# Delineating soil management zones using a proximal soil sensing system in two commercial potato fields in New Brunswick, Canada

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**Abbreviations: $\mathbf{EC_a}$**, apparent soil electrical conductivity; **MZ**, management zone; **PA**, precision agriculture; **PSS**, proximal soil sensing

## ABSTRACT

Stagnating potato (*Solanum tuberosum* L.) yields in eastern Canada have resulted in loss of competitive advantage in global potato markets. Therefore, there is a need to investigate the potential to increase yield by adopting precision agriculture technology. This study evaluated the efficiency of an apparent soil electrical conductivity ($EC_a$) sensor to delineate management zones (MZs) in two commercial potato fields in New Brunswick, Canada using an unsupervised fuzzy k-means clustering algorithm. Georeferenced soil samples from 0-15 cm depth were analyzed for physicochemical properties. Tuber yields were recorded using a yield monitor. The two MZs delineated using soil $EC_a$ differed significantly in soil physicochemical properties for both fields, however, tuber yield differed significantly between MZs only in Field 1. The yield difference (7.1 Mg ha$^{-1}$) in Field 1 was attributed to a difference in soil moisture (23.5 vs 28.5%) resulting from a difference in clay content (141 vs 189 g kg$^{-1}$). The lack of a yield difference between MZs in Field 2 may reflect relatively low within-field spatial variability. The soil $EC_a$ sensor showed promise for use in commercial potato production in New Brunswick, especially in fields with high spatial variability.

## INTRODUCTION

The goal of precision agriculture (PA) is to increase profitability of crop production and improve product quality, while protecting the environment (Adamchuk et al. 2004). This goal may be achieved by modifying management practices in response to spatio-temporal variability in soil and crop properties. Recent technological advances in PA have made it possible to identify, analyze and manage such variability at the field scale. Despite the importance of within-field variability, the conventional practice still consists in managing fields uniformly without considering the spatial variation of soils and crop performances. Conventional management limits crop yield below potential, reduces crop quality, and results in unnecessary losses of agricultural inputs to the environment (Corwin and Lesch 2010).

One approach to implement PA is through the use of management zones (MZs) (Mulla 1989). This agricultural concept is based on the existence of within-field spatially structured soil and crop variability (Cambouris et al. 2006). This approach requires identification of subfield regions with homogeneous characteristics (Peralta and Costa 2013), such that the within-region variability is minimized while the among-region variability is maximized (Tripathi et al. 2015). Subdividing a field into MZs found to be an effective way of controlling the spatial variation of various factors (i.e., soil, climate, management, pests and crops) that affect crop yield (Corwin and Lesch 2010). Use of MZs has been shown to be a promising approach to fertilizer management in intensive potato (*Solanum tuberosum* L.) production in Quebec, Canada (Cambouris et al. 2006; 2014). The high cost of crop inputs, and the sensitivity of potato tuber yield and quality to crop management and environmental conditions, have resulted in increased producer interest in variable within-field crop management (Allaire et al. 2014; Morier et al. 2015).

One of the biggest limitations to adoption of PA is the inability to measure soil characteristics rapidly and inexpensively (Adamchuk et al. 2004). Intensive soil sampling, which is time-consuming, costly (Shaner et al. 2008) and also limited to point measurements (Toy et al. 2010), is not practical for identification of MZs. Commercially available proximal soil sensing (PSS) instruments allow rapid and inexpensive mapping of soil properties at relatively high spatial resolution, and are therefore suitable for delineation of MZs.

Most PSS systems rely on electrical, electromagnetic, optical, radiometric, mechanical, acoustic, pneumatic, and electrochemical measurement concepts (Adamchuk et al. 2015). Commercial sensors based on electromagnetic induction are among the most commonly used PSS systems in agriculture (Sudduth et al. 2001). Electromagnetic induction instruments provide efficient, non-contact, on-the-go means to measure apparent soil electrical conductivity ($EC_a$) representing different depths of investigation depending on the geometry of primary and secondary inductors, their relative position, height above ground and electric frequency of operation. Such $EC_a$ measurements are usually temporally stable (Cambouris et al. 2006) and may be related to numerous soil physical and chemical properties including texture, organic matter, soil moisture, salinity, pH, nitrogen, P, K, and Al (Sudduth et al. (2003). Although the relationships between soil $EC_a$ and soil nutrient contents are indirect and limited to very specific crop production settings, several studies have shown the effectiveness of using soil $EC_a$ in combination with remotely sensed soil topography imagery and other spatial data to delineate MZs for studying the effect of soil variability on crop response to management practices, such as fertilization. For example, Cambouris et al. (2014) used MZ to manage P, K and N fertilizer in potato production and Peralta et al. (2015) delimited MZs to optimize nutrient management in wheat.

Although the use of PSS systems to map soil $EC_a$ had been used successfully in many regions, the relationship between soil properties and soil $EC_a$ measurements varies considerably across locations (Mueller et al. 2003). Potato is the most important agricultural crop in New Brunswick, grown on over 20,000 ha and with a total value of over $150 million (Agriculture and Agri-Food Canada 2017). Over half of the potato crop is grown for French fry production, and exported primarily to eastern US. However, stagnating potato yields in eastern Canada have resulted in loss of competitive advantage in global potato markets, and therefore there is a need to investigate the potential of PA technology to improve the competitiveness and sustainability of the potato industry, as well as to mitigating adverse environmental impacts from production (Canadian Potato Council 2016). Moreover, the potential to map the spatial variability of soil properties of fields under potato production in New Brunswick has not been extensively examined. The aim of this study was to characterize soil spatial variability, and examine the potential to use an electromagnetic induction based PSS system to delineate MZs in two commercial potato fields in New Brunswick, Canada.

## MATERIALS AND METHODS

### Experimental site

The study was conducted in two commercial fields under intensive potato production located in Saint-André (21 ha, referred to as Field 1) and Centreville (18 ha, referred to as Field 2), New Brunswick, Canada. The 30-year (1981-2010) mean annual air temperature is 4.4 and 7.0 °C, the mean annual precipitation is 1099 and 966 mm, and the mean growing season precipitation is 640 and 600 mm at Field 1 and Field 2, respectively (Environment Canada 2016).

Soils in Field 1 are classified as Holmesville (Orthic Ferro-Humic Podzol), Undine (Orthic Humo-Ferric Podzol), Johnville (Gleyed Humo-Ferric Podzol) and Siegas (Brunisolic Gray Luvisol), which are good to poorly drained, sandy loam to clay loam, and of glacial till origin (Fig. 1a; (Langmaid et al. 1980). Soils in Field 2 belong to the Caribou (Podzolic Gray Luvisol) and Carleton (Orthic Humo-Ferric Podzol) soil series, which are moderately well drained, loam to silt loam, and of glacial till origin (Fig. 1b; (Fahmy and Rees 1996). Both fields are gravelly, with coarse fragments representing approximately 15 to 35% of the soil volume. According to Milburn et al. (1989), soil depths varied from 0.30–0.65 m for all soil series, except for Caribou, which varied from 0.65–1.00m. The slope varies from 0.5 to 5.0% at Field 1 and from 0.5 to 9.0% at Field 2. Field 1 has greater pedodiversity [i.e., greater variation of soil properties (McBratney 1992)] than Field 2.

The fields were planted with potato cv Russet Burbank on 10 May 2013, 15 May 2014 and 20 May 2016 for Field 1, and 30 May 2014 and 21 May 2016 for Field 2. Crop management and fertilization followed recommended New Brunswick potato industry practices (New Brunswick Government 2001). Weed, insect and disease pests were controlled following grower standard practices. No irrigation was applied as is common in this rain-fed production area.

**Soil sampling and analyses**

A triangular grid with a sampling interval of 33 m on 12 ha (center of Field 1 and east side of Field 2), and of 71 m on the rest of the field, was established in each field (Fig. 1). The sampling grid was designed with the ET Geowizards tool in ArcGIS version 9.3.1 (ESRI, Redlands, CA, USA). The average soil sampling density was 7 samples per hectare for Field 1 (154 samples) and 10 samples per hectare for Field 2 (141 samples).

One composite sample was collected from each sampling location on 22 Sept 2015 and 23 Sept 2015 for Field 1 and 2, respectively. Each composite sample consisted of five soil cores from 0–15 cm depth, and within 1.5 m radius of each sampling point, collected using a 0.05-m diameter Dutch auger. A subsample of each sample was oven-dried at 105 °C for 24 h to determine gravimetric water content (soil moisture), and the rest of the sample was air-dried, ground and sieved through a 2-mm sieve. Soil pH (1:2 water) was measured according to Hendershot et al. (2008). Soil particle size distribution was determined using the pipette method following organic matter removal (Kroetsch and Wang 2008). The particle size analysis was completed for one out of four samples totalling 41 and 37 soil samples for Field 1 and Field 2, respectively (Fig. 1). Soils were extracted with a soil solution ratio of 1:10 using Mehlich-3 solution (Ziadi and Tran 2008), and the concentrations of P, K, Ca, Mg, and Al in the extract were determined by inductively-coupled plasma optical emission spectroscopy (ICP–OES; Model, 4300DV, Perkin Elmer, Shelton, CT, USA). Total nitrogen and carbon content were measured with an Elementar varioMAX CN analyzer (Elementar Analysensysteme GmbH, Hanau, Germany).

**Data collection using proximal soil sensing**

Apparent soil electrical conductivity ($EC_a$) measurements were carried out during the fall of 2015 after harvest of cereal crops with a Veris® mapping unit (Veris-MSP3, Veris Technologies, Inc., Salina, KS, USA), which consists of three sensor systems, including a galvanic contact resistivity sensor with six coulter electrodes (in Wenner array configuration). The system simultaneously recorded soil $EC_a$ from two depths: 0–0.3 m ($EC_{a0–0.3m}$) and 0–1.0 m ($EC_{a0–1m}$) (Kweon et al. 2012). The data were collected along parallel transects spaced approximately 10 m apart with 1 Hz logging frequency, corresponding to a measurement every 2 to 3 m when operating with the speed approximately 10 km $h^{-1}$. The data density was about 400 measurements per hectare. A Global Positioning System (GPS) receiver (Garmin 17x HVS; Garmin International, Inc., Olathe, Kansas, USA) was used to obtain geographic coordinates for each measurement. As proposed by Sanches et al. (2018), any measurement deviating from the mean by more than three standard deviations was treated as an outlier and was removed from the dataset.

**Tuber yield**

Spatial distributions of tuber yield were measured mechanically on 29 September 2013, 19 September 2014 and 2 October 2016 for Field 1 and on 10 October 2014 and 9 October 2016 for Field 2. Two four-row harvesters equipped with yield monitors worked in tandem across each field. In Field 1, tubers from the six rows on each side of the four row harvest area were deposited into the harvest area just before harvest using a six-row side digger, such that tuber yield was monitored on a 15 m width (i.e., 16 rows x 0.91 m). A similar approach was used in Field 2, except that a four row side digger was used, and yield was monitored on an 11 m width (i.e., 12 rows x 0.91 m). The RiteYield system (Greentronics, Inc., Elmira, ON, Canada) yield monitor was installed on harvesters in both fields. The tractors pulling the harvesters were equipped with RTK (real time kinematic) GPS systems (Trimble Navigation, Ltd., Sunnyvale, CA, USA), which supplied the GPS signal to the Trimble FmX potato yield monitor data unit. Yield monitors were calibrated once against weighed truckloads of tubers at the beginning of the harvest season, and then the yield monitor load cells were re-zeroed (tared) each morning.

**Statistical and geostatistical analysis**

Descriptive statistics were carried out with the MatLab® version 8.3 (MathWorks, Inc, Natick, MA, USA) software package. According to the chi-square goodness-of-fit test, the non-normal distributed data were transformed using logarithmic or Box-Cox to stabilize the variance. The Pearson correlation coefficient (r) between the soil $EC_a$, tuber yield, elevation and physicochemical soil properties measurements were conducted using MatLab's 'corr' function. The correlations were performed using the average value of soil $EC_a$, tuber yield and elevation measured within a 5-m radius of the soil sampling locations.

Geostatistical Analyst in ArcGIS version 10.4.1 (ESRI, Redlands, CA, USA) was used to perform all the geostatistical computations and model validations. The spatial structure of different properties was evaluated via isotropic and anisotropic semivariograms. Experimental semivariograms, the main component of kriging, are an effective tool for evaluating spatial variability (Wu et al. 2009). Semivariogram parameters for each theoretical model (spherical, exponential and Gaussian) were generated. The corresponding sill, nugget, and range values of the best-fitting theoretical model were calculated. Nugget ratio, expressed as the percent of the total semivariance, was used to define for spatial dependency of soil variables. Semivariograms with nugget ratio of ≤ 25%, 25 to 75%, or ≥ 75% were considered to have a strongly, moderately or weakly dependent spatial structure, respectively (Cambardella et al. 1994). After selection of the suitable theoretical model for each dataset and the corresponding semivariogram parameters, spatial variability maps were generated using ordinary kriging. Kriged map reliability was evaluated using cross-validation analysis ($R^2_{CV}$) (Kravchenko et al. 2002). Then, leave-one-out cross-validation procedure was used as a method of validating the kriging predictions.

The soil $EC_a$ dataset was used to delineate the MZs using naturally occurring clusters in the data (Chang et al. 2014). A k-means clustering with a no-spatial constraint of proximity was carried out using FuzME software (Minasny and McBratney 2002). Cluster analysis based on Mahalanobis metric distance was used to determine the similarity between two random multidimensional variables taking into account the correlation between the variables. The methodological details of fuzzy clustering and the application of generalized fuzzy k-means has been described by McBratney and Gruijter (1992). As described by Cambouris et al. (2006), the variance reduction due to zone partitioning (stratified vs simple random sampling) was used to determine the optimal number of MZs in the experimental field. One-way analysis of variance (ANOVA) and multicompare statistical test using MatLab's Multcompare function were performed to determine statistically significant differences ($\rho \leq 0.05$) between MZ averages by using the multiple comparison test (LSD).

## RESULTS AND DISCUSSION

### Explanatory data

Most soil physicochemical properties had CV values within the range of 5 to 38% for both fields (Table 1). The greatest variability (38%) was obtained for soil Mg content, while the lowest variability was observed for soil Al content and soil pH (6 to 8%). Other studies evaluating spatial variation also found lowest variability for soil pH (Cox et al. 2003; Farooque et al. 2012), which is due to the logarithmic scale of pH measurement.

Overall, Field 1 showed greater variability in soil physical and chemical properties than Field 2. This is probably due to the greatest pedodiversity of Field 1 as suggested by the observed high variation in soil drainage and texture classes of the different soil series (Fig. 1). The CV values of soil texture parameters and soil moisture content were greater in Field 1 than in Field 2. In contrast, soil K content had low and moderate variability in Field 1 and Field 2, respectively. Previous studies evaluating spatial variation reported moderate to high CV values of soil properties (Case 2000; Farooque et al. 2012) in New Brunswick and Nova Scotia, whereas CV values in the current study are generally lower.

The CV values for soil $EC_a$ were greater in Field 1 than in Field 2 (Table 1), probably due to the greatest pedodiversity within Field 1, and in particular to greater variability in soil texture and soil moisture content. Tuber yield varied moderately with CV values ranging from 21 to 28% and 23 to 32% for Field 1 and Field 2, respectively (Table 1). Average tuber yield for Field 1 was 40.5 Mg ha$^{-1}$ in 2013, 36.9 Mg ha$^{-1}$ in 2014 and 34.2 Mg ha$^{-1}$ in 2016. The tuber yield variability among years in this field may reflect variation in growing season (May to September) precipitation; growing season precipitation was 684 mm in 2013, 430 mm in 2014 and 459 mm in 2016 (New Brunswick Government 2016). Similarly for Field 2, greater tuber yield in 2016 over 2014 (41.9 Mg $ha^{-1}$ vs 39.0 Mg $ha^{-1}$) is consistent with greater growing season precipitation in 2016 over 2014 (721 mm vs 561 mm) (New Brunswick Government 2016).

Greater within-field variability would require more samples to achieve good prediction accuracy (Nyiraneza et al. 2011). In this study, the moderate variability of the soil physicochemical properties was promising for mapping these agricultural fields. The CV values were generally good indicators of the degree of variability, but not of its nature (i.e., structured or randomized variability; (Cambouris et al. 2006).

**Spatial variability**

Among the available models for fitting with experimental semivariogram, Gaussian, spherical, and exponential models were the best fit for most of the soil physicochemical properties and elevation in both fields (Table 2). However, the pure nugget models were the best fit for soil K content in Field 1 and clay content in Field 2. The pure nugget effect may be a result of sampling errors, random inherent variability, and/or short-range variability and indicated a complete lack of spatial structure. Spatial ranges for measured soil properties varied from 45 to 447 m. The spatial ranges of the soil properties were greater than the 33 m grid spacing, indicating that the grid sampling intensity used to characterize the spatial variability of both fields was appropriate in this study. Except for the pure nugget semivariogram models, most soil property nugget ratio values indicated moderate to strong spatial dependence.

The best fit semivariogram models for soil $EC_a$ and tuber yield were generally exponential and spherical, respectively (Table 2). For soil $EC_a$ measurements, the range varied from 57 to 95 m and the nugget ratio was ≤ 15% for both fields (Table 2). This suggested that the nugget effect (random variance) was very low and reliably modelled by the sampling strategies (434 soil $EC_a$ measurements per $ha^{-1}$) (Cambouris et al. 2006; Simard et al. 2001). Similar results were reported by Moral et al. (2010) for soil $EC_a$ in silt loam soils from southwestern Spain. The tuber yield nugget ratio varied from 1 to 28% and the spatial range varied from 13 to 39 m for both fields. These results also indicated that soil $EC_a$ and tuber yield are strong spatially dependent properties and are probably controlled by intrinsic factors (e.g., soil texture, structure, mineralogy and microorganisms) (Cambardella and Karlen 1999; Cambardella et al. 1994).

High $R^2_{CV}$ values (i.e., > 0.60) indicated that good fits were obtained for most of the densely measured properties (i.e., elevation, soil $EC_a$, and tuber yield) for both fields (Table 2). This suggests that these properties can then be used to delineate MZs. Good fit models were also obtained for the soil particle size distribution and soil moisture in Field 1 ($R^2_{CV}$ = 0.49 to 0.83), whereas the fit was relatively weaker in Field 2 ($R^2_{CV}$ = 0.03 to 0.21). In contrast to Field 2, the $R^2_{CV}$ values suggested that the spatial dependence of properties in Field 1 could be influenced mostly by intrinsic soil factors (Cambardella and Karlen 1999).

Soil $EC_a$ values were generally greatest in the northern part of Field 1, with lower soil $EC_a$ values in the central and southern parts of the field (Fig. 2a, b). There was a consistent and constant variability of tuber yield in 2013, 2014 and 2016 in Field 1 (Fig. 2c, d, e). Therefore in Field 1, the within-field variation in yield attributable to spatial variability in physicochemical properties was greater than induced by seasonal climatic conditions. The spatial variability of clay, soil moisture and P contents showed good visual similitude in Field 1 (Fig. 2f, g, h). Greater clay and soil moisture contents were associated with lower P content. The lowest area of P content could be related to the recent land clearing (<5 yr) and potato cultivation in the northern part of the field. It is known that uniform application of fertilizer in the entire field could also contribute to maintaining this difference (Cambouris et al. 1999).

In contrast, soil $EC_a$ measurements did not show similar spatial patterns as the soil texture parameters in Field 2 (Fig. 3a, b). The spatial pattern of tuber yield varied between years, indicating the pattern of yield was not temporally stable (Fig. 3b, c).The Ca and the P content maps showed similarities in Field 2, where areas with high Ca content were characterized by low P content (Fig. 3d, e).

**Relationships between $EC_a$, soil properties and crop yield**

Soil $EC_a$ values were strongly correlated with soil texture and soil moisture in Field 1 (Table 3). Soil $EC_a$ values, clay and soil moisture contents were greater in the areas characterized by poorly drained soils (Fig. 2a, b, f, g). Previous studies reported similar relationships between soil $EC_a$ values and soil texture under similar soil and topographic conditions (Landrum et al. 2015; Moral et al. 2010). Mehlich-3 extractable elements, total carbon and nitrogen and soil pH were also generally significantly correlated with the soil $EC_a$ values in Field 1. Overall, the strong correlations of soil properties with soil $EC_a$ values suggested that soil $EC_a$ can be used to predict the spatial distribution of soil properties, to visualize their impact on crop yield, and ameliorate productive and unproductive areas within a field. Soil $EC_a$ measurements were negatively correlated with tuber yield in 2013, 2014 and 2016 for Field 1 (Table 3). Stronger correlations were obtained in 2013, which may be associated with greater growing season precipitation. The correlation coefficients between soil $EC_a$ and tuber yield were similar to those reported by Cambouris et al. (2006) ($r = 0.25$ to $0.49$). Areas of the field with the greatest clay content (Fig. 2f) had the lowest tuber yield (Fig. 2c, d, e). Low yield areas were also characterized by high soil moisture content (Fig. 2g), which indicates poorly drained soil. Potato production is severely impeded due to drainage. For example, healthy root and tuber development can be affected by the free movement of oxygen with excessive water. The surplus of water in soil can also limit the efficiency of nutrient uptake, increase fungal diseases, increase the risk of soil compaction not to mention the delays of spring tillage and planting (New Brunswick Department of Agriculture 2018; Stark et al. 2004). Low yield areas were also characterized by low P content (Fig. 2h), which is essential for root development (Nyiraneza et al. 2017).

In contrast, there is no apparent relationship between soil $EC_a$ and soil texture in Field 2 (Table 3). There is, however, a strong correlation between the Mehlich-3 extractable elements (Ca, Al and P) and the soil $EC_a$ measurements (Table 3). The area with increased $EC_a$ had greater Ca content and lower P and Al contents (Fig. 3). Soil $EC_a$ measurements were not related to tuber yield in 2014 or 2016 in Field 2. Significant negative correlations of soil $EC_a$ measurements with elevation (Table 3) suggested a linear trend, indicating that the ground conductivity values were strongly influenced by the topography in Field 2. In accordance with previous results, soil $EC_a$ showed superior performance in explaining the spatial variability in soil properties in the studied fields, especially for Field 1.

**Determination of the optimum number of management zones**

The fuzzy k-means clustering algorithm was used to partition the fields into two to five MZs (Fig. 4). When the analysis was first carried out with a spatial constraint of proximity, the algorithm could not handle the spatial structure, and led to the delineation of artificial regions based only on the numerical values of spatial coordinate and not on the geographical proximity (data not shown). Consequently, the analysis was performed without a spatial constraint of proximity. As expected, increasing the number of MZs from one to five decreased the total within-zone variance of the soil and yield parameters (Cambouris et al. 2006). Similar to previous studies (Li et al. 2007; Moral et al. 2010; Xin-Zhong et al. 2009), the magnitude of the reduction in total within-zone variance was used to select the optimum number of MZs.

At Field 1, going from one to two MZs decreased total within-zone variance of soil $EC_a$ by 71 to 77% (Fig. 5a). This magnitude in the decrease of variance for soil $EC_a$ values is comparable with that reported by Cambouris et al. (2006) and Corwin and Lesch (2005). Additional MZs resulted in a limited reduction in total within-zone variance of soil $EC_a$, and consequently two MZs was determined to be most suitable for this field. The decrease in variance for total yield in going from one to two MZs varied among years, with total within-zone variance decreased by 18% in 2013, 8% in 2014 and 6% in 2016 (Fig. 5c). Clay content and soil moisture showed a total variance reduction of 63% and 23%, respectively, with two MZs compared to single zone or whole field as a management unit (Fig. 5e). For soil chemical properties, going to two MZs decreased the total variance for P and Al contents by 19 and 29%, respectively (Fig. 5g). Moral et al.

(2010) also identified two MZs as the optimum number when using electromagnetic induction to classify their field.

At Field 2, going from one to two MZs decreased the total within-zone variance of soil $EC_a$ values by 46 to 65% (Fig. 5b). Based on the total yield and most of the physicochemical properties, the subdivision of Field 2 from one to five MZs resulted in a decrease in the total variance of less than 10% (Fig. 5d, f, h). In contrast, going from one to two MZs decreased the total variance of Ca and Al contents by 28 and 27%, respectively (Fig. 5h). For Field 2, the decrease in variance followed a less homogeneous behaviour than in Field 1, and did not show any clear pattern of MZs. This may be attributed to the relatively homogeneous spatial variability and a weaker spatial structure for soil properties in Field 2. Corwin and Lesch (2005) noticed that performance of soil $EC_a$ sensors varies from field to field, especially when the field is dominated by one or two intrinsic factors such as soil moisture or clay content which make the interpretation of soil $EC_a$ values highly specific to the field.

**Practical applications of management zone within these fields**

Spatial variability in crops is the result of a complex interaction of biological, edaphic, anthropogenic, topographic, and climatic factors (Corwin and Lesch 2003). Measurements of soil $EC_a$ have been used at field scale to map spatial variability of soil properties and yield by MZs. According to Cambouris et al. (2006), the optimal number of MZs must show a balance between the spatial variation of soil properties, yield stability over time and a manageable spatial representation. Analysis of variance was conducted to provide an indication of statistical distinction among different MZs (Chang et al. 2014). In general, three or more MZs were not considered significant at the chosen

5% level (data not shown), and effectively only two MZs were significantly different based on soil $EC_a$ values in both fields (Table 4).

In Field 1, the two MZs delineated using soil $EC_a$ measurements differed significantly in tuber yield for all three years and in most of the soil physicochemical properties measured (Table 4). When averaged across the three years, tuber yield was 6.8 Mg ha$^{-1}$ greater for the low ECa zone than for the high ECa zone. The high ECa zone, which had lower yield, was characterized by greater soil pH and contents of clay, soil moisture, total carbon and nitrogen, Ca and Mg, while it had lower contents of sand, gravel, P and Al. Since the soil physicochemical properties varied significantly between MZs, it may be relevant to manage soil properties using the selected MZs. For example, the high soil $EC_a$ zone was characterized by the wettest soil, the finest soil texture and the lowest tuber yield. The wet soil conditions in the high ECa zone could be managed with specific drainage or land levelling to prevent water accumulation, leading to increase in the tuber yield potential. This confirms that by identifying the underlying factors responsible for the variation in crop yield, it may be possible for potato producers to use MZs in order to optimize their profitability (De Caires et al. 2015).

For Field 2, the high $EC_a$ MZ had greater soil pH and total N content, and lower contents of P, K, and Al compared with the low ECa MZ (Table 4). In contrast, tuber yield for two years, soil texture, soil moisture, total C and Ca content were not significantly different between MZ. Sim

A site-specific crop management can be implemented in agricultural fields to manage plant breeding, pest management, weed management, soil fertility and crops based upon spatial variations within a field (Khosla et al. 2010). Two MZs could be determined in both fields; however, only the MZs delineated in Field 1 were related to tuber yield. The zone delineation has the potential to facilitate cost-effective, environmentally friendly and energy efficient management of the fields (De Caires et al. 2015), particularly when the field shows high spatial variability such as in Field 1.

## CONCLUSIONS

In this study, soil $EC_a$ was effective in delineating within-field differences in soil physicochemical properties in two agricultural fields. Consequently in these fields, soil $EC_a$ is an efficient variable to stratify and reduce the within-field soil variability by delineating homogeneous soil MZs on the basis of soil characteristics. The MZs delineated with soil $EC_a$ coincided with the spatial variation in tuber yield in Field 1. This field showed high pedodiversity in soil texture and soil moisture, and these properties influenced soil water availability, and consequently potato yield. The spatial distribution of potato tuber yield in Field 1 was also stable over time, and thus could be used for implementing site-specific crop management. In contrast, the spatial distributions of potato tuber yield in Field 2 did not follow the spatial pattern of other soil physiochemical properties measured. However, some soil Mehlich-3 extractable elements (P, K and Al) were significantly different between high and low soil ECa MZs. Soil proximal sensors, such as Veris®, performances to map spatial variability of intrinsic soil properties is promising in potato production in New Brunswick, especially in fields with high pedodiversity.

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Fig. 1. Soil series, drainage classes and sampling grid at a) Field 1 and b) Field 2.

Fig. 2. Kriging maps of the apparent soil electrical conductivity ($EC_a$) measured a) $EC_{a0-0.3m}$ and b) $EC_{a0-1m}$; tuber yield c) 2013, d) 2014 and e) 2016; and f) clay, g) soil moisture and h) Mehlich-3 extractable P of Field 1.

Fig. 3. Kriging maps of the apparent soil electrical conductivity ($EC_a$) a) $EC_{a0-0.3m}$ and b) $EC_{a0-1m}$; tuber yield c) 2014, and d) 2016; and Mehlich-3 extractable e) Ca and f) P of Field 2.

Fig. 4. Management zones (MZs) delineated using the $EC_{a0-0.3m}$ and $EC_{a0-1m}$ kriged data matrix with the fuzzy k-means analysis with no-spatial constraint of proximity at Field 1 (a-c-e-j) and Field 2 (b-d-f-k).

Fig. 5. Decrease of the total within-zone variance of a-b) soil electrical conductivity, c-d) yields 2013, 2014 and 2016 from yield monitor, e-f) soil particles sizes (clay, silt, sand), gravel and soil moisture, g-h) Mehlich-3 extractable elements (P, K, Ca, Mg and Al) into management zone (MZs) based on the MZs delineated with the Veris® at Field 1 and Field 2, respectively.

Table 1. Descriptive statistics of the soil physicochemical properties, elevation, soil electrical conductivity and tuber yield for Field 1 and Field 2

| | | ------------------------Field 1------------------------ | | | | | | ------------------------Field 2------------------------ | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Unit | *n* | Mean | Min | Max | STD[a] | CV[b] % | *n* | Mean | Min | Max | STD | CV % |
| Soil Particle size | | | | | | | | | | | | | |
| Clay | g kg$^{-1}$ | 41 | 151 | 119 | 210 | 25 | 16 | 37 | 161 | 138 | 182 | 10.8 | 7 |
| Silt | g kg$^{-1}$ | 41 | 508 | 382 | 609 | 52 | 10 | 37 | 485 | 443 | 557 | 22.4 | 5 |
| Sand | g kg$^{-1}$ | 41 | 341 | 190 | 483 | 73 | 22 | 37 | 354 | 267 | 409 | 27.9 | 8 |
| Gravel | g kg$^{-1}$ | 154 | 237 | 73 | 411 | 67 | 28 | 141 | 251 | 146 | 358 | 41.8 | 17 |
| Soil moisture | % | 154 | 24.4 | 14.0 | 36.5 | 4.0 | 16 | 141 | 24.0 | 13.1 | 33.2 | 2.5 | 11 |
| Total carbon | mg kg$^{-1}$ | 154 | 2.1 | 1.1 | 2.8 | 0.2 | 11 | 141 | 2.3 | 1.7 | 4.1 | 0.3 | 14 |
| Total nitrogen | mg kg$^{-1}$ | 154 | 0.2 | 0.1 | 0.3 | 0.0 | 9 | 141 | 0.2 | 0.2 | 0.4 | 0.0 | 11 |
| Soil $pH_{water}$ | | 154 | 5.8 | 5.2 | 7.2 | 0.4 | 7 | 141 | 5.8 | 5.1 | 6.7 | 0.3 | 6 |
| Mehlich-3 extractable elements | | | | | | | | | | | | | |
| P | mg kg$^{-1}$ | 154 | 238 | 68 | 358 | 57 | 24 | 141 | 213 | 88 | 347 | 213 | 24 |
| K | mg kg$^{-1}$ | 154 | 183 | 105 | 336 | 43 | 24 | 141 | 191 | 87 | 439 | 191 | 36 |
| Ca | mg kg$^{-1}$ | 154 | 809 | 351 | 1693 | 260 | 32 | 141 | 1107 | 565 | 2458 | 1107 | 27 |
| Mg | mg kg$^{-1}$ | 154 | 116 | 50 | 285 | 44 | 38 | 141 | 167 | 75 | 349 | 167 | 38 |
| Al | mg kg$^{-1}$ | 154 | 1814 | 1439 | 1999 | 111 | 6 | 141 | 1582 | 1172 | 1768 | 1582 | 8 |
| Elevation (DGPS[c]) | | | | | | | | | | | | | |
| Elevation | m | 8737 | 214.3 | 205.6 | 220.9 | 3.5 | 2 | 4992 | 126.5 | 117.8 | 137.1 | 4.0 | 3 |
| Soil electrical conductivity | | | | | | | | | | | | | |
| $EC_{a0\text{-}0.3m}$[d] | mS m$^{-1}$ | 9502 | 1.7 | 0.3 | 8.2 | 1.1 | 63 | 7291 | 2.9 | 1.1 | 7.5 | 0.8 | 29 |
| $EC_{a0\text{-}1m}$[e] | mS m$^{-1}$ | 8704 | 2.5 | 0.4 | 18.1 | 1.7 | 68 | 7094 | 4.0 | 1.5 | 8.5 | 1.1 | 27 |
| Tuber yield | | | | | | | | | | | | | |
| $Yield_{2013}$ | Mg ha$^{-1}$ | 16482 | 40.5 | 6.5 | 70.0 | 10.4 | 26 | [f]n.a. | n.a. | n.a. | n.a. | n.a. | n.a. |
| $Yield_{2014}$ | Mg ha$^{-1}$ | 16586 | 36.9 | 3.0 | 62.5 | 10.3 | 28 | 31722 | 39.0 | 0.1 | 81.4 | 11.9 | 32 |
| $Yield_{2016}$ | Mg ha$^{-1}$ | 14602 | 34.2 | 15.7 | 55.9 | 7.3 | 21 | 27787 | 41.9 | 6.3 | 77.5 | 9.6 | 23 |

**Note:**
[a]STD, standard deviation,

[b]CV, coefficient of variation;
[c]DGPS, differential global positioning system;
[d]$EC_{a0\text{-}0.3m}$, shallow measurements of soil $EC_a$ measured at 0-0.3 m;
[e]$EC_{a0\text{-}1m}$, deep measurements of soil $EC_a$ measured at 0-1.0 m;
[f]n.a., not available.

Table 2. Geostatistical parameters of the soil physicochemical properties for Field 1 and Field 2

| | ---Field 1--- | | | | ---Field 2--- | | | |
|---|---|---|---|---|---|---|---|---|
| | Model | Nugget ratio[a], % | Range[b] | $R^2_{CV}$[c] | Model | Nugget ratio, % | Range | $R^2_{CV}$ |
| Particle size | | | | | | | | |
| Clay | Gauss | 0.2 | 261 | 0.83 | P.N. | 100.0 | - | - |
| Silt | Sph | 20.6 | 176 | 0.58 | Gauss | 14.0 | 159 | 0.10 |
| Sand | Gauss | 15.7 | 175 | 0.74 | Exp | 16.4 | 152 | 0.09 |
| Gravel | Sph | 33.8 | 175 | 0.49 | Exp | 44.9 | 232 | 0.21 |
| Soil moisture | Gauss | 46.4 | 260 | 0.54 | Exp | 10.7 | 45 | 0.18 |
| Total carbon | Sph | 54.1 | 157 | 0.32 | Exp | 33.1 | 237 | 0.41 |
| Total nitrogen | Exp | 49.9 | 447 | 0.29 | Exp | 37.0 | 242 | 0.38 |
| Soil $pH_{water}$ | Sph | 6.1 | 201 | 0.61 | Exp | 41.1 | 219 | 0.27 |
| Mehlich-3 extractable elements | | | | | | | | |
| P | Gauss | 29.2 | 294 | 0.61 | Gauss | 22.1 | 284 | 0.62 |
| K | P.N. | 100.0 | n.a. | n.a. | Exp | 47.4 | 432 | 0.26 |
| Ca | Gauss | 25.2 | 150 | 0.58 | Gauss | 15.3 | 265 | 0.57 |
| Mg | Exp | 8.4 | 332 | 0.61 | Exp | 13.8 | 216 | 0.53 |
| Al | Exp | 33.8 | 228 | 0.27 | Exp | 25.5 | 241 | 0.53 |
| Elevation (DGPS[d]) | | | | | | | | |
| Elevation | Gauss | 0.05 | 472 | 0.99 | Gauss | 2 | 389 | 0.98 |
| Soil electrical conductivity | | | | | | | | |
| $EC_{a0\text{-}0.3m}$[e] | Exp | 3.0 | 57 | 0.96 | Exp | 8.9 | 66 | 0.80 |
| $EC_{a0\text{-}1m}$[f] | Exp | 8.3 | 59 | 0.94 | Exp | 15.0 | 95 | 0.81 |
| Tuber yield | | | | | | | | |
| $Yield_{2013}$ | Exp | 19.2 | 39 | 0.82 | n.a.[g] | n.a. | n.a. | n.a. |
| $Yield_{2014}$ | Exp | 1.2 | 39 | 0.92 | Exp | 27.8 | 29 | 0.65 |
| $Yield_{2016}$ | Exp | 11.4 | 29 | 0.82 | Sph | 10.2 | 13 | 0.84 |

**Note:** Gauss, Gaussian; Sph, spherical; Exp, exponential; P.N., pure nugget;
[a]Nugget ratio, (nugget semivariance/total semivariance) × 100;
[b]Range, distance at which a semivariance becomes constant;
[c]$R^2_{CV}$, coefficient of determination of cross-validation;
[d]DGPS, differential global positioning system;
[e]$EC_{a0\text{-}0.3m}$, shallow measurements of soil $EC_a$ measured at 0-0.3 m;
[f]$EC_{a0\text{-}1m}$, deep measurements of soil $EC_a$ measured at 0-1.0 m;
[g]n.a., not available.

Table 3. Pearson correlation coefficients (r) of the soil electrical conductivity (Veris®) with soil properties, elevation (DGPS) and tuber yield (yield monitor) at Field 1 and Field 2

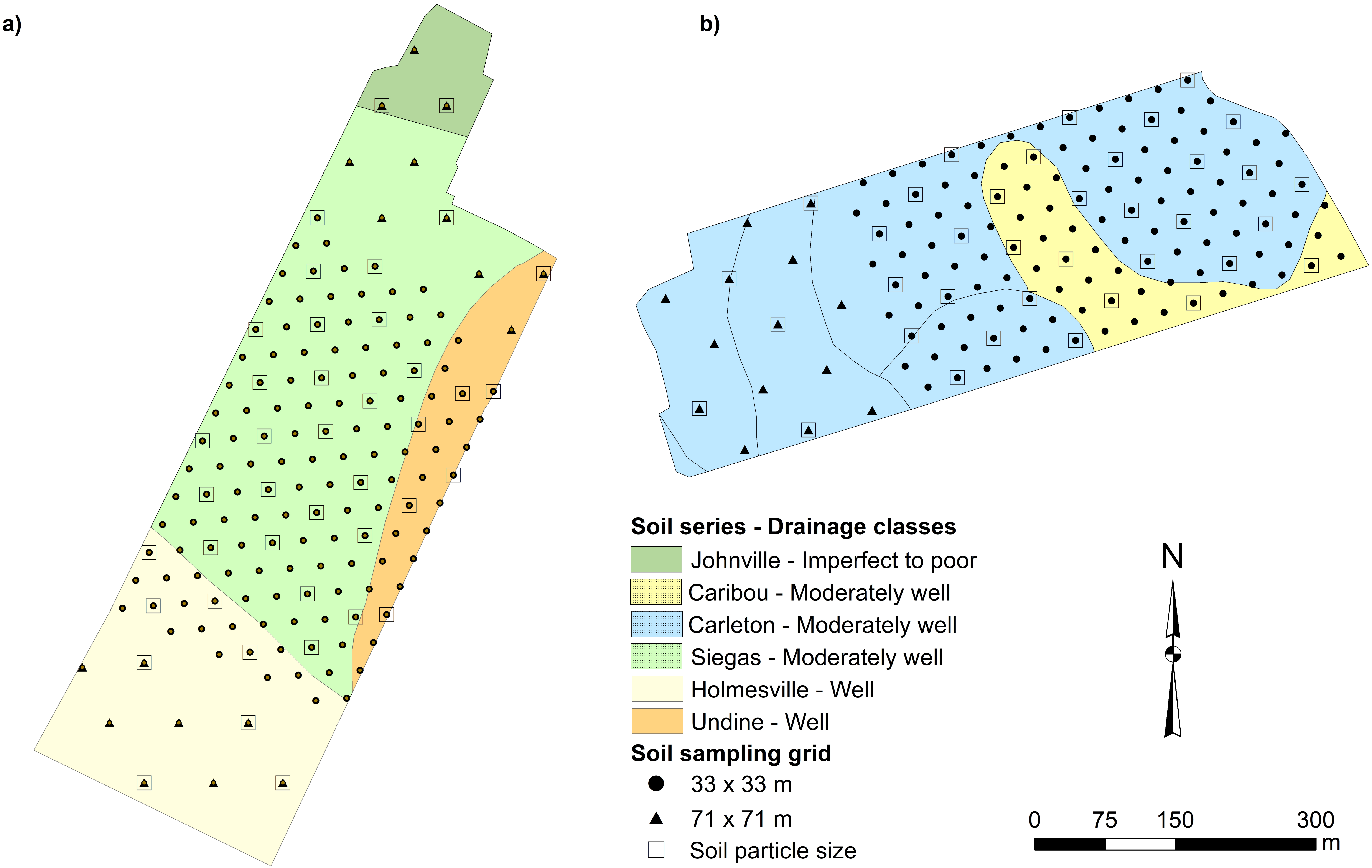
| | -------Field 1------- | | -------Field 2------- | |
|---|---|---|---|---|
| | $EC_{a0\text{-}0.3m}$[a] | $EC_{a0\text{-}1m}$[b] | $EC_{a0\text{-}0.3m}$ | $EC_{a0\text{-}1m}$ |
| Particle size | | | | |
| Clay | 0.81 *** | 0.85 *** | -0.22 ns | -0.19 ns |
| Silt | 0.61 *** | 0.60 *** | 0.16 ns | 0.16 ns |
| Sand | -0.71 *** | -0.71 *** | -0.04 ns | -0.06 ns |
| Gravel | -0.61 *** | -0.60 *** | -0.04 ns | 0.02 ns |
| Soil moisture | 0.58 *** | 0.54 *** | 0.07 ns | 0.01 ns |
| Total carbon | 0.25 ** | 0.24 ** | 0.20 * | 0.20 * |
| Total nitrogen | 0.23 ** | 0.23 ** | 0.27 *** | 0.29 *** |
| Soil $pH_{water}$ | 0.36 *** | 0.30 *** | 0.34 *** | 0.29 *** |
| Mehlich-3 extractable elements | | | | |
| P | -0.48 *** | -0.46 *** | -0.31 *** | -0.39 *** |
| K | 0.26 ** | 0.20 * | -0.14 ns | -0.22 ** |
| Ca | 0.48 *** | 0.43 *** | 0.72 *** | 0.70 *** |
| Mg | 0.53 *** | 0.49 *** | 0.07 ns | -0.02 ns |
| Al | -0.66 *** | -0.64 *** | -0.71 *** | -0.73 *** |
| Elevation (DGPS[c]) | | | | |
| Elevation | -0.13 ns | -0.15 ns | -0.31 ** | -0.38 *** |
| Tuber yield | | | | |
| $Yield_{2013}$ | -0.44 *** | -0.41 *** | n.a.[d] | n.a. |
| $Yield_{2014}$ | -0.30 *** | -0.30 *** | -0.02 ns | -0.05 ns |
| $Yield_{2016}$ | -0.32 *** | -0.28 *** | -0.08 ns | -0.08 ns |

**Note:** *, significant ρ <0.05; **, significant ρ <0.01; ***, significant ρ <0.001 and ns, non-significant
[a]$EC_{a0\text{-}0.3m}$, shallow measurements of soil $EC_a$ measured at 0-0.3 m;
[b]$EC_{a0\text{-}1m}$, deep measurements of soil $EC_a$ measured at 0-1.0 m;
[c]DGPS, differential global positioning system;
[d]n.a., not available.

Table 4. Comparison of soil electrical conductivity ($EC_a$) into two management zones at Field 1 and Field 2

| | Unit | --------Field 1-------- | | --------Field 2-------- | |
|---|---|---|---|---|---|
| | | High $EC_a$ zone | Low $EC_a$ zone | High $EC_a$ zone | Low $EC_a$ zone |
| Soil particle size | | | | | |
| Clay | g kg$^{-1}$ | 191 a | 142 b | 159 a | 162 a |
| Silt | g kg$^{-1}$ | 561 a | 495 b | 488 a | 483 a |
| Sand | g kg$^{-1}$ | 248 b | 363 a | 353 a | 355 a |
| Gravel | g kg$^{-1}$ | 158 b | 254 a | 253 a | 249 a |
| Soil moisture | % | 28.5 a | 23.5 b | 23.8 a | 24 a |
| Total carbon | mg kg$^{-1}$ | 2.2 a | 2.0 a | 2.3 a | 2.3 a |
| Total nitrogen | mg kg$^{-1}$ | 0.2 a | 0.1 a | 0.23 a | 0.22 b |
| $pH_{water}$ | | 5.9 a | 5.8 a | 5.8 a | 5.7 b |
| Mehlich-3 extractable elements | | | | | |
| P | mg kg$^{-1}$ | 188 b | 249 a | 193 b | 226 a |
| K | mg kg$^{-1}$ | 195 a | 181 a | 176 b | 201 a |
| Ca | mg kg$^{-1}$ | 956 a | 778 b | 1311 a | 981 a |
| Mg | mg kg$^{-1}$ | 148 a | 109 b | 166 a | 168 a |
| Al | mg kg$^{-1}$ | 1681 b | 1842 a | 1497 b | 1636 a |
| Elevation (DGPS[a]) | | | | | |
| Elevation | m | 216 b | 217 a | 125 b | 127 a |
| Soil electrical conductivity | | | | | |
| $EC_{a0\text{-}0.3m}$[b] | mS m$^{-1}$ | 3.5 a | 1.2 b | 3.6 a | 2.5 b |
| $EC_{a0\text{-}1m}$[c] | mS m$^{-1}$ | 5.1 a | 1.6 b | 5.0 a | 3.4 b |
| Tuber yield | | | | | |
| $Yield_{2013}$ | Mg ha$^{-1}$ | 31.9 b | 41.2 a | n.a.[d] | n.a. |
| $Yield_{2014}$ | Mg ha$^{-1}$ | 30.5 b | 37.4 a | 37.3 a | 40.0 a |
| $Yield_{2016}$ | Mg ha$^{-1}$ | 30.9 b | 35.0 a | 40.8 a | 42.4 a |

**Note:** Means followed by the same letter are not significantly different at 5% significance level according to LSD test;
[a]DGPS, differential global positioning system;
[b]$EC_{a0\text{-}0.3m}$, shallow measurements of soil $EC_a$ measured at 0-0.3 m;
[c]$EC_{a0\text{-}1m}$, deep measurements of soil $EC_a$ measured at 0-1.0 m.
[d]n.a., not available.


a)
b)
Soil series - Drainage classes
Johnville - Imperfect to poor
Caribou - Moderately well
Carleton - Moderately well
Siegas - Moderately well
Holmesville - Well
Undine - Well
Soil sampling grid
33 x 33 m
71 x 71 m
Soil particle size
N
0
75
150
300
m

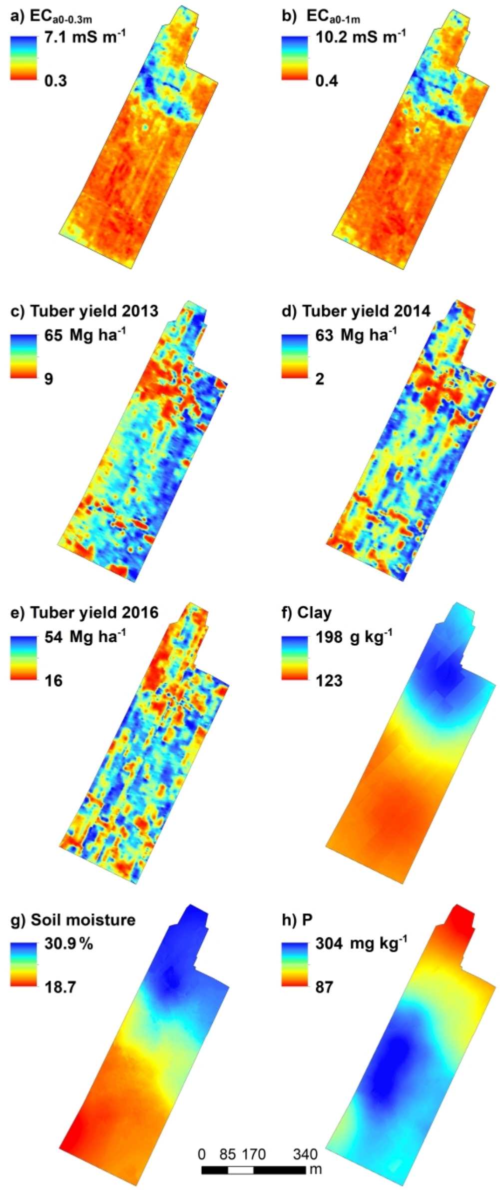



Fig. 2. Kriging maps of the apparent soil electrical conductivity (EC$_a$) measured a) EC$_{a0-0.3m}$ and b) EC$_{a0-1m}$; tuber yield c) 2013, d) 2014 and e) 2016; and f) clay, g) soil moisture and h) Mehlich-3 extractable P of Field 1.

254x558mm (300 x 300 DPI)

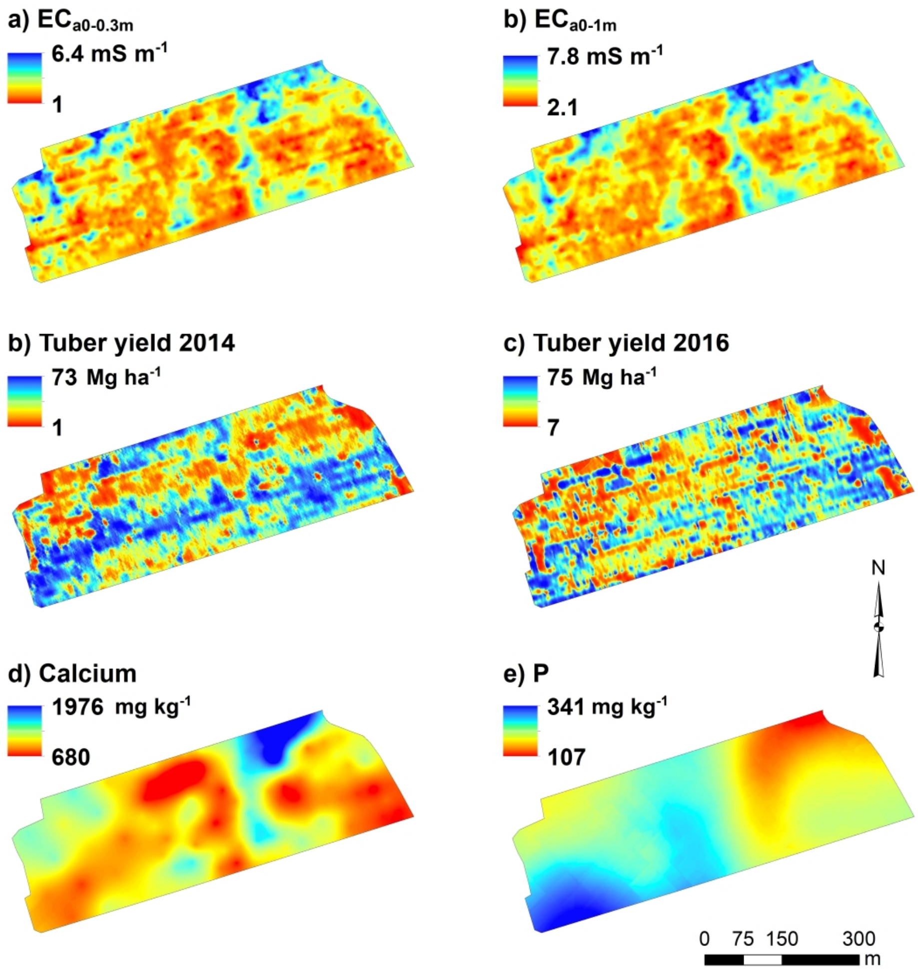



Fig. 3. Kriging maps of the apparent soil electrical conductivity ($EC_a$) a) $EC_{a0\text{-}0.3m}$ and b) $EC_{a0\text{-}1m}$; tuber yield c) 2014, and d) 2016; and Mehlich-3 extractable e) Ca and f) P of Field 2.

431x431mm (300 x 300 DPI)

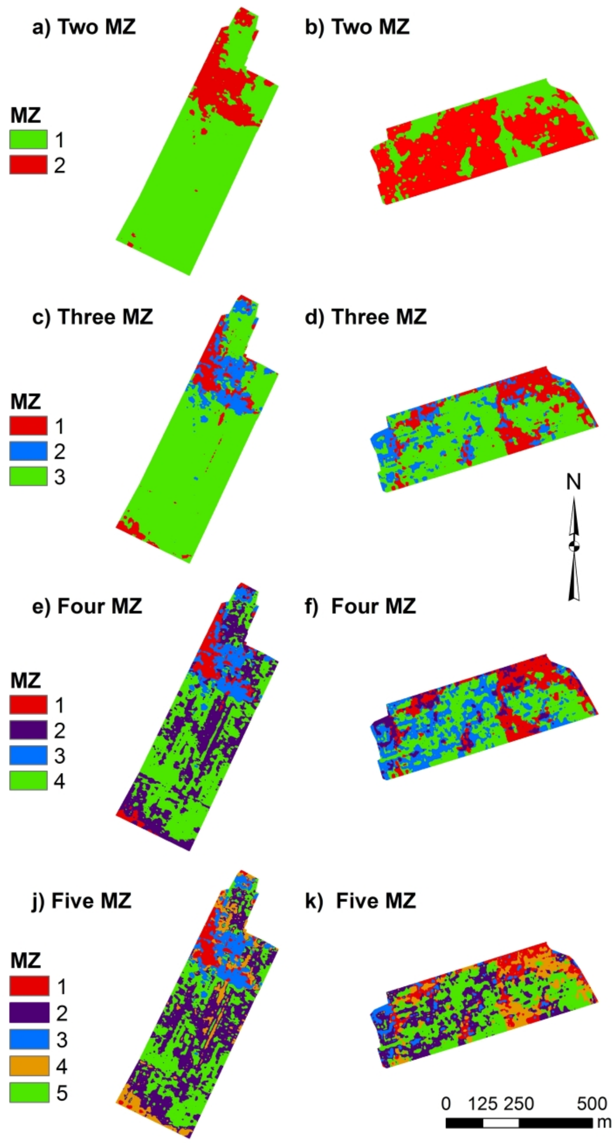



Fig. 4. Management zones (MZs) delineated using the Veris® $EC_{a0-0.3m}$ and $EC_{a0-1m}$ kriged data matrix with the fuzzy k-means analysis with no-spatial constraint of proximity at the field 1 (a-c-e-j) and field 2 (b-d-f-k).

431x667mm (300 x 300 DPI)

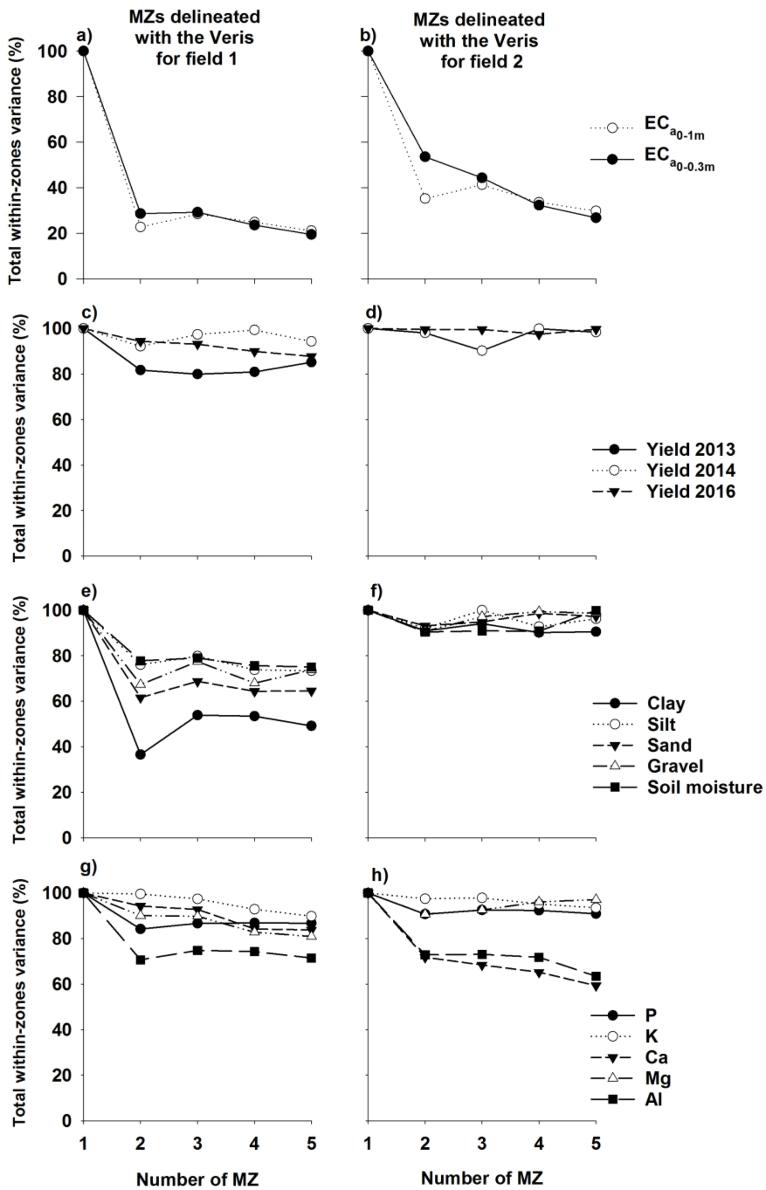



Fig 5. Decrease of the total within-zone variance of a-b) soil electrical conductivity using the Veris®, c-d) yields 2013, 2014 and 2016 from yield monitor, e-f) soil particles sizes (clay, silt, sand), gravel and soil moisture, g-h) Mehlich-3 extractable elements (P, K, Ca, Mg and Al) into management zone (MZs) based on the MZs delineated with the Veris® at the field 1 and field 2, respectively.

215x278mm (300 x 300 DPI)