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AGRONOMY AND SOILS

Zonal Application of Plant Growth Regulator in Cotton to Reduce Variability and Increase Yield in a Highly Variable Field

Carlos M.P. Vaz*, Júlio C. Franchini, Eduardo A. Speranza, Ricardo Y. Inamasu, Lúcio A. de C. Jorge, Ladislau M. Rabello, Ivani de O.N. Lopes, Sérgio das Chagas, Jefferson L.R. de Souza, Márcio de Souza, Amandio Pires, and James Schepers

ABSTRACT

Variable-rate application has great potential to reduce variability and increase yield by spatially optimizing agricultural inputs. In cotton, plant growth regulators (PGRs) control excessive growth and provide suitable plant height for harvest operations. This study evaluates the effect of variable-rate PGR application compared to constant-rate application to reduce yield spatial variability and increase yield. The variable-rate approach was carried out in 2020 based on zonal applications defined by clustering analysis using soil electrical conductivity, vegetation indexes, and yield maps. Application doses and timings were determined by integrating plant height measurements for the whole field in 2019 and by zone in 2020. To compare the two procedures, cultivar and plant populations were kept constant; fertilization and accumulated rain were similar in both seasons. A reduction in yield spatial variability due to the zonal application was observed, with yield coefficient of variation (CV) decreasing from 18% in 2019 to 12% in 2020. Spatial and temporal analysis of Normalized Difference Vegetation Index satellite images showed higher CV values in 2019 (constant-rate) reaching 30% at the end of the season, whereas in 2020 (variable-rate) CV was constant (approximately 10%). Cotton yield increased from 3.5 to 4.3 t ha^{-1} between 2019 and 2020, which can be partially attributed to the variable-rate approach. The variable-rate approach based on application zones and plant height measurements was a viable strategy for reducing yield spatial variability and likely increasing yield in a highly variable cotton field.

Brazil is an important world cotton producer, ranking fourth in cotton lint yield and second in exports in the 2021/2022 season (USDA, 2023). The major production areas are the Brazilian savanna-like Cerrado, which can be characterized as having highly weathered and acidic soils, low cation exchange capacity, low natural fertility, flat landscape, and average annual precipitation of 800 to 2,000 mm (rainy season from October to March). The most common production system on large farms is rainfed, double-crop cotton after soybean with intensive high-input management. In general, large commercial field units of approximately 100 to 400 ha are individually managed to maximize their production potential for the specific soil type, topography, climate, and cultivar. At this scale, field units exhibit large natural variability (soil texture, organic matter, topography, climatic variables, etc.), causing large in-field yield variations when treated as homogeneous units. In this scenario, variable-rate application (VRA) technology has potential for reducing variability on the production units and increasing yield and profitability by spatially optimizing the agricultural input applications, considering both natural and anthropic spatial variations.

Variable-rate application technology has been gaining prominence in the last few decades. Advances in the agricultural machinery industry have provided methods for site-specific application of liquid and granular fertilizers, lime, pesticides, seed, plant growth regulators (PGRs), defoliants, and ripeners based on predefined georeferenced application maps (Martins et al., 2020; Nawar et al., 2017) or by on-the-go approaches using sensors (Stamatiadis et al., 2020; Yu et al., 2019). However, compared to other precision agriculture tools

C.M.P. Vaz*, R.Y. Inamasu, L.A.de C. Jorge, and L.M. Rabello, Brazilian Agricultural Research Corporation, Embrapa Instrumentation, São Carlos, SP, Brazil; J.C. Franchini and I. de O.N. Lopes, Brazilian Agricultural Research Corporation, Embrapa Soybean, Londrina, PR, Brazil; E.A. Speranza, Brazilian Agricultural Research Corporation, Embrapa Digital Agriculture, Campinas, SP, Brazil; S. das Chagas and J.L.R. de Souza, Amaggi Group, Sapezal, MT, Brazil; M. de Souza and A. Pires, Mato Grosso Cotton Institute, Cuiabá, MT, Brazil; and J. Schepers, University of Nebraska, Agronomy and Horticulture Department, Lincoln, NE.
*Corresponding author: carlos.vaz@embrapa.br

such as Global Navigation Satellite System (GNSS) guidance, sprayer boom control, and planter row or section shutoff, VRA technology is less popular among farmers (Fountas et al., 2005; Lowenberg-DeBoer and Erickson, 2019; Zhou et al., 2017). This is probably because farmers like the idea of using VRA in general, but they are not completely convinced of its value (Lowenberg-DeBoer and Erickson, 2019). One important challenge is establishing inexpensive and technically efficient protocols to generate prescription maps and create application strategies to deliver the right doses varying spatially and timely, for specific crops, regions, and production systems (Campanella, 2000; Jin et al., 2019; Nawar et al., 2017).

Plant growth regulators are commonly applied in cotton to restrict excessive vegetative growth, redirecting photosynthates to reproductive growth, and providing benefits as early flowering and increasing boll retention lower on the plant and setting plant architecture favorable for mechanized harvesting (Fang et al., 2019; Samples et al., 2015). Some studies indicate that PGR also can provide yield increments (Leal et al., 2020; Sawan, 2018; Tung et al., 2020), whereas others report negative or no effects on cotton yield and fiber quality (O'Berry et al., 2009; Vistro et al., 2017).

Several studies have evaluated the agronomic and economic benefits of VRA of PGR in cotton to control excessive vegetative growth (Sawan, 2018; Tung et al., 2020). These applications reduced spatial variability in plant height and yield and increased total cotton lint yield and profitability. Spatial and temporal variability of cotton plant height, height-to-node ratio (HNR) and length of top five internodes, were evaluated by Thurman and Heiniger (1999b) who showed that uniform application of PGR on highly variable fields increased plant height and HNR variability. The study concluded that spatial analysis of plant growth improved the effectiveness of PGR application, and that large field variability justifies VRA of PGR. A procedure for VRA of PGR based on plant height using a tractor-mounted infrared light sensor, a crop simulation model, and relationships between plant height and total plant weight for eight cotton cultivars was developed by Landivar et al. (1999). Results showed a reduction in the plant height coefficient of variation (CV) (from 12.6% before the VRA to 7.6% after two PGR applications). However, yield increments due to the VRA of PGR were negligible and the lack of response was mainly attributed to the dry season experienced during the reproductive period, thus masking possible yield benefits of the VRA.

Baio et al. (2018) applied PGR and fruit ripener at variable rates in a large commercial cotton field based on vegetation index (VI) maps acquired with an optical canopy sensor and phenological measurements. Three homogeneous application zones were defined according to VI variability, delineating low, average, and high VI zones. Plant height and growth rate were then monitored during the growing seasons for each zone to support PGR application decisions (timing and doses). The VRA procedure increased the uniformity of plant height and fruit opening among application zones, resulting in seed cotton yield and net revenue increments of 265 kg ha^{-1} and \$152 USD ha^{-1}, respectively (averaged over two growing seasons).

Trevisan et al. (2018) evaluated two optical canopy and ultrasound sensors to detect spatial variability of plant height and generated prescription maps for VRA of PGR. The applied procedure reduced PGR cost by 17% but had no effect on cotton yield. Similarly, Bethel et al. (2003) obtained PGR application rate reductions varying from 10 to 53% using a variable-rate procedure based on Normalized Difference Vegetation Index (NDVI) maps to establish application zones.

In summary, these studies have shown benefits of using VRA of PGR, which include control of plant growth for harvesting and decrease of in-field yield variability (Baio et al., 2018; Landivar et al., 1999; Thurman and Heiniger, 1999a), reduction in the amount of applied PGR (Bethel et al., 2003; Trevisan et al., 2018), and improved yields (Baio et al., 2018; Thurman and Heiniger, 1999b) when compared to PGR applied at constant-rates. However, although some studies of VRA of PGR have shown positive effects on reducing in-field variability, the total amount of PGR applied, yield, and revenues; in some experiments, no improvements were observed in yield or in the reduction of production costs (Bethel et al., 2003; Landivar et al., 1999; Nelson, 2006; Trevisan et al., 2018). Additional studies are needed to evaluate the agronomic and economic gains of VRA of PGR, understand soil, topography, climate and plant variability effects on the VRA performance, and establish effective protocols for VRA of PGR at the farm level, considering regional and local specificities and different production systems. Contributing to the difficulty, the present study evaluates the performance of zonal application of PGR in a highly variable cotton field unit (soil clay content varying from 7 to 37%) at farm level. Spatial variability was assessed by soil apparent electrical conductivity maps, VI images, and cotton yield maps to establish the application zones. The performance of the variable-rate approach applied to three different zones was compared to uniform PGR application.

MATERIALS AND METHODS

The study was conducted in a commercial cotton field of 169 ha (13º 35' S, 58º 53' W) located in Sapezal, Mato Grosso State, Brazil (Tucunaré Farm, Amaggi Group) during two growing seasons (2019 and 2020). In the 2019 season, PGR was applied at constant rate according to the procedure adopted by the farm technical team that included plant height measurements and the historical management of the area. In 2020, PGR was applied with different doses in three delineated zones based on soil, crop imagery, and yield maps acquired in the 2019 season. Doses and application dates of PGR in 2019 and 2020 are presented in Tables 1 and 2.

Application zones in 2020 were established based on cluster analysis, considering soil apparent electrical conductivity (EC_a) maps, VI images (NDVI and Normalized Difference Red Edge [NDRE]), and the 2019 cotton yield map. In 2019, plant height was measured at nine locations (Fig. 1c shows geographic locations) for seven dates (44, 61, 67, 80, 88, 102, and 123 days after sowing [DAS]) and averaged for the whole field on the different dates. In 2020, cotton plant height was measured and averaged by zone, approximately every 5 d (19 dates from 35 to 135 DAS) at locations shown in Fig. 1d (approximately 40 points by zone). One plant height was determined for each point and date in both cases (2019 and 2020). Plant growth regulator (Mepiquat chloride, Sponsor 250 g L^{-1}) (FMC Química do Brasil Ltda, Brazil) was applied 94 DAS in 2019, and 57 and 65 DAS in 2020 (Table 2), when plant heights were approximately 80 to 90 cm.

Table 1. Cotton management and production parameters for the 2019 and 2020 seasons in the experimental field

Parameter	Unit	2019	2020
Cultivar	-	TMG 81 WS	
Row spacing	*m*	0.9	
Plant population	*plant m^{-1}*	9	
Post-planting Nitrogen	*kg ha^{-1}*	202	248
Number of N applications	-	6	7
Post-planting Potassium	*kg ha^{-1}*	246	245
Number of K applications	-	3	3
Total PGR applied[z]	*g ai ha^{-1}*	12.5	42.5
Number of PGR applications	-	1[y]	2[x]
Cumulative precipitation[w]	*mm*	1,070	1,171
Sowing date	-	21 Jan 2019	27 Dec 2019
Harvesting date	-	06 Aug 2019	13 July 2020
Cotton Yield	*kg ha^{-1}*	3,399	4,152

[z] Mepiquat chloride, Sponsor (250 g active ingredient L^{-1})

[y] Uniform application

[x] Variable-rate application

[w] For the whole crop season

Table 2. Mepiquat chloride (Sponsor, 250 g L^{-1}) doses and application data for the two growing seasons. Z1, Z2, and Z3 are the application zones defined by clustering analysis (Fig. 2)

Season	PGR Applications		DAS	Dose (g ai ha^{-1})		
	Type	Date		Z1	Z2	Z3
2019	uniform	24 April 2019	94	12.5	12.5	12.5
2020	variable	21 Feb 2020	57	20	25	12.5
	variable	29 Feb 2020	65	20	30	20

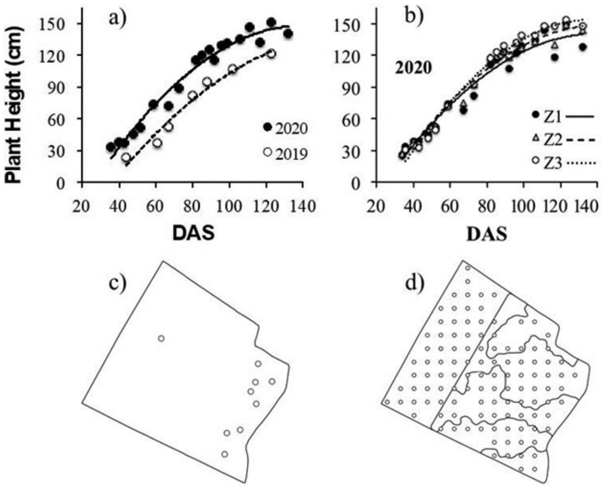

Figure 1. Average cotton plant height measured for (a) the two growing seasons and (b) by zone (Z1, Z2, and Z3) in the 2020 season. Data fitted with polynomial equation of second degree. DAS: days after sowing. In 2019, plant height was measured and averaged in (c) the whole field for the different dates and (d) by zone in 2020. Dots indicate the coordinates of measured plant height.

Cotton cultivar, linear seed density, and row spacing were kept the same for the two growing seasons to allow comparisons between the constant-rate and variable-rate PGR approaches. In-season potassium application and accumulated precipitation for both seasons were similar, whereas in-season nitrogen application was 23% higher in 2020 than in 2019 (Table 1).

Soil and Vegetation Index Maps for Delineation of Application Zones. The EC_a maps (0-30 and 0-90 cm depths) were acquired on 19 January 2019 using the Veris 3100 system (Veris Technology, Salina, KS) pulled by a tractor at 10 km h^{-1} on 15-m spaced transects and acquisition intervals of 1 s, georeferenced using a GNSS receiver model AG114 DGPS (Trimble, Sunnyvale, CA). The soil clay content map was obtained by collecting and analyzing 170 georeferenced soil samples (0-20 cm depth) at a regular grid sampling (100 m x 100 m) and interpolated by analysis using the software VESPER (University of Sydney, Australia). The cotton canopy spatial variability was assessed by NDVI and NDRE images acquired by a Matrice 200 drone (DJI, Shenzhen, China) with a high resolution RedEdge-M camera (MicaSense, Seattle, WA) on 15 May and 7 June 2019 (end of flowering/boll development and beginning open boll, respectively). The acquired images were georeferenced by field-defined ground control points (six points on the boundary and three in the middle) using a model AG114 DGPS GNSS receiver and the orthomosaics were generated in the pix4DMapper platform (Pix4D S.A., Switzerland).

Cluster analyses were performed with seven acquired maps: two EC_a (0-30 and 0-90 cm) maps, two NDVI (May and June) maps, two NDRE (May and June) maps, and the 2019 cotton yield map. For this, the agglomerative hierarchical Ward's unsupervised clustering method (Ward-Junior, 1963) was applied, implemented in the R programming environment, as illustrated in Fig. 2. Prior to the analysis, the data were normalized and re-sampled to a regular grid of 10 m x 10 m, because each attribute was mapped with different sampling densities. Additionally, data distribution in a regular spatial grid is a prerequisite for the correct execution of the clustering algorithm so that it does not follow a bias focused only on geographic location. This resolution is sufficient to identify spatial variability and delineate management zones for a 169-ha plot and compatible with the platform width of the machinery used by the farmer for PGR interventions. The Ward's method provides a tree of clusters, known as a dendrogram, by fusion of similar groups in each level, based on the lower increment of the mean square error. To avoid small area clusters, a hierarchical clustering initialization method known as initial tessellation (Ruβ and Kruse, 2011) was applied and number of clusters was selected using the silhouette width internal validation criteria (Rousseeuw, 1987).

NDVI Temporal Series from Satellite Images. NDVI images obtained from Sentinel-2 (10-m spatial resolution) and Landsat-8 (30-m resolution) satellites were used to assess the cotton plant growth spatial variability in the two harvesting seasons, evaluating and comparing the effect of the two PGR application methods. The Earth Engine API (Google, Menio Park, CA) was used to evaluate, select, and download the NDVI images for the two cotton seasons, providing NDVI temporal series for the spatial variability evaluations. Only images without clouds were selected for the analysis. In that region, the rainiest period for the cotton season is from December to February; therefore, few NDVI images without clouds were obtained in the first three growing months in both years. In 2019 cotton was sown on 21 January 2019 and harvested on 6 August 2019; whereas in 2020, cotton was sown on 27 December 2019 and harvested on 13 July 2020. Average, standard deviation (SD), and coefficient of variation (CV) of NDVI for the whole field and for the application zones were determined and compared in the two growing seasons to evaluate the effect of the VRA in reducing plant spatial variability.

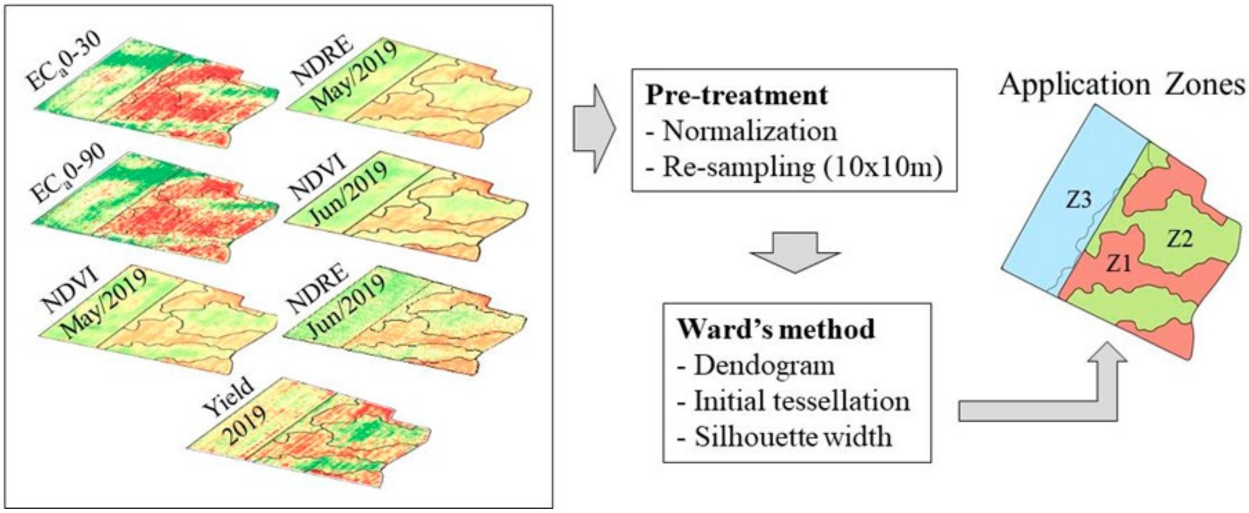

Figure 2. Illustration of the clustering procedure employed to generate the application zones (Z1, Z2, and Z3). The border of Z3 with Z1 and Z2 (dotted line) was rectified (solid line), as shown on the map of the delimitated zones, to facilitate the zonal application of the plant growth regulator.

Cotton Management and Harvesting. The cotton cultivar TMG 81WS (Tropical, Melhoramento & Genética, Cambé, Brazil) was sowed at 0.9-m spaced rows with 9 seeds m^{-1} density in the two growing seasons, using a Hercules 10000 distributor (Stara, Não-Me-Toque, RS, Brazil). Plant growth regulator was applied at one uniform dose on 24 April 2019 (12.5 g ai ha^{-1}) and at two variable doses applied on 21 February and 29 February 2020, in the previously established application zones (total applied by zone was 40 g ai ha^{-1} in Z1; 55 g ai ha^{-1} in Z2; and 32.5 g ai ha^{-1} in Z3), using a self-propelled sprayer PV 4730 (John Deere, Moline, IL) in 2019 and the Uniport 3030 (Jacto, Pompéia, SP, Brazil) in 2020. Granular fertilizers were applied (Table 1) with the Hercules 10000 distributor. Cotton yield maps were obtained using the cotton picker model CP690 (John Deere, Moline, IL) that was properly calibrated before use.

RESULTS AND DISCUSSION

All parameters mapped in the experimental field are presented in Fig. 2. Soil clay content correlated relatively well to EC$_a$ (linear determination coefficient, r^2 = 0.65 and 0.62 for depths 0-30 and 0-90 cm, respectively). Seed cotton yield, EC$_a$, NDVI, and NDRE maps displayed similar spatial variability patterns in 2019 and were selected for clustering analysis to generate the PGR application zones. Elevation and slope were not included in the clustering analysis due to low in-field variations and low spatial correlation with the other relevant parameters, although clay content was discarded due to its intimate relation with EC$_a$ observed in the experimental field, thus avoiding redundancy. Three application zones were defined using Ward's method along with the criteria to select the most appropriate number of clusters (Fig. 2). The border between application zone 3 (Z3) and the others were straightened, as shown on the map of the delimitated zones in Fig. 2, to facilitate PGR application in that zone.

The mapped parameters shown in Fig. 3 reveal large spatial variability of soil and plant features (EC$_a$, clay content, NDVI, and NDRE), which in turn impacted the cotton yield spatial variability, as also indicated by frequency distribution graphs (Fig. 4). Clay content, EC$_a$, and cotton yield histograms present three peaks (obtained by deconvolution of peaks using the Multiple Peak Fit tool of the Origin software), whereas NDVI and NDRE acquired by drone in June 2019 exhibit two peaks, which is in accordance to the number of clusters selected (three zones).

To complement the zonal application of PGR in the 2020 season, plant heights were measured in the three zones up to approximately 140 DAS. Fig. 1a shows plant height averaged along the entire field for each collection dates during the 2020 and 2019 seasons, and Fig. 1b shows the plant height averaged by collected date for each zone in 2020 (no measurement was made by zone in the 2019 season). A significant difference (p < 0.001) in plant height was observed between the two growing seasons (Fig. 1a), according to the ANOVA test applied to the quadratic model fitting data, showing an average plant height difference of 0.27 m between the two crop seasons. Differences in plant growth and cotton yield were likely influenced by the higher dose of post-planting fertilizer N applied, better rain distribution in the 2020 season (Fig. 5) and by the zonal application of PGR, contributing to the improved cotton yield in 2020, which was 22% higher than in 2019 (Table 1).

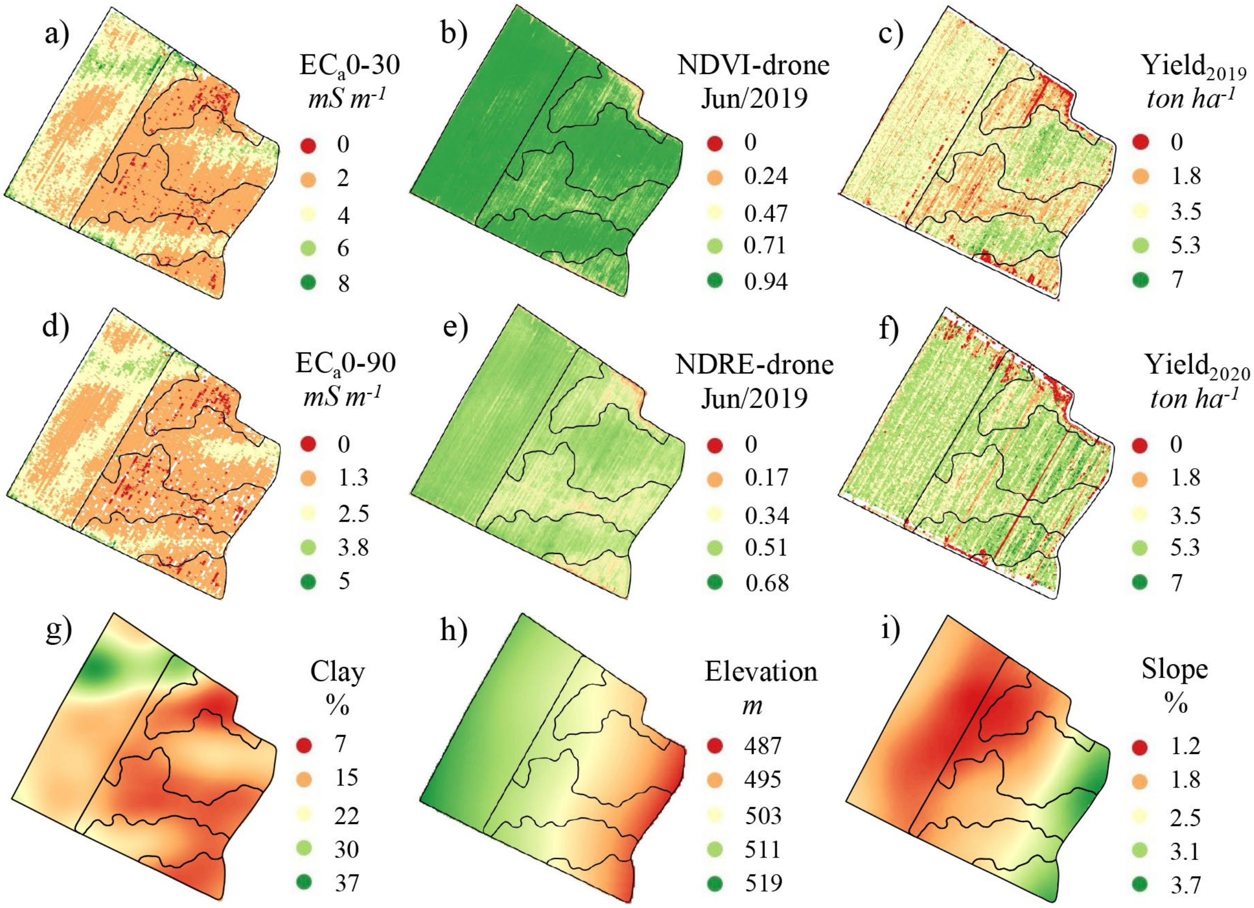

Figure 3. Soil parameters maps (apparent electrical conductivity, EC_a, at 0-30 and 0-90 cm depths, and clay content), vegetation indexes images (NDVI and NDRE obtained by drone), topographic parameters (elevation and slope obtained by drone measurements), and cotton yields maps obtained with a harvesting monitor system in the 2019 and 2020 seasons.

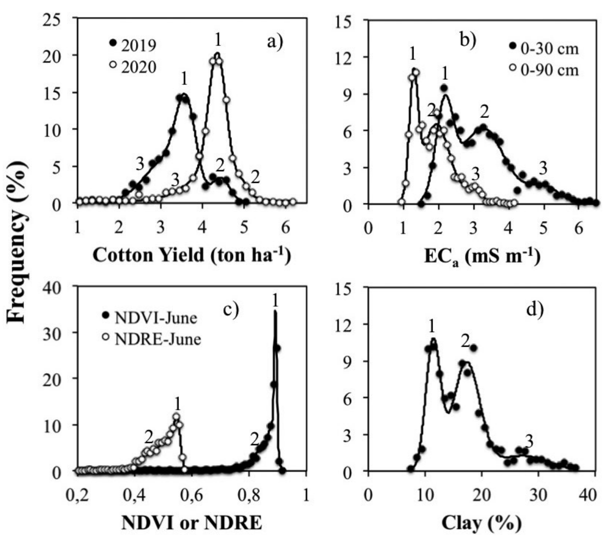

Figure 4. (a) Frequency distribution of cotton yields in the 2019 and 2020 seasons, (b) apparent electrical conductivity, (c) NDVI and NDRE drone acquired vegetation indexes, and (d) soil clay content. Peaks 1, 2, and 3 were obtained by deconvolution of peaks using Origin software.

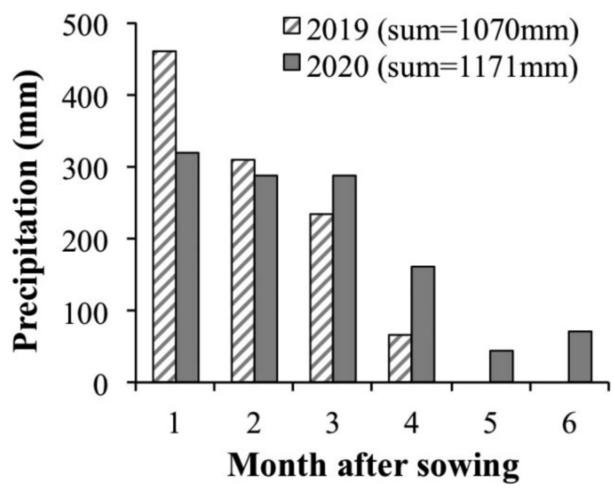

Figure 5. Monthly accumulated precipitation in the experimental field from sowing to harvesting for the two growing seasons.

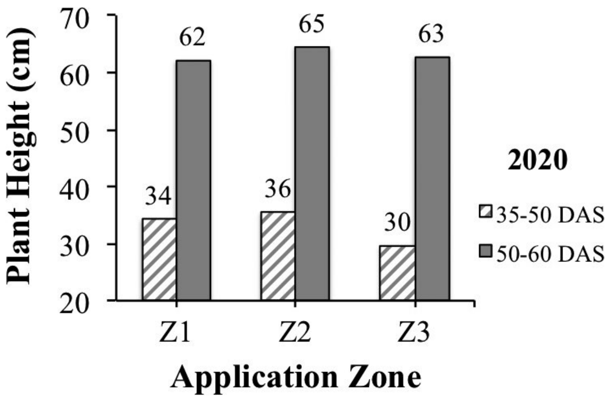

Figure 6. Average plant height measured at the three application zones at 35-50 and 50-60 DAS in the 2020. Measurements to subsidize PGR doses in the different zones in 2020.

Mepiquat chloride was applied at 12.5 g ai ha^{-1} in 2019 (one uniform application) and an average of 42.5 g ai ha^{-1} in 2020 (two applications, variable by zone, detailed in Table 2). The higher PGR dose in 2020 was necessary due to larger plants growing in that year, compared to 2019 (Fig. 1a). Different doses for each zone in 2020 (Table 2) were defined based on plant height measurements in the three zones taken between 35 and 60 DAS (Fig. 6) and on previous experiences in that area regarding plant growth due to in-season climate variation, application of fertilizers, and cultivar following the State of Mato Grosso Best Management Practices Manual (Echer et al., 2020), resulting in 32.5 g ai ha^{-1} for Z3 (lowest dose applied), 55 g ai ha^{-1} for Z2 (highest dose applied), and 40 g ai ha^{-1} for Z1.

The effect of PGR applied by zone (2020 season) on cotton yield spatial variability reduction can be evaluated by the yield CV obtained for the entire field and for each zone (Table 3). In the whole field, yield CV decreased from 17.9% in 2019 to 12.4% in 2020 (5.5% reduction), but inside the application zones the differences between the two seasons were much lower (about 1% reduction). This is due to the strategy adopted (different PGR doses per zone), which reduced whole-field yield variability, but had less effect on reducing internal zone variability in that PGR was applied at constant-rate within each zone. Alternatively, another approach would be to apply PGR at continuously variable-rate, based on plant height maps obtained by sensors as a potentially more effective way to reduce spatial variability (Bethel et al., 2003). However, this VRA approach requires special sprayers that were not available in this study. The approach adopted here for the zonal application was implemented by adjusting PGR doses prior to the applications and turning the system on when inside and off when outside. In this case, three sprayer passes were necessary in the first PGR application (doses of 12.5, 20, and 25 g ai ha^{-1}) and two in the second (doses of 20 and 30 g ai ha^{-1}) to accomplish the variable-rate application by zone in 2020 (Table 2).

Yield is the primary metric used by producers when evaluating changes in management practices. However, producers cannot ignore the impact of soil properties, nutrient availability, water supply, and climatic interactions. Water typically has a great influence on yield, so factors that influence soil water holding capacity like clay content and infiltration rate are primary considerations when comparing yields. Zonal delineation in this study incorporated many of these considerations in terms of their absolute values (range across zones) more so than the variability within zones. Lowest yields in both years were attained in Z1 and highest in Z2 (Table 3). Positive correlations with yield were obtained with clay content, EC_a, and the previous year's VIs (NDRE and NDVI).

Data analysis within zones showed that the CV for yield was larger for Z1 (approximately 17%) and lower for Z3 (approximately 7%) and Z2 (about 11%) in both years. Lower yields in Z1 can be partially attributed to lower clay content and lower EC_a (i.e., contributed to lower water holding capacity and likely to be less fertile) compared to Z2 and Z3. Zone 2 was intermediate to Z1 and Z3 in terms of clay content and EC_a but received the largest amount of PGR and had the highest yields in 2019 and 2020. The need for the highest dose of PGR in Z2 implies that plant height had a major role in determining the PGR rate. Cotton grown in this zone was unique in that lush plant growth was present in 2020 (taller plants) that could not be explained by soil clay content, EC_a or any of the other considerations. This observation illustrates the opportunity for real-time sensing of crop biomass to help guide the application rate of PGR.

The problem with whole-field research is that it does not lend itself to replications unless the area is divided, which can be difficult considering field shape, topography, and soil type. To complicate matters further, this type of research requires a great deal of background information before one can develop a management strategy for the next crop.

Table 3. Mean, standard deviation (SD), and coefficient of variation (CV) values in the whole field (W) and the application zones (Z1, Z, Z3) for cotton yield, soil clay content, apparent electrical conductivity (EC_a), NDVI-drone (June 2019), NDRE-drone (June 2019), land elevation, and slope

Parameter	Zone	Mean	SD	CV
Yield – 2019	W	3.5	0.6	17.9
	Z1	2.8	0.05	17.5
	Z2	4.0	0.5	12.3
	Z3	3.5	0.3	7.4
Yield – 2020	W	4.3	0.5	12.4
	Z1	3.9	0.6	16.8
	Z2	4.5	0.5	10.1
	Z3	4.3	0.3	6.8
Clay Content (%)	W	16.4	5.5	33.5
	Z1	11.8	2.1	18.1
	Z2	16.2	3.9	24.2
	Z3	20.9	5.3	25.5
EC_a 0-30 cm (mS m^{-1})	W	3.2	0.9	29.2
	Z1	2.2	0.3	14.1
	Z2	3.2	0.8	26.3
	Z3	3.7	0.7	19.8
NDVI – Drone	W	0.87	0.04	4.9
	Z1	0.82	0.05	6.0
	Z2	0.88	0.02	1.8
	Z3	0.89	0.01	1.1
NDRE – Drone	W	0.50	0.05	9.5
	Z1	0.44	0.03	7.7
	Z2	0.51	0.03	5.4
	Z3	0.55	0.01	2.2
Land Elevation (m)	W	504	7	1.3
	Z1	501	6	1.2
	Z2	500	5	1.0
	Z3	511	3	0.5
Slope (%)	W	2.0	0.6	29.4
	Z1	2.1	0.7	31.8
	Z2	2.2	0.6	25.6
	Z3	1.6	0.2	15.1

In addition to the analysis on cotton yield CV to assess spatial variability reduction due to the zonal application of PGR, NDVI satellite images, such as the ones from Sentinel-2 and Landsat-8 platforms, provide a good tool to evaluate plant vigor dynamics spatially. In the experimental field, 21 and 13 NDVI images without cloud interference were obtained in the 2019 and 2020 cotton seasons, respectively (Table 4) and used for spatial and temporal analysis. Fig. 7 shows NDVI images (Sentinel-2) in four different DAS during the growing seasons. The internal lines delineate the application zones. NDVI frequency distributions for the two seasons are also given in Fig. 7. A visual analysis of these images indicates larger NDVI variability in 2019, especially in the 159 and 189 DAS images, which is confirmed by the presence of two well-defined and spaced peaks in the frequency distribution graphs in that year (Figs. 7k and 7l).

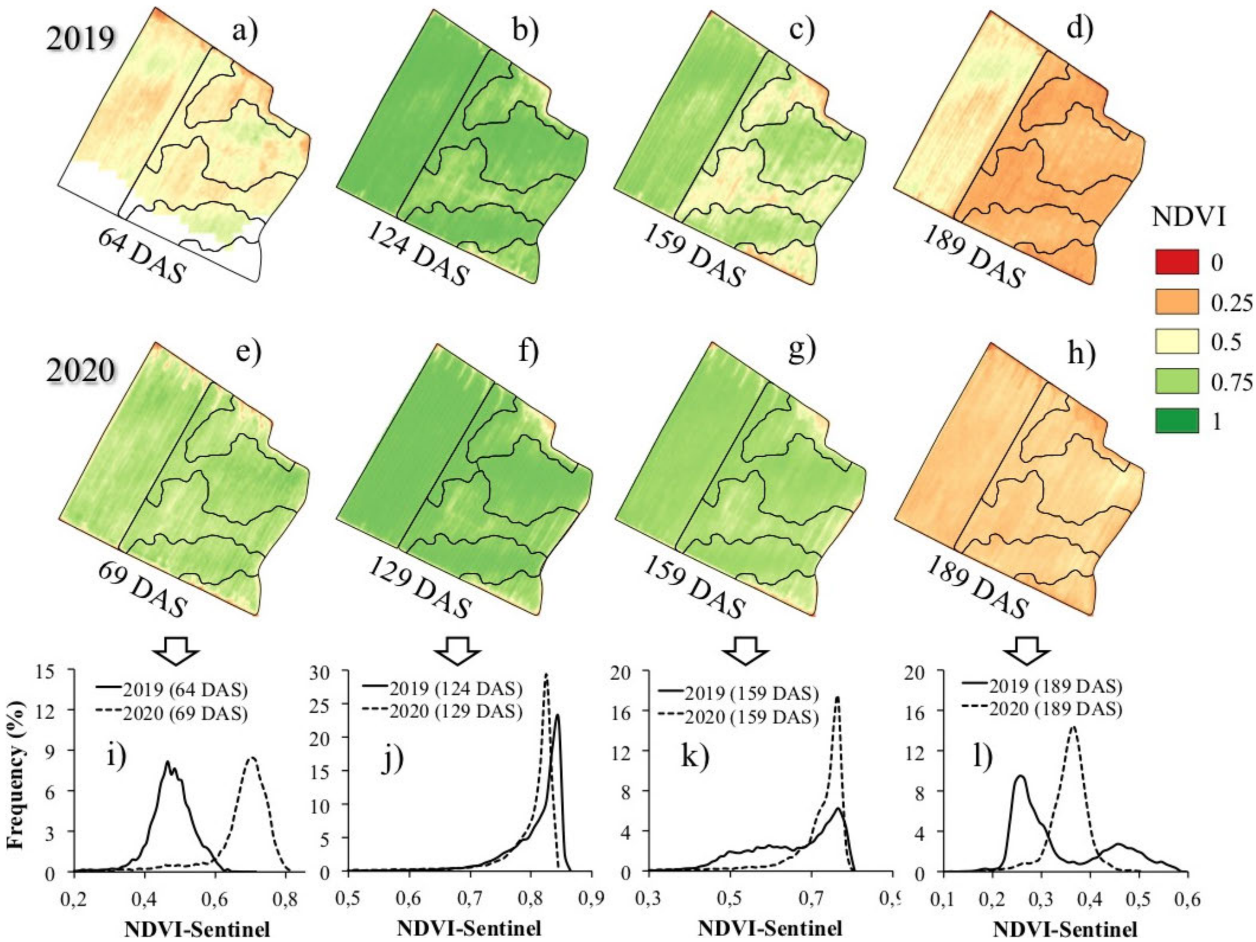

Figure 7. NDVI images from Sentinel-2 along the (a, b, c, d) 2019 and (e, f, g, h) 2020 cotton seasons at different days after sowing (DAS). Internal lines delineate the application zones (Fig. 2). NDVI frequency distributions (i, j, k, l) are compared at similar DAS for the two seasons.

Table 4. Number of satellite images without cloud interference obtained from Sentinel-2 and Landsat-8 at the experimental field during the 2019 and 2020 seasons

Season	Satellite	Number of NDVI images			
		0-90 DAS[z]	90-140 DAS	140-190 DAS	Total
2019	Sentinel	1	6	9	16
	Landsat	0	2	3	5
2020	Sentinel	2	1	6	9
	Landsat	1	1	2	4

[z] **DAS, days after sowing**

NDVI variability (SD and CV) with DAS (Fig. 8) was similar in both years up to approximately 130 DAS and deviated significantly from that point forward. A sharp increase in CV at the end of the crop season in 2019 was present, whereas this factor was nearly constant in 2020. Close to harvesting (189 DAS), CV was approximately 30% in 2019 and 10% in 2020 (Fig. 8b). The lower NDVI spatial variability in 2020 was likely caused by the zonal application of PGR in that year. Regarding variations of SD with DAS (Fig. 8a), a noticeable decrease of SD after approximately 175 DAS was observed in both years, likely caused by the application of defoliant and ripener (applied at 170-175 DAS) that homogenized cotton maturation. Such decrease was not observed in the CV graph (Fig. 8b) because CV expresses the ratio between SD and the mean value and mean reduction was more intense than SD.

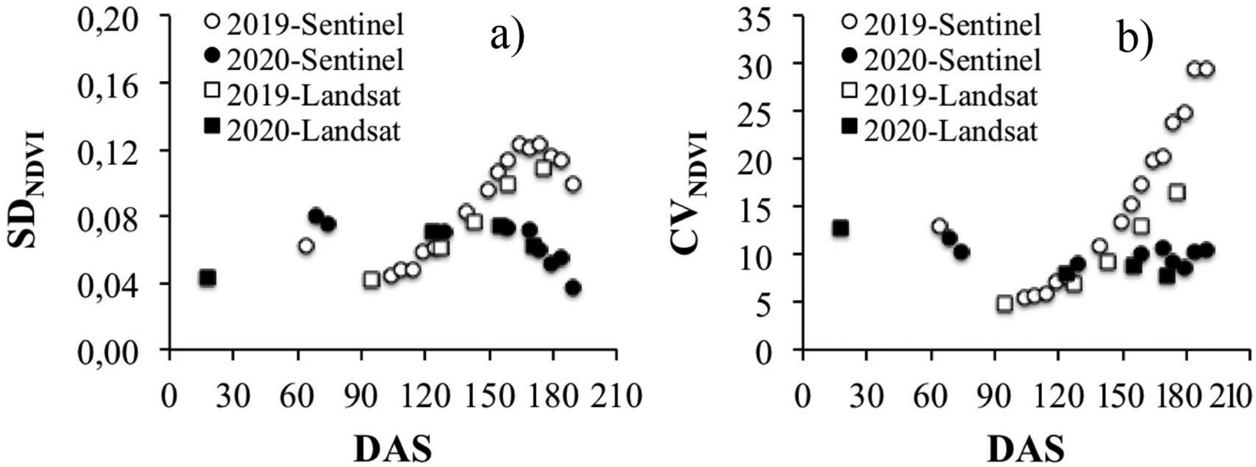

Figure 8. (a) Standard deviation and (b) coefficient of variation of NDVI from Sentinel-2 and Landsat-8 satellite images determined for the whole field. DAS: days after sowing.

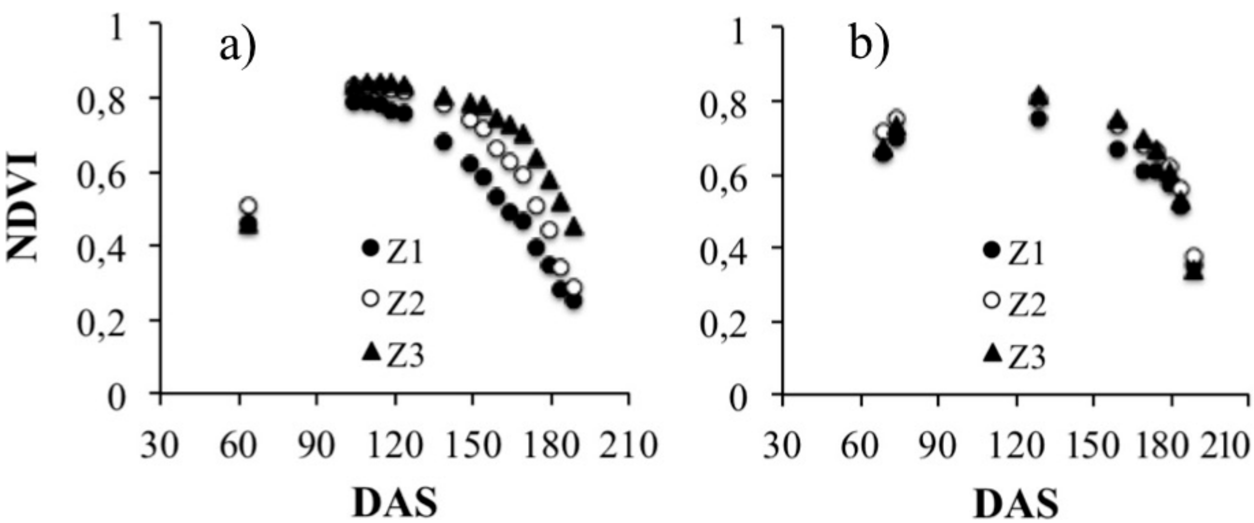

Figure 9. NDVI temporal series from Sentinel-2 satellite images averaged for the three zones (Z1, Z2, and Z3) in the (a) 2019 and (b) 2020 growing seasons. DAS: days after sowing.

NDVI temporal series for each zone are presented in Fig. 9, showing larger differences among the zones in 2019 (Fig. 9a), as expected, with Z3 exhibiting the highest NDVI values and Z1 the lowest. In 2020, differences were much lower, having a similar trend in NDVI among zones, especially later in the growing season, but slightly larger NDVI for Z3 and lower for Z1 from approximately 120 to 170 DAS. The large NDVI variations among zones in 2019 and low variations in 2020 (Fig. 9) agrees with the yield CV reduction in 2020 (Table 3) and highlights the effect of the zonal application of PGR on spatial variability reduction in 2020 as compared to the uniform PGR application in 2019.

Plant vigor, expressed by NDVI, has been correlated to yield for several crops (Baio et al., 2019; Huang et al., 2013; Johnson, 2016). In cotton, an additional aspect that must be considered is PGR use, due to the indeterminate growth habit of cotton plants that affects plant height, vigor, and yield. To evaluate the correlations between plant vigor and cotton yield spatially and temporally, yield was plotted against NDVI for different DAS (Fig. 10) in the two seasons. In such analysis, data were re-sampled to 40-x-40-m pixels, due to the different spatial resolutions of these two variables and, additionally, pixels in the borders between two zones were not included to allow a better evaluation by zone.

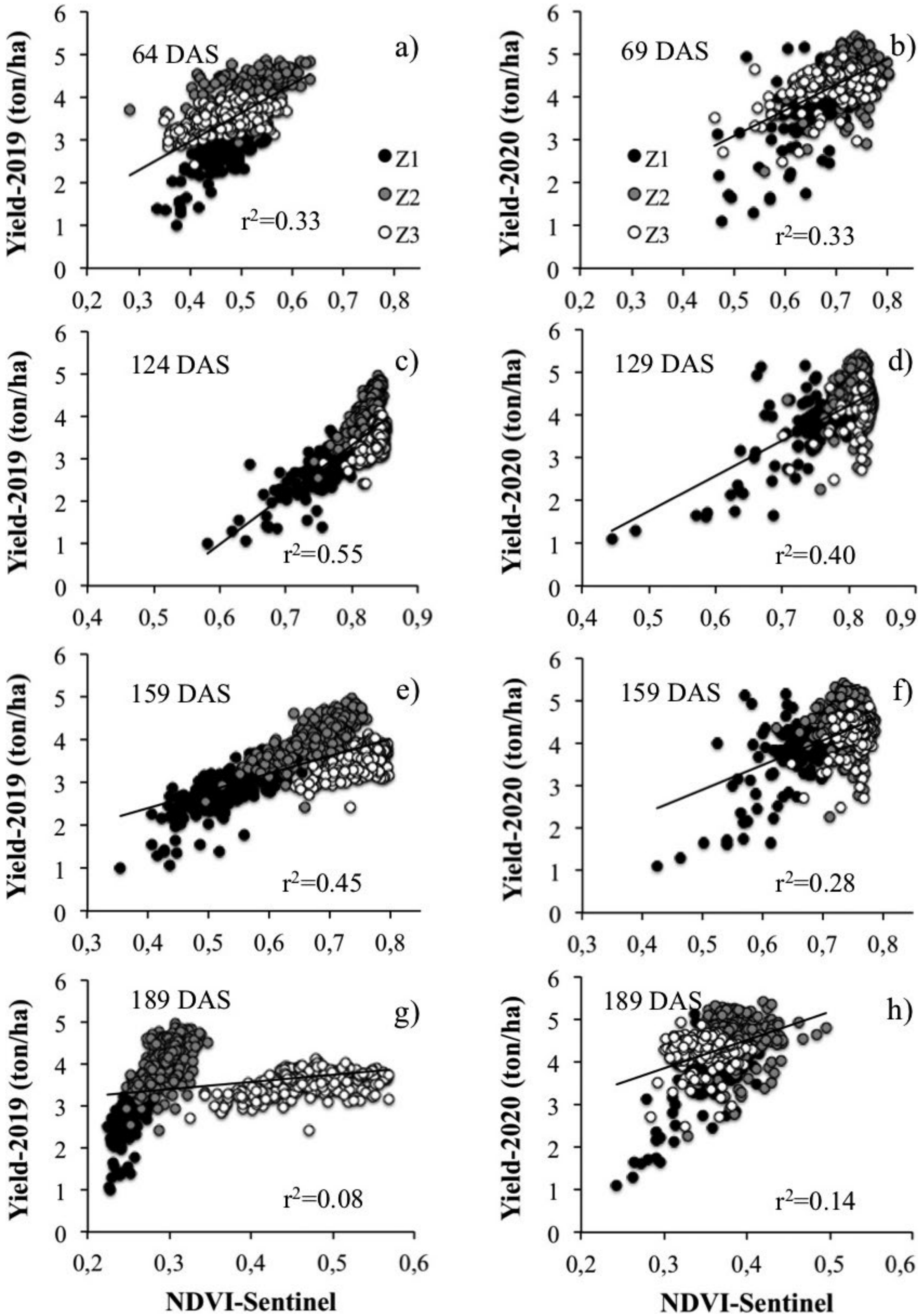

Figure 10. NDVI (Sentinel-2) at different DAS, correlated spatially to cotton yield in (a, c, e, g) 2019 and (b, d, f, h) 2020. Distinct symbols are used for the application zones.

Linear trends between yield and NDVI were observed for all DAS in 2020 when PGR was applied at different doses by zone, although determination coefficients (r^2) decreased in the late season (after approximately 130 DAS) due to the effects of PGR, defoliant, and ripener. In 2019 (uniform PGR application), the data for Z3 gradually deviated from the other two zones as DAS increased and NDVI values in Z3 obtained close to harvest shifted significantly from the others. This behavior is probably an effect of the PGR application at constant-rate. As Z3 has the highest average soil clay content (Table 3), it likely retained more water leading to higher plant height comparatively to the other two zones, demanding larger amounts of PGR compared to the other zones. Additionally, in a year where rain distribution was uneven, as it was in 2019 (almost no rain after 100 DAS, as shown in Fig. 5), such differences in plant growth among zones tends to be exacerbated. Although no plant height measurement was made by zone in 2019, the NDVI satellite images clearly indicates the larger NDVI values in Z3, which can be associated with higher vegetative growth and insufficient application of PGR. Average NDVI values by zone at 189 DAS were 0.46 (Z3), 0.29 (Z2), and 0.25 (Z1) in 2019 and 0.35 (Z3), 0.38 (Z2), and 0.34 (Z1) in 2020.

CONCLUSIONS

The zonal application of PGR provided a decrease in the yield CV across the field from 17.9% in 2019 to 12.4% in 2020 (5.5% reduction), although for each zone reductions were much lower (about 1% CV reduction from 2019 to 2020). This likely happened because inside the zones PGR was applied at constant rates. In 2020, Z1 presented the larger yield CV (approximately 16.8%) compared to Z2 (10.1%) and Z3 (6.8%), indicating the need to re-evaluate and re-define the zones for future VRA of PGR in this field, aiming to reduce even further the cotton yield variability. Cotton yield increased from approximately 3.5 t ha^{-1} in 2019 to 4.3 t ha^{-1} in 2020 (increment of 0.764 t ha^{-1} or 22%), when PGR was applied at variable-rate by zone. Inside the zones, increments were 1.101 t ha^{-1} (40%) in Z1, 0.535 t ha^{-1} (13%) in Z2, and 0.728 t ha^{-1} (21%) in Z3. These increments cannot be attributed solely to the PGR variable-rate approach. Although cultivar, row spacing, and seed density were kept constant, 23% more post-planting N fertilizer was applied in 2020 and the better precipitation distribution in that season could have a significant impact on cotton yield. Nevertheless, the data and the analysis presented herein suggest that the applied PGR variable-rate procedure reduced the yield spatial variability. Satellite images and subsequent NDVI data offer a powerful tool to evaluate the spatial variability dynamically, especially for the second crop in Brazil, which is generally sowed in the summer (rainy season) and harvested in the winter (dry season). In this case, a considerable number of satellite images without cloud interference can be accessed. In 2019, when PGR was applied at constant rate, the NDVI coefficient of variation increased significantly from approximately 130 DAS, reaching 30% close to harvesting; whereas in 2020 (PGR applied at variable-rate), CV was essentially constant (approximately 10%). Temporal series NDVI data by zone showed large differences among zones in 2019 (highest values for Z2 and lowest values for Z1), from 130 to 190 DAS and minor differences in the 2020 season. The spatial and temporal analysis performed with the NDVI satellite images agrees and complements the spatial variability analysis made with the cotton yield maps, allowing effective evaluation of the agronomic impacts and benefits of the zonal application of PGR compared to uniform application on a highly variable field. This study indicates that VRA of PGR based on application zones and plant height measurements can be a viable strategy for reducing spatial variability in highly variable cotton fields. Nevertheless, more research is necessary to evaluate the effect of VRA of PGR in agricultural fields with different levels of variability and under variable climatic conditions among years.

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REFERENCES

Baio, F.H.R., D.C. Neves, and P.E. Teodoro. 2019. Soil chemical attributes, soil type, and rainfall effects on normalized difference vegetation index and cotton fiber yield variability. Agron. J. 111:2910–2919. https://doi.org/10.2134/agronj2019.05.0375

Baio, F.H.R., D.C. Neves, H.B. Souza, A.J.F. Leal, R.C. Leite, J.P. Molin, and S.P. Silva. 2018. Variable rate spraying application on cotton using an electronic flow controller. Precis. Agric. 19:912–928. https://doi.org/10.1007/s11119-018-9564-7

Bethel, M., T. Gress, S. White, S. Johnson, T. Sheely, B. Roberts, M. Paggi, and N. Groenenberg. 2003. Image-based, variable rate plant growth regulator application in cotton at Sheely Farms in California. p. 1755–1766 *In* Proc. Beltwide Cotton Conf., Nashville, TN. 6-10 Jan. 2003, Natl. Cotton Counc. Am., Memphis, TN.

Campanella, R. 2000. Testing components toward a remote-sensing-based decision support system for cotton production. Photogramm. Eng. Remote Sens. 66(10):1219–1227.

Echer, F.R., P.R. Mello, and C.A. Rosolem. 2020. Management of plant growth regulators. *In* J.L. Belot and P.M.C.A. Vilela (ed.), Best Management Practices for Cotton in Mato Grosso State (in Portuguese), 4th edition. IMAmt-AMPA, Cuiabá, MT.

Fang, S., K. Gao, W. Hu, S. Wang, B. Chen, and Z. Zhou. 2019. Foliar and seed application of plant growth regulators affects cotton yield by altering leaf physiology and floral bud carbohydrate accumulation. Field Crops Res. 231:105–114. https://doi.org/10.1016/j.fcr.2018.11.012

Fountas, S., S. Blackmore, D. Es, S. Hawkins, G. Blumhoff, J. Lowenberg-deBoer, and C.G. Sorensen. 2005. Farmer experience with precision agriculture in Denmark and the US Eastern Corn Belt. Precis. Agric. 6:121–141. https://doi.org/10.1007/s11119-004-1030-z

Huang, Y., R. Sui, S.J. Thomson, and D.K. Fisher. 2013. Estimation of cotton yield with varied irrigation and nitrogen treatments using aerial multispectral imagery. Int. J. Agric. Biol. Eng. 6(2):37–41. https://doi.org/10.3965/j.ijabe.20130602.005

Jin, Z., V.S. Archontoulis, and D.B. Lobell. 2019. How much will precision nitrogen management pay off? An evaluation based on simulating thousands of corn fields over the US Corn-Belt. Field Crops Res. 240:12–22. https://doi.org/10.1016/j.fcr.2019.04.013

Johnson, D.M. 2016. A comprehensive assessment of the correlations between field crop yields and commonly used MODIS products. Int. J. Appl. Earth Obs. Geoinf. 52:65–81. https://doi.org/10.1016/j.jag.2016.05.010

Landivar, J.A., S. Searcy, and J. Stewart. 1999. A variable-rate chemical application system for cotton production in south Texas. p. 581–583 *In* Proc. Beltwide Cotton Conf., Orlando, FL. 3-7 Jan. 1999. Natl. Cotton Counc. Am., Memphis, TN.

Leal, A.J.F., G.L. Piati, R.C. Leite, M.S. Zanella, C.R.W.S. Osorio, and S.F. Lima. 2020. Nitrogen and mepiquat chloride can affect fiber quality and cotton yield. Rev. Bras. de Eng. Agricola e Ambient. 24(4):238–243. https://doi.org/10.1590/1807-1929/agriambi.v24n4p238-243

Lowenberg-DeBoer, J., and B. Erickson. 2019. Setting the record straight on precision agriculture adoption. Agron J. 111(4):1552–1569. https://doi.org/10.2134/agronj2018.12.0779

Martins, R.N., F.A.C. Pinto, A.D. Moura, W.C. Siqueira, and F.M. Villar. 2020. Nitrogen variable rate fertilization in corn crop prescribed by optical sensor. J. Plant Nutr. 43(11):1681–1688. https://doi.org/10.1080/01904167.2020.1729805

Nawar, S., R. Corstanje, G. Halcro, D. Mulla, and A.M. Mouazen. 2017. Delineation of soil management zones for variable-rate fertilization: A review. Adv. Agron. 143:175–245. https://doi.org/10.1016/bs.agron.2017.01.003

Nelson, J.R. 2006. Site-specific management and remote sensing based plant growth regulator application decisions in cotton. Ph.D. diss. North Carolina State University, Raleigh. http://www.lib.ncsu.edu/resolver/1840.16/734

O'Berry, N.B., J.C. Faircloth, M.A. Jones, D.A. Herbert-Jr, A.O. Abaye, T.E. McKemie, and C. Brownie. 2009. Differential responses of cotton cultivars when applying mepiquat pentaborate. Agron. J. 101(1):25–31. https://doi.org/10.2134/agronj2007.0333

Rousseeuw, P.J. 1987. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. J. Comput. Appl. Math. 20:53–65. https://doi.org/10.1016/0377-0427(87)90125-7

Ruβ G., and R. Kruse. 2011. Exploratory hierarchical clustering for management zone delineation in precision agriculture. p. 161–173 *In* P. Perner (ed.), Advances in Data Mining. Applications and Theoretical Aspects. ICDM 2011. Lecture Notes in Computer Science, Book Series, v. 6870. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-642-23184-1_13

Samples, C., D.M. Dodds, A.L. Catchot, B.R. Golden, J. Gore, and J.J. Varco. 2015. Determining optimum plant growth regulator application rates in response to fruiting structure and flower bud removal. J. Cotton Sci. 19:359–367.

Sawan, Z.M. 2018. Mineral fertilizers and plant growth retardants: Its effects on cottonseed yield; its quality and contents. Cogent Biol. 4:1–9. https://doi.org/10.1080/23312025.2018.1459010

Stamatiadis, S., J.S. Schepers, E. Evangelou, A. Glampedakis, M. Glampedakis, N. Dercas, C. Tsadilas, N. Tserlikakis, and E. Tsadila. 2020. Variable-rate application of high spatial resolution can improve cotton N-use efficiency and profitability. Precis. Agric. 21:695–712. https://doi.org/10.1007/s11119-019-09690-6

Thurman, M.E., and R.W. Heiniger. 1999b. Evaluation of variable rate Pix (mepiquat chloride) application by soil type. p. 524–526 *In* Proc. Beltwide Cotton Conf., Orlando, FL, 3-7 Jan. 1999. Natl. Cotton Counc. Am., Memphis, TN.

Thurman, M.E., and R.W. Heiniger. 1999a. Using GPS to scout cotton for variable rate Pix (mepiquat chloride) application. p. 953–961 *In* P.C. Robert, R.H. Rust, and W.E. Larson (ed.). Proc. Fourth Int. Conf. on Precision Agric., St. Paul, MN, 19–22 Jul. 1998. ASA, CSSA, and SSSA Books.

Trevisan, R.G., N.S. Vilanova-Júnior, M.T. Eitelwein, and J.P. Molin. 2018. Management of plant growth regulators in cotton using active crop canopy sensors. Agriculture 8(7):101. https://doi.org/10.3390/agriculture8070101

Tung, S.A., Y. Huang, A. Hafeez, S. Ali, A. Liu, M.S. Chattha, S. Ahmad, and G. Yang. 2020. Morpho-physiological effects and molecular mode of action of mepiquat chloride application in cotton: A review. J. Soil Sci. Plant Nutr. 20:2073–2086. https://doi.org/10.1007/s42729-020-00276-0

United States Department of Agriculture [USDA]. 2023. Cotton: World Markets and Trade. Available at https://apps.fas.usda.gov/psdonline/circulars/cotton.pdf (verified 15 Feb. 2023).

Vistro, R., Q.I. Chachar, S.D. Chachar, N.A. Chachar, A. Laghari, S. Vistro, and I. Kumbhar. 2017. Impact of plant growth regulators on the growth and yield of cotton. Int. J. Agric. Technol. 13:353–362.

Ward-Junior, J.H. 1963. Hierarchical grouping to optimize an objective function. J. Am. Stat. Assoc. 58(301):236–244. https://doi.org/10.1080/01621459.1963.10500845

Yu, J., X. Yin, T.B. Raper, S. Jagadamma, and D. Chi. 2019. Nitrogen consumption and productivity of cotton under sensor-based variable-rate nitrogen fertilization. Agron. J. 111(6):3320–3328. https://doi.org/10.2134/agronj2019.03.0197

Zhou, X.V., B.C. English, J.A. Larson, D.M. Lambert, R.K. Roberts, C.N. Boyer, M. Velandia, L.L. Falconer, and S.W. Martin. 2017. Precision farming adoption trends in the Southern U.S. J. Cotton Sci. 21:143–155. https://doi.org/10.56454/GGKY6251