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Analysis of Four Delineation Methods to Identify Potential Management Zones in a Commercial Potato Field in Eastern Canada

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Abstract: Management zones (MZs) are delineated areas within an agricultural field with relatively homogenous soil properties, and therefore similar crop fertility requirements. Consequently, such MZs can often be used for site-specific management of crop production inputs. This study evaluated the effectiveness of four classification methods for delineating MZs in an 8-ha commercial potato field located in Prince Edward Island, Canada. The apparent electrical conductivity (EC_a) at two depths from a commercial Veris sensor were used to delineate MZs using three classification methods without spatial constraints (i.e., fuzzy k-means, ISODATA and hierarchical) and one with spatial constraints (i.e., spatial segmentation method). Soil samples (0.0–0.15 m depth) from 104 sampling points was used to measure soil physical and chemical properties and their spatial variation in the field were used as reference data to evaluate four delineation methods. Significant Pearson correlations between EC_a and soil properties were obtained ($0.22 < r < 0.85$). The variance reduction indicated that two to three MZs were optimal for representing the field's spatial variability of soil properties. For two MZs, most soil physical and chemical properties differed significantly between MZs for all four delineation methods. For three MZs, there was greater discrimination among MZs for several soil properties for the spatial segmentation-based method compared with other delineation methods. Moreover, consideration of the spatial coordinates of the data improved the delineation of MZs and thereby increased the number of significant differences among MZs for individual soil properties. Therefore, the spatial segmentation method had the greatest efficiency in delineation of MZs from statistical and agronomic perspectives.

Keywords: soil apparent electrical conductivity; fuzzy k-means; ISODATA; hierarchical; spatial segmentation

1. Introduction

Potato (*Solanum tuberosum* L.) production in eastern Canada is an important contributor to the economy, yet the widely adopted uniform crop input management leads to a reduction in productivity, sub-optimal use of resources and adverse impacts on the environment [1–4]. Consequently, producers are evaluating the potential of precision agriculture (PA) to increase revenues and protect the environment through the site-specific management of crop inputs [5–7]. The delineation of management zones (MZs) can make it possible to manage spatial variability within an agricultural field by subdividing it into zones with more homogenous soil properties, and are of particular interest for implementation of site-specific management of nutrients and water [8–14].

Many commercial soil proximal sensors (e.g., galvanic-contact resistivity, electromagnetic induction electrical conductivity, capacitively-coupled resistivity, gamma-ray spectroscopy, ground penetrating radar) have been developed and explored in agriculture over the two past decades. Galvanic contact resistivity proximal sensing instruments measuring apparent electrical conductivity (EC_a) are commonly used to obtain high spatial density soil measurements that can be used for delineating MZs [7,13,15]. The effectiveness of this technology for characterizing spatial variability of soil properties, and therefore for delineating MZs, had been demonstrated in eastern Canada [16,17].

There are various mathematical principles that have been used to delineate MZs. Among the available techniques for the delineation of MZs, unsupervised classification techniques are the most commonly used [2]. The fuzzy k-means is the conventional and most used unsupervised classification technique used for this purpose [11,12,18,19]. The concept of fuzzy classification was introduced by Ruspini [20] and the fuzzy k-means classification method was introduced by Dunn [21]. This method has been used to delineate MZs using EC_a data alone [16], or has been used in combination with other mapped data including soil texture [22], soil organic matter content [23], soil depth and crop yield [24], and elevation [25].

More recently, other classification algorithms (e.g., ISODATA, hierarchical, spatial segmentation) have been developed and may have advantages over fuzzy k-means in terms of reduced processing time and delineation of more compact and operationally manageable MZs for agricultural machinery. A well-known extension of k-means is called the Iterative Self-Organizing Data Analysis (ISODATA) technique [26]. It is a simple and quick classification algorithm-based technique [27] and does not require the introduction of class characteristics before classification (unsupervised classifier) [28]. Several authors have adopted the ISODATA technique to delineate MZs [2,28–30]. However, the technique requires the variables to be normally distributed and with equal variances to cluster similar characteristics by mean vectors and a covariance matrix [26]. Another unsupervised classification method, called hierarchical, has also been used effectively for delineating MZs in agricultural fields [31–33].

The three delineation methods mentioned above are based solely on the attributes of soil data recordings and do not consider the spatial structure of the data. The development of spatial segmentation algorithms that take the spatial constraint of the data into account has led to their routine use in image processing in environmental applications [34,35]. However, these segmentation algorithms have not been widely applied to PA practices [36]. The spatial segmentation delineation method generates discrete zones, rather than classes, by taking spatial constraint of the data into account and subdivides an agricultural field into MZs [37]. Few studies have compared MZ delineation methods in agricultural fields [2,28,31,37]. However, there is no information available in comparing the delineation methods under potato production fields in eastern Canada, despite the contribution of the potato crop to the economy of the region. Prince Edward Island (PEI) was chosen as a study region in eastern Canada because of the economic importance, as well as social and historical importance, of potato production.

The objective of this study was to compare four MZ delineation methods, specifically three unsupervised methods (i.e., fuzzy k-means, ISODATA and hierarchical) and one supervised method (i.e., spatial segmentation), in terms of effectiveness at delineating MZs using ECa. A soil EC_a dataset obtained using proximal soil sensing (Veris®mapping unit) from a commercial potato field was chosen to carry out this comparison and illustrate the performance of these data-clustering techniques. The selected field site was located in Prince Edward Island PEI, a province in eastern Canada that produces approximately one quarter of all Canadian potatoes, estimated in 2017 at 1.07 million tons on a harvested area of 33,700 ha [38]. The ECa data were used in all four delineation methods. The optimal number of MZs was determined through variance reduction, and validation of the MZs was carried out using the soil physical and chemical properties.

2. Materials and Methods

2.1. Experimental Site

A commercial field under intensive potato production located near Springfield West, PEI, Canada (46°41′ N, 64°22′ W) was selected. The 8-ha field was under surface irrigation using a linear ramp system. Soils at the study site belong to the Alberry series, with a moderately coarse to coarse soil texture, a highly acidic ground moraine with good drainage, and are classified as Orthic Humo-Ferric Podzols [39]. The slope class of the site was classified as very gentle (2% to 5%) according to the Canadian soil classification system [39].

2.2. Soil Sampling and Analyses

Soil sampling was carried out on 6 October 2016, following a triangular grid (Figure 1a) with a sampling interval of 29 m (sampling density: 13 samples/ha), using a grid sampling approach like that used by Cambouris et al. [16] and Perron et al. [17] A total of 104 point locations were sampled at 0.0–0.15 m depth. Each soil sample was a composite of five soil cores from 0 to 15 cm in depth, taken within a radius of 1.5 m of each sampling point using a 0.05 m diameter Dutch auger.

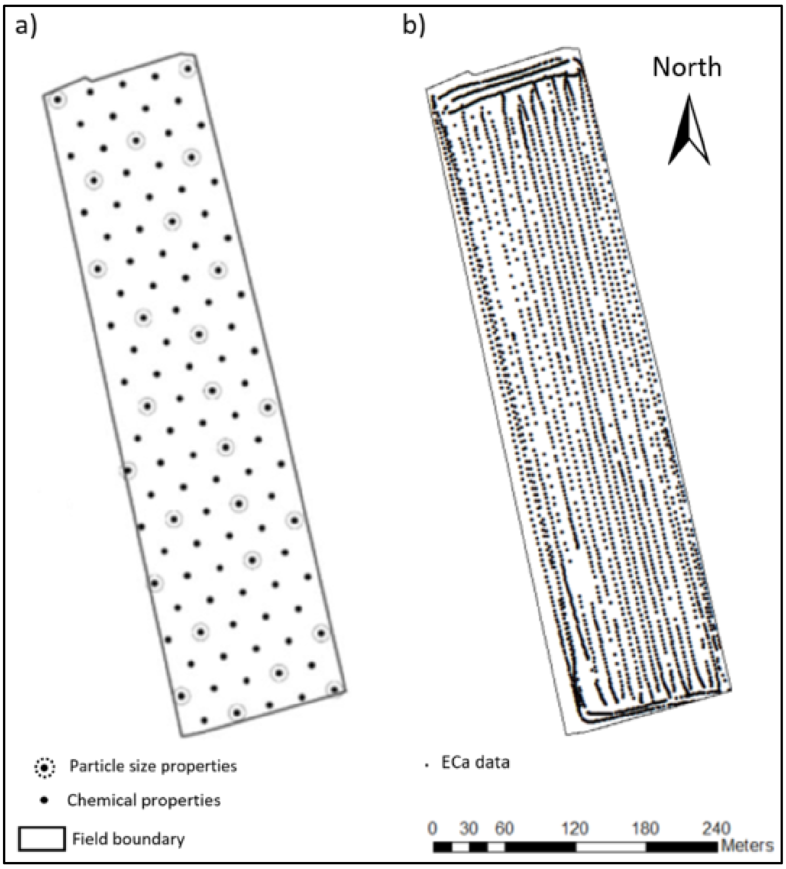

Figure 1. (**a**) Triangular sampling grid strategy for soil and pattern of (**b**) soil electrical conductivity data acquisition.

The samples were air-dried at room temperature, and ground to pass through a 2 mm sieve. The soil pH was measured at a 1:1 soil-to-water ratio [40]. The total carbon (Total C) and total nitrogen (Total N) contents were measured by dry combustion using a Vario Max CN Elemental Analyzer (Elementar Analysensysteme GmbH, Hanau, Germany). Soils were extracted with a 1:10 soil-to-solution ratio using Mehlich-3 solution [41], and the extract concentrations of phosphorus (P), potassium (K), calcium (Ca), magnesium (Mg) and aluminum (Al) were determined by inductively coupled plasma optical emission spectroscopy (ICP-OES) (model 4300DV; Perkin Elmer, Shelton, CT, USA). One sample out of four was analyzed to determine the soil particle size distribution using the pipette method [42].

2.3. Soil EC_a Data

On 5 October 2016, apparent soil electrical conductivity (EC_a) data were acquired using a commercial Veris-3100 galvanic contact resistivity sensor (Veris Technologies, Inc., Salina, KS, USA) equipped with a Garmin GPS 17x HVS sensor (Garmin International, Olathe, KS, USA) with an accuracy of less than 1 m. This sensor was configured according to the Wenner array using six coulter-electrodes (one pair to inject current and two pairs to measure change in electrical potential), as described by Sudduth et al. [43] This resulted in two depths of investigation: approximately 0.0–0.3 m (EC_{a30}) and 0.0–1.0 m (EC_{a100}). The data from the sensor were acquired on parallel transects spaced approximately 7 m apart using a 1 Hz logging frequency, which corresponds to a measurement every 2–3 m when operating at a speed of approximately 10 km/h, giving a density of at least 245 samples/ha (Figure 1b). Erroneous EC_a data were eliminated by the exclusion of points exceeding three standard deviations [44].

2.4. Statistical and Geostatistical Analysis

Descriptive statistical analyses (mean and coefficient of variation (CV)) were carried out using the PROC UNIVARIATE procedure in the SAS version 9.4 statistical software package (North Carolina, Raleigh, NC, USA) [45]. The Pearson correlation was performed following the PROC CORR procedure in SAS [45]. To determine the relationship between EC_a and the soil physical and chemical properties, the EC_a data were extracted from 5-m radius buffer zones around each soil sample created using the ArcGIS Software "Buffer" tool [46]. Then, the "Intersect" tool was used to calculate the intersection of the buffer zones with the data points of the EC_a transects. Next, an average of the EC_a measurements was calculated for each buffer zone using the "Summarize" tool. Each buffer zone was represented by a single EC_a value and was used to examine correlations with the soil physical and chemical properties. Finally, the PROC CORR procedure in SAS was performed between the EC_a mean at each soil sampling point and the soil properties.

The ECa data were kriged with the Ordinary Kriging Type option of the Geostatistical Analyst tool in ArcGIS Software version 10.3 (California, USA). A better fit for the variogram was obtained using the Spherical model with the following calibration parameter values: 10 m for the Lag size, 64 m for the Range, 0.2092 for the Nugget and 0.9748 for the Partial sill. The uncertainty generated in the interpolation procedure was evaluated using the "leave-one-out" cross-validation test as an indicator of the magnitude of the error and using root mean square error (RMSE) measurements in order to more accurately assess the reliability of the kriging maps. The lower the RMSE, the more reliable and precise the kriging. An RMSE of 0.48 was obtained. The kriged ECa was rasterized (1 m^2) and the image produced was used with the four delineation methods to create the MZs.

2.5. Delineation of Potential Management Zones

Specific input management based on MZs is a common way of managing within-field variability in agricultural production. The EC_a-based zones were expected to be relatively homogeneous in terms of water holding capacity, which might be linked to some soil properties and tuber yield. There are various methods to delineate MZs, including fuzzy k-means, ISODATA, hierarchical, and spatial segmentation. Figure 2 presents the modus operandi for the evaluation of the delineation methods using EC_{a100} data to delineate management zones (MZs) based on soil properties.

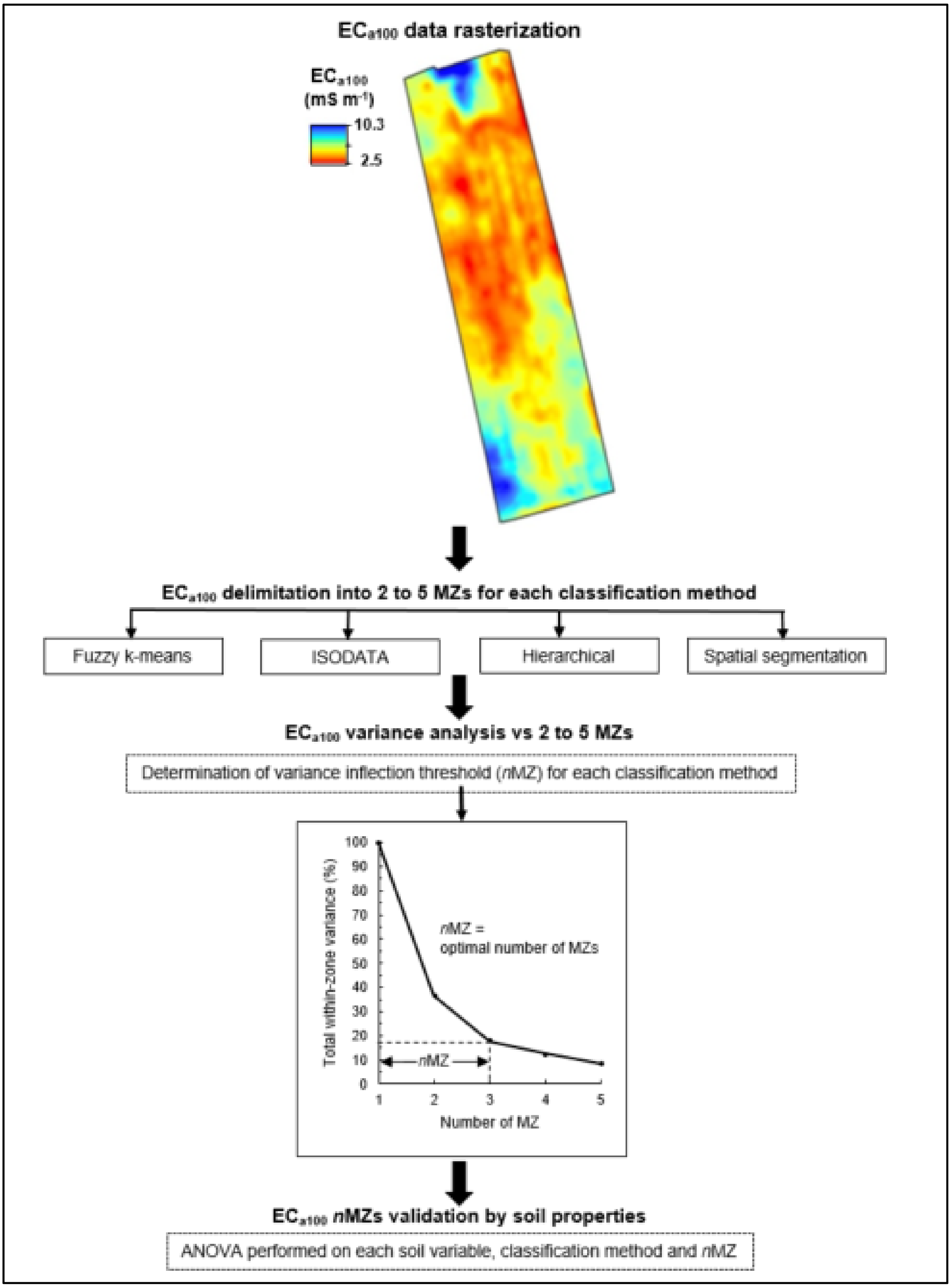

Figure 2. Flowchart for the evaluation of the delineation methods using EC_{a100} data to delineate management zones (MZs) based on soil properties.

2.5.1. Fuzzy k-Means

The fuzzy k-means method was used as a reference method in the delineation of MZs. It was performed with the FuzME software package version 3.0 (Sydney, Australia) developed by Minasny and McBratney [47]. To ensure the stability of the clusters, the process was repeated until the convergence criterion of 0.0001 was reached, or the maximum number of iterations reached 500. The fuzziness exponent was set at the conventional value of 1.30 [48].

2.5.2. ISODATA

The ISODATA algorithm started by attributing the data arbitrarily to different classes. Then, through an iterative process, the algorithm changed the membership of the data points from one cluster to another and attempted to find the optimal clusters where the Euclidean distance between the data points and the center of the cluster was a minimum [2]. Based on the similarities between the clusters, the ISODATA algorithm can remove, split, or merge the clusters at the end of each iteration [46,49]. The ISODATA method was carried out using the Iso Cluster Unsupervised Classification function of the ArcGIS software package version 10.3 (California, USA) [46]. The two default parameters, minimum class size and sampling interval, were set at 20 and 10, respectively. This method uses "means" vectors and "covariance" matrices to assign each cell to a cluster based on statistical probability, hence the data should exhibit an approximately Gaussian distribution for each cluster [2,26,50].

2.5.3. Hierarchical

The hierarchical classification is often used to cluster similar individuals. In this technique, the individuals are successively integrated into a distance matrix calculated from the data, to ultimately obtain a dendrogram containing the classes [31]. In this study, the hierarchical classification is carried out using the R statistical software package version 3.4.2 (Vienna, Austria) [51]. Euclidean distance is used as the default distance for the "dist" function. This method makes it possible to form initial clusters from the pairing of individual points, after which the next clusters are formed by merging the preceding pairs. The classification continues in this way until all the sub-clusters are merged into a single cluster [52]. The hierarchical classification was carried out using the ward.D2 method [53] as a selected parameter in the "hclust" function. The appropriate number of classes were determined after the generation of dendrogram following the hierarchical algorithm "rec.hclut".

2.5.4. Spatial Segmentation

Unlike the previous three methods which use mathematical proximity based only on ECa data, the spatial segmentation method explicitly uses spatial proximity based on ECa data and geographic coordinates data. The basic processing units of the spatial segmentation image are pixels, and the classification of a certain number of neighboring pixels forms primitive objects. The creation of primitive objects is an intermediate step with the goal of obtaining the objects of interest [34]. This method makes objects spatially continuous and automatically eliminates inclusions and small isolated areas. The spatial segmentation method makes it possible to increase the space between uncorrelated data using the shape and topology of the data, and to define the close relationship between real-world objects and image objects [34].

The spatial segmentation algorithm was applied using the eCognition Developer 8.64 software package (München, Germany) [54]. The initial objects were created by beginning to cluster pixels using the bottom-up multiresolution segmentation technique based on the homogeneity and scale criteria [55].

User-defined settings such as color (the spectral value of the objects) and the shape (texture) were weighted to form the heterogeneity threshold. The homogeneity criterion (f) was composed of two parameters: color heterogeneity (h_{colour}) and shape heterogeneity (h_{shape}), and was written as:

$$f = W_{\text{colour}} * h_{\text{colour}} + W_{\text{shape}} * h_{\text{shape}} \tag{1}$$

where W_{colour} (the defined weight for colour) ϵ (0.1), and W_{shape} (the defined weight for shape) ϵ (0.1).

The weights for the shape and color are complementary, and their sum is equal to 1. In fact, the more heavily weighted the color heterogeneity, the less the shape heterogeneity influence segmentation, and vice versa. A weight of 0.5 was selected as default parameter for both color and shape. In addition, for shape heterogeneity, the compactness and the smoothness values also influenced object creation:

$$h_{shape} = W_{compactness} * h_{compactness} + W_{smoothness} * h_{smoothness} \quad (2)$$

A weight of 0.5 was also chosen for the compactness and smoothness. A value scale equal to 19 was chosen using the ESP tool (Estimation of Scale Parameters) of the eCognition Developer 8.64 software package (München, Germany) [56]. The second part of the segmentation was performed using the spectral difference segmentation technique, which made it possible to create homogenous and larger objects.

The objects that had a spectral difference below a certain threshold were merged [29,57]. The thresholds selected in this study are as follows: 255 for two MZs; 255 and 256 for three MZs; 240, 255 and 256 for four MZs; and 240, 251, 255 and 256 for five MZs. After large objects were created, a classification was performed using the "assign class" function.

2.6. Determination and Validation of the Optimal Number of MZs

Variance reduction was used to determine the optimal number of MZs [2]. Using this approach, the total within-zone variance was expressed as a percentage of the variance for the entire field (i.e., a MZ) [16]. The inflection point of the EC_{a100} variance decrease curve was estimated to determine the optimal number of MZs. After the optimal number of MZs was selected, normality of soil properties was tested using the PROC UNIVARIATE procedure in SAS [45]. For normally distributed parameters, an ANOVA combined with an LSD multiple comparison test (p–value < 0.05) was performed to determine if the soil properties varied significantly among the MZs. Non-normally distributed parameters were analyzed using non-parametric tests (Wilcoxon and Kruskal–Wallis) in the PROC NPAR1WAY procedure [45]. The significant differences in soil properties within the delineated MZs made it possible to determine how well EC_a captures the within-field spatial variability of soil properties [10] and to evaluate the delineation efficiency for each of the classification algorithms used.

3. Results and Discussion

3.1. Variability of Soil Properties

The coefficient of variation (CV) of the particle sizes ranged from 8% to 17% (Table 1). Similar CV values (ranging between 3% and 24%) were also observed for all the soil chemical properties except soil K (47%). The lowest CV (3%) was observed for soil pH. The variations of these soil properties were comparable to the CV values obtained in a study conducted on a medium-textured soil from New Brunswick [17,58]. The low CV value for pH measured in the current study was similar to that measured in a field in Nova Scotia and may be due in part to the logarithmic scale of the pH measurements [59].

The CVs of the soil EC_a measurements exhibited moderate and similar variations, at 27% and 25% for EC_{a30} and EC_{a100}, respectively (Table 1). These values are similar to the CVs obtained for soil EC_a measured in sandy to loamy fine sand soils in Quebec [16] and a medium-textured soil in New Brunswick [17].

Table 1. Descriptive statistics of the soil physical and chemical properties, and soil EC_a.

	Unit	Depth (m)	Mean	SD ^{z}	CV ^{y} (%)
			Particle size analyses (n = 23)		
Clay	g/kg	0–0.15	83	14	17
Silt	g/kg	0–0.15	247	40	16
Sand	g/kg	0–0.15	669	54	8
			Chemical analyses (n = 104)		
Total C	%	0–0.15	1.24	0.22	18
Total N	%	0–0.15	0.99	0.20	20
pH		0–0.15	6.2	0.2	3
P	mg/kg	0–0.15	199	44	22
K	mg/kg	0–0.15	105	49	47
Ca	mg/kg	0–0.15	641	154	24
Mg	mg/kg	0–0.15	98	22	22
Al	mg/kg	0–0.15	1478	237	16
			Soil electrical conductivity measured by Veris (n = 1981)		
EC_{a30} ^{x}	mS/m	0–0.30	5.2	1.3	25
EC_{a100} ^{w}	mS/m	0–1.00	5.3	1.4	27

^{z}: Standard Deviation; ^{y}: Coefficient of variation; ^{x}: Shallow soil apparent electrical conductivity (0–0.3 m) measured with Veris 3100; ^{w}: Deep soil apparent electrical conductivity (0–1.0 m) measured with Veris 3100.

3.2. Relationships between EC_a and Soil Properties

The strongest relationships were obtained between soil EC_a and soil texture. Clay and silt were significantly positively correlated with soil EC_a ($0.79 \leq r \leq 0.84$), while sand was significantly negatively correlated with soil EC_a ($-0.83 \leq r \leq -0.82$) (Table 2). Previous studies also reported strong correlations ($r > 0.60$) between EC_a and soil texture in Oxisol and Inceptisol soils in a field located in Ponta Grossa, Brazil [60] and in a Rhodoxeralf soil in a field located in southern Spain [22]. This indicates that there is a strong relationship between soil EC_a and soil texture across diverse soil types.

Table 2. Pearson correlations (r) between soil apparent electrical and soil properties.

		Pearson Correlations (r)			
		EC_{a30} ^{z}		EC_{a100} ^{y}	
Particle size (0–0.15 m)					
	Clay	0.84	*** ^{x}	0.82	***
	Silt	0.80	***	0.79	***
	Sand	−0.83	***	−0.82	***
Chemical properties (0–0.15 m)					
	Total C	0.42	***	0.44	***
	Total N	0.35	***	0.36	***
	pH	0.15	NS ^{w}	0.14	NS
	P	0.22	*	0.25	*
	K	0.34	***	0.36	***
	Ca	0.25	**	0.28	**
	Mg	0.16	NS	0.18	NS
	Al	−0.26	**	−0.26	**

^{z}: Shallow soil apparent electrical conductivity (0–0.3 m) measured with Veris 3100; ^{y}: Deep soil apparent electrical conductivity (0–1.0 m) measured with Veris 3100; ^{x}: *, **, *** = significant at 0.05, 0.01, 0.001, respectively; ^{w}: Not significant.

Soil EC_a presented weak, but significant, correlations with all soil chemical properties except soil pH and Mg (Table 2). The strongest positive correlations were between Total C and EC_{a30} (r = 0.42) and EC_{a100} (0.44), between Total N and EC_{a30} (r = 0.35) and EC_{a100} (0.36), and between K and EC_{a30} (r = 0.34) and EC_{a100} (0.36). Similarly, Cambouris et al. [16]

reported significant correlations (r = 0.23 to 0.50) between soil EC_a and soil chemical properties (P, K, Ca, Mg, and Al) under potato production in Quebec, Canada. Significant correlations was also reported by Perron et al. [17] between soil chemical properties (P, K, Ca, Mg, and Al) and EC_{a30} (r = 0.26 to 0.72) and EC_{a100} (r = 0.20 to 0.73) for two potatoes fields in New Brunswick, Canada.

The two electrical signals, EC_{a30} and EC_{a100}, exhibited a similar degree of correlation with soil properties. In this study, only EC_{a100} was utilized to delineate the MZs with the four methods of segmentation because the deep Veris electrical signal was more stable over time compared to surface EC_a measurements [10,61,62], likely due to greater changes in soil water contents near the soil surface.

3.3. Reduction of Variance and Management Zone Delineation

When the number of MZs was increased from one to five, the total within-zone variance of the EC_{a100} measurements decreased from 100% to 6%, 7%, 9% and 19%, according to the fuzzy k-means, ISODATA, hierarchical and spatial segmentation delineation methods, respectively (Figure 3). Other studies also showed a large reduction in the total within-zone variance of soil EC_a when the number of MZs was increased from one to five [16].

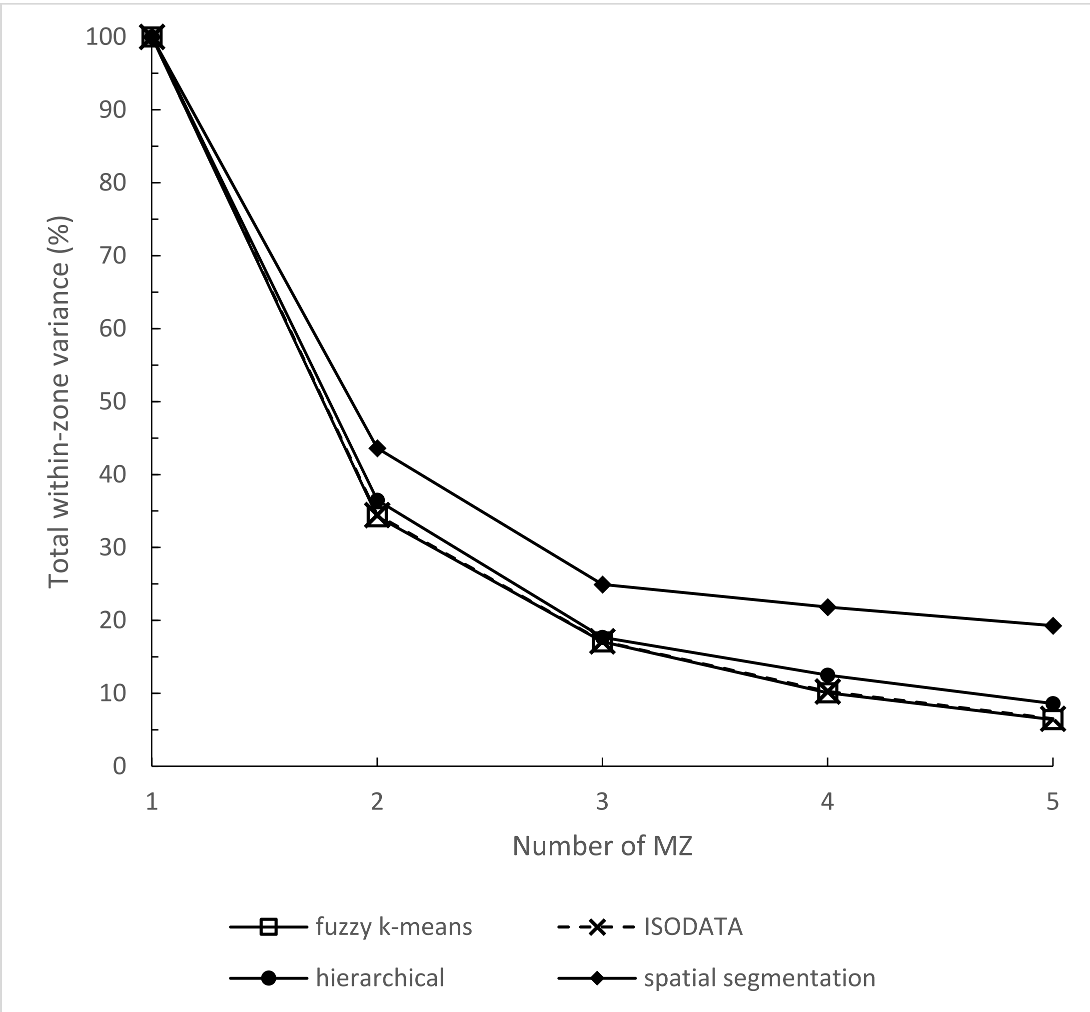

Figure 3. Total within-zone variance reduction in delineating management, zones with the deep (0–1.0 m) soil apparent electrical conductivity (EC_{a100}), according to four delineation methods: fuzzy k-means, ISODATA, hierarchical and spatial segmentation.

All the delineation methods showed the greatest decrease in the variance when the number of MZs was increased from one to two, with an average variance reduction of 60%. From two to three MZs, the total within-zone variance of the EC_{a100} measurements decreased further, by approximately 20%. For a finer partitioning (i.e., four or five MZs), the within-zone variance reduction of the EC_{a100} measurements was lower and negligible.

The delineations into two and three MZs, using the three classification methods without spatial constraints (i.e., fuzzy k-means, ISODATA and hierarchical), produced a similar partitioning of MZs (Figure 4a–c,e–g). However, the spatial segmentation method (Figure 4d,h) resulted in more compact MZs compared to the other classification methods due to the spatial segmentation inherent algorithm bias.

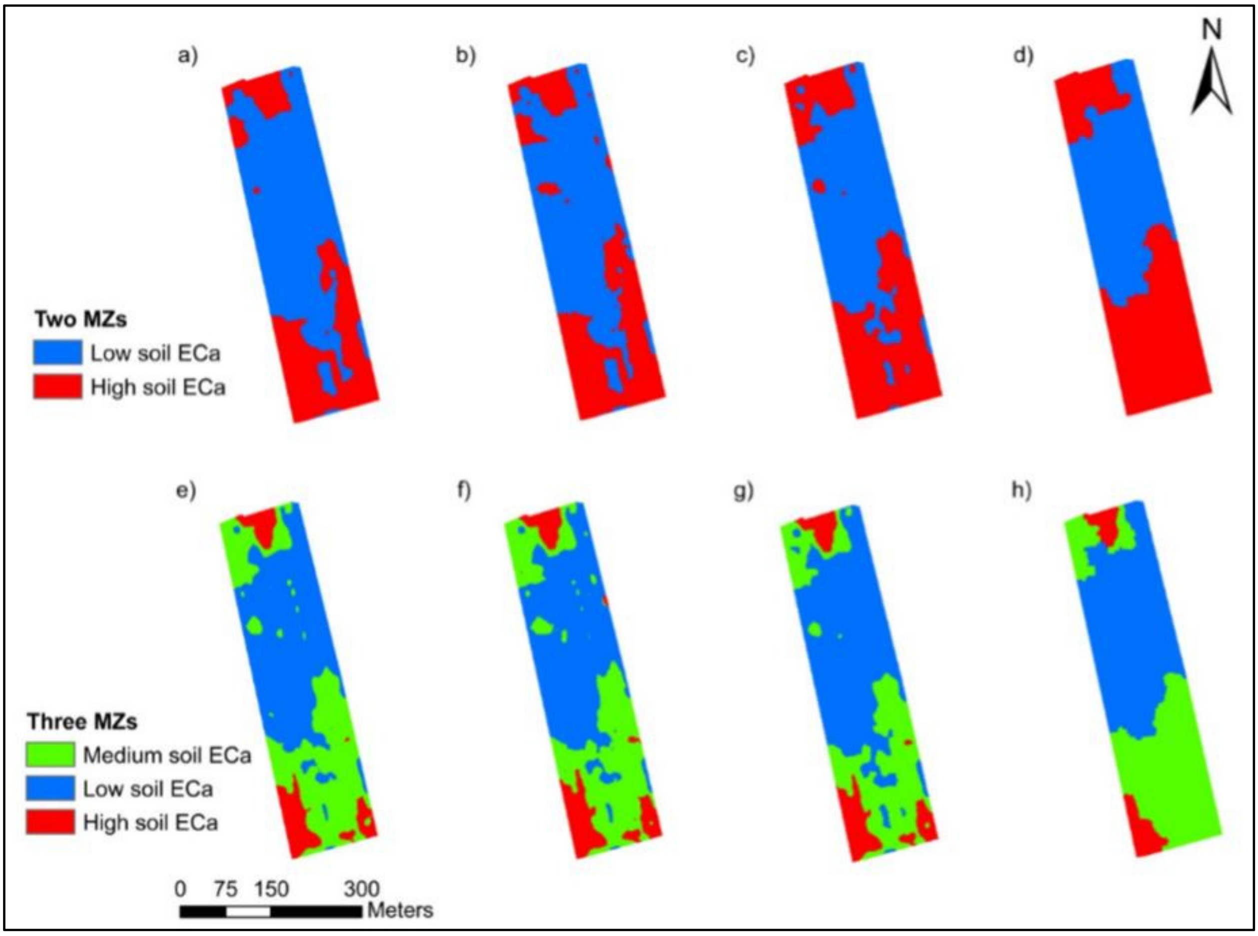

Figure 4. Management zones (MZs) delineated with EC_{a100} kriged data according to four delineation methods: fuzzy k-means (**a**,**e**), ISODATA (**b**,**f**), hierarchical (**c**,**g**) and spatial segmentation (**d**,**h**).

A finer delineation of MZs further reduced the total field variability. However, it may not be feasible to take advantage of this finer delineation due to the width of agricultural equipment. Based on the magnitude of the decrease in the variance of EC_{a100}, and the balance between the spatial variability of the various soil properties and the need to have operationally manageable and spatially well-distributed zones, two or three MZs appeared to be the optimal for the field under study. When delineating the field into two or three MZs, all the MZs generated with the different delineation methods exhibited significant ($p < 0.05$) differences in soil EC_{a100} (Table 3).

Table 3. Variation in mean values of soil physical and chemical properties (0–0.15 m depth) among management zones (MZ) when either two or three MZs are delineated using the four delineation methods under study.

Number of MZ		Soil Properties at 0–0.15 m Depth																							
		EC_{a100} [y]		Clay		Silt		Sand		Total C		Total N		pH		P		K		Ca		Mg		Al	
	Delineation Method	mS/m		g/kg		g/kg		g/kg		%		%				mg/kg		mg/kg		mg/kg		mg/kg		mg/kg	
2 MZ	Fuzzy k-means	4.5	B [x]	76	b	229	b	695	a	1.15	b	0.09	b	6.22	a	193	b	92	b	614	b	95	b	1523	a
		6.6	a	97	a	281	a	622	b	1.36	a	0.11	a	6.26	a	210	a	128	a	687	a	105	a	1402	b
	ISODATA	4.4	b	74	b	224	b	703	a	1.16	b	0.09	b	6.22	a	191	b	90	b	614	b	94	b	1527	a
		6.5	a	96	a	278	a	626	b	1.35	a	0.11	a	6.26	a	211	a	127	a	680	a	105	a	1408	b
	Hierarchical	4.3	b	73	b	222	b	705	a	1.13	b	0.09	b	6.23	a	193	a	92	b	614	a	95	a	1559	a
		6.3	a	94	a	275	a	631	b	1.35	a	0.11	a	6.24	a	206	a	120	a	669	a	102	a	1394	b
	Spatial segmentation	4.2	b	72	b	217	b	711	a	1.12	b	0.09	b	6.22	a	194	a	90	b	604	b	94	b	1567	a
		6.1	a	92	a	271	a	637	b	1.35	a	0.11	a	6.25	a	204	a	121	a	677	a	103	a	1392	b
3 MZ	Fuzzy k-means	4.2	a	76	b	234	b	690	a	1.12	b	0.09	b	6.23	a	192	b	90	a	613	b	95	b	1562	a
		5.8	b	85	b	245	b	670	a	1.34	a	0.10	a	6.26	a	198	b	111	b	639	b	100	ab	1374	b
		7.8	c	101	a	293	a	606	b	1.35	a	0.11	a	6.20	a	234	a	146	c	757	a	108	a	1467	ab
	ISODATA	4.2	a	73	a	217	b	710	a	1.12	b	0.09	b	6.22	a	193	b	91	a	613	b	95	b	1568	a
		5.7	b	89	b	266	a	645	b	1.35	a	0.10	a	6.26	a	196	b	110	b	639	b	100	ab	1371	b
		7.6	c	101	c	293	a	606	b	1.35	a	0.11	a	6.20	a	234	a	146	c	757	a	108	a	1467	ab
	Hierarchical	4.3	a	73	b	222	b	705	a	1.13	b	0.09	b	6.23	a	193	b	92	b	614	b	95	a	1559	a
		5.9	b	91	a	265	a	644	b	1.35	a	0.11	a	6.25	a	198	b	113	a	645	b	101	a	1463	ab
		7.7	c	101	a	293	a	606	b	1.34	a	0.11	a	6.23	a	238	a	143	a	757	a	107	a	1375	b
	Spatial segmentation	4.3	a	72	a	217	b	712	a	1.10	b	0.09	b	6.20	a	196	a	90	a	609	b	94	b	1568	a
		5.9	b	88	b	262	a	651	b	1.37	a	0.11	a	6.28	a	198	a	113	b	654	ab	101	ab	1385	b
		8.1	c	111	c	299	a	591	c	1.32	a	0.12	a	6.21	a	224	a	149	c	749	a	111	a	1458	ab

[y]: Deep (0–1.0 m) soil apparent electrical conductivity measured with Veris 3100; [x] Means followed by the same letter are not significantly different at the 5% significance level according to the LSD test.

A validation of the MZs with the soil physical and chemical property measurements was carried out using ANOVA. In cases where the field was divided into two MZs, most of soil physical and chemical properties differed significantly between MZs for all delineation methods (Table 3). For fuzzy k-means and ISODATA, all the parameters except soil pH differed significantly between MZs. For hierarchical, all the parameters except soil pH and P, Ca, and Mg content showed significant differences between MZs. For spatial segmentation, all the parameters except soil pH and P content differed significantly between MZs. Thus, for delineation of the field into two MZs, the four delineation methods yielded similar validation results.

Overall, for two MZs, a greater EC_{a100} value was characterized by greater clay, silt, Total C and Total N contents, and lower sand and Al contents (Table 3). The P, K, Ca, and Mg contents were also generally greater for the MZ with greater EC_{a100} values, although this was not true for all delineation methods (Table 3). Thus, the high soil EC_a MZ was characterized by a finer soil texture and higher nutrient contents (Figure 4). In this regard, the delineations into two MZs according to the four delineation methods used were all effective and yielded similar, and in some cases identical, results. Previous studies have shown similar classification results between the fuzzy k-means and ISODATA methods [2,28,29]. Other comparable studies indicated a similarity between the fuzzy k-means method and the hierarchical method in terms of their MZ delineation performance [31].

In the case when the number of MZs was increased to three, the delineation with the spatial segmentation method identified three soil properties (clay, sand and K content) which differed significantly among all MZs in the 0–0.15 m layer (Table 3). The delineation into three MZs with the ISODATA algorithm exhibited two soil properties (clay and K content) which differ significantly among all three MZs in the 0–0.15 m layer (Table 3). For the fuzzy k-means method, only one soil property (K content) differed significantly among all three MZs in the 0–0.15 m layer (Table 3). For the hierarchical method, no physical or chemical property in the 0–0.15 m layer exhibited a significant difference among all three MZs. Similar to the delineation into two MZs, there was also a significant relationship between EC_{a100} and some of soil properties for delineation of three MZs. A high EC_{a100} was also characterized by greater clay, silt, and K contents and by lower sand content.

Overall, for three MZs, the fuzzy k-means, ISODATA and hierarchical delineation methods exhibited similar comparison results. The spatial segmentation method (with spatial constraints) proved to be more effective in terms of delineation into three MZs compared to the other classification methods (without spatial constraints) as indicated by clearer and more compact delineation of MZs and more manageable units for agricultural practices (Figure 4). Conversely, the fuzzy k-means, ISODATA and hierarchical methods sometimes yielded small isolated zones that were not operationally manageable and clumps of outliers that had to be smoothed manually after classification. From an agronomic standpoint, small areas where agricultural machinery cannot operate reliably can be impractical to manage [63]. In addition, the spatial segmentation method was the only delineation method evaluated that took the spatial constraints of the data into account. The influence of the spatial dimension on the improvement and precision of the MZ delineation was thus clearly visible. Furthermore, previous studies demonstrated that the application of the spatial segmentation algorithm proved to be more effective than the conventional fuzzy k-means classification method [35,37].

3.4. Practical Implication of MZs

For the case of delineation into two MZs, the high EC_a MZ had 2% greater clay content and 5% to 6% greater silt content than the low EC_a MZ, averaged across the delineation method. The increase in the percentage of fines in the high EC_a MZ would be expected to result in more effective retention of water and nutrients compared to the low EC_a MZ. The practice of differential irrigation could be a good strategy to compensate for the reduced water retention at the low EC_a MZ. An MZ with a low water retention can be associated with an increased susceptibility to leaching [16]. However, although statistically significant, the differences in mean nutrient levels found between MZ were small and likely of limited agronomic significance. Consequently, delineation into two MZs would have little effect on crop fertilization under the current fertilization guidelines in PEI [64].

For the case of delineation into three MZs, it is useful to compare the MZs with the greatest and the lowest EC_a. The high EC_a MZ had greater concentrations of plant nutrients (i.e., P, K, Ca), and the differences were great enough that recommended crop fertilization practices could differ between MZ based on the current fertilization guidelines in PEI. In addition, the high EC_a MZ had greater soil fines than the low EC_a MZ and may be used as the basis for differential irrigation management. From an agronomic standpoint for the potato crop, the intermediate EC_a MZ zone was relatively similar to the low EC_a MZ, and therefore the low and intermediate EC_a MZ could receive the same fertilizer and water management practices. Similarly, in previous studies in which three MZs were identified based on EC_a, not all three MZs were distinct in terms of recommended agricultural practices and consequently two MZs may be grouped for practical purposes [32,65].

For this study site, delineation into two MZs would have little effect on crop fertilization because the difference between the two MZs is small from an agronomic standpoint. In contrast, delineation into three MZs gives the potential for two MZs (i.e., low plus intermediate vs high soil EC_a), which are distinct in terms of soil properties and can be used as the basis for site-specific nutrient and water management.

4. Conclusions

The current study compared four delineation methods (fuzzy k-means, ISODATA, hierarchical, and spatial segmentation) for identification of MZs in a commercial potato field in PEI. This comparison revealed some differences in the working methodology and also in the results for each delineation method used. For the case of delineation into three MZs, the spatial segmentation method (with spatial constraints) proved more effective in capturing the spatial variation in soil physical and chemical properties compared with the other classification methods (without spatial constraints) as indicated by more parameters which differed significantly among all three MZs. From an agronomic standpoint, the spatial segmentation method also exhibited more compact and operationally more manageable zones than the other methods.

Regarding data distribution, a non-Gaussian distribution of the data for the ISODATA method can give misleading results while the fuzzy k-means and hierarchical delineation methods do not require Gaussian distribution of the data. In terms of the ability to separate soil properties, the spatial segmentation method had the greatest efficiency in delineation of MZs from statistical and agronomic perspectives, and generated more visually compact MZs. Hence, the ability of the spatial segmentation method to take the spatial dimension of the data into account was an important factor in improving the quality of the MZ delineation.

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