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Small-Scale Spatial Variability in Winter Wheat Production

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*Spatial variability is well documented in agricultural crops. Research has shown that average differences in grain yield for neighboring corn (*Zea mays *L.) plants can vary by as much as 4211 kg ha^{-1}; however, little work has been done in winter wheat (*Triticum aestivum *L.) to determine the amount and scale of spatial variability that exists in grain yields. This study used 22-m × 0.9-m transects, partitioned in 0.9-m × 0.9-m subplots, to document the spatial variability that occurred in winter wheat yields. Average yields of each transect ranged from 1023 to 3807 kg ha^{-1}. Within transects, there was a 1.7- to 2.3-fold difference between the highest and lowest yielding units. This study documented large levels of variability over distances of <1 m. Agronomists working toward precisely managing crop inputs for their most efficient use should account for spatial variability, as significant differences in winter wheat grain yield were found in adjacent 1-m × 1-m plots.*

Keywords Spatial variability, winter wheat

Introduction

One of the biggest challenges for precision farming is to accurately identify and treat spatial variability to maximize net returns (Batchelor, Basso, and Paz 2002). Managing spatial variability has become the subject of much research in corn and soybeans throughout the Midwest to maximize yields. Spatial variability has been well documented and studied by researchers at varying levels from field scales of 100 ha (Buttafuco et al. 2010) to the submeter level (Solie, Raun, and Stone 1999). Solie, Raun, and Stone (1996) proposed calling the finest area that is treated the field element. The field element is the size of an area where similar nutrient and crop growth status could be expected. An area that was treated uniformly at a size greater than this fundamental field element would not be as effective because individual field elements would require differing levels of treatment. Conversely, a treatment that was smaller than the field element would be inefficient because the area within the field element is already similar and thus the treatment would be equal.

Although the idea of a field element is straightforward, finding the size of the field element becomes much more difficult. The field element could be considered the area where no relationship exists between it and the neighboring field element (Solie, Raun, and Stone 1999). As precision farming advances, many researchers have proposed different opinions about the ideal field element. Sadler et al. (1998) concluded that the ideal field element

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was less than a 100-m grid, which is often used in precision agriculture. Wollenhaupt, Wolkowski, and Clayton (1994) determined that a 97-m grid was the maximum allowable size for precision agriculture, whereas Franzen and Peck (1993) determined that 30-m grids would be the maximum allowable size for precision fertilizer application. In addition, Wibawa et al. (1993) showed that 15-m grids provided more reliable data for determining spatial variability. Although these researchers all proposed maximum values, which vary significantly in size, no minimum field element size was proposed. While it is possible that minimum size could be set by implement width, technology has progressed to a point that boom controllers make it possible to treat areas finer than 15 m in resolution.

As the area of treatment decreases, researchers have noted a decrease in error associated with variability. Enclona et al. (2004) used a 4-m grid and documented more spatial variability by using this finer resolution than would have been documented using a larger resolution. Solie, Raun, and Stone (1999) showed that mean error decreased as much as 50% when they decreased the area of analysis from 6 m $\times$ 60 m to 2 m $\times$ 2 m. Using geostatistics, they hypothesized the minimum field unit should be 0.75 m $\times$ 0.75 m and by using such a small area nutrient and plant measurements could be taken precisely. Cahn, Hummel, and Brouer (1994) also showed that error could be reduced significantly by reducing the size of the fundamental unit. Raun et al. (1998) proposed some of the smallest fundamental units of 0.3 m $\times$ 0.3 m. Their work using a 0.3-m grid showed large variability in nutrients including optimal nitrogen (N) fertilizer recommendations that changed 10–50 kg ha^{-1} over distances <2 m. They suggested that the field element would be the area from which plant roots could extract nutrients from a horizontal area, and thus the maximum field element would be 0.3 m $\times$ 0.3 m. Their work showed significant variability both in mobile and immobile nutrients in these sampling elements, further supporting the need for submeter precision.

Martin et al. (2005) documented spatial variability in maize throughout the world and showed that average plant-to-plant variation in grain yield exceeded 2926 kg ha^{-1} (47 bu ac^{-1}) at all sites. Coefficients of variation (CV) ranged from 20 to 45%. They proposed that factors affecting yield should be treated on areas less than 0.5 m. For six winter wheat fields over 9 years, Washmon et al. (2002) computed CVs on wheat yields collected at a resolution of 25 m grids. In this work they found that CVs for the same field varied significantly over time. This showed that temporal variations influenced the expression of spatial variability within each field. Similar work by Vieira and Gonzalez (2003) noted that factors affecting crop variability can change from year to year and may change based on the crop, specifically finding a difference in spatial variability in rice and soybeans. This would suggest that in addition to spatial variability there is a component of temporal or time variability. This sentiment is further echoed by Schepers et al. (2004), who found that temporal variability could result in yield difference of 25% or more during some years and less than 5% during other years. Porter et al. (1998) reported that temporal variability was three and four times greater than spatial variability in soybean and corn respectively. Thus there is a need to recognize both spatial variability and temporal variability to properly manage fields with precision agriculture as only accounting for one source of variability will likely be insufficient to produce maximum returns (Schepers et al. 2004).

Even though there has been much research to understand and manage variability in field crops, there has been little research in wheat documenting the spatial variability and scale. Our objectives were to analyze wheat yields on a small scale, <1-m grids, to determine the level of spatial variability and to identify levels of variability at this resolution using precision sensing technology. In addition to identifying spatial variability, we also used precision sensing to identify temporal variability as other researchers have reported remote sensing as a method to overcome temporal variability (Raun et al. 2002; Shanahan et al. 2003).

Materials and Methods

During the winter wheat crop cycles of 2010 and 2011 six wheat transects were evaluated in north central Oklahoma. Four locations were used for the 2010 season. They included Manchester, Lake Carl Blackwell (LCB), EFAW, and Lahoma. Two transects were implemented during the 2011 crop year, one at LCB and one at EFAW. The transects were 22 m × 0.9 m in size (75 ft ×3 ft), and divided into 0.9-m × 0.9-m (3-ft × 3-ft) segments. Transects were placed within existing research locations or farmer fields (Manchester). Soil fertility was assumed to be the same for each transect, as transects were not located within any other field trial and followed the regular farmer practice for the entire transect area. At Feekes growth stage 5 (Large 1954), normalized difference vegetative index (NDVI) sensor data was collected using a GreenSeeker sensor (Trimble Navigation, Sunnyvale, Calif.) for each 0.9-m × 0.9-m segment of the transect. The NDVI index was determined as NDVI = (NIR – Red) / (NIR + Red), where NIR and Red are the fraction of emitted raditation returned from the sensed area (reflectance) for the 770-nm and 660-nm bands, respectively.

Transects were split into two 22-m × 0.45-m sizes, and forage biomass was collected from half of the transect at Feekes growth stage 5 on 0.9-m × 0.45-m grids. The other half of each transect was allowed to reach physiological maturity where biomass and grain yield were collected on the remaining 0.9-m × 0.45-m grids. Table 1 shows the location, variety, planting date, date of biomass and NDVI collection, growing degree days from planting until NDVI sensing and biomass collection, and growth stage.

Each segment of these transects was hand harvested, both for forage biomass and grain yield. Plots were then dried at 70 °C for 48 h before weighing for both the Feekes 5 biomass and grain yield. After drying, final biomass and grain yields in kg ha^{-1} were calculated. Statistical analysis included the computation of transect standard deviation, CV, and yield range.

Table 1
Location, year, variety, planting date, biomass harvest and NDVI collection date, growing degree days (GDD) from planting until biomass harvest, and Feekes growth stage, Oklahoma, 2010–2011

Location	Year	Variety	Planting date	Biomass and NDVI	GDD	Growth stage
EFAW	2010	Endurance	8 Nov. 2009	12 April 2010	1799	Feekes 5
Lahoma	2010	OK Bullet	7 Oct. 2009	7 April 2010	2124	Feekes 5
LCB	2010	Endurance	11 Nov. 2009	14 April 2010	1823	Feekes 6
Manchester	2010	Santa Fe	26 Oct. 2009	7 April 2010	1704	Feekes 6
Lahoma	2011	OK Bullet	6 Oct. 2010	15 March 2011	2031	Feekes 5
LCB	2011	Centerfield	29 Sept. 2010	16 March 2011	2391	Feekes 5

Results

Grain yields for each transect along with maximum, minimum, average, maximum/minimum, CV, and range of yield (maximum–minimum) are illustrated in Table 2. In Figure 1(a–f), grain yield is plotted against distance for all transects.

Over the six site-years, average transect grain yields ranged from 1023 to 3807 kg ha^{-1} (15–56 bu ac^{-1}) with a standard deviation (SD) among transects that ranged from

Table 2
Grain yield by transect, minimum, maximum, mean, standard deviation, minimum/maximum, range, and coefficient of variation (CV), Oklahoma, 2010–2011

Year	Location	Min. (kg ha^{-1})	Max. (kg ha^{-1})	Mean (kg ha^{-1})	SD (kg ha^{-1})	Range (kg ha^{-1})	Max./min.	CV (%)
2010	EFAW	1614	3284	2430	423	1670	2.0	17
2010	Lahoma	828	1474	1179	180	646	1.8	15
2010	LCB	1588	2952	2340	358	1365	1.9	15
2010	Manchester	1609	3531	2537	589	1921	2.2	23
2011	Lahoma	2868	4978	3807	534	2110	1.7	14
2011	LCB	714	1636	1023	243	922	2.3	24

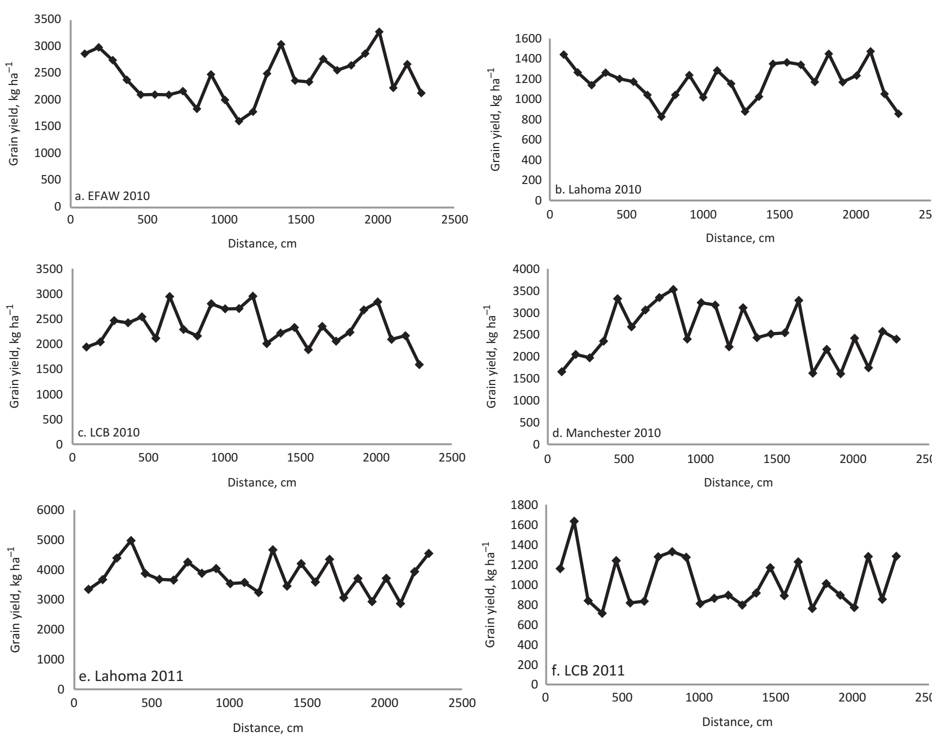

Figure 1. Grain yield by distance, for each 90-cm × 45-cm unit, EFAW, Lahoma, LCB, and Manchester, 2010–2011.

180 to 589 kg ha^{-1} (3–9 bu ac^{-1}). In general, as grain yields increased the standard deviation increased. This trend has also been noticed by other researchers (Taylor, Payton, and Raun 1999; Dobermann et al. 2003). Within each transect, the highest yielding plot was an average of 1.7 to 2.3 times greater than the lowest yielding plot. All transects had CV values between 14 and 24%.

The dry forage biomass collected at Feekes 5 over all transects ranged from 315 to 1907 kg ha^{-1} (277–1678 lbs ac^{-1}) with standard deviations from 128 to 393 kg ha^{-1} (113–346 lbs ac^{-1}). Within transects, there was more variability as the greatest yielding biomass plots were 1.8 to 3.3 times greater than the lowest yielding plot. This variation was also seen in the greater CV values that ranged from 15 to 40%. Table 3 highlights the dry forage biomass yield, minimum, maximum, average, SD, maximum/minimum, CV, and range for each transect.

Discussion

Expression of Spatial Variability

Considerable variation in grain yield and total biomass was documented within all transects and all site-years. While there was no standard treatment (e.g. fertilizer, variety) among transects, each plot within each individual transect was managed the same from planting to harvest. Each individual transect was assumed to have experienced the same weather including temperature, moisture, and solar radiation. In addition, data collection took place at the same time for all individual transects. It was noted that yields differed by a factor of 2 across all transects. While this work did not account for differences encountered from side to side, within 0.9-m × 0.45-m areas in the transect row, there was still considerable variability. However, extreme values (maximum and minimum values) were usually not found at ends of the transects. The distance between yield extremes in these transects ranged from 2 to 17 m (Table 4). Graphically, although some areas of the transect appeared to yield more, there were no transects that showed major differences between the maximum and minimum yields that would support a conclusion of a much greater yield potential at one location of the transect compared to other locations in the transect.

This research is similar to the findings of Raun et al. (1998) and Solie, Raun, and Stone (1999) that large spatial changes could be found in areas less than 1 m apart. While

Table 3

Dry forage biomass at Feekes growth stage 5, by transect, minimum, maximum, mean, standard deviation, maximum/minimum, range, and coefficient of variation (CV), Oklahoma, 2010–2011

Year	Location	Min. (kg ha^{-1})	Max. (kg ha^{-1})	Mean (kg ha^{-1})	SD (kg ha^{-1})	Range (kg ha^{-1})	Max./min.	CV (%)
2010	EFAW	562	1871	941	299	1310	3.3	32
2010	Lahoma	160	583	315	128	423	3.6	40
2010	LCB	1009	1816	1402	221	808	1.8	16
2010	Manchester	688	1735	1169	302	1047	2.5	26
2011	Lahoma	1338	2447	1907	288	1109	1.8	15
2011	LCB	858	2199	1542	393	1341	2.6	26

Table 4
Distance between the minimum and maximum winter wheat grain yields within each transect for each location and year, Oklahoma, 2010–2011

Year	Location	Distance (m)
2010	EFAW	9
2010	Lahoma	14
2010	LCB	11
2010	Manchester	11
2011	Lahoma	17
2011	LCB	2

their work focused on soil properties, this work focused on the resulting plant growth. The most likely causes of variability seen in these transects were plant stand heterogeneity and soil variability, which would influence plant nutrients, water-holding capacity, and other variables that affect crop growth.

Prediction of Variability

While the expression of variability was expected, the more challenging issue is how to identify and treat variability for maximum crop and profit potential. With the advances in precision technology, it would be inefficient to simply treat each field as a single unit, and many farmers have transitioned to zones within a field or grid management. Even with better management, variability both spatially and temporally has to be evaluated accurately to provide the benefits of precision agriculture. This study shows variability both in final grain yield and forage biomass at growth stage Feekes 5 at 0.9-m resolution.

It is possible to recognize spatial variability during the growing season and to treat this variability appropriately to maximize yields. However, any application should be able to appropriately predict grain yield for the given environmental condition, temperature, and seasonal rainfall. If a model were to only recognize spatial variability and not account for changes in temporal variability (weather, seasonal rainfall), it would fall short of being useful under a wide range of conditions. We investigated the relationships among forage biomass, NDVI, growing degree days, and final grain yield. Figure 2 shows the relationship between forage biomass and grain yield. Figure 3 illustrates the relationship between NDVI at Feekes growth stage 5 and final grain yield. Figure 4 shows the relationship between in-season estimated yield [INSEY, determined by dividing NDVI by growing degree days (GDD) from planting to NDVI measurement] and final grain yield (Raun et al. 2005). Forage biomass and grain yield were not correlated. Grain yield and NDVI determined at Feekes growth stage 5 were positively correlated (Figure 3). The index INSEY, which accounts for some temporal variability, provided the best correlation with grain yield. Over sites, INSEY—which uses NDVI—accounts for some of the temporal variability by including GDD (planting to sensing), which differed across sites. This provides a method to account for a particularly dry or cool season as the growth would be reflected by days where growth is possible. Also, INSEY provides an estimate of the amount of biomass that is produced on favorable days or an amount of biomass (growth per day), and thus allows for a more comprehensive prediction of yield (Raun et al. 2005).

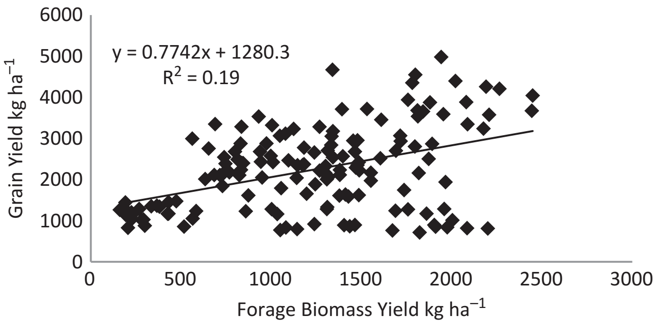

Figure 2. Relationship between forage biomass collected at growth stage Feekes 5 and winter wheat grain yield, four locations, 2010–2011.

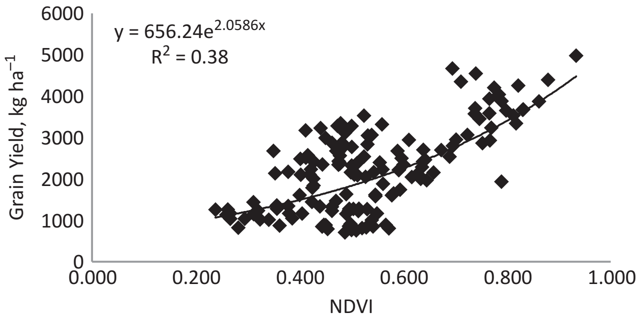

Figure 3. Relationship between NDVI, at growth stage Feekes 5, and winter wheat grain yield, four locations, 2010–2011.

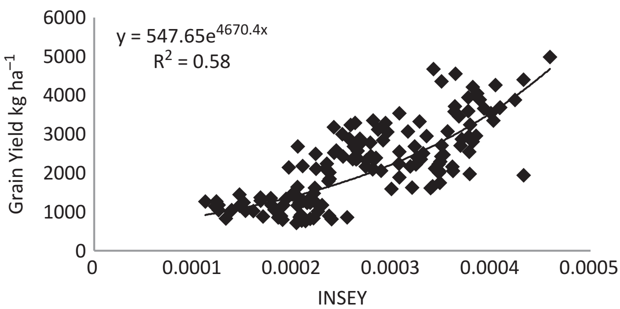

Figure 4. Relationship between INSEY (in-season estimated yield), at growth stage Feekes 5, and winter wheat grain yield, four locations, 2010–2011.

Conclusions

Spatial variability has been well documented by numerous researchers. Our findings show that large differences in winter wheat grain yield exist over short distances as has been documented in corn. The majority of the transects analyzed showed that the maximum and minimum yield values were noted less than 14 m apart. This would suggest that at a minimum, a grid of 15-m would be too coarse to adequately account for spatial variability. One transect even had the maximum and minimum yields occurring less than 2 m apart, and many transects had adjacent plots that differed by more than one standard deviation. The use of NDVI, coupled with GDD, accounted for spatial and temporal variability. To obtain the most benefit from precision farming in winter wheat, field management at a 1-m scale or less would provide the best resolution to account for spatial variability.

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