

Full Length Research Paper

Two approach comparison to define crop management zones (MZs)

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The use of yield-level management zones (MZs) has demonstrated high potential for site-specific management of crop inputs in traditional row crops. Two approaches were used: all variables approach (all_Var) and stable variables approach (sta_Var). In each approach, variables selected had significant correlation with yield, while all redundant and non-autocorrelated variables were discarded. Two fields were used in this study: Field 1 (17.0 ha soybean field located in Cascavel, Paraná, Brazil); and Field 2 (35.0 ha corn field located in Wiggins, Colorado, US.). Two, three, four, and five MZs were created using fuzzy c-means clustering technique. The proposed methodology for defining MZs is simple and allowed to create good-quality MZs. It also found that not-stable-over-time variables are not useful to define MZs.

Key words: Precision agriculture, spatial variability, fuzzy clustering, autocorrelation, cross-correlation.

INTRODUCTION

A management zone (MZ) is a sub-region of a field that expresses a relatively homogeneous combination of yield-limiting factors for which a single rate of a specific crop input is appropriate (Doerge, 1996). Delineation of MZs and management of crop inputs have proved economical for application of variable rate inputs (Koch et al., 2004). Several researchers have successfully used one or more of these factors in combination with yield maps and sometimes use only multiple year yield maps in delineating MZs (Blackmore, 2000; Fraisse et al., 2001; Johnson et al., 2003; Schepers et al., 2004).

Numerous approaches are presented in literature for purpose of delineating MZs using yield maps, using cluster analysis, such as K-means and Fuzzy C-means (Taylor et al., 2007; Li et al., 2007). Although several techniques have been developed to delineate MZs, only few studies compared MZs in terms of their accuracy (Hornung et al., 2006). The following cluster performance indices can be used:

1. Variance reduction (VR; Ping and Dobermann, 2003; Xiang et al., 2007)

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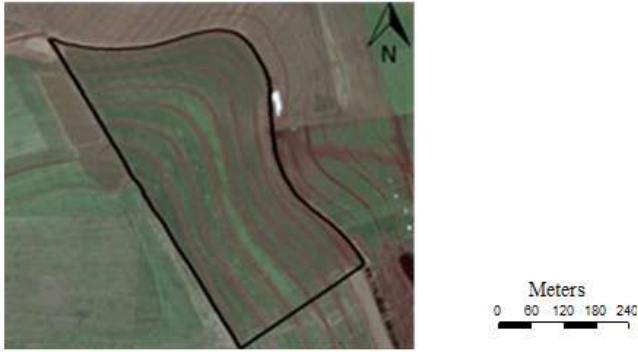


Figure 1. Experimental field 1, (Cascavel/Paraná, Brazil), cultivated with soybean crop.

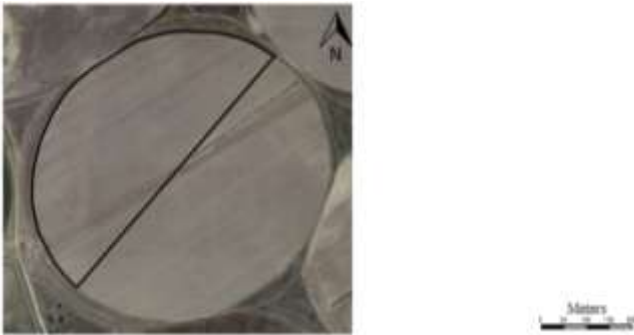


Figure 2. Experimental field 2, (Wiggins, CO, USA), cultivated with corn crop.

2. Fuzziness performance index (FPI); and
3. Modified partition entropy index (MPE; Fridgen et al., 2004). To evaluate the quality of the cluster process, two analyses could be conducted:

The average comparison test (analysis of variation, ANOVA; Bazzi et al., 2015)

Smoothness index (SI; Schenatto et al., 2016), which is a measure of the smoothness of the contour curves.

Although a careful definition of MZs requires a lot of steps and analysis about data. The goal of this study was to analyze viability of MZs definition using stable and non-stable variables and use methodology to define best number of zones for each case. This would be very interesting for producers who are only starting to use precision agriculture.

MATERIALS AND METHODS

Study site and data collection

Field 1: Data from a 16.9 ha soybean field (Figure 1) were evaluated. It is located in a rural area of municipality of

Cascavel, Paraná state, Brazil (24°57'13"S and 53°34'02"W, average elevation: 650 m). The soil is classified as dystroferic red latossol (Embrapa, 1999) with 70% clay. A Trimble Geo Explorer XT 2005 Geodesic Differential Global Positioning System (GDGPS) with post-processing was used for georeferencing the research area. Soil samples ($n = 87$) were irregularly spaced throughout field. The following soil attributes were measure:

1. Soil texture (clay, silt, and sand)
2. Cone index (0 to 10 cm, CI_0_10; 10 to 20 cm, CI_10_20; and 0 to 20 cm, CI_0_20)
3. Chemical attributes: organic C, pH, Ca, and Mg, P and K, Cu, Zn, Fe, and Mn, and H+Al; and
4. Physical attributes: bulk density. The methodology from Embrapa (2009) was used to measured these variables. These attributes were used to define management zones because they have influence with potential yield to corn and soybean crops. Numerous researches were used for these attributes to define management zones, such as, Blackmore (2000), Fraisse et al. (2001), Johnson et al. (2003), Schepers et al. (2004), Taylor et al. (2007) and Li et al. (2007).

Field 2 (Figure 2) was approximately 35 ha in size and was nearly level (0 to 2% slope), with an average elevation of 1437 m. The area was cultivated with corn and is located in the rural area of the municipality of Wiggins, Colorado, USA (40°19'59"N and 104°01'50"W). The dominant soil types were Valentine fine sand (mixed, mesic, Typic Ustipsamment) and Dwyer fine sand (mixed, mesic, Ustic Torripsamment) series (USDA, 1986). The following soil attributes were measure: soil texture (clay, silt, and sand); ammonium; cation exchange capacity (CEC); nitrate; organic matter (OM); and chemical attributes (P, pH, K, Zn).

Exploratory analysis and data interpolation

Exploratory analysis was apply to characterize variability in soil data with coefficient of variation (CV). The Anderson–Darling and Kolmogorov–Smirnov tests applied to test normality data at 0.05 significance level. Potential outliers were identify using box-plots. Inverse distance weighting (IDW) was apply to interpolate field data. IDW was choose because of its simplicity, and successful results of interpolation of field data have been reported (Jones et al., 2003). A leave-one-out cross-validation applied to identify number of neighbors and exponent distance used in interpolation of each variable. For this methodology, a routine was write using software R.

Spatial correlations

Moran's bivariate spatial autocorrelation statistics (Czaplewski and Reich, 1993) were apply to assess spatial correlation between analyzed attributes and to establish spatial correlation matrix. This matrix checks and identifies attributes that influence yield positively or negatively, and checks if a sample was correlate spatially (spatial autocorrelation). The attributes used in the generation of MZs were selected by the variable selection method proposed by Bazzi et al. (2013):

1. Elimination of variables with non-significant spatial correlation at 5% probability level
2. Elimination of variables that had no spatial correlation with yield
3. Ordering variables according to the degree of spatial correlation with yield; and
4. Elimination of redundant variables (that are spatially correlated with each other), giving preference to the maintenance of variables that have a higher correlation with yield.

Table 1. Data layers used for the delineation of management zones.

Field	Variable	No. of data points	Data density (points ha ⁻¹)	Stable variable approach (sta_Var)	All variables approach (all_Var)
1	Yield	68	4.02	x	x
	Elevation, slope	87	5.15	x	x
	Soil organic matter	87	5.15	x	x
	Soil texture (clay, silt, and sand)	45	2.66	x	x
	CI_0_10; CI_10_20; and CI_0_20	87	5.15	x	x
	Chemical attributes: C, Ph, H+Al, Ca, Mg, K, Cu, Zn, Fe, Mn	87	5.15		x
	Physical attributes: bulk density	87	5.15	x	x
	Selected variable			Elevation, slope	CI_10_20
2	Yield	63	1.80	x	x
	soil texture (clay, silt, and sand)	63	1.80	x	x
	Ammonium, CEC, Nitrate, OM, chemical attributes (P, pH, K, Zn)	85	2.43		x
	Selected variables	-	-	Sand	OM

CI - Cone index; CEC - cation exchange capacity; OM - Organic Matter; CI_0_10 - averaged CI from 0 – 10 cm; CI_10_20 - averaged CI from 10 – 20 cm; CI_0_20 - averaged CI from 0 – 20 cm.

Delineation of management zones

Clustering methods are appropriate for dividing data into groups with homogeneous characteristics. Of these, the Fuzzy C-Means is used most often (Li et al., 2007; Fu et al., 2010; Zhang et al., 2013; Li et al., 2013; Moral et al., 2010). This algorithm uses a weighting exponent to control the degree of sharing between classes (Bezdek, 1981), allowing individuals to exhibit partial adhesion in each of the classes, which is important when dealing with the continuous variability of natural phenomena (Burrough, 1989).

Usually only those attributes that do not vary appreciably over time as chemical attributes are used to create MZs that are intended for use for many years (Doerge, 1996). However, for special conditions, MZs are used for nutrients and lime application in the following year. Chemical attributes may be included as MZ attribute variables. Two approaches were applied to delineate MZs: all variables approach (all_Var) and stable variables approach (sta_Var). In the first approach, variables with a significant spatial cross-correlation with the yield were selected to delineate MZs. The selected variables may or may not be stable over time. In sta_Var, only those variables that were stable over time (Table 1) and spatially cross-correlated with the yield (Doerge 1996) were considered for delineation MZs (Table 1).

Two to five MZs were created using interpolated data and fuzzy c-means clustering; for this purpose, Software for Defining Management Zones (SDUM; Bazzi et al., 2013). Each variable was standardized according to Eq. 2 prior to clustering:

$$VS_z = \frac{V_z - M}{R} \quad (1)$$

where: VS_z is the value of the standardized variable at the spatial location of position z ; V_z is the value of the original variable at the spatial location of z ; M is the median; and R is the range of the

data (Mielke and Berry, 2007).

Evaluation of management zone delineation

Variance reduction (VR; Equation 2; Xiang et al., 2007):

$$RV = 1 - \frac{\sum_{i=1}^c (W_i * V_{um_i})}{V_{area}} * 100 \quad (2)$$

where c is the number of MZs; W_i , the proportion of the area in each MZ; V_{um_i} , the variance of the sample data of each MZ; and V_{area} , the variance of the sample of the data for the entire field.

Fuzziness Performance Index (FPI; Equation 3; Fridgen et al., 2004)

$$FPI = 1 - \frac{c}{(c-1)} \left[1 - \sum_{j=1}^n \sum_{i=1}^c (u_{ij})^2 / n \right] \quad (3)$$

where c is the number of clusters; n , the number of observations; u_{ij} , the element of the fuzzy membership matrix.

Modified partition entropy (MPE; Equation 4; Boydell and Mcbratney, 2002)

$$MPE = \frac{-\sum_{j=1}^n \sum_{i=1}^c u_{ij} \log(u_{ij}) / n}{\log c} \quad (4)$$

Table 2. Descriptive statistics of attributes of Field 1 – Cascavel.

Variable	Minimum	Mean	Median	Maximum	CV	Skewness ¹	Kurtosis ²
Yield (Mg ha ⁻¹)	1.55	2.65	2.58	4.34	22.52	-0.40 ^a	-0.12 ^A
Elevation (m)	701	706	705	713	0.48	0.35 ^a	-1.12 ^C
*Slope (%)	0.08	1.83	1.59	5.12	63.8	0.84 ^b	0.09 ^A
P (ppm)	9.60	19.85	18.10	71.60	41.61	3.25 ^b	17.4 ^B
C	21.82	28.87	29.22	36.62	10.99	-0.08 ^a	-0.50 ^A
Ph	5.00	5.55	5.60	6.10	4.64	0.00 ^a	-0.68 ^A
H+Al	3.18	4.91	4.96	7.20	18.95	0.27 ^a	-0.45 ^A
Ca	5.52	7.56	7.48	9.86	12.95	0.11 ^a	-0.49 ^A
Mg	1.51	2.44	2.40	3.69	16.55	0.34 ^a	0.32 ^A
K	0.15	0.30	0.29	0.89	33.82	2.36 ^b	11.1 ^B
Cu	1.20	2.56	2.50	4.10	27.57	0.18 ^a	-0.80 ^C
Zn	1.00	4.15	2.60	17.90	81.67	1.48 ^b	2.31 ^B
Fe	28.00	34.55	35.00	47.00	10.13	0.60 ^b	1.03 ^A
Mn	39.00	67.06	67.00	98.00	18.09	0.03 ^a	0.00 ^A
Clay (%)	60.00	70.42	72.00	79.00	7.13	-0.74 ^c	-0.36 ^A
Silt (%)	15.00	19.69	19.00	25.00	11.40	0.57 ^b	-0.27 ^A
Sand (%)	6.00	9.89	9.00	19.00	38.58	1.26 ^b	0.48 ^A
CI_0_10 (MPa)	1099.70	1643.50	1633.60	2380.4	17.25	0.08 ^a	-0.39 ^A
CI_10_20 (MPa)	1550.80	2347.10	2220.5	3769.30	18.02	1.13 ^b	0.88 ^A
CI_0_20 (MPa)	1482.50	1995.30	1900.20	2995.30	15.55	0.91 ^b	0.50 ^A
Density (kg kg ⁻¹)	0.82	1.13	1.14	1.30	6.78	-1.00 ^c	2.51 ^B

¹ Skewness: symmetric (a), positive skewness (b), negative skewness (c); ² Kurtosis: mesokurtic (A), platykurtic (B), leptokurtic (C); * is not normally distributed at the 0.05 level of significance.

where C is the number of clusters; n , the number of observations; and u_{ij} , the ij -th elements of the fuzzy membership matrix.

RESULTS AND DISCUSSION

Descriptive statistics

The descriptive statistics for selected attributes of Field 1 are indicated that all variables, except for slope, were it is normally distributed (Table 2). Most variables showed symmetric and mesokurtic distributions. The CV was low for elevation, pH, bulk density, and clay; medium for Fe, C, silt, Ca, cone index (0 to 10 cm, CI_0_10; 10 to 20 cm, CI_10_20; and 0 to 20 cm, CI_0_20), Mg, Mn, and H+Al; high for the yield and Cu; and very high for K, sand, P, the slope, and Zn. In case of Field 2 (Table 3), clay, silt, sand, OM, pH, and Zn were normally distributed. The CV was low for the pH and sand; medium for yield; high for Zn, OM, CEC, ammonium, and K; and very high for P, nitrate, clay, and silt.

Spatial autocorrelation and cross-correlation

The attributes analyzed values for Field 1 were show at Table 4. Variables Cu, clay, elevation, CI_10_20,

CI_0_20, sand, slope, P, C, Zn, and bulk density had significant positive autocorrelations. Variables CI_10_20, elevation, CI_0_20, bulk density, slope, sand, clay, silt, pH, P, and H+Al were significantly cross-correlated with yield. Bazzi et al. (2013) found a high correlation between soybean yield with soil sand percentage, generating agricultural area MZs with this layer. Similarly, Schenatto et al. (2016), Peralta and Costa (2013) and Gavioli et al. (2016) generated MZs from elevation data and CI in experimental soybean and cornfields.

The values for Field 2 were show in Table 5. Variable yield, P, nitrate, Zn, CEC, OM, K, clay, sand, silt, and ammonium exhibited significant autocorrelations. Variables OM, CEC, sand, NH₃, clay, K, silt, and Zn were significantly cross-correlated with the yield. Other studies yielded similar results: for example, Bansod and Pandey (2013) and Jaynes et al. (2003) identified high correlation between CEC and yield.

Management zones

Figure 3 shows the MZs as a function of zone number (from two to five) and approach (sta_Var and all_Var) for Field 1 (Cascavel) and Field 2 (Wiggins). In all cases, this can be see when the number of zones increased, the amount of fragments of the area is bigger.

For Field 1, data layers selected to delineate MZs using

Table 4. Contd.

K	0.00 NS	0.01 NS	0.01 NS	-0.01 NS	0.02 NS	0.01 NS	-0.00 NS	-0.01 NS	-	-	-	-	-	-	-	-	-	-	-	-	-
Cu	0.00 NS	-0.09 **	-0.17 **	-0.01 NS	0.05 **	0.04 *	-0.02 NS	-0.00 NS	0.33 **	-	-	-	-	-	-	-	-	-	-	-	-
Zn	0.00 NS	-0.00 NS	0.05 **	-0.01 NS	-0.01 NS	-0.00 NS	0.02 NS	0.01 NS	-0.06 **	0.04 **	-	-	-	-	-	-	-	-	-	-	-
Fe	0.00 NS	0.00 NS	0.03 NS	0.02 NS	-0.02 NS	0.01 NS	0.01 NS	0.00 NS	-0.05 **	0.02 NS	-0.00 NS	-	-	-	-	-	-	-	-	-	-
Mn	-0.01 NS	-0.01 NS	-0.05 **	0.00 NS	0.02 NS	0.00 NS	0.00 NS	0.01 NS	0.10 **	0.01 NS	-0.01 NS	0.03 NS	-	-	-	-	-	-	-	-	-
Cl_0_10	0.01 NS	-0.01 NS	0.02 NS	0.00 NS	-0.01 NS	0.02 NS	0.02 NS	0.01 NS	-0.01 NS	0.01 NS	-0.01 NS	0.02 NS	0.00 NS	-	-	-	-	-	-	-	-
Cl_10_20	0.08 **	-0.06 **	-0.07 **	0.03 *	-0.01 NS	0.03 *	-0.04 *	-0.03 *	0.08 **	-0.05 **	-0.02 NS	0.00 NS	0.01 NS	0.18 **	-	-	-	-	-	-	-
Cl_0_20	0.08 **	-0.06 **	-0.07 **	0.03 *	-0.02 NS	0.03 NS	-0.03 *	-0.02 NS	0.08 **	-0.04 **	-0.02 NS	-0.00 NS	0.01 NS	0.16 **	0.14 **	-	-	-	-	-	-
Elevation	0.08 **	-0.09 **	-0.08 **	0.02 NS	-0.00 NS	0.03 NS	-0.05 **	-0.02 NS	0.11 **	-0.07 **	0.01 NS	0.01 NS	-0.04 **	0.17 **	0.15 **	0.19 **	-	-	-	-	-
Clay	-0.04 **	0.09 **	0.13 **	0.01 NS	-0.04 **	-0.04 **	0.03 NS	-0.00 NS	-0.28 **	0.04 **	0.05 **	-0.08 **	0.02 NS	-0.11 **	-0.12 **	-0.13 **	0.31 **	-	-	-	-
Silt	0.04 **	-0.04 *	-0.07 **	0.00 NS	0.02 NS	0.03 *	-0.02 NS	-0.01 NS	0.10 **	-0.03 NS	-0.02 NS	0.02 NS	-0.01 NS	0.08 **	0.08 **	0.08 **	-0.12 **	-0.00 NS	-	-	-
Sand	0.05 **	-0.08 **	-0.08 **	-0.00 NS	0.02 NS	0.05 **	-0.03 NS	-0.02 NS	0.17 **	-0.02 NS	-0.03 *	0.04 **	-0.01 NS	0.11 **	0.10 **	0.11 **	-0.20 **	0.06 **	0.10 **	-	-
Slope	-0.05 **	-0.01 NS	-0.07 **	-0.02 NS	0.04 **	-0.01 NS	0.03 *	0.00 NS	0.12 **	-0.05 **	-0.01 NS	0.03 NS	-0.02 NS	-0.04 **	-0.04 *	0.01 NS	-0.05 **	0.01 NS	0.02 NS	0.07 **	-
Density	-0.07 **	0.07 **	0.05 **	-0.01 NS	-0.01 NS	-0.03 NS	-0.01 NS	0.01 NS	-0.09 **	0.03 *	0.01 NS	-0.02 NS	0.02 NS	-0.11 **	-0.10 **	-0.13 **	0.12 **	-0.04 **	-0.07 **	0.00 NS	0.03 *
	Yield	C	P	pH	H_Al	Ca	Mg	K	Cu	Zn	Fe	Mn	Cl_0_10	Cl_10_20	Cl_0_20	Elevation	Clay	Silt	Sand	Slope	DE

* Significant at 0.05 level; ** Significant at 0.01 level; Cl - cone index; DE: Density.

Table 5. Spatial autocorrelation from analyzed attributes in Field 2 (Wiggins).

Yield	0.08 **	- -	- -	- -	- -	- -	- -	- -	- -	- -	- -	- -
Clay	0.11 **	0.15 **	- -	- -	- -	- -	- -	- -	- -	- -	- -	- -
Sand	-0.12 **	-0.14 **	0.15 **	- -	- -	- -	- -	- -	- -	- -	- -	- -
Silt	0.08 **	0.06 **	-0.08 **	0.08 **	- -	- -	- -	- -	- -	- -	- -	- -
Ammonium	-0.01 NS	0.03 *	-0.00 NS	-0.04 **	0.04 **	- -	- -	- -	- -	- -	- -	- -
CEC	0.12 **	0.11 **	-0.15 **	0.14 **	-0.05 **	0.20 **	- -	- -	- -	- -	- -	- -
Nitrate	0.11 **	0.09 **	-0.13 **	0.14 **	-0.02 NS	0.18 **	0.27 **	- -	- -	- -	- -	- -
OM	0.13 **	0.13 **	-0.15 **	0.13 **	-0.04 **	0.19 **	0.19 **	0.19 **	- -	- -	- -	- -
P	0.00 NS	0.02 NS	-0.03 *	0.02 NS	0.05 **	0.01 NS	0.17 **	0.04 **	0.31 **	- -	- -	- -
pH	-0.01 NS	-0.02 NS	0.01 NS	0.01 NS	-0.03 **	0.02 NS	0.01 NS	0.01 NS	0.01 NS	0.01 NS	- -	- -
Potassium	0.11 **	0.09 **	-0.12 **	0.12 **	-0.05 **	0.18 **	0.18 **	0.17 **	0.04 **	0.03 *	0.15 **	- -
Zn	0.07 **	0.08 **	-0.10 **	0.09 **	0.03 NS	0.11 **	0.23 **	0.14 **	0.24 **	0.02 NS	0.12 **	0.23 **
	Yield	Clay	Sand	Silt	Ammonium	CEC	Nitrate	OM	P	pH	Potassium	Zn

*Significant at 0.05 level; ** Significant at 0.01 level; OM - Organic Matter; CEC - Cation Exchange Capacity.

sta_Var (approach) were elevation and slope, whereas MZs based on all_Var based on CI_10_20. CI_10_20 was not selected as sta_Var because it was not stable over time. However, because it showed highest spatial correlation with yield and was cross-correlated with elevation and slope, it was included in all_Var selection. In this sense, in the lower areas, soybean yield was lower probably because rainfall was higher than average during cultivation, which may have resulted in excessive water in soil (Fausey, 1999). For Field 2, MZs based on sta_Var approach were delineated using sand, whereas in all_Var approach, OM used it. As in Field 1 case, OM was not select as sta_Var because it was not stable over time. In

both approaches, selected correlated layers (sand and OM) were negatively spatially correlate with yield. In addition, sand and OM were correlate to CEC, meaning that this variable used to define MZs if sample and analysis costs were prohibitive.

The average yields differed significantly between two MZs (Table 6) in both fields. With three, four, and five zones only for Field 2, the average yields differed significantly. From these results and those reported by Zhang et al. (2013), it can be seen that the division of the area into two MZs was adequate for producing zones with different yields.

The VR of an MZ indicates whether MZ delineation

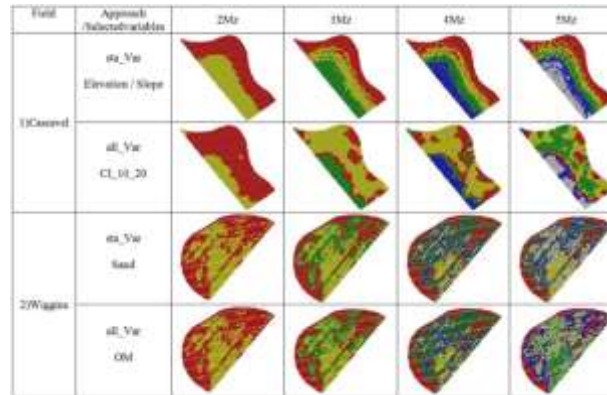


Figure 3. Management Zones (MZs) as a function number of zones (from two to five), and layers section approach (stable variables (sta_Var) and all variables (all_Var) for the Field 1, Cascavel (Brazil) and Field 2, Wiggins (USA), using Fuzzy C-means.

Table 6. Average Yield in each zone for both approaches (sta_Var – stable variables and all_Var – all variables) in Fields 1 (Cascavel) and 2 (Wiggins).

Field	No. of zones	MZ approach	Selected layers	Averaged Yield in t ha ⁻¹ in each Zone (% of area)					VR%	FPI	MPE	ICVI	SI
				Zone 1	Zone 2	Zone 3	Zone 4	Zone 5					
1	2	sta_var	Elevation / Slope	2.32a (56.0)	2.78 (44.0)	-	-	-	21.1	0.11	0.02	0.28	97.8
		all_var	CI_10_20	2.41a (78.1)	2.93b (21.9)	-	-	-	12.1	0.04	0.01	0.24	98.0
	3	sta_var	Elevation / Slope	2.37a (40.6)	2.44a (30.9)	2.90b (28.5)	-	-	12.0	0.17	0.03	0.56	90.2
		all_var	CI_10_20	2.46a (24.2)	2.41a (57.4)	2.92b (18.5)	-	-	13.9	0.09	0.02	0.42	93.7
	4	sta_var	Elevation / Slope	1.77a (35.9)	1.55a (22.4)	2.50a (20.8)	1.92b (20.9)	-	19.6	0.21	0.04	0.56	87.0
		all_var	CI_10_20	2.43a (28.9)	2.35a (44.6)	2.64ab (11.4)	2.97b (15.2)	-	13.5	0.11	0.02	0.55	90.4
5	sta_var	Elevation / Slope	2.47a (30.8)	2.02a (19.4)	2.78ab (15.3)	2.91ab (16.4)	2.85b (18.1)	14.5	0.26	0.05	0.77	80.4	
	all_var	CI_10_20	2.48a (15.7)	2.51a (31.9)	2.29a (31.8)	3.34bc (8.4)	2.86ac (12.2)	11.8	0.14	0.03	0.72	87.0	
2	2	sta_var	Sand	10.3a (53.5)	13.0b (46.5)	-	-	-	49.9	0.07	0.01	0.52	87.2
		all_var	OM	10.5a (59.1)	13.1b (40.9)	-	-	-	45.2	0.07	0.01	0.34	87.1
	3	sta_var	Sand	9.6a (35.7)	13.2b (34.0)	12.1c (30.3)	-	-	68.2	0.09	0.02	0.36	77.6
		all_var	OM	9.7a (38.1)	13.3b (31.1)	12.2c (30.7)	-	-	66.2	0.10	0.02	0.35	77.3
	4	sta_var	Sand	9.2a (29.7)	13.5b (22.4)	11.7c (25.3)	12.6d (22.7)	-	75.1	0.11	0.02	0.15	68.6
		all_var	OM	9.0a (32.0)	13.5b (29.9)	11.7c (27.4)	12.7d (10.6)	-	77.6	0.26	0.04	0.69	68.9
5	sta_var	Sand	8.8a (23.6)	13.5b (19.7)	11.2c (17.9)	12.1d (19.9)	12.8e (18.9)	81.1	0.12	0.02	0.13	61.9	
	all_var	OM	8.4a (18.9)	12.3b (20.2)	13.6c (17.0)	11.2d (26.6)	12.9e (17.3)	84.5	0.13	0.02	0.35	62.6	

Within a row, means with different letters are significantly different at p <0.05; CI - Cone Index.

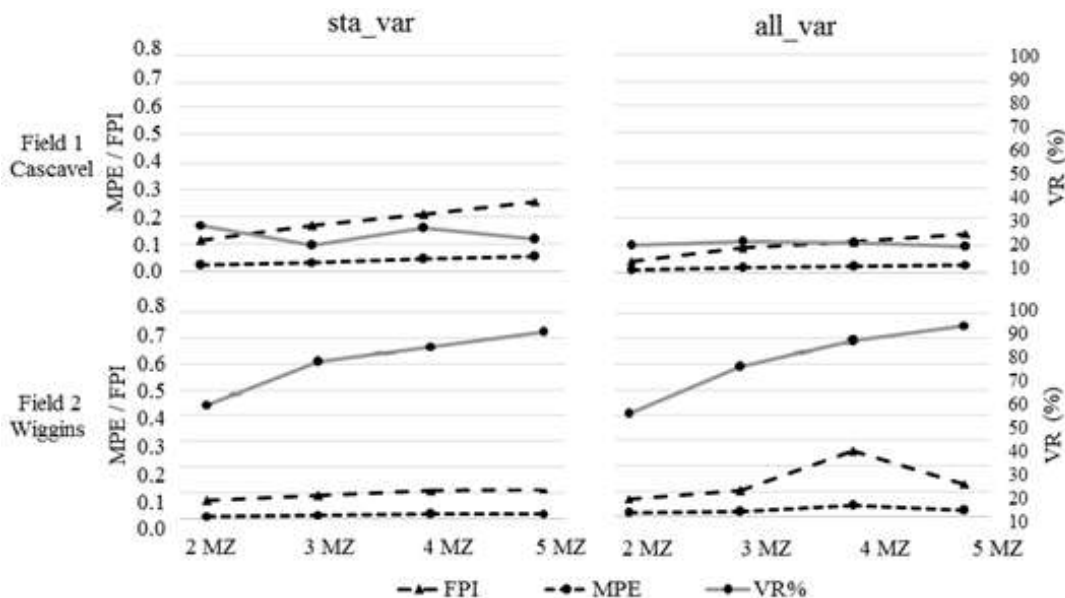


Figure 4. Evaluation indices MPE, FPI, VR, SI and ICVI used by evaluate management zones as a function of number of management zones.

is more efficient than having no MZs on field. In all cases (Table 6 and Figure 4), VR values were positive, indicating that in all cases, total variance reduced, as expected. In case of Field 1, VR remained reasonably constant with MZs number. However, in Field 2 case, VR increased with MZ number. The VR results confirm ANOVA results because it turns out that divisions within each zone did not show much variance from average, indicating regions of similar productive potential. These results corroborates those obtained by Xiang et al. (2007) and indicated that when divisions are satisfactory, VR tends to increase despite an increase in MZs number because there is smaller variation within each zone.

ANOVA shows for Field 1, that best division was two MZs (for sta_Var and all_Var) and up to five MZs for Field 2 (sta_Var and all_Var) (Table 6). The FPI, MPE, and VR indices (Figure 4) were also evaluated; smaller FPI and MPE, shows better clustering test for both fields, considering FPI and MPE. Best efficiency was obtain with two MZs, but best option with VR was two (sta_Var) and three (all_Var) MZs for Field 1 and five MZs for Field 2 (sta_Var and all_Var).

Two approaches comparison (sta_Var and all_Var) for two MZs (selected as best number of MZs) showed that sta_Var provides better VR. That means there is no meaning of using all variables (time stable or not) in defining MZs. The sta_Var MZs (with two MZs) presented a reduction in variance from 21 (Field 1) to 50% (Field 2). Because the MZ definition through Fuzzy c-means does not use variable yield only if several years' yields could find other important and not redundant variable, the MZs would be same.

Conclusions

The methodology proposed for MZs define has practical value and allowed MZs definition with good quality. This results may be confirmed on the analysis of the variance reduction and Anova. For divisions in two zones (best division by MPE and FPI indexes), the variance reduction and Anova showed have different yield potential in each zone when the fields were divided. The stable variables approach performed better than all variables in all cases because they showed better results on the analysis from variance reduction and Anova, indicating that stable variables have influence in the yield capacity and can be used to define management zones that must be used for a long time. The stable variables approach also served as the source of recommendation and soil analysis and pre-plant or in-season fertilizer recommendation for precision agriculture.

Conflicts of Interests

The authors have not declared any conflict of interests.

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