RELATIONSHIP OF SOIL PROPERTIES TO APPARENT GROUND CONDUCTIVITY IN WILD BLUEBERRY FIELDS

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ABSTRACT

One of the fundamental deficiencies in high value crops is the lack of detailed, up-to-date and pertinent geo-referenced soil information for site-specific crop management to improve productivity. This experiment was designed to estimate and map soil properties rapidly and reliably using an electromagnetic induction (EMI) method. Two wild blueberry (Vaccinium angustifolium Ait) fields were selected in central Nova Scotia. A grid pattern of sampling points (20 x 20 m) was established (n=50) at each experimental site. Soil samples were collected from established grid points at 0 to 15, 15 to 45, 45 to 75 cm depth intervals below the soil surface and analyzed for soil texture, gravel (coarse aggregate), organic matter content (SOM), volumetric moisture content (Θ_v), pH and electrical conductivity (EC). The EC_a was measured and recorded with DualEM-2 at the same selected grid points to calibrate the Dual EM-2 for developing relationships and predicting soil properties. Comprehensive surveys were conducted in those fields to measure the ground conductivity for estimation of soil properties in real-time using DualEM and a differential global positioning system (DGPS). Regression analysis showed that EC_a was significantly correlated ($p < 0.01$) with clay, SOM, EC and Θ_v. The maps were developed for predicted soil parameters from ground conductivity survey data using kriging interpolation in ArcGIS 10 (ESRI, Redlands, CA) software. The maps showed substantial variation in selected soil properties within both fields. This information could be helpful to develop variable rate technologies to increase crop productivity and mitigate environmental risks.

Keywords: Apparent ground conductivity, EMI, DGPS, GIS, DualEM, soil properties

INTRODUCTION

Traditionally, farm managers consider fields as uniform and thus, fertilizers, pesticides, irrigation, seed rate etc., are applied without taking into account spatial variations in field characteristics. When fields are managed uniformly, it results in over-application or under-application in some areas within a field. Under treated zones do not reach optimum levels of exploitation whereas the over-treated ones there may pose risk of environmental pollution and an increase in costs (Bouma, 1997).

Features and inconsistency of soil parameters have been extensively examined in precision agriculture research and application (Hache, 2003). Different sensing technologies are under development and others are already being put on in order to gather data from the soils precisely. Soil properties differ from one study to another depending on the accessibility of sources for investigation, purposes, and awareness of field variability (Hache, 2003).

Soil moisture content states to the quantity of water held by the soil (Hache, 2003). Soil is a spongy medium, which contains different sizes of pores and the water that enters the soil either remains in the pores, percolates through them (Baver, 1961) or evaporates (Havlin et al., 2005). Organic matter presence in the soil aids to retain moisture content (Baver, 1961). Deficiency of moisture may cause a reduction in subsequent growth or may even be deadly during periods of active growth (Black, 1957). Plant growth is basically an increase in volume resulting from the creation and expansion of cells and if there is deficiency of water the growth of shoot parts of plants is limited (Black, 1957). Waterlogging can also disturb plant growth and yield, given that water moves air from the pore spaces, inducing a stop in growth of roots resulting in a severe drop in the uptake and transport of mineral nutrients (Marschner, 1995).

Soil organic matter is the most critical soil property because of its effect on many biological, chemical and physical properties intrinsic in a productive soil (Havlin et al., 2005), and therefore its contribution to plant growth and improvement (Tatabatai, 1996). Organic matter in soils has two major functions: (a) a nutritional one causing from mineralization of organic nitrogen, sulphur and phosphorus (Tatabatai, 1996; Mengel and Kirkby, 2001) and (b) a physical one linking to the upgrading of physical properties (Mengel and Kirkby, 2001). It also gives a pH buffering action retaining a uniform soil pH (Havlin et al., 2005).

Texture defines the soil's internal geometry and porosity, its connections with fluids and solutes (Hillel, 1998). This time-invariant static parameter has a direct effect on the nature of the dynamic soil parameters. The most important dynamic soil property influenced by the time-invariant static soil physical properties is soil moisture content. Soil moisture status is serious to plant growth, crop quality, chemical fate and transport, and microbial processes (Abdu, 2009). Soil structure and texture are important properties monitoring the hydraulic conductivity and infiltration capacity of a soil system.

pH is a degree of soil acidity and a main chemical property because it disturbs the accessibility of nutrients to plants and the activity of microorganisms in the soil (Hache, 2003). Reduction in soil pH is affected by numerous factors including the use of commercial fertilizers, especially NH_4^+ sources that make H^+ during nitrification and decomposition of organic residues (Havlin et al., 2005).

Electrical conductivity is a major soil parameter as it correlates to soil parameters influencing crop productivity (PPI, 1996). Some grain crops (e.g., rice, wheat, corn and barley) are relatively salt tolerant at germination and maturity but are very sensitive during early seedling and, in some cases, vegetative growth stages. In contrast, sweet potato, safflower, soybean, and many bean crops are sensitive during germination. This result depends on variety, especially with soybean (Marshner, 1995; Havlin et al., 2005). In precision agriculture some devices are being developed to record this soil parameter on real-time.

Soils are varied, and wide heterogeneity can occur even in fields that seem uniform (Havlin et al., 2005; Farooque et al., 2011, 2012). The first step in precision agriculture is to measure important factors that specify or influence the efficiency of the growing crop (Blackmore et al., 2002). Intensive soil sampling is the most valuable way to quantify variability (Havlin et al., 2005), but it demands human effort and time. Therefore, there exists the need for new methods that enable rapid measurement of soil parameters. The objective of this study was to develop relationship between selected soil properties and EC_a for predicting those soil properties in a rapid and non-destructive manner.

MATERIALS AND METHODS

Two wild blueberry fields in central Nova Scotia were selected to develop relationships between soil properties and EC_a. A grid pattern of sampling points was established at both experimental sites based on the range of influence of semivariograms to collect soil samples (Fig. 1). The soil samples were analyzed for SOM, texture, θ_v, pH, and EC using standard methods. Soil texture and pH were measured once at the onset of the experiment since these parameters do not tend to change significantly in two monitoring years. Other soil properties were determined twice during the study. The ground conductivity values (HCP and PRP) using DualEM were recorded at each sampling point along with soil samples. The coordinates of each sampling point were recorded with a Real-time kinematics (RTK) GPS. The boundary of the fields was also marked using a RTK-GPS. Samples were collected at 0 to 15, 15 to 45, and 45 to 75 cm soil depths. These sampling depths were selected because we were most appealed in

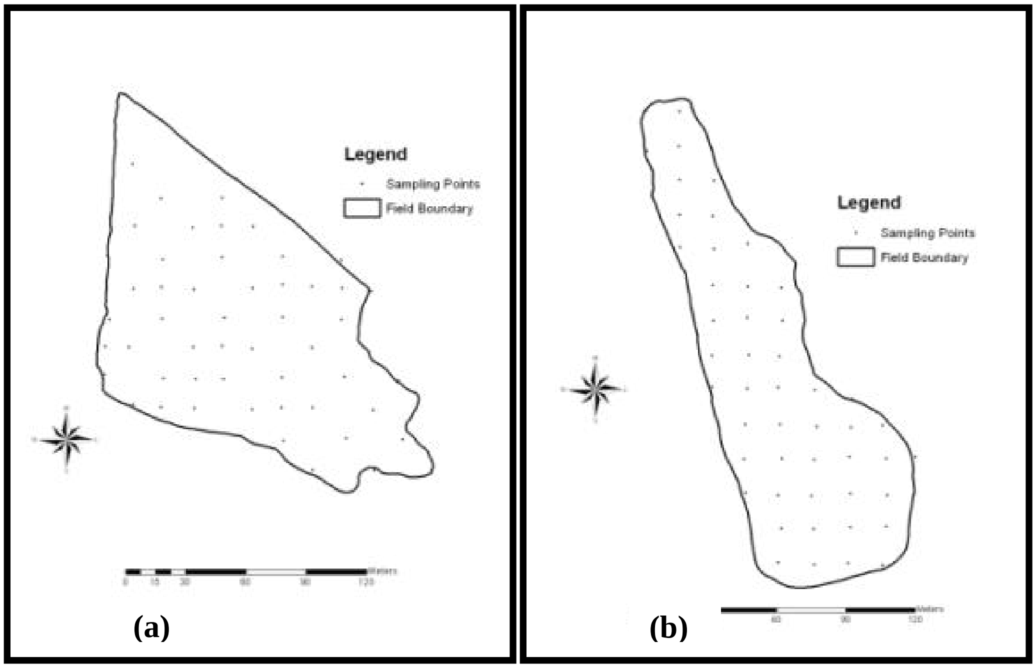


Fig. 1. Field layout for selected fields (a) North River (b) Carmel Site

soil properties associated with the concept of soil quality, and these depths coincide with many previous similar investigations (Wander and Bollero, 1999; Brejda et al., 2000; Kettler et al., 2000; Johnson et al., 2001). The samples were air dried and ground to pass a sieve with 2 mm openings. Elevation was also measured and mapped once using RTK-GPS.

STATISTICAL ANALYSIS

Means, minimums, maximums, medians, skewness, and coefficient of variations (CVs) of selected soil properties were calculated using Minitab 16 statistical software. Data normality was tested using Anderson-Darling (A-D) test using Minitab 16 statistical software at a significance level of 5%. Pearson correlation coefficients were calculated for all pairs of soil property and EC_a data.

Regression models were derived to calibrate the DualEM-2, and to predict soil properties using EC_a in each field separately (n = 50). Transformed, linear, logarithmic, quadratic, and cubic models of EC_a were evaluated to find the best-fitting models. Soil samples (n=20) were obtained from the same field during the summer of 2011, analyzed in the laboratory using the same procedures. The calibration equations of first year for each selected field were used to predict soil properties in second year data for validation. Calibration and validation of regression equations/models, coefficient of determination (R^2) and root mean square (RMSE) were calculated using Minitab 16 statistical software.

RESULTS AND DISCUSSION

Sampling Strategy

The apparent ground conductivity survey conducted by DualEM-2 was utilized to develop a sampling strategy to collect soil samples from both fields. The semivariogram for EC_a data were developed and spherical models of semivariogram were found to best fit the data set in the fields. The grid size to collect soil samples was then established based on the range of the influence from semivariogram which was found to be around 60 m for both blueberry fields (Fig. 2 and 3). The grid pattern for sampling is one third or half of the range of variability (Kerry and Oliver, 2003; Farooque et al., 2012). Based on the range of the variability, a grid size of 20 x 20 m was selected for sampling.

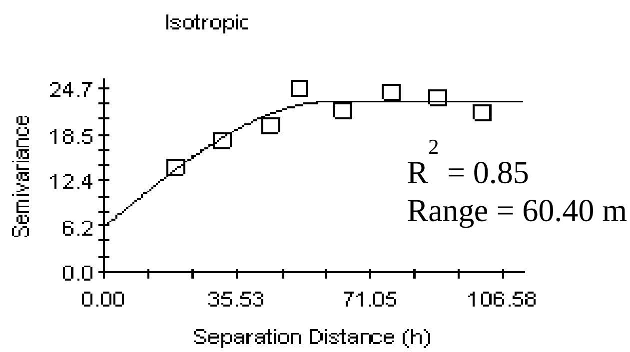


Fig. 2. Semivariogram of EC_a at North River Site

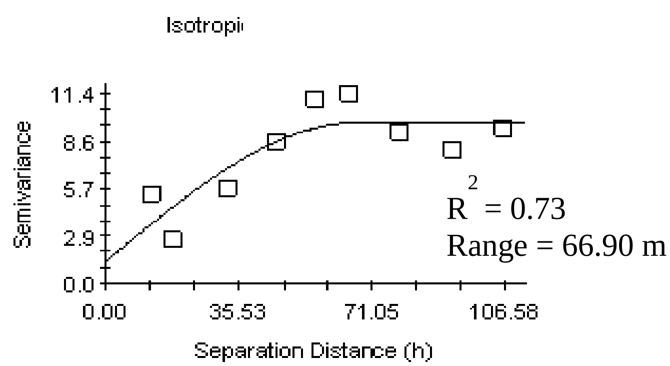


Fig. 3. Semivariogram of EC_a at Carmel Site

Descriptive Statistics of Soil Properties

Soil properties at the deepest sampling depth (45-75 cm) were generally more normally distributed than at the shallower sampling depths (Table 1) (Due to space constraint, the results of North River will be presented).Similarly, most soil property values at the deepest depth were noticeably different from the shallower sampling depths. Mean values of clay content and θ_v at the 45 to 75

Table 1. Descriptive statistics of soil properties at North River Site.

Properties	n	Depth†	Min.	Max.	Mean	CV (%)	Skewness
Clay, %	50	1	0.0	20.0	7.8	78.0	0.40
	35	2	0.0	20.0	13.0	49.0	-0.50
	7	3	12.0	30.0	17.0	33.0	2.10
Silt, %	50	1	15.0	43.0	28.0	25.0	0.20
	35	2	12.0	44.0	27.0	24.0	0.10
	7	3	20.0	38.0	30.0	25.0	-0.30
Sand, %	50	1	44.0	84.0	64.0	16.0	-0.01
	35	2	38.0	80.0	60.0	17.0	-0.07
	7	3	32.0	65.0	52.0	23.0	-0.70
Gravel, %	50	1	33.0	73.0	53.0	17.0	-0.20
	35	2	32.0	79.0	56.0	17.0	-0.20
	7	3	26.0	52.0	39.0	29.0	0.06
SOM, %	50	1	4.4	13.0	8.4	22.0	0.50
	35	2	4.4	11.0	6.6	23.0	0.90
	7	3	4.0	8.0	5.2	25.0	1.80
θ_v, $m^3 m^{-3}$	50	1	5.9	35.0	22.0	31.0	-0.20
	35	2	6.2	32.0	24.0	29.0	0.40
	7	3	8.4	37.0	29.0	26.0	1.50
EC, μS	50	1	36.0	103.0	54.0	24.0	2.10
cm^{-1}	35	2	37.0	180.0	55.0	47.0	3.80
	7	3	37.0	55.0	45.0	16.0	0.30
	50	1	5.0	6.2	5.6	10.0	3.10
pH	35	2	5.2	6.5	5.6	4.5	1.60
	7	3	5.5	6.6	5.8	6.9	2.30
	50		0.1	21.0	6.3	60.0	1.70
PRP, mS m^{-1}	50		0.1	20.0	6.2	76.0	1.00
HCP, mS m^{-1}							

† 1, 0 to 15 cm sampling depth; 2, 15 to 45 cm sampling depth; 3, 45 to 75 cm sampling depth.

Note: Clay, silt, sand, SOM, EC, pH, and θ_v at 2nd and 3rd sampling depth were measured once in June, 2010. θ_v at 1st sampling depth was measured bi-weekly from June to October, 2010.

cm sampling depth were higher than at shallower depths (Table 1). Clay content at the deepest depth was more than twice that of the shallower sampling depths. The proportion of the sand and SOM were clearly higher at the 0-15 cm depth than the deeper sampling depths (Table 1).

Differences between the shallow sampling depth and the deeper sampling depths can be recognized to the following factors. First, mowing operations are necessary management practices in wild blueberry fields to improve crop production. Consequently, organic matter from plant residue assimilation as well as fertilizer amendments was mostly stratified within the surface 15 cm of soil. Second, the 2nd and 3rd sampling depths were twice the thickness of the first sampling depth. Therefore, these deeper sampling depths had a greater possibility of including multiple horizons compared with the shallowest sampling depth. This second point is reinforced by the generally higher CV of most soil properties at the 15 to 45 and 45 to 75 cm depth samples compared with the shallowest depth (Table 1) (Jung et al., 2005). The HCP and PRP were normally distributed for all four fields (Table 1). HCP produced higher values compared with PRP at Carmel Site.

Soil Properties Correlated and Regressed to EC_a

Table 2. Correlation coefficients among soil properties and EC_a at North River Site.

Properties	n	Depth†	PRP	HCP
Clay, %	50	1	0.24*	0.36*
	35	2		0.64**
	7	3	0.64**	0.26*
Silt, %	50	1	0.68**	0.44*
	35	2	0.62**	0.30*
	7	3	0.26*	0.14
Sand, %	50	1	0.76*	-
	35	2	-0.56**	0.52**
	7	3	-0.58*	-0.58*
SOM, %	50	1	-0.82**	-0.02
	35	2	0.26*	0.36*
	7	3	0.32*	0.23*
θ_v, $m^3 m^{-3}$	50	1	0.58*	0.80**
	35	2		0.56***
	7	3	0.63***	0.59**
EC, $\mu S\ cm^{-1}$	50	1	0.67**	
	35	2		0.65***
	7	3	0.72***	0.39*
	50	1	0.37*	0.57**
pH	35	2		0.62**
	7	3	0.66***	-0.06
			0.82**	0.42
			0.00	-0.48
			0.60	

	-0.06

† 1, 0 to 15 cm sampling depth; 2, 15 to 45 cm sampling depth; 3, 45 to 75 cm sampling depth

* Significant at the 0.05 probability level

** Significant at the 0.01 probability level

*** Significant at the 0.001 probability level

The EC_a was significantly positively correlated with clay content with correlation values greater at the two deep sampling depths but low correlation value was observed. The low value of correlation is because of soil volume measured with DualEM-2 is larger than that used for soil sampling. These results were supported by the findings of Mueller et al. (2003).

Soil texture in the soil profile can be an important factor contributing to EC_a (Sudduth et al., 2003, 2005). Physical contact between soil particles allows for higher electrical conductivity and is known to be greater with clay than with sand- or silt-sized particles (Rhoades et al., 1976; Corwin and Lesch, 2003). Therefore, it is not surprising that correlations for clay are generally significant as compared to silt and sand contents.

The PRP component was generally more correlated at North River site as compared to HCP component (Table 2). It might be due to more rocky nature of soils at North River Site (Farooque, 2010). As the HCP has more sensing depth so the sand, underlying gravels and crystalline rocks at the deeper depths contribute to HCP resulting weak and non-significant correlation with soil properties. The positive significant correlation indicated higher values of EC_a in the area where soil parameters were higher and vice versa. It also showed that DualEM can be used to predict the soil properties in a rapid and non-destructive manner. Soil pH was generally not well correlated to EC_a in all sampling depths. θ_v was significantly positively correlated with EC_a at all three sampling depths. As would be expected, EC_a is directly related to θ_v and clay suggesting greater water holding capacity of fine clay particles. EC was also significantly correlated with EC_a and

Table 3. Calibration models using EC_a to predict soil properties at North River Site.

Depth†	Property	n	Model	R^2
1	Clay, %	50	3.4+3.80HCP-0.24HCP^2+0.005	0.46
1	Silt, %	50	HCP^3	0.70
1	Sand, %	50	25.3+1.80PRP+ 0.007PRP^2 -	0.61
1	SOM, %	50	0.003PRP^3	0.44
1	θ_v, m^3 m^{-3}	50	81.3-4.2PRP+0.24PRP^2 -	0.75
1	EC, µS m$^-$	50	0.006PRP^3	0.45
2	1	35	9.2+0.58HCP-	0.69
2	Clay, %	35	0.12HCP^2+0.004HCP^3	0.43
2	SOM, %	35	11.4+2.9PRP-0.05PRP^2-	0.73
2	θ_v, m^3 m^{-3}	35	0.008PRP^3	0.72
3	EC, µS m$^-$	7	47.7-0.4HCP+0.62HCP^2-	0.74

3	1	7	$0.03HCP^3$	0.88
3	Clay, %	7	$7.26+3.07HCP-0.8HCP^2 +0.04$	0.82
3	SOM, %	7	HCP^3	0.87
	θ_v, m^3 m^{-3}		2.98 – 23.6 PRP	
	EC, μS m^- 1		$13.8+2.2PRP-0.07PRP^2$- $0.008PRP^3$	
			$51.7-8.6PRP+1.9PRP^2$ - $0.12PRP^3$	
			$9.4+5.55HCP-0.63HCP^2$ -0.01 HCP^3	
			$2.7+3.56HCP-0.47HCP^2$ +0.09 HCP^3	
			$23.2+4.5HCP-1.6HCP^2$- $0.07HCP^3$	
			$58.5-6.4HCP-0.71HCP^2$ $+0.4HCP^3$	

† 1, 0 to 15 cm sampling depth; 2, 15 to 45 cm sampling depth; 3, 45 to 75 cm sampling depth

Table 4. Validation models using second year data at North River Site.

Depth †	Property	n	Model	R^2	RMSE
1	Clay, %	2	$3.9-0.89HCP+0.39HCP^2$-	0.4	2.6
1	Silt, %	0	$0.02\ HCP^3$	0	3.7
1	Sand, %	2	$32.9-2.98PRP+0.46PRP^2$	0.5	5.3
1	SOM,	0	$-0.02PRP^3$	5	0.7
1	%	2	$65.7+1.2PRP-0.33PRP^2$	0.4	3.0
1	θ_v, m^3	0	$+0.01PRP^3$	8	8.8
2	m^{-3}	2	8.9+0.40HCP-	0.3	2.1
2	EC, μS	0	$0.12HCP^2+0.01HCP^3$	9	0.5
2	m^{-1}	2	$10.9+2.9PRP-0.12PRP^2$-	0.7	3.4
2	Clay, %	0	$0.001PRP^3$	7	6.8
3	SOM,	2	$49.6+0.6HCP+0.52HCP^2$	0.4	2.0
3	%	0	$-0.04HCP^3$	1	0.4
3	θ_v, m^3	2	$8.8+1.8HCP-0.2HCP^2$	0.5	3.1
3	m^{-3}	0	$+0.006\ HCP^3$	5	5.2
	EC, μS	2	3.3+ 0.06 PRP-	0.3	
	m^{-1}	0	$0.002PRP^2$ $-PRP^3$	4	
	Clay, %	2	$15.9+3.6PRP-0.04PRP^2$-	0.6	
	SOM,	0	$0.01PRP^3$	8	
	%	2	$56.5-5.6PRP+1.5PRP^2$ -	0.5	
	θ_v, m^3	0	$0.06PRP^3$	9	
	m^{-3}	7	$7.0+6.4HCP-0.47HCP^2$ -	0.6	

EC, µS	7	$0.03\ HCP^3$	7
m^{-1}	7	$1.4+1.05HCP-0.3HCP^2$	0.8
	7	$+0.03\ HCP^3$	2
		$21.2+3.9HCP-1.9HCP^2-$	0.7
		$0.04HCP^3$	8
		$56.8-4.6HCP-0.37HCP^2$	0.8
		$+0.10HCP^3$	0

† 1, 0 to 15 cm sampling depth; 2, 15 to 45 cm sampling depth; 3, 45 to 75 cm sampling depth

higher values were observed in deeper depths as compared to the first sampling depth. Improved correlation was attributed in the deeper depths due to the fact that the clay contents were more in these two depths. Mowing affects the first layer, but does not seem to contribute other two layers. EC_a was significantly positively correlated with SOM and the correlation values for SOM were higher in deeper sampling depths (Table 2). The low correlation coefficient and R^2 values somewhere can be explained as follows:

- It is possible that EC_a is highly governed by soil property (Allred et al., 2005) not listed in Tables 1 and 2, and it is clear on the basis of results that EC_a is not affected by a single soil property but more than one soil properties contributing and influencing the EC_a measurements.
- The EC_a measured with EMI methods is an effective value for a large soil volume, and the overall properties of this large volume might not be well represented by a relatively small soil sample (Allred et al., 2005; Ristolainen et al., 2009).

Soil properties at each sampling depth were regressed against EC_a. Coefficients of determination (R^2) for linear and cubic regression model between EC_a and soil properties were calculated. Cubic regression models were found to be best fit to predict soil properties using EC_a. At the deepest sampling depth, predictions of many soil properties were improved using a cubic model of EC_a instead of the simple linear regression. For example, prediction of clay content in the surface sample at Carmel Site was greatly improved by using the cubic model (coefficient of determination improved from 43 to 78 %). In general, soil properties were better estimated from the EC_a cubic model. Using a similar approach, other transformations of EC_a were considered such as log, quadratic and exponential models. Regressions using these transformed terms almost always gave a coefficient of determination less than models using a cubic term.

The selected soil properties correlated significantly with EC_a in blueberry fields (R^2 varied from 0.43 to 0.90; $P < 0.05$) (Table 3). The correlation between actual and predicted soil properties (R^2 varied from 0.34 to 0.82; $P < 0.05$; RMSE ranged from 0.4 to 8.8) were also significant (Table 4). The root mean square error (RMSE) between observed and predicted soil properties, are shown for these selected models (Table 4). We conclude that the models derived from soil EC_a could provide reasonable estimates of these soil properties.

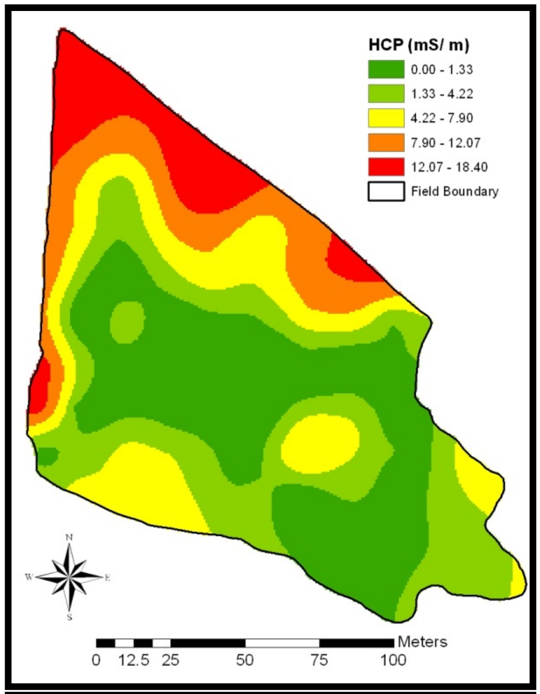
Interpolation and Mapping of Soil Properties

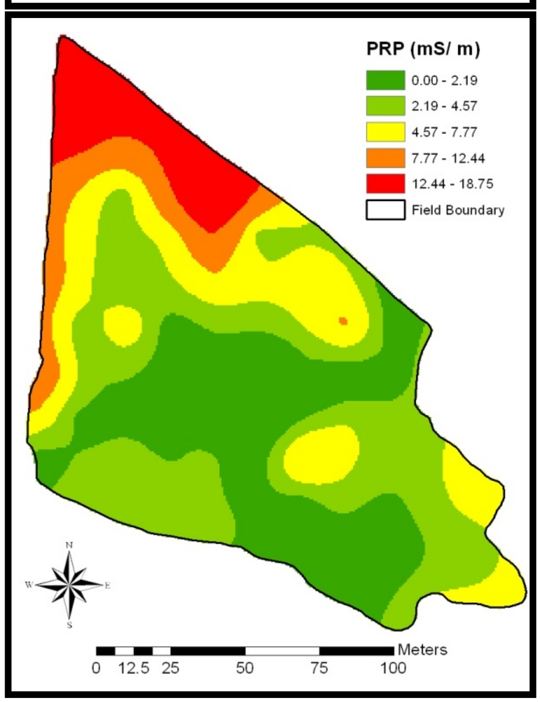
The soil properties, fields boundary and EC_a data were imported into ArcGIS 10 software and shape files were created for visual display of North River Site (Fig. 4 and 5).

GIS combined with geo-statistics was applied to analyze the spatial variability in soil properties for both fields. Soil parameters were interpolated using kriging combined with semivariogram parameters to generate detailed maps. The kriging interpolation is considered to be more accurate and reliable than other methods such as inverse distance weighting (IDW) or trend surface models (Mulla et al., 1992). The maps of soil properties were generated using ArcGIS 10 software at the same scale and equal number of classes in order to allow easier comparison.

The interpolated maps of HCP, PRP, θ_v, EC, SOM, sand, silt and clay at North River Site (Fig. 4 and 5) showed gradual spatial variability with significantly different values across the field. Spatial patterns of variation for PRP, HCP, θ_v, EC, silt and clay (Fig. 4 and 5) were almost similar, showing higher value in the northwest, north central region, and medium values were generally observed in the south eastern region of the field. The lower values were observed in the center of the field. The variation in soil properties might be due to the variation in elevation with the high values of these soil parameters in low lying areas and vice versa. These results were in agreement with the findings of Farooque et al. (2011).

The map of SOM (Fig. 5) at North River Site indicated the substantial variation across the field. The map of sand content showed lower values in the northwest and southeast region of the field. Higher values were observed in southwest, southeast and south central region indicating textural variation within field. It was observed that most of the crop areas were contained with more sand than clay for North River Site. The ground inspections revealed that the areas with higher clay content within field were weeds, bare spots and grasses. Overall the maps of soil properties indicated the large spatial variation within field.


HCP (mS/ m)
0.00 - 1.33
1.33 - 4.22
4.22 - 7.90
7.90 - 12.07
12.07 - 18.40
Field Boundary
N
W
E
S
Meters
0
12.5
25
50
75
100


PRP (mS/ m)
0.00 - 2.19
2.19 - 4.57
4.57 - 7.77
7.77 - 12.44
12.44 - 18.75
Field Boundary
N
W
E
S
Meters
0
12.5
25
50
75
100

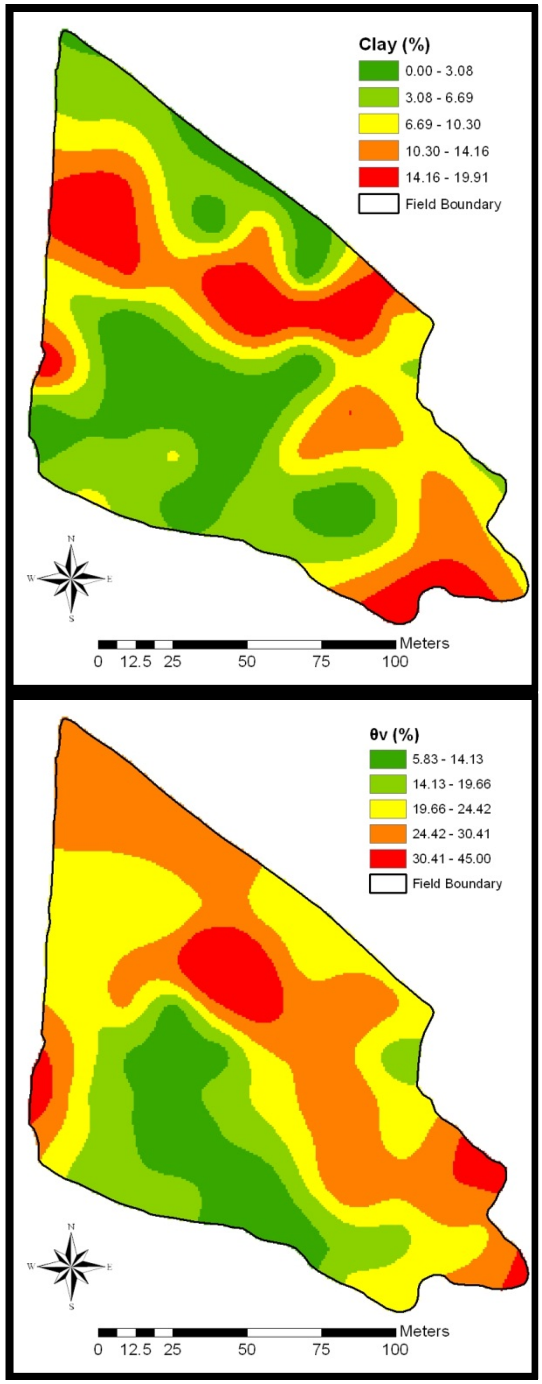
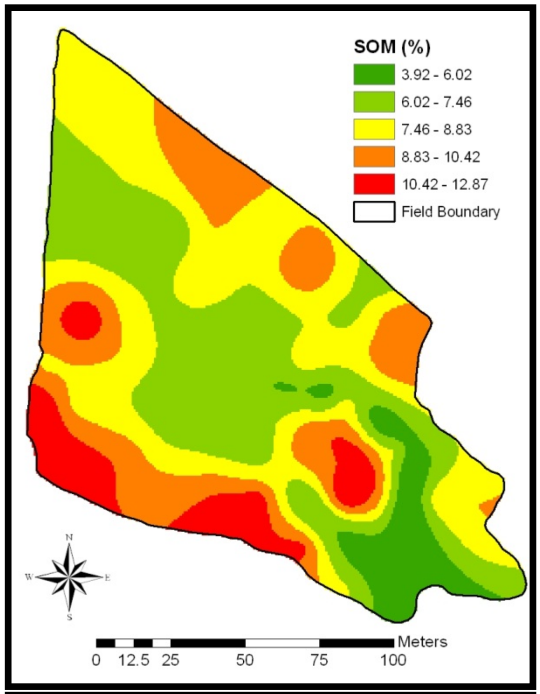
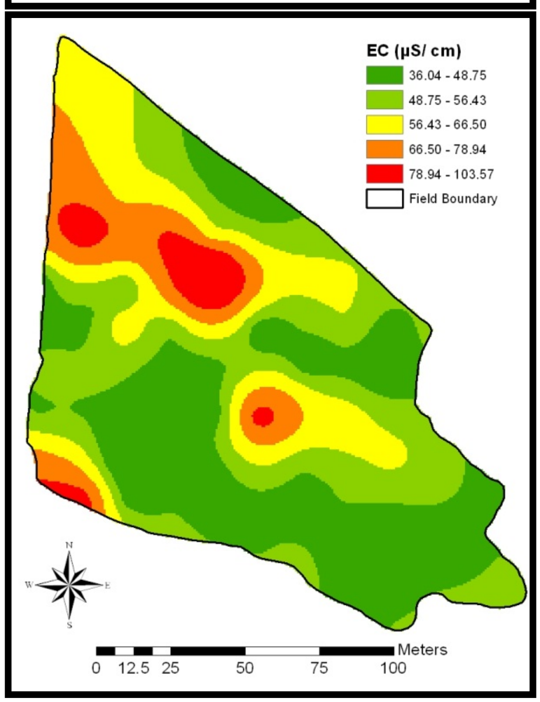


Fig. 4. Kriged maps of HCP, PRP, clay and θ_v for North River Site


SOM (%)
3.92 - 6.02
6.02 - 7.46
7.46 - 8.83
8.83 - 10.42
10.42 - 12.87
Field Boundary
N
W
E
S
Meters
0
12.5
25
50
75
100


EC (µS/ cm)
36.04 - 48.75
48.75 - 56.43
56.43 - 66.50
66.50 - 78.94
78.94 - 103.57
Field Boundary
N
W
E
S
Meters
0
12.5
25
50
75
100

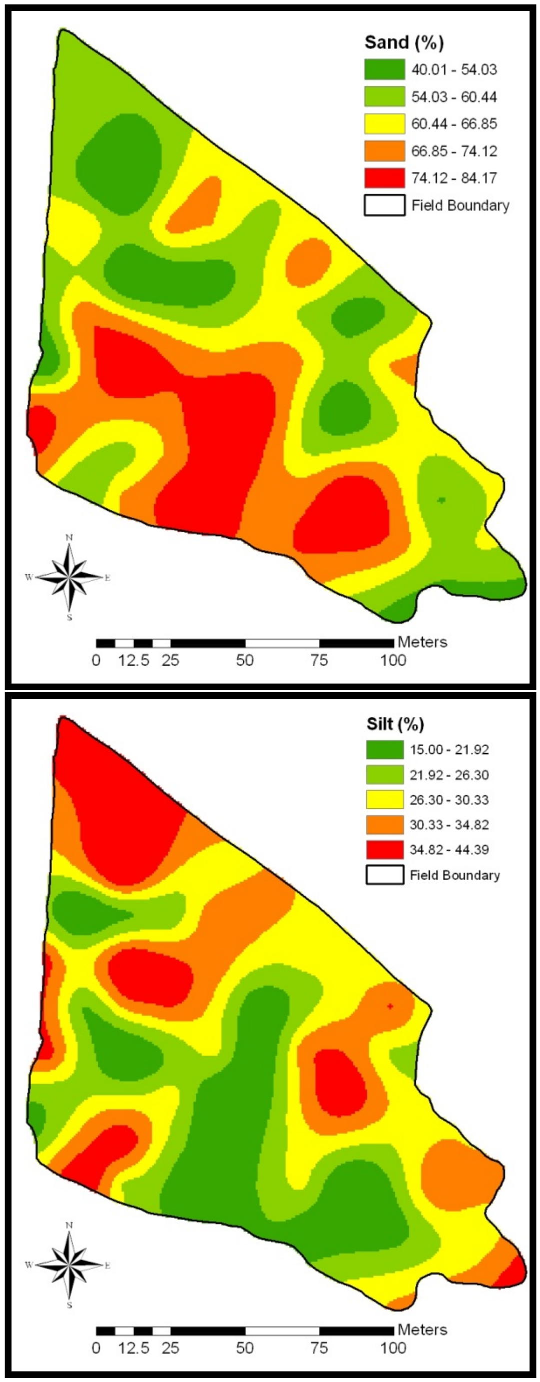


Fig. 5. Kriged maps of SOM, EC, sand and silt for North River Site

CONCLUSION

The procedure of measuring EC_a using DualEM provided the good relationship between EC_a and soil properties with the top 75 cm in the fields. The EC_a can provide important information for characterizing soil properties. In this study, we compared soil physical and chemical properties to EC_a during two years for two wild blueberry fields. We found that EC_a was significantly correlated to some soil properties (clay content, θ_v, SOM, and EC). Most regressions were significantly improved using a cubic term in EC_a, when using EC_a to predict soil properties. Approximately 60-90% of the variation in clay for the 45 to 75 cm depth could be predicted using EC_a. Regression models were validated with soil sample data set (n = 20). Soil properties were almost similar between measured and predicted soil properties.

This study showed that while soil properties varied greatly by depth, EC_a were significantly correlated with soil properties, especially some physical properties that impact crop yield. It was concluded that EC_a has the ability to serve as a soil quality indicator for soil productivity.

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