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ON-FARM RESEARCH

Combining Spatial and Temporal Corn Silage Yield Variability for Management Zone Development

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ABSTRACT

Precision agriculture requires an understanding of yield variability. The objectives of this study were to (i) document the temporal and spatial variability of corn (*Zea mays* L.) silage yields on dairy farms in New York, and (ii) derive farm-based management zones that account for both types of variability. Silage yield data from 847 fields (9084 ha; six farms) were collected by yield monitoring systems between 2015 and 2017. Raw yield data were cleaned of errors via a standardized postharvest data cleaning protocol. The whole-farm area-weighted average yield across years and the temporal SD of yield across years for fields with 3 yr of data were used to divide each field into 10- by 10-m grid-cells. Each grid-cell was assigned a quadrant (Q), with Q1 and Q4 having consistently higher and lower yield than the farm average yield, respectively; Q2 having variable but higher yield than the farm average; and Q3 having variable and lower yield than the farm average. The evaluation showed variability in average yield per farm, yield per field, and within-field yield, in addition to variability across years. Spatial and temporal variability were uncorrelated, suggesting that management zones need to consider both spatial and temporal variability. The area per farm classified as variable (Q2 and Q3) ranged from 30 to 44%, illustrating the importance of implementing precision agriculture technologies and in-season management adjustments. Research is needed to determine the optimum number of zones per farm and the number of crop years to include in developing yield stability zones.

Core Ideas

- Corn silage yield monitors collect relevant yield data for dairy farmers.
- Management zones can be developed from yield stability maps.
- Both temporal and spatial variability are important factors to consider.
- A yield-stability-based approach can generate precision management zones.

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Precision agriculture has the potential to increase crop yield and reduce the agricultural environmental footprint by applying precise inputs that meet the needs of the crops in each subsection of a field. Technology is advancing with improvements in the collection and processing of yield monitor data (Kharel et al., 2019; Khosla and Flynn, 2008), imagery from active crop and soil sensors (Li et al., 2014; Solari et al., 2008; Tagarakis and Ketterings, 2017), data from sensors mounted on planes (Cilia et al., 2014; Maresma et al., 2018; Scharf and Lory, 2002; Sripada et al., 2005), and data from unmanned aerial vehicles or satellites (Bausch et al., 2008; Bausch and Khosla, 2010; Maresma et al., 2016; Sakamoto et al., 2013), as well as advances in capturing and prediction of weather over time. The various layers of information each have their own spatial and temporal resolution, requiring careful evaluation of information in addition to development of better strategies to integrate and use the information for decision-making at the farm, field and within-field scales.

Crop consultants who provide guidance on precision agriculture typically derive management zones from historic yield data (e.g., Blackmore, 2000), elevation data, soil survey maps (Franzen et al., 2002), soil electrical conductivity maps (Johnson et al., 2003), and/or soil samples obtained by grid sampling within a field (Clay et al., 2017; Miao et al., 2018). The aim is to develop a manageable number of zones, within which variability is reduced and resource management can be consistent. However, variability among zones should be maximized, allowing for the allocation of resources to the zones where the greatest yield responses are expected.

Historical yield records reflect in-field reality, including effect of soil, elevation, rooting depth, drainage, fertilizer allocation, seed density, timing of planting, depth placement, and weather. Typically, data from multiple years are standardized and relative yield values are used to develop management zones. However, fields and areas within fields can vary both spatially and temporally. Eghball and Varvel (1997) compared temporal and spatial variability in corn, soybean [*Glycine max* (L.) Merr.], and sorghum [*Sorghum bicolor* (L.) Moench] grain yield from a long-term study (1975–1995) via a fractal analysis method. Their study showed higher temporal variability than spatial variability, leading the authors to conclude that management

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Abbreviations: Q, quadrant.

zones developed solely based on spatial variability may not be very useful and that temporal variability needs to be taken into account. Similar conclusions were drawn by Porter et al. (1998), who used yield data from 1988–1998 showing that corn grain yield variability over years was four times higher than variability among replications of the same treatment in their long-term study. In a more recent study, Maestrini and Basso (2018) used yield monitor datasets from several Midwest fields to draw the same conclusion. These studies confirm historical yield records combined with yield variability over time are needed for improved zone delineation.

Most studies in the literature that discuss zone-based field management describe zone development for individual fields or a small number of fields and use relative yield rather than absolute yield values to derive management zones (Table 1). When relative yield data are used to develop zones on a per-field basis (each field individually), this can result in differences in management zones across multiple fields on the same farm and an excessive number of zones to manage. This issue can be solved by deriving management zones with the use of multi-year, whole-farm yield datasets. As yield data are often collected across all fields during a particular harvest season, such farm-specific approaches are now feasible to implement for crops that are harvested with a combine or chopper equipped with yield monitoring system.

Evaluations of the effectiveness of zone-based management are primarily reported in two ways in the literature: (i) yield variability within vs. among zones (Fraisse et al., 2001; Blackmore et al., 2003; Brock et al., 2005; Basso et al., 2007; and Kleinjan et al., 2007), and (ii) yield response and profitability per zone by conducting field experiments and/or simulation experiments with added management inputs as a treatment (Monzon et al., 2018; Hoffmann et al., 2017; Hornung et al., 2006; and Moshia et al., 2015).

Long and Ketterings (2016) developed yield stability zones by using 14+ years of whole-farm weigh-wagon-measured yield data. In their approach, at least 3 yr of yield data for each fields were needed. Based on the mean yield and CV values, fields were divided into four quadrants (Q1–Q4) on the basis of the overall weighted mean yield and the mean CV of the whole farm as cutoffs for the quadrants: Q1: above mean yield and below mean CV; Q2: above mean yield and above mean CV; Q3: below mean yield and above mean CV; Q4: below mean yield and below mean CV (Long and Ketterings, 2016). This approach is similar to the method described by Kleinjan et al. (2007), with the major difference being that the classification here is based on whole-farm datasets.

The objectives of this study are (i) to document the temporal and spatial variability of corn silage yields on dairy farms in New York, and (ii) develop management zones that take both temporal and spatial variability into account. We use a variance reduction method and ANOVA test to evaluate these zones. We further explored whether field size impacts temporal and spatial variability and document opportunities for within-field management based on use of the yield stability zones. Our aim is to develop management zones similar to Long and Ketterings (2016) but with expansion to within field scale through the use of whole-farm yield monitoring datasets of six dairy farms. Research to evaluate crop response to additional N across management zones on individual farms is ongoing.

MATERIALS AND METHODS

Datasets

Corn yield monitor data from 2015, 2016, and 2017 were obtained for all the corn fields of six New York dairy farms located in four regions of the state (Table 2). The number of fields per farm ranged from 81 to 185; total area per farm ranged from 1080 to 2371 ha. Data were obtained from 847 field years (9084 ha) for the six farms combined, 78 fields of which had 3 yr of yield data. Yield data were collected with CLAAS (CLAAS, Harsewinkel, Germany; two farms) and John Deere (John Deere, Moline, IL; four farms) forage choppers with header widths varying from 4.6 m (six rows of corn spaced at 0.76 m apart) to 9.1 m (12 rows of corn). Harvest data were logged every second, except at one farm, where data were recorded every 2 s.

Raw yield monitor data were evaluated for errors and cleaned via the approach described in Kharel et al. (2019). In short, Spatial Management System software (Ag Leader Technology, Ames, IA) was used to read and transfer the data to Ag Leader Advanced format text files without applying any processing settings, as outlined in Griffin et al. (2007). Yield Editor (Sudduth and Drummond, 2007) was used to clean the data after deriving appropriate filter settings for the equipment and harvest season for a subset of ten representative fields (Kharel et al., 2019). This semiautomated approach quickly identifies and removes errors and adjusts yield values on the basis of the applied filters, including start pass delay, end pass delay, flow delay, and moisture delay, as well as overlapped passes and individual data points with large deviations in yield compared directly with neighboring passes. A moisture filter was applied to eliminate data points with less than 45% moisture, as outlined in Kharel et al. (2019).

Spatial vs. Temporal Variability Assessment

Each of the 78 fields with 3 yr of yield data was mapped into 10- by 10 m regular grid-cells. The inverse distance weighted method was applied for yield mapping with the 'gstat' package in the R statistical computing environment (Pebesma, 2004). The default method of interpolating a field's yield data onto the 10- by 10-m grid used all the sample points with varying weights relative to their distance to the prediction grid. A temporal SD for each 10- by 10-m grid-cell was calculated and averaged across grid-cells for individual fields with 3 yr of data. A spatial SD was calculated for each field and each individual year for the same 10- by 10-m grid-cell yield map. Relationships between temporal SD and spatial SD (each year separately, as well as averaged over the 3 yr) for each field were documented for this study. Additionally, the relationship between yield level, and spatial and temporal SD was explored and a similar analysis was conducted to determine the relationship between field size and spatial and temporal SDs.

Yield Stability Zone Development

Yield-stability-based management zones were developed for each field with at least 3 yr of yield data, according to a modification of the approach described by Long and Ketterings (2016). The modification included the use of a 10- by 10-m grid-cell (versus the whole-field approach of Long and Ketterings, 2016) and SD in yield rather than CV. Specifically, yield stability zones were developed via the following steps: First, the

Table 1. Literature on zone development methodology.†

Citation	Data source	Methodology	Basis of zoning
Anastasiou et al., 2017	Vineyard quality data (2015 and 2016) with respect to soil EC (EM38‡) data	MZA software was used to develop zones (fuzzy K-means clustering) from soil EC data (EM38)	1.4-ha vineyard, field
Basso et al., 2007	Yield monitor data (1998–2002) for corn, wheat, soybean	Relative yield from multiyear multicrop datasets. Temporal variance (stable vs. variable)	Field (relative yield)
Bazzi et al., 2015	Yield monitor data (four fields, single-year yield data), production cost, sale price of the product	Yield data interpolated from 5- by 5-m plots via IDW (12 NN) and kriging	Field (single year data
Blackmore, 2000	Yield monitor data (1993–1998)	Multicrop with relative yield (grain), single field. High-yielding stable, low-yielding stable and unstable zones	Field (relative yield)
Brock et al., 2005	Yield monitor data (corn, soybean).	Relative yield approach, 5-m grid IDW raster, Fuzzy c-means clustering. Classification based on each field separately. Clustering optimization resulted in four to six zones (optimum number of zone)	Field (relative yield)
Cox and Gerard, 2007	Yield monitor data (three fields, soybean yield 1998–2004)	Temporal variable zone vs. consistently high, average and low yield zone for each field separately	Field (relative yield)
De Lara et al., 2018	Soil water content data (neutron probe) in 2012, soil samples for routine soil test and texture, EM38MK2‡ EC.	MZA software was used to create soil EC zones. SWC were assessed for each zone.	4.8-ha field
Diker et al., 2004	Two fields, yield monitor dataset (1997–2000 corn grain harvest)	IDW-interpolated yield data (6.1 m to match harvest width, 10 nearest neighbors), grid values were classified as above (as 1) and below (as 0) the within-year field mean. The final map was based on the number of years (0, 1, 2, 3) the grid showed above-average yield	Field based (absolute yield)
Fraisse et al., 2001	Topographic attributes and soil EC	PC of soil attributes. ISODATA algorithm (unsupervised clustering). Two to six zones for each field; normalized yield data were compared (yield uniformity within the zone)	Field (soil attributes, relative yield)
Gili et al., 2017	Soil (OM, P, EC, clay + silt, elevation), manual harvest yield data (at each grid point) were used to evaluate zones	Spatial principal component of soil variables were used to make homogenous zones (fuzzy K-means clustering)	Single field (absolute yield)
Georgi et al., 2017	Satellite (RapidEye NIR) time series (2009–2015), 5.5-d frequency, 5-m resampled spatial resolution	Automatic segmentation algorithm (five classes) for a single field. Relative yield (different crops) was compared with yield expectation zones or segmentation outcomes.	Field (relative yield)
Hoffmann et al., 2017	EM38 EC, soil sample, APSIM simulated yield (Australia)	EM38 data to separate into dune, midslope, and swale. Separated zones were evaluated on the basis of soil characteristics as well as APSIM-simulated N fertilizer response.	4 fields, zones based on EC data
Hornung et al., 2006; Khosla et al., 2008; Moshia et al. (2015).	Bare soil imagery, OM, CEC, soil texture, yield map from previous growing season	Soil attribute surface (median-polish kriging), yield data (ordinary kriging) for a 10-m grid. K-means cluster (three zones: high, medium, and low productivity) for each field	Field (absolute yield for 1 yr)
Johnson et al., 2003	Veris 3100-measured apparent soil EC (eight fields), corn and wheat yield monitor data for evaluation	EC data interpolated to a 10-m grid (nearest neighbor). Four management zones (low to high EC values) for each field separately.	Field (soil EC), absolute yield values were evaluated for each zone (each field)
Leroux et al., 2018; Santesteban et al. (2013).	90-ha vineyard (27 fields), airborne NDVI. (2007 and 2008), EM38 EC, elevation, vine vigor, soil, and water	The GeoFIS tool was used to create risk map (fuzzy rule) from collected data (2008 images, soil, plant info). A segmentation algorithm was used to create within field risk zones.	(i) field level (ii) Whole vineyard level (no temporal variability, just the spatial part was used)
Maestrini and Basso, 2018	Yield monitor data (571 fields from Midwest, >4 yr of data)	Scaled yield data (mean = 0, SD = 1) based on each field separately. Each field had 20% of pixels as unstable and 80% as stable (80th percentile was used)	Field (relative yield)
Melo Damian et al., 2016	Soil properties, wheat grain yield, spikes m^{-2}, grains per spike, grain weight measured in 50- by 50-m grids in 2012 (18 grid locations, 4.7-ha field).	K-means clustering of the soil properties	One field
Monzon et al. (2018).	Several years of soil depth, frost risk and water table data (1999–2012)	Four zones based on soil and topography information (soil depth, frost risk, water table) of the whole farm (5000 ha)	Farm-level data

† Abbreviations: MZA, Management Zone Analyst (USDA-ARS); EC, electrical conductivity; ; IDW, inverse distance weighted; NN, nearest neighbor; SWC, soil water content; PC, principal component; OM, organic matter; NIR, near infrared; APSIM, Agricultural Production Systems sIMulator; CEC, cation exchange capacity; NDVI, normalized difference vegetation index.

‡ EM38 (Geonics Ltd, Mississauga, ON, Canada); EM38MK2 (Geonics Ltd., Mississauga, ON, Canada)

Table 2. Summary of corn silage harvest yield monitor data from six New York dairy farms (2015–2017).

Farm	Region	Area	Fields	Yield Avg.	Yield Field SD†	Yield Temporal SD†
		ha	n	Mg ha^{-1}		
1	Northern New York	1682	91	45.37	13.23	10.96
2	Eastern New York	1238	185	41.49	10.98	10.02
3	Western New York	1080	81	41.25	12.11	15.42
4	Western New York	1339	146	38.02	9.19	7.02
5	Central New York	2371	163	47.86	7.62	7.58
6	Western New York	1374	181	39.03	8.07	8.68
All		9084	847	42.17	10.20	9.95

† Field SD is the SD of the fields' yearly yield data; temporal SD is the 0.4-ha-grid based variability in the 3-yr yield data, as described in Eq. [2].

area-weighted farm average silage yield (M_{farm}, 3 yr combined) was calculated, including all the fields as:

$$M_{farm} = \frac{\sum\left(\bar{y}_{ij} \times a_{ij}\right)}{\sum a_{ij}}, \quad [1]$$

where $\bar{y}_{ij}$ and a_{ij} are the average yield and area of field i ($i = 1 \ldots N$) in year j ($j = 1, 2, 3$), respectively.

Second, the temporal yield variability of each farm (SD of yield over time) was determined on the basis of fields with 3 yr of yield data only ($N = 78$). Each field was subdivided into 0.4-ha grid-cells. Within each grid-cell, the yield value of an individual year was predicted from the inverse distance weighted method and all data points for that year and field. Three separate yield maps (one map for each year) for each field were produced. The temporal SD of each grid-cell g within a field i (SD_{ig}) was calculated from the grid-cell yield in each year $\bar{y}_{i1g}$, $\bar{y}_{i2g}$, and $\bar{y}_{i3g}$; where 1, 2, and 3 represent year and $\bar{y}$ represents the yield value for the grid-cell. The grid-cells within the farm (N) were summed together and the average farm temporal SD was calculated as:

$$SD_{farm} = \sqrt{\frac{\sum_{ig} SD_{ig}^2}{N}}, \quad [2]$$

where SD_{farm} represents the average (or pooled) temporal SD of the farm and SD_{ig} represents temporal SD of the grid-cell g of field i. This 0.4-ha grid-cell approach to determining temporal SD, as opposed to use of whole-field yield data, was chosen to obtain better estimates of the farm-specific temporal variability, given only 78 fields across three farms had 3 yr of yield data. The 0.4 ha grid-cell is commonly used in grid sampling approaches. Actual yield mapping, zone development and evaluation were performed using the 10- by 10-m grid scale, an option chosen on the basis of the size of the farm equipment most commonly operated for planting, manure spreading, and harvest on dairy farms.

Next, temporal SDs for each field with 3 yr of silage yield data (SD_i; i = field) and average yield ($\bar{y}_i$) maps were developed from a 10- by 10-m grid-cell (as described above). The inputs for these maps were the inverse-distance-weighted yield maps developed for each year.

Lastly, each grid-cell was classified into yield stability zones (Q1, Q2, Q3, and Q4) on the basis of its average yield relative to the whole-farm yield [Eq. 1] and its temporal SD relative to the average farm temporal SD [Eq. 2]: Q1: above mean yield and below mean SD; Q2: above mean yield and above mean SD; Q3: below mean yield and above mean SD; and Q4: below mean yield and below mean SD.

Farm Variability Evaluation Method

The effectiveness of stability zones in reducing variance was evaluated for each field with 3 yr of data. The evaluation method used by Fraisse et al. (2001), Blackmore et al. (2003), Brock et al. (2005), Basso et al. (2007), and Kleinjan et al. (2007) was followed to compare the total variance in the silage yield for a field (when the entire field was considered to be one management unit) with the variance of each zone within the field. The weighted variance of stability zone Z was expressed as:

$$\sigma_z^2 = \left[\frac{1}{n_z} \Sigma_{i=1}^{n_z} \left(Y_i - \bar{Y}_z\right)^2\right] \times \frac{n_z}{n_T}, \quad [3]$$

where σ_z^2 is the weighted variance of zone Z, Y_i is the yield value at location i within the zone Z, $\bar{Y}_z$ is the average yield of zone or quadrant Z, n_z is the number of grid-cells in zone Z, and n_T is the total number of grid-cells in the field. The first part of the equation calculates variance for a zone Z and the ratio $\frac{n_z}{n_T}$ is the weighting factor to remove differences caused by differences in the number of measurements in each zone. The total variance (σ_{tot}^2) of the field was expressed as the sum of the individual weighted variances of each zone for that field:

$$\sigma_{tot}^2 = \sigma_1^2 + \sigma_2^2 + \ldots + \sigma_z^2. \quad [4]$$

The whole-field variance, σ_{wf}^2, was then calculated as:

$$\sigma_{wf}^2 = \frac{1}{N} \Sigma_{i=1}^{N} \left(Y_i - \bar{Y}_{wf}\right)^2, \quad [5]$$

where N is the total number of grid-cells in the field, Y_i is the yield value at grid-cell i, and $\bar{Y}_{wf}$ is the field's average yield value. The variance explained by using the quadrant-based stability zones was calculated as:

$$\sigma_{explained}^2 = 100 - \frac{\sigma_{tot}^2}{\sigma_{wf}^2} \times 100. \quad [6]$$

A null hypothesis (no difference in yield and temporal SD across management zones) was tested by an F-test (ANOVA) and the LSD at the 5% significance level (LSD0.05). All calculations and mapping of silage yield values to each of the 10- by 10-m grids were performed with R computing software (R Core Team, 2017) with the help of the 'sp' and 'gstat' packages (Pebesma and Bivand, 2005; Bivand et al., 2013; Pebesma, 2004).

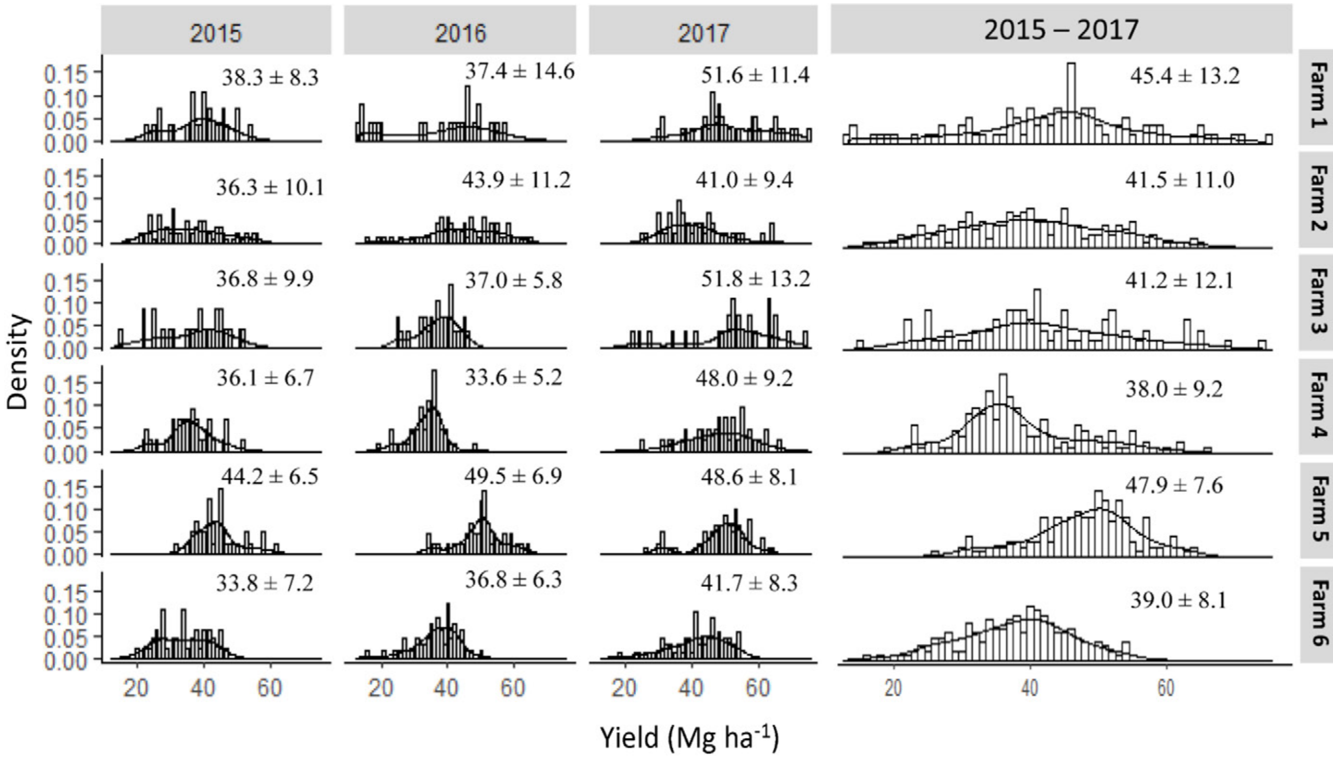

Fig. 1. Corn silage yield distribution for a total of 847 fields years over 3 yr (2015, 2016, and 2017) for six New York dairy farms. Corn silage yield (Mg ha^{-1}) are expressed at 35% dry matter. Numbers at the top of each graph represent average yield ± SD.

RESULTS AND DISCUSSION

Whole-Farm and Field Yield Variability over Time

Average farm silage yield (in a single year, across all farms) ranged from 33.6 to 51.8 Mg ha^{-1}, with a SD ranging from 5.2 to 14.6 Mg ha^{-1} (at 35% dry matter), reflecting substantial field-to-field variability within a farm, as well as farm-to-farm variability (Fig. 1). Yield values were higher in 2017 than 2015 and 2016 for four of the farms and somewhat lower in 2017 than 2016 for the remaining two farms. Summarized across the 3 yr of data, the area-weighted average yield per farm ranged from 38.0 to 47.9 Mg ha^{-1}, with a SD ranging from 7.6 to 13.2 Mg ha^{-1} (Table 2, Fig. 1). The temporal SD for the farm calculated from the 0.4-ha grid-cells ranged from 7.0 to 15.4 Mg ha^{-1} (Table 2). It should be noted that not all fields had 3 yr of yield data and thus the temporal variation is based on a subset of fields within each farm.

Within-Field Spatial and Temporal Variability

The silage yields of the 10- by 10-m grid-cells showed both spatial and temporal variability. In the examples shown in Fig. 2, yields were higher in 2017 but, most importantly, yield patterns within fields varied from year to year. For some fields, the high-yielding areas switched among years (e.g., Field 2 in Fig. 2). These observations suggest that within-field spatial and temporal variability are not necessarily correlated, which was confirmed by the analyses of temporal and spatial SDs for all fields (Fig. 3A).

In general, the temporal SD tended to be higher than the spatial SD but the differences were not statistically significant, as shown by the overlapping error bars on the average value (Fig. 3B). Eghball and Varvel (1997), Porter et al. (1998), and Maestrini and Basso (2018) all reported that temporal variability exceeded spatial variability in their studies. The lack of a significant difference in our study could, in part, reflect the greater variability in yield and topography in New York than what was present in the Midwest studies. In addition, aggregation scale and crop type could have some effect on the result. For example, Eghball and Varvel (1997) and Porter et al. (1998) used long-term study plot averages (plots ~10 m wide and 30 m long) to calculate variability across multiple replications, whereas Maestrini and Basso (2018) aggregated yield monitor data to a 30- by 30-m grid-cell. In addition, Maestrini and Basso (2018) removed data from headlands, whereas in our current study, headland areas were included and 10- by 10-m grid-cells were used for spatial and temporal SD comparisons. The inclusion of headlands is expected to increase spatial variability (headland areas are typically lower yielding) while decreasing temporal variability (more consistent yields on headlands from year to year).

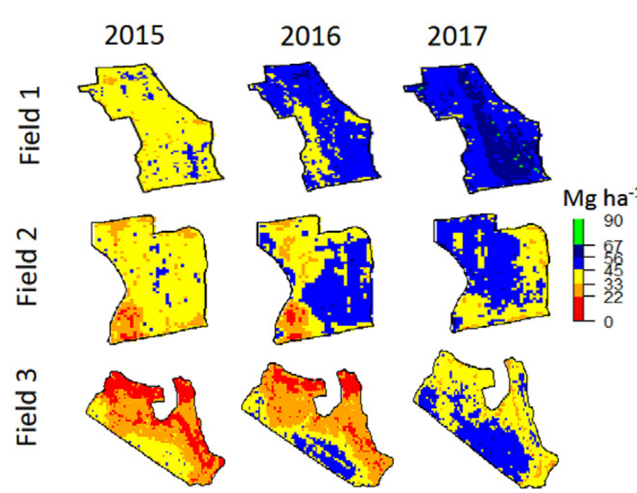

Fig. 2. Example of three fields showing the temporal and spatial yield variability of corn silage.

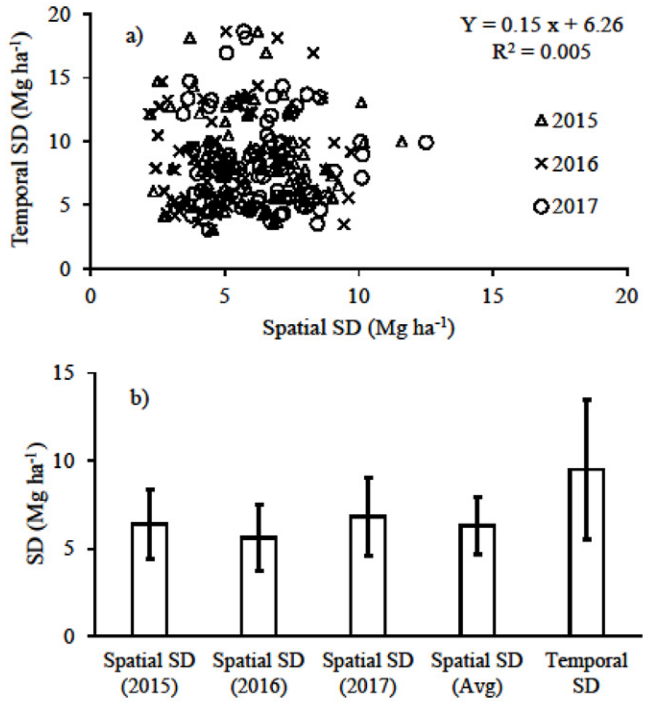

Fig. 3. Relationship between the spatial and temporal variability of corn silage yield for 78 fields (78 × 3 = 234 field years) from six New York dairy farms: (a) scatterplot of temporal and spatial SD; (b) bar graph showing the spatial and temporal SD. Spatial SD is the SD of a field for each year that was mapped into 10- by 10-m grid-cells; temporal SD is the SD of the yield value (3 yr) for each of grid-cells that was averaged for the field. Average spatial SD is the average of 3-yr spatial SD.

Table 3. Area (in percent) in each stability zone within fields based on the number of 10 × 10 m grid cells in each zone in each farm.

Farm	Quadrant	Grid cells	% of field
		n	
1	1	3314	27.3
1	2	525	4.3
1	3	3067	25.3
1	4	5225	43.1
2	1	6554	35.4
2	2	3690	19.9
2	3	3072	16.6
2	4	5182	28.0
3	1	2703	44.1
3	2	2111	34.4
3	3	377	6.2
3	4	939	15.3
4	1	2101	28.3
4	2	1675	22.6
4	3	832	11.2
4	4	2810	37.9
5	1	7975	45.5
5	2	2747	15.7
5	3	3377	19.3
5	4	3417	19.5
6	1	2704	27.1
6	2	2453	24.6
6	3	1970	19.7
6	4	2856	28.6

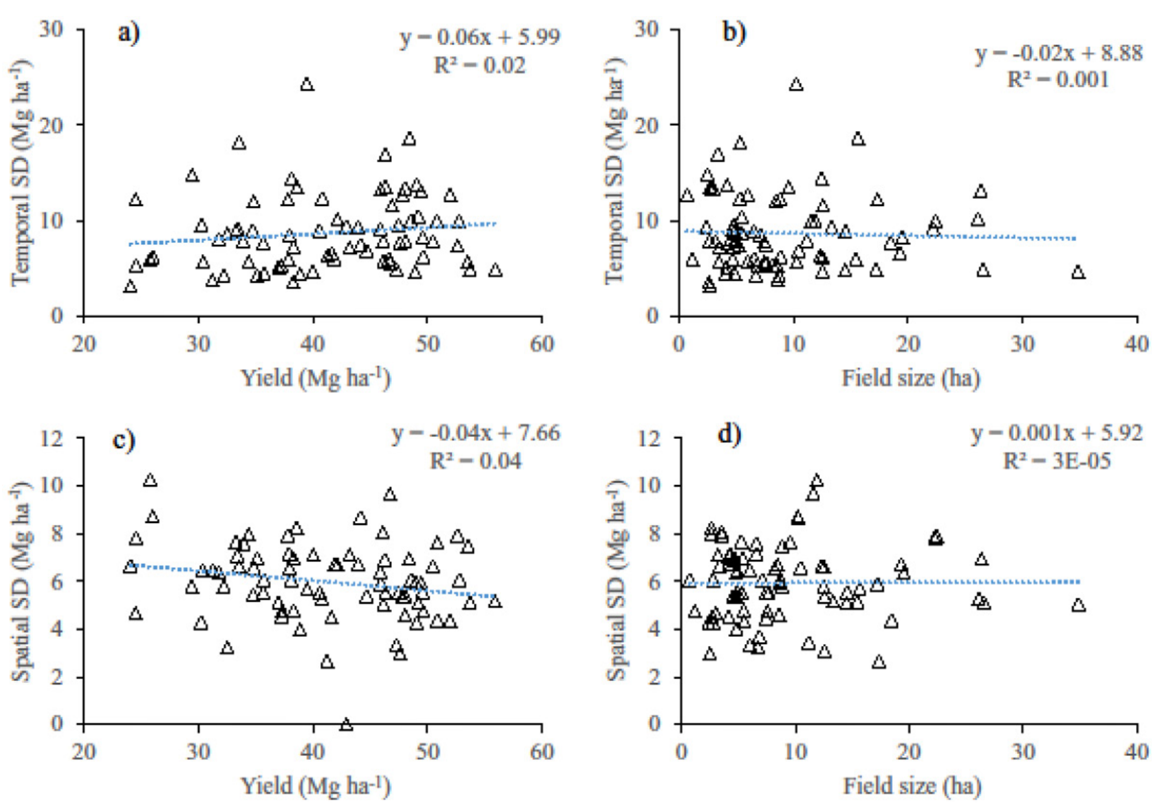

Fig. 4. Relationship between (a) temporal SD and corn silage yield, (b) temporal SD and field size, (c) average spatial SD and corn silage yield, and (d) average spatial SD and field size. Average spatial SD is the SD of a field for each year that was mapped to 10- by 10-m grid-cells and then averaged over years; temporal SD is the SD of the yield value (3 yr) for each of grid-cells that was averaged for the field.

Table 4. Spatial variability (variance) in yield explained by each stability zone

Farm	Variance† Whole field	Q1	Q2	Q3	Q4	Zones summed	Explained by zones
							%
1	3.7 (±3.7)	0.5	0.1	0.6	1.2	2.4	35.1
2	6.9 (±4.0)	1.4	0.8	0.4	1.0	3.6	47.8
3	3.5 (±0.8)	1.2	0.7	0.1	0.2	2.2	37.1
4	3.5 (±1.6)	0.3	0.3	0.3	1.0	1.9	45.7
5	3.0 (±1.1)	0.4	0.2	0.4	0.3	1.3	56.7
6	6.5 (±2.4)	0.4	0.2	0.7	1.8	3.1	52.3

† Variance for each zone [Quadrant (Q)1 to Q4] was calculated via Eq. [3]; variance for the whole field was calculated via Eq. [5].

The corn silage spatial yield variability ranged from 5.6 Mg ha^{-1} in 2016 to 6.4 and 6.8 Mg ha^{-1} for 2015 and 2017, respectively (Fig. 3B). The average spatial variability over the 3-yr period was 6.3 Mg ha^{-1} compared with temporal variability of 9.5 Mg ha^{-1}. Both spatial and temporal variability in our study were higher than the yield variability of 4.24 Mg ha^{-1} for corn silage reported by Long and Ketterings (2016). The difference in yield variability between the two studies reflects in part a difference in the spatial and temporal scale (whole-farm versus 10- by 10-m grids). In comparison, for corn grain yield, Porter et al. (1998) reported a temporal variability of 2.17 Mg ha^{-1}, whereas Martin et al. (2005) reported an average corn grain plant-to-plant variability of 2.8 Mg ha^{-1} across several countries and years. These comparisons suggested that greater spatial and temporal variability in corn silage yield was seen in our current study than in earlier studies published in the literature.

Yield and Field Size Effects on Variability

Temporal and spatial variability showed no relationship (Fig. 3A), whereas the magnitudes of both sources of variability were large. These findings suggest that both spatial and temporal variability need to be taken into account for the development of management zones.

Martin et al. (2005) reported that plant-to-plant variation, represented as SD of yield, increased with yield level. In our study, we found no such relationship between yield variability and yield value; neither temporal nor spatial SD were significantly correlated with yield (Fig. 4, temporal $R^2 = 0.02$; spatial $R^2 = 0.04$). Field size showed no relationship with temporal or spatial variability (Fig. 4) either. These results imply that management zones developed as described in this study will be applicable for a range of field sizes and yield levels.

Yield Stability Zone Development and Evaluation

The total area in management zones with high year-to-year variability in yield (Q2 and Q3) ranged from 30 to 44% (Table 3), suggesting great potential for increasing production efficiency with within-season precision agriculture technologies for all six dairy farms. These variable zones (Q2 and Q3) responded differently each year, depending primarily on the weather condition combined with management practices. Further field research is needed to determine yield-limiting factors and accurately predict corn's response to management changes under various weather scenarios. Combined with in-season sensor technology, variable yielding zones provide opportunities to improve yield and resource allocation over time. Stable zones (Q1 and Q4) are likely to be easier to manage, as yield can be predicted in advance with a greater accuracy. However, research is needed to identify which management strategies (e.g., tillage practices, nutrient management approaches, etc.) result in yield increases and greater production sustainability over time.

The yield stability management zones in this study (Q1, Q2, Q3, and Q4) were able to explain 35 to 57% of the initial whole-field variance (Table 4), indicating that this approach can identify more homogenous zones within farm fields. The ANOVA result showed significant differences in the 3-yr average yield between the high-yielding zones (Q1 and Q2) and low-yielding zones (Q3 and Q4) (Table 5). As expected, there were no differences in yield between the high-yielding Q1 and Q2 and between the low-yielding Q3 and Q4 zones. Similarly, temporal SDs were significantly different between stable (Q1 and Q4) and variable (Q2 and Q3) zones.

These results, as well as research by Moshia et al. (2015) and Hornung et al. (2006), show the potential for improved resource management through the use of yield stability zones. Further research is needed to define the appropriate number of zones per farm to address both spatial and temporal variability adequately.

Table 5. ANOVA *F*-test on 3-yr average yield (2015–2017) and temporal SD (Temp SD) by yield stability zone.

Zone	Farm 1 Yield	Farm 1 Temp SD	Farm 2 Yield	Farm 2 Temp SD	Farm 3 Yield	Farm 3 Temp SD	Farm 4 Yield	Farm 4 Temp SD	Farm 5 Yield	Farm 5 Temp SD	Farm 6 Yield	Farm 6 Temp SD
	Mg ha^{-1}											
Q1	49.0a†	6.9b	48.6a	7.0b	47.9a	12.9b	41.3a	4.6b	51.5a	5.1b	42.6a	6.1b
Q2	50.0a	16.2a	47.7a	13.6a	47.8a	17.9a	41.9a	9.5a	51.4a	10.4a	42.7a	11.0a
Q3	34.7b	14.1a	35.1b	13.0a	39.1b	17.7a	32.5b	9.0a	43.8b	10.9a	32.0b	10.9a
Q4	33.4b	7.6b	34.5b	6.8b	38.3b	12.6b	33.3b	4.2b	44.1b	5.3b	32.5b	6.1b
LSD (0.05)	3.8	2.6	1.1	0.6	1.5	1.1	1.5	0.4	0.8	0.6	0.9	0.4
DF	27	27	95	95	16	16	34	34	43	43	55	55

† Means followed by the same lowercase letter are not significantly different at a *P*-value of 0.05.

CONCLUSIONS

This study shows that variability exists in average yield per farm, yield per field, and within-field yield over time. Spatial and temporal variability were not correlated and each was substantial enough to warrant the development of stability-based yield zones that minimized input and/or maximized output. A whole-farm quadrant-based approach described in this paper allows both sources of variability to be integrated for the development of a limited number of management zones across fields on a specific farm. This unique farm-based approach eliminates problems associated with single field- and relative yield-based management zones. Further research is needed to determine if the number of zones per farm should or could be increased, and if inclusion of a larger number of years could help in the development of more predictable crop yield and resource allocation.

CONFLICT OF INTEREST DISCLOSURE

The authors declare that there is no conflict of interest.

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