary for biomass or variable rate application. Measurements of NDVI using drones has also correlated to winter wheat biomass at late flowering when flown at 40-m heights and had higher accuracy than handheld active sensors (Hassan et al., 2019). This was attributed to the ability of drone imagery to capture the entire plot for an average value (Hassan et al., 2019). Using drones, yield has also been correlated to NDVI at both flowering and grain fill stages (Hassan et al., 2019; Guan et al., 2019; Duan et al., 2017). There is also good correlation between drone and handheld NDVI measurements of wheat, but drone NDVI values are often higher (Condorelli et al., 2018; Duan et al., 2017).

This study was designed to build upon previous work in winter wheat, to determine whether tiller counts could be performed using drone imagery, the best growth stage to collect imagery, and whether the maximum 120-m elevation was adequate.

Core Ideas

- Drones flown at 120 m can detect differences in winter wheat planting populations over the growing season.
- Change in NDVI between stages can help find lower populations in the field.
- Aerial imagery can be used to make decisions on re-seeding or N applications.

2 | MATERIALS AND METHODS

In the fall of 2017, 2018, and 2019 winter wheat ('Shirley') was planted into 1.5- by 6.1-m plots in Georgetown, DE using a plot planter. Wheat was planted at six seeding rates (222, 297, 371, 445, 494, and 544 seeds m^{-2}) with five replications in a completely randomized design. Nitrogen was split applied with 56 kg ha^{-1} ammonium sulfate at Zadooks growth stage (GS) 23 and GS30, for a total of 112 kg ha^{-1}. The second N application included a broadleaf herbicide application, and a fungicide application was made at flowering. Tillers counts (main stem plus tillers with three leaves) were performed by hand prior to greenup (GS21–23) along three sections of 0.91 m (3 ft) per linear row. Fields were harvested using a plot combine in June of each year.

Version of Record at: https://doi.org/10.1002/agj2.20539

Drone flights were performed at 30, 60, and 120 m above ground level (AGL). In 2017–2018, a 3DR Solo quadcopter drone (3D Robotics, Berkley, CA) was equipped with a Parrot Sequoia multispectral camera and sunshine sensor (Paris, France). Mission planning for the quadcopter was performed using the Tower app (3D Robotics, Berkley, CA) at a 75% overlap. During the 2018–2019 growing season, emergence was the only growth stage flown with the quadcopter due to an error with the sunshine sensor. Flights were instead obtained with a fixed wing drone (Model Parrot DiscoPro Ag) equipped with the Parrot Sequoia multispectral camera and sunshine sensor. Software restricts the lower limit of the fixed wing drone to 50 m, so the 30-m AGL flight could not be obtained over the 2018–2019 growing season. Over the 2019–2020 growing season, a DJI Matrice equipped with a Micasense Altum multispectral camera was able to collect imagery at all three flying heights. Flights were performed at emergence (GS11, Nov.) and subsequent growth stages (tillering [GS21, Feb.], greenup [GS23, early Mar.], jointing [GS30, late Mar.], and boot [GS45, Apr.]) through the growing season.

Orthomosaics were generated for each camera band using Pix4DMapper desktop software (Pix4D SA, Switzerland). Five ground control points were used to georeference each orthomosaic and images were calibrated using reflectance panels for each flight. The NDVI orthomosiac was calculated by Pix4D and exported as a GeoTIFF for analyses in ArcGIS Desktop 10.1 (ESRI, Redlands, CA). Plot level data was extracted using a shapefile created in AutoCAD Civil3D (San Rafael, CA) by the methods laid out in Miller and Adkins (2020). Each plot was offset 0.5 m from the edge to reduce soil reflectance from alleys. Average plot NDVI was calculated using the Zonal Statistics tool in ArcGIS and exported using the Table to Excel tool. Yields and average NDVI plot values were analyzed as a complete randomized design using Proc GLM in SAS 9.4 software (Cary, NC). Means were separated with the LSD at $\alpha = .10$. Pearson correlation coefficients of yield, NDVI, and tiller counts were also performed using Proc Corr in SAS.

A random forest (RF) classifier was used to model NDVI measurements across the wheat growing season versus tiller (stem) counts in SAS Enterprise Miner (Cary, NC). To make recommendations for N application in the Mid Atlantic, tiller counts were split by their threshold for split spring application of N (538 tillers m^{-2}). The 22 model variables included all individual NDVI measurements for each plot over the growing season, the change in NDVI between fall and spring growth stages, and the season the flights were performed. The dataset was randomly split into a training (80% of the total dataset) and validation (20% of the total dataset) set using the data partition node. The model was tuned in a SAS code node to vary the number of trees for the RF, the number of leaves at each terminal node, and the number of variables used. Based on this, Proc HPFOREST was set to 150 trees, the default leaf setting, and four variables. In this case, four variables are close to the square root of the total variables used. Since many of the NDVI measurements were correlated to each other, the RF classification model was also performed on measurements only made at the 30 m (highest resolution) and 120 m (lowest resolution) NDVI plot values.

3 | RESULTS AND DISCUSSION

3.1 | Yields

When averaged across all three season, the lowest planting populations (S1 and S2) also had the lowest yields, whereas the higher populations (S3–S4) were not different from each other (Table 1). Previous research on small grain seeding rates have similar results, with increases in yield being limited above 371 seeds per m^{-2} and dropping with increasing seeding rates (Joseph, Alley, Brann, & Gravelle, 1985; North Carolina Cooperative Extension, 2013). Tiller counts were greatest at the S5 and S6 planting population, in the middle for S3 and S4 populations, and lowest for S1 and S2 (Table 1). This was prior to N application, so the similarity in yield between the S3–S6 populations indicates additional tillers may have been formed at the middle rates, whereas N applications did not assist in forming enough tillers at the lowest populations (Table 1). On average, tiller counts were low (less than 538 tillers m^{-2}) among planting populations, and therefore in need of split N applications (Alley, Scharf, Brann, Baethgen, & Hammons, 2019).

By year, 2020 had the highest yield, whereas 2018 and 2019 were similar and there was no interaction with planting population (Table 1). Tiller count was also significantly different by year, with 2019 having the highest tiller (stem) counts (Table 1).

3.2 | Normalized difference vegetation index (NDVI)

Among seeding rates, differences in NDVI were observed across all growth stages and heights flown (Tables 2, 3, 4). These measurements were taken after emergence (GS11–12) and at Zadooks GS21, GS23, GS30, and GS45. The NDVI measurements in this study are similar to those from handheld radiometers (Aase & Siddoway, 1980) for early growth stages (.20–.30) and maximizing at heading (.60–.80). This same range in NDVI over wheat growth stages has also been observed from drone imagery, starting at .20 at stem elongation and reaching .70–.80 at heading (Guan et al., 2019). Aase and Siddoway (1980) found differences in both dry leaf matter and linear relationships across six different seeding rates, even though NDVI at the boot stage appeared similar.

TABLE 1 Yields (Mg ha^{-1}) and wheat tillers (stems m^{-2}) by seeding rate (S) and year. Values followed by a different letter are significantly different (α = 0.1)

Parameter	Yields	Tillers
	Mg ha^{-1}	stems m^{-2}
Planting population		
S1, 222 seeds m^{-2}	5.7b	370c
S2, 297 seeds m^{-2}	5.7b	395c
S3, 371 seeds m^{-2}	6.3a	446b
S4, 445 seeds m^{-2}	6.2a	439b
S5, 494 seeds m^{-2}	6.2a	455ab
S6, 544 seeds m^{-2}	6.1a	484a
Pr > F	.0726	<.0001
Year		
2018	5.5b	358c
2019	5.6b	506a
2020	7.0a	431b
Pr > F	<.0001	<.0001
Population × Year	.2798	.2048

TABLE 2 Average normalized difference vegetation index (NDVI) for the 2019–2020 growing seasons by growth stage (GS) at 30 m above ground level. Values followed by a different letter are significantly different (α = .1)

Parameter	GS11	GS21	GS24	GS30	GS45
	NDVI				
Seeding rate					
S1, 222 seeds m^{-2}	.1777e	.4034b	.4700b	.7178b	.9236b
S2, 297 seeds m^{-2}	.1899d	.4086b	.4695b	.7144b	.8209b
S3, 371 seeds m^{-2}	.2053c	.4503a	.5156a	.7400a	.8441a
S4, 445 seeds m^{-2}	.2170b	.4502a	.5056a	.7403a	.8538a
S5, 494 seeds m^{-2}	.2342a	.4565a	.5182a	.7509a	.8554a
S6, 544 seeds m^{-2}	.2414a	.4761a	.5269a	.7463a	.8586a
Pr > F	.0001	.0121	0414	.0440	.0090
Year					
2018	.1885b	.2408b	.3332b	.5936b	.7626b
2019[a]	.0671c	–	–	–	–
2020	.3772a	.6430a	.6688a	.8864	.9222a
Pr > F	.0001	.0001	.0001	.0001	.0001
Rate × Year	.0001	.7195	.6459	.6620	.0590

aDrone flights could not be performed at 30 m in 2019.

At the first stage flown (GS11), NDVI values ranged from .17 to .28, which is common in the early stages of wheat growth as imagery includes soil reflectance (Aase & Siddoway, 1981; Guan et al., 2019). Flights performed at higher elevations may reduce soil reflectance as image resolution decreases, which may explain why higher NDVI was measured for plant populations at 120 m AGL (Table 4). At GS11, separation by NDVI among seeding rates was evident at all heights AGL (Tables 2, 3, 4), with complete separation evident at 120 m AGL (Table 4). This is a positive result, as higher flights require less flight time, produce less photos, and take less time to process.

From GS11 to GS45, there was a steady increase in NDVI, which typically increases until heading (Aase & Siddoway, 1981; Guan et al., 2019). At GS21, NDVI values increased to 0.34–0.47, as more tillering and plant growth occurred in late fall and early winter. Among planting populations, this additional tillering reduced the separation that was more

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TABLE 3 Average normalized difference vegetation index (NDVI) for the 2019–2020 growing seasons by growth stage (GS) at 60 m above ground level. Values followed by a different letter are significantly different (α = .1)

Parameter	GS11	GS21	GS24	GS30	GS45
	NDVI				
Seeding rate					
S1, 222 seeds m^{-2}	.1748e	.3434b	.4243b	.6284bc	.8275b
S2, 297 seeds m^{-2}	.1875d	.3488b	.4189b	.6199c	.8213b
S3, 371 seeds m^{-2}	.2007c	.3833a	.4607a	.6487a	.8334a
S4, 445 seeds m^{-2}	.2133b	.3856a	.4504a	.6455ab	.8471a
S5, 494 seeds m^{-2}	.2285a	.3975a	.4606a	.6548a	.8470a
S6, 544 seeds m^{-2}	.2357a	.4056a	.4686a	.6529a	.8502a
Pr > *F*	.0001	.0001	.0093	.0103	.0016
Year					
2018	.1750b	.2308c	.3495b	.5950b	.7477c
2019	.0757c	.2594b	.3241c	.4242c	.8563b
2020	.3606a	.6418a	.6681a	.9059a	.9142a
Pr > *F*	.0001	.0001	.0001	.0001	.0001
Rate × Year	.0001	.8199	.7306	.9711	.0992

TABLE 4 Average normalized difference vegetation index (NDVI) for the 2019–2020 growing seasons by growth stage (GS) at 120 m above ground level. Values followed by a different letter are significantly different (α = .1)

Parameter	GS11	GS21	GS24	GS30	GS45
	NDVI				
Seeding rate					
S1, 222 seeds m^{-2}	.2118f	.3460b	.4146bc	.6257bc	.8014b
S2, 297 seeds m^{-2}	.2291e	.3516b	.4120c	.6188c	.7950b
S3, 371 seeds m^{-2}	.2473d	.3864a	.4475a	.6464a	.8156a
S4, 445 seeds m^{-2}	.2614c	.3866a	.4365ab	.6421ab	.8200a
S5, 494 seeds m^{-2}	.2790b	.3989a	.4456a	.6534a	.8212a
S6, 544 seeds m^{-2}	.2875a	.4082a	.4516a	.6510a	.8225a
Pr > *F*	.0001	.0002	.0217	.021	.0034
Year					
2018	.2143b	.2399b	.3145b	.5767b	.7219c
2019	.0871c	.2554b	.3123b	.4334c	.8069b
2020	.4566a	.6436a	.6771a	.9086a	.9090c
Pr > *F*	.0001	.0001	.0001	.0001	.0001
Rate × Year	.0001	.8109	.6069	.9789	.3011

evident at emergence (Tables 2, 3, 4). Higher planting populations (S3–6) were similar to each other at later growth stages and heights flown, which follows the yield results observed (Table 1). Therefore, higher populations having similar NDVI values in this study is not an issue, as we are more concerned with differentiating between lower yielding versus higher yield regions of the field. This can potentially be performed, as the lowest performing planting rates also had the lowest NDVI measurements at all growth stages. Therefore, at GS21, it is possible to detect portions of a field that need split applied N for additional tillers (Phillips et al., 2004) in the S1 and S2 planting populations. However, based on mid-Atlantic recommendations (Alley et al., 2019), almost all individual plots had tiller counts in need of split N application at GS21.

One issue with attempting to separate higher and lower performing portions of a field is how small the NDVI difference was among seeding rates (∼.02), a range that could be

Version of Record at: https://doi.org/10.1002/agj2.20539

TABLE 5 Change in normalized difference vegetative index (NDVI) between growth stage (GS) GS11 to GS21 (change in the fall or ΔFall) and GS21 to GS24 (change in the spring or ΔSpring) by height above ground level, year, and interaction (year × seeding rate). Values followed by a different letter are significantly different (α = .1)

	30 m		60 m		120 m	
Parameter	ΔFall	ΔSpring	ΔFall	ΔSpring	ΔFall	ΔSpring
	NDVI					
Seeding rate						
S1, 222 seeds m^{-2}	.0313e	.0667	.0774f	.0809a	.0024d	.0686a
S2, 297 seeds m^{-2}	.0418d	.0608	.0867e	.0773a	.0092cd	.0603b
S3, 371 seeds m^{-2}	.0558c	.0594	.0983d	.0700b	.0153bc	.0611b
S4, 445 seeds m^{-2}	.0619bc	.0554	.1055c	.0647bc	.0221ab	.0499c
S5, 494 seeds m^{-2}	.0694b	.0617	.1140b	.0631c	.0279a	.0467c
S6, 544 seeds m^{-2}	.0799a	.0508	.1219a	.0630c	.0267a	.0434c
Pr > *F*	.0001	.1340	.0001	.0001	.0001	.0001
Year						
2018	.0470b	.0925a	.1385a	.1187a	.0184b	.0746a
2019	−.0084c	–	.0414c	.0646b	−.0049c	.0569b
2020	.1240a	.0257b	.1220b	.0263c	.0383a	.0335c
Pr > *F*	.0001	.0001	.0001	.0001	.0001	.0001
Rate × Year	.0031	.0007	.0006	.0069	.0001	.0025

observed between plots with the same planting population. However, in a larger field setting, these regions may present a larger pattern that can be separated through spatial statistics.

Among all heights flown, there were measurable differences between years, particularly at the earliest growth stage, where NDVI ranged from .07 to .45 (Tables 2, 3, 4). In 2020, a warmer fall and early winter produced greater growth, which obviously influenced NDVI measurements. This carried throughout the entire growing season, where NDVI was greatest in 2020 at every growth stage and height flown. At GS11, there was an interaction between planting population and year for all flights but was not present for most other measurements (Tables 2, 3, 4). Early season measurements may differentiate between populations well, (prior to tillering), but early growth may change quickly and not give consistent NDVI values every year.

3.3 | Relative changes in NDVI between growth stages

If multiple flights are made over small grains during the growing season, the change in NDVI between growth stages can be measured (Table 5). When earlier growing stage NDVI was subtracted from the next stage (e.g., GS21 minus GS11), patterns of growth could be observed among the seeding rates. Planting populations could be separated by changes in NDVI at all three heights AGL between the GS11 to GS21 (change over the fall or ΔFall) and GS21 to GS24 (change over the spring or ΔSpring) growth stages. Depending on the height flown, the change in NDVI (plant growth) was observed between planting populations in the fall, with separation between all treatments at 60 m AGL (Table 5). There may not be any important relationship with the image resolution at this height and could be a random effect from this study. At 120 m AGL, the lowest populations (S1 and S2), which also had the lowest tillers and yields, could be separated from the higher populations (S5 and S6). As noted above, any flight at the highest legal height will reduce time and labor in drone flights and allows for more acreage to be covered. More importantly, during the first week of emergence, there was a greater change in NDVI at the higher planting populations, due to the overall higher biomass at planting (Table 5.) This relationship was reversed when NDVI at GS21 was subtracted from NDVI at GS24 (ΔSpring). Over this period, ΔSpring differentiated between plant populations, but it was the lower seeding rates that had a greater change (increase) in NDVI (Table 5). During spring greenup, lower populations (S1, S2) are seeing increased growth as they attempt to make up for lower populations by adding more tillers. In this case, this additional spring growth was not able to makeup yield due to the low planting populations of S1 and S2 (<371 stems m^{-2}). However, this study did not observe the effects of variable N rates and timings, which could alter the results of tillering in the spring.

The benefits of multiple drone flights can be two-fold. First, a single flight may uncover low populations due to emergence

Version of Record at: https://doi.org/10.1002/agj2.20539

or winter survival issue at either GS11 or GS21, but multiple flights can then be compared to see where greater growth was. Even if stem counts cannot be predicted this way, a concentrated effort in regions of the field can determine through manual tiller counts whether replanting in the fall or split N in the spring is warranted.

3.4 | Correlations of NDVI to yield and tiller counts

Data from all three growing seasons was analyzed for correlations between NDVI, yield, and tiller counts (Table 6). At 30 m AGL, yields had higher correlations to greenup and tillering growth stages than any other height flown, ranging from .54 to .59 with *p*-values < .0001 (Table 6). Small grain yields have correlated to NDVI in other studies (Goodwin et al., 2018), particularly at the heading stage (Guan et al., 2019; Marti et al., 2007). In this study, earlier correlation to yield is observed because the range in planting populations has a greater control over yield than tillering would have been if one rate had been used. The strongest GS24 correlation was at 30 m ($r = .59$, $p = < .0001$), which was also the highest correlation to yield from any year or height. The range of GS21 to GS24 has the highest correlation to yield at 30 m, similar to GDD > 0 observed to predict yield (97–112 GDD) by Dhillon et al. (2019). These values were adjusted based on the regional mid-Atlantic base of 0 -°C in the calculation, where the original calculation in Oklahoma would have placed the range between GS30 and GS45, which correlates to yield at all heights flown (Table 6).

Tiller counts were significant at all stages but had their highest correlations to NDVI during the period spring N recommendations would be made (Phillips et al., 2004). This is also the period when tiller counts were performed, so the results should be expected. Tiller counts drop off in their correlations after this period since additional stem formation would have occurred that was not made in the hand count. Tiller counts were positively correlated to fall growth (r = .31 to .67, p = < .0001), but negatively to spring growth (−.57 to .61, p = < .0001). As mentioned above, fall correlations are related to the initial planting population, whereas negative spring correlations are related to lower populations showing greater NDVI changes with more tillering (Table 6).

To continue to uncover this relationship, future studies should consider varying N rate, timing, and the addition of zero and high N strips, as has been recommended in many other studies (Phillips et al., 2004; Raun et al., 2001). Measurement of NDVI by drone may be higher and more compressed than handheld devices (Duan et al., 2017) and current algorithms may need to be updated based on drone imagery.

TABLE 6 Pearson correlation coefficients for normalized difference vegetative index (NDVI) vs for yield and tiller counts at each growing stage (GS; growing degree days >0) and height above ground level

Height above ground level	GS11 (19)	GS21 (96)	GS24 (120)	GS30 (144)	GS45 (161)	ΔFall	ΔSpring
Yield							
30 m	−.19243*	.57767****	.5911****	.54428****	.56183****	−.14699ns	−.4522***
60 m	−.15764ns	.08289ns	.01249ns	−.22586**	.48363****	−.46777****	−.35451****
120 m	−.16197ns	.06571ns	.03182ns	−.18921*	.34656***	−.18538*	−.30656****
Tillers							
30 m	.6227****	.77214****	.78916****	.73331****	.75847****	.67532****	−.60878****
60 m	.626****	.78277****	.78675****	.68702****	.62975****	.30744**	−.56756****
120 m	.62982****	.78361****	.77587****	.70156****	.70959****	.61534****	−.60312****

*Significant at the .05 probability level; **Significant at the .01 probability level; ***Significant at the .001 probability level; ****Significant at the .0001 probability level; ns, not significant.

Version of Record at: https://doi.org/10.1002/agj2.20539

TABLE 7 Random Forest variable importance for normalized difference vegetative index (NDVI) measurements at all growing stages and heights and selected for the lowest (30 m) and highest (120 m) heights flown to classify wheat tillers for spring split N application. RMSE, root mean square error; ΔSpring, change in the spring; ΔFall, change in the fall

Top 10 variables	All variables	30 m	120 m
1	ΔSpring 60 m	ΔFall	ΔFall
2	ΔFall 30 m	GS11	ΔSpring
3	GS11 120 m	ΔSpring	GS30
4	ΔSpring 120 m	GS45	GS11
5	ΔFall 120 m	GS30	GS45
6	ΔFall 30 m	Year	GS21
7	GS21 120 m	GS21100	GS24
8	GS45 30 m	GS24100	Year
9	GS11 30 m	–	–
10	GS11 6 m	–	–
Training RMSE	.125	.224	.125
Validation RMSE	.163	.366	.163
Validation misclassification rate	.200	.250	.200
Validation misclassification #	0	4	0

3.5 | Random forest classification using drone NDVI

With the difference in yearly NDVI based on growth (Tables 2, 3, 4), and potential variation in final stands due to germination and winter kill, predicting actual tiller counts by NDVI will be difficult. Application of NDVI by tractor-mounted sensors used a range of indicators, including a high and low N strip (Phillips et al., 2004; Ruan et al., 2001) which were not used in this population study. What can be performed is possible a comparison of adequate to inadequate populations that may need split applied N, which is 538 tillers m^{-2} in the Mid-Atlantic (Alley et al., 2019).

A random forest (RF) model was performed on variables to discern if NDVI measurements over the season could help predict where this split may occur. Twenty-two total variables were used to classify tiller counts, including all NDVI measurements at each image resolution and wheat growth stage (Table 7). The top two variables to help classify tiller counts were both based on measuring change in NDVI between stages, for spring (60 m) and fall (30 m), respectively (Table 7). These change in NDVI variables made up five of the top six and included all three heights flown. The most important single flight was at GS11, which was used three times in the top 10 variables. The very last variable of importance was year, which is a positive outcome. Although NDVI can vary year to year, measuring NDVI across a field at two different time points may reduce yearly variability.

As it is not practical to fly a drone at several heights across a field during several growth stages, only NDVI measurements at both 30 and 120 m were also evaluated for their ability to classify tiller counts. This task is also important because most of these individual NDVI variables are correlated to each other and may not be needed each year. For both heights flown, change in NDVI in the fall and spring were in the top three predictors (Table 7). At 30 m, year had a greater effect on predicting tillers, probably due to higher resolution picking up on more field variability. At 120 m, year was the least important variable, whereas change in NDVI as well as earlier growth stages (GS11, GS30) were important.

The misclassification rate of the validation sets was .20, .25, and .20 for all, 30 m, and 120 m variables, respectively (Table 7). Using only NDVI measurements at 30 m also resulted in four misclassified tiller counts, compared to zero for both all and NDVI at 120 m. These results indicate that just using NDVI measurements from the higher flight (lower camera resolution) may be adequate when placing tillers into split vs no-split applied N categories.

Practically, the fewer flights performed, the more useful drone imagery becomes. If measurements of all heights and growth stages are needed, drone imagery does not necessarily reduce the labor and time involved in tiller counts. High resolution satellite imagery may also perform this function, where an image may be acquired from both late fall and early winter to calculate differences in growth and perform ground truthing with a few tiller counts.

4 | CONCLUSION

In this study, drone derived NDVI can separate between plant populations to find potentially lower yielding portions of a winter wheat field. The range in plant populations used in this study would not represent normal seeding rates but could be the result of poor planting conditions or lower winter survival. Flights at 30 m (higher camera resolution) did not necessarily improve accuracy, so flights made at the highest legal limit (120 m) could be adequate for separating tillers into low and high categories, assisting with the decision to split spring N applications for small grains. Multiple flights (fall and spring) can assist with differentiating wheat growth rates, rather than using a single flight to determine tillers. For this study, measuring wheat growth with two flights in the fall was a good predictor of high and low tillers according to a random forest classification. For an individual flight, emergence was an important time to differentiate, however that may be related to the range in planting populations performed.

This study should be limited in application, as the purpose was to determine if lower camera resolution (higher flight AGL) was adequate to differentiate between plant populations. Future studies that combine this information with variations in N rate, planting date, and cultivars will be needed to improve wheat management using drone imagery. For larger fields, satellite imagery may also be adequate to perform this task, as obtaining one image from late fall and another from early spring could be achievable for researchers, farmers, and crop consultants.

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CONFLICT OF INTEREST

The authors report no conflict of interest.

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REFERENCES

Aase, J. K. (1978). Relationship between leaf area and dry matter in winter wheat. *Agronomy Journal*, *70*, 563–565. https://doi.org/10.2134/agronj1978.00021962007000040011x

Aase, J. K., & Siddoway, F. H. (1980). Determining winter wheat stand densities using spectral reflectance measurements. *Agronomy Journal*, *72*, 149–152. https://doi.org/10.2134/agronj1980.00021962007200010028x

Aase, J. K., & Siddoway, F. H. (1981). Assessing winter wheat dry matter production via spectral reflectance measurements. *Remote Sensing of the Environment*, *11*, 267–277. https://doi.org/10.1016/0034-4257(81)90025-0

Alley, M. M., Scharf, P., Brann, D. E., Baethgen, W. E., & Hammons, J. L. (2019). *Nitrogen management for winter wheat: Principles and recommendations* (Virginia Cooperative Extension Publication No. 424-026). Blacksburg, VA: Virginia Tech.

Aparacio, N., Villegas, D., Casadesus, J., Araus, J. L., & Royo, C. (2000). Spectral vegetation indices as nondestructive tools for determining wheat yield. *Agronomy Journal*, *92*, 83–91. https://doi.org/10.2134/agronj2000.92183x

Condorelli, G. E., Maccaferri, M., Newcomb, M., Andrade-Sanchez, P., White, J. W., French, A. N., … Tuberosa, R. (2018). Comparative aerial and ground based high throughput phenotyping for the genetic dissection of NDVI as a proxy for drought adaptive traits in durum wheat. *Frontiers in Plant Science*, *9*, 1–17.

Dhillon, J. S., Figueiredo, B. M., Eickhoff, E. M., & Raun, W. R. (2019). Applied use of growing degree days to refine optimum times for nitrogen sensing in winter wheat. *Agronomy Journal*, *112*, 537–549. https://doi.org/10.1002/agj2.20007

Duan, T., Chapman, S. C., Guo, Y., & Zheng, B. (2017). Dynamic monitoring of NDVI in wheat agronomy and breeding trials using an unmanned aerial vehicle. *Field Crops Research*, *210*, 71–80. https://doi.org/10.1016/j.fcr.2017.05.025

Erdle, K., Mistele, B., & Schmidhalter, U. (2011). Comparison of active and passive spectral sensors in discriminating biomass parameters and nitrogen status in wheat cultivars. *Field Crops Research*, *124*, 74–84. https://doi.org/10.1016/j.fcr.2011.06.007

Goodwin, A. W., Lindsey, L. E., Harrison, S. K., & Paul, P. A. (2018). Estimating wheat yield with normalized difference vegetation index and fractional green canopy cover. *Crop, Forage and Turfgrass Management*, *4*, 1–6. https://doi.org/10.2134/cftm2018.04.0026

Guan, S., Fukami, K., Matsunaka, H., Okami, M., Tanaka, R., Nakano, H., … Sakai, T. (2019). Assessing correlation of high-resolution NDVI with fertilizer application level and yield of rice and wheat crops using small UAVs. *Remote Sensing*, *11*, 1–19. https://doi.org/10.3390/rs11020112

Hassan, M. A., Yang, M., Rasheed, A., Yang, G., Reynolds, M., Xia, X., … He, Z. (2019). A rapid monitoring of NDVI across the wheat growth cycle for grain yield prediction using a multi-spectral UAV platform. *Plant Science*, *282*, 95–103. https://doi.org/10.1016/j.plantsci.2018.10.022

Hatfield, J. L., Gitelson, A. A., Schepers, J. S., & Walthall, C. L. (2008). Application of spectral remote sensing for agronomic decisions. *Agronomy Journal*, *100*, S117–S131. https://doi.org/10.2134/agronj2006.0370c

Hochheim, K. P., & Barber, D. G. (1998). Spring wheat yield estimation for Western Canada using NOAA NDVI data. *Canadian Journal of Remote Sensing*, *24*, 17–27. https://doi.org/10.1080/07038992.1998.10874687

Joseph, K. D. S. M., Alley, M. M., Brann, D. E., & Gravelle, W. D. (1985). Row Spacing and Seeding Rate Effects on Yield and Yield Components of Soft Red Winter Wheat. *Agronomy Journal*, *77*, 211–214. https://doi.org/10.2134/agronj1985.00021962007700020009x

Labus, M. P., Nielsen, G. A., Lawrence, R. L., Engel, R., & Long, D. S. (2002). Wheat yield estimates using multi-temporal NDVI satellite imagery. *International Journal of Remote Sensing*, *23*, 4169–4180. https://doi.org/10.1080/01431160110107653

Marti, J., Bort, J., Slafer, G. A., & Araus, J. L. (2007). Can wheat yield be assessed by early measurements of Normal Difference Vegetation Index? *Annals of Applied Biology*, *150*, 253–257. https://doi.org/10.1111/j.1744-7348.2007.00126.x

Miller, J. O., & Adkins, J. (2020). *Creating a Grid Plot Map in AutoCAD Civil3D* (University of Delaware Extension Publication No. PA-120). Newark, DE: University of Delaware.

Mulla, D. J. (2013). Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosystems Engineering*, *114*, 358–371. https://doi.org/10.1016/j.biosystemseng.2012.08.009

North Carolina Cooperative Extension. (2013). *Small grain production guide*. AG-580 (Revised). Raleigh, NC: North Carolina State University.

Prasad, B., Carver, B. F., Stone, M. L., Babar, M. A., Raun, W. R., & Klatt, A. R. (2007). Potential use of spectral reflectance indices as a selection tool for grain yield in winter wheat under Great Plains conditions. *Crop Science*, *47*, 1426–1440. https://doi.org/10.2135/cropsci2006.07.0492

Phillips, S. B., Keahey, D. A., Warren, J. G., & Mullins, G. L. (2004). Estimating winter wheat tiller density using spectral reflectance sensors for early-spring, variable rate nitrogen applications. *Agronomy Journal*, *96*, 591–600. https://doi.org/10.2134/agronj2004.0591

Royo, C. N., Aparicio, D., Villegas, J., Casadesus, P., Monneveux, P., & Araus, J. L. (2003). Usefulness of spectral reflectance indices as durum wheat yield predictors under contrasting Mediterranean conditions. *International Journal of Remote Sensing*, *24*, 4403–4419. https://doi.org/10.1080/0143116031000150059

Ruan, W. R., Solie, J. B., Johnson, G. V., Stone, M. L., Lukina, E. V., Thomason, W. E., & Schepers, J. S. (2001). In-season prediction of potential grain yield in winter wheat using canopy reflectance. *Agronomy Journal*, *93*, 131–138. https://doi.org/10.2134/agronj2001.931131x

Thapa, S., Rudd, J. C., Xue, Q., Bhandari, M., Reddy, S. K., Jessup, K. E., … Baker, S. (2019). Use of NDVI for characterizing winter wheat response to water stress in a semi-arid environment. *Journal of Crop Improvement*, *33*, 633–648. https://doi.org/10.1080/15427528.2019.1648348

Tilley, M. S., Heiniger, R. W., & Crozier, C. R. (2019). Tiller initiation and its effects on yield and yield components in winter wheat. *Agronomy Journal*, *111*, 1323–1332. https://doi.org/10.2134/agronj2018.07.0469

Tucker, C. J., Holben, B. N., Elgin, J. H., McMurtrey, J. E. (1980). Relationship of spectral data to grain yield variation. *Photogrammetric Engineering and Remote Sensing*, *46*, 657–666.

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