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Evaluation of DualEM-II sensor for soil moisture content estimation in the potato fields of Atlantic Canada

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Abstract: The conventional gravimetric methods of estimating soil moisture content (θ) are laborious, time-consuming, and destructive to agricultural fields. We evaluated the performance of DualEM-II sensor in non-destructive way of θ prediction and for predicting θ variations within potato fields in Atlantic Canada. Values of θ were measured from four potato fields in New Brunswick and Prince Edward Island using a pre-calibrated (R^2 = 0.98) time domain reflectometry (TDR) from root zone of potato tubers under grid sampling arrangements. Horizontal co-planar (HCP) and perpendicular co-planar (PRP) readings were taken using DualEM-II sensor from the same locations of θ measurements. There was a better correlation between PRP and θ (r: 0.64–0.83) was calculated than between HCP and θ (r: 0.41–0.79). There was no significant difference (R^2: 0.60–0.69; RMSE (root mean square error): 2.32–4.02) between the θ values measured with TDR (θ_M) and those predicted with DualEM-II (θ_P) confirming that the use of electromagnetic induction technique, evaluated during this study, is labor saving, quick, non-destructive, and accurate and can be considered a precision agriculture tool for efficiently managing soil water in potato fields.

Keywords: irrigation management; monitoring water stress; precision farming; soil variability; tuberous crop

Canada is a global leader in potato production. In Atlantic Canada, the provinces of Prince Edward Island (PEI) and New Brunswick (NB) respectively contribute 24.5% and 13.6% of the total potato production in Canada (Agriculture and Agri Food Canada 2017). A majority of fields in Atlantic Canada are non-irrigated and rely heavily on rainfall to meet water requirements for potato growth and productivity. Rainfall patterns are increasingly irregular because of climate change, resulting in insufficient water supply during critical growth periods, and can cause a significant decline in tuber yields in PEI and NB. For example, in 2017, total precipitation in May was significantly higher as compared to August (Government of Canada 2018). Weather conditions (Escuredo et al. 2018, Zrcková et al. 2018) and seasonal precipitation (Le et al. 2018) have major effects on potato cultivations.

Potato production is sensitive to water deficiency in all stages during growing season (Lynch et al. 1995), and water stress affects both total potato yield (Elzner et al. 2018) and tuber quality (Ward 1988). The water requirement for Canadian potato production varies from 400 mm to 500 mm annually depending on the potato cultivar and weather conditions (Council 2003). The deficiency of water in root zones can lower the tuber number per plant and marketability if the plants are faced with moisture stress during the bulking stage.

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Conventional technologies for soil moisture content (θ) determination including time domain reflectometry (TDR) are invasive, time consuming, and provide local information only. Spatial geo-referenced mapping of θ can provide rapid information over large areas to facilitate decision making related to irrigation scheduling (Terry et al. 2018). A number of studies have been conducted to evaluate the relationships between electromagnetic inductions readings (EC_a calculated from HCP (horizonal coplanar geometry) and PRP (perpendicular/vertical coplanar geometry)) and soil properties for vineyards (Rodríguez-Pérez et al. 2011), soybean and corn (Singh et al. 2016), wild blueberries (Farooque et al. 2012) and in other scenarios (Kachanoski et al. 1988). However, very limited research has been conducted to assess the prediction accuracy of the DualEM-II sensor to estimate θ in root zone depth for potato production in Atlantic Canada. The use of electromagnetic techniques as a research tool (Huang et al. 2017) to measure and monitor θ and for the purpose of precision irrigation (Sadler et al. 2005) has numerous advantages over the previously used techniques including neutron (Kodikara et al. 2013), capacitance-probes (Fares and Alva 2000), time-domain reflectometry (Wraith et al. 2005) and wireless soil moisture sensor networks (Bogena et al. 2010, Martini et al. 2015).

The above mentioned use of technology in measurement of θ, uneven precipitation patterns in Atlantic Canada as a result of climate change, and an increasing public demand for sustainable agriculture practices in PEI and NB emphasize the need to manage water in agricultural fields in an optimal way that considers variations in soil, θ, and the crop properties. Therefore, the objective of this study was to evaluate the performance of DualEM-II sensor in non-destructive way of θ prediction and for predicting θ variations within potato fields in Atlantic Canada, since the commonly practiced gravimetric method for estimating θ is laborious, time-consuming, and destructive for use in field-scale.

MATERIAL AND METHODS

Site selection and sampling strategy. Four potato fields in Atlantic Canada were selected to collect DualEM-II sensor (DUALEM Inc., Milton, Canada) and time domain reflectometry (Spectrum Technologies, Inc, Plainfield, USA) data. The fields included two in New Brunswick (Field 1: Grand Falls 47.100965°N, 67.777873°W and Field 2: Riverveiw 46.384169°N, 67.7226°W) and two in Prince Edward Island (Field 3: Souris 46.3550°N, 62.2518°W and Field 4: O'Leary (46.7071°N, 64.2269°W). All the fields had sandy loam soil (Orthic Humo-Ferric Podzol) and were under conventional management practices for potato production over the past 9–10 years. Major soil and land properties of these fields are given in Table 1. The field layout and geographic location of the selected sites are presented in Figure 1. A grid pattern of sampling (25 × 25 m; n = 40) was established at each experimental site to collect DualEM-II and TDR data.

In DualEM-II sensor, two coil array geometries, HCP and PRP, are integrated, which use a common transmitter coil oriented with a vertical dipole. The HCP array has a horizontal dipole receiver coil and the PRP array has a vertical dipole receiver coil. The two array geometries used in DualEM-II sensor differ in their penetration depths. The response attained from HCP and PRP are cumulative responses based on approximations of Wait's (1962) equations. Low induction numbers are valid for low conductivity values as present in potato fields (McNeill 1980, Callegary et al. 2007). HCP and PRP readings were obtained using the DualEM-II manually by placing the instrument on the ground parallel to the rows and by ensuring to avoid any metallic objects. Five HCP and PRP

Table 1. Area, average values of soil cation exchange capacity (CEC), soil pH, soil organic carbon, and ranges of field elevation as well as slope experimental Fields 1 and 2 in New Brunswick (NB) and Fields 2 and 3 in Prince Edward Island (PEI)

Field		Area (m^2)	CEC ($mmol_+/100$ g)	pH	Organic carbon (%)	Elevation (m a.s.l.)		Slope (deg.)	
						min	max	min	max
1	NB	31 970	9.72	6.00	2.00	232	237	0.10	4.88
2		33 754	9.95	5.81	2.19	136	143	0.10	4.86
3	PEI	18 661	6.80	5.73	1.29	1.34	5.04	0.40	5.80
4		30 652	4.10	5.99	0.97	31.5	35.5	0.60	5.02

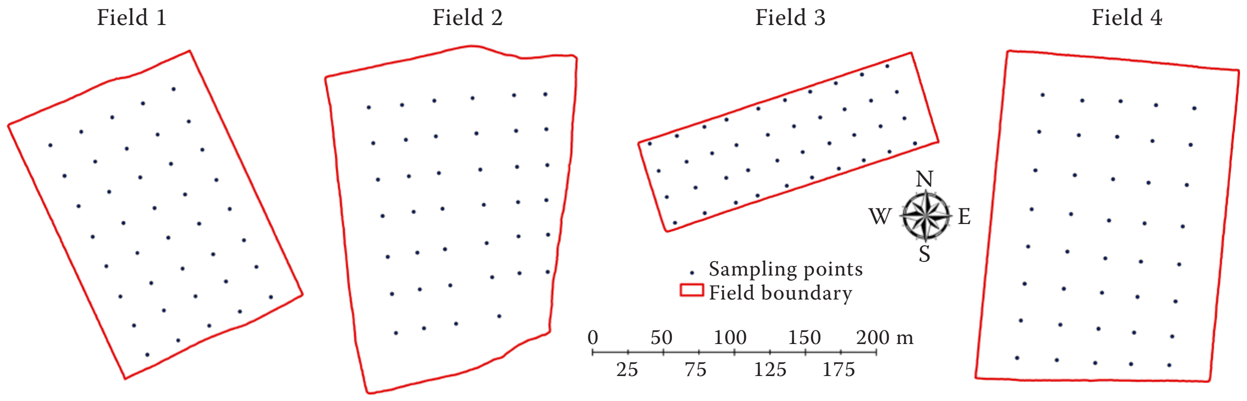

Figure 1. Layout of the selected potato fields: Fields 1 and 2 in New Brunswick, and Fields 3 and 4 in Prince Edward Island for sampling of soil moisture data

readings were obtained at each location by manually moving the DualEM-II to random positions within a 2 m radius of each location. Technical description and specifications of DualEM-II used in this study of DualEM-II sensor include (i) operating frequency = 9 kHz; (ii) power supply of 3 W from 12 (± 3) V DC through AC-micro connector; (iii) instrument diameter = 0.089 m; (iv) instrument length = 2.41 m; (v) instrument weight = 8 kg, and (vi) conductivity range up to 3000 mS/m.

The HCP and PRP readings were recorded using the DualEM-II instrument at each sampling location shown in Figure 1. Since, the DualEM-II sensor measures the conductivity of soil for 3 m deep soil layer, this response was approximated for 15 cm depth using the equation provided by the manufacturer (DualEM Inc., Milton, Canada). The purpose of this conversion was to match the θ values recorded from TDR probes with the predicted θ using DualEM-II sensor.

The ground conductivity surveys were conducted in each field to establish an appropriate grid size to facilitate θ and geo-referenced electromagnetic induction sampling. The geo-statistical analysis of the DualEM-II sensor data were plotted as semi-variograms. Various models of semivariogram (Gaussian, exponential, linear, and spherical) were used to best fit the collected data. The highest coefficients of determination (R^2) and minimum residual sum of squares (RSS) were the criteria to select the best-fitted model. Kerry and Oliver (2003) suggested that one third or half of the range of influence from semivariogram could be used to establish a grid pattern sampling. Based on the range of variability, a grid size was selected at each monitoring site. The coordinates for each sampling point and field boundary in each field were recorded using a real-time kinematics global positioning (RTK-GPS) system.

Readings of θ were recorded in each grid within selected fields to ensure precise measurement of θ using a pre-calibrated FieldScout TDR-300 sensor (R^2 = 0.98; (root mean square error) 0.6%) to record five replicates of θ at 15 cm below the soil surface within the radius of 1 m of each grid point in each field. The TDR probe was inserted on the top of ridges during samplings 1 and 2 when tubers were not established and in the side of the ridges to avoid hitting tubers

Table 2. Values of coefficient correlation (r) between horizontal, vertical coplanar geometries (PRP and HCP) and soil moisture content (θ) measured with DualEM-II in the four selected fields of the provinces of New Brunswick (NB) and Prince Edward Island (PEI)

Sampling		1		2		3		4	
		PRP	HCP	PRP	HCP	PRP	HCP	PRP	HCP
Field 1	NB	0.75*	0.79*	0.67*	0.66*	0.62*	0.42**	0.81*	0.75*
Field 2		0.73*	0.60*	0.83*	0.64*	0.74*	0.42**	0.79*	0.62*
Field 3	PEI	0.75*	0.79*	0.78*	0.77*	0.78***	0.78*	0.78*	0.78*
Field 4		0.64*	0.66*	0.78*	0.75*	0.76*	0.68*	0.73*	0.41*

$^{*}P = 0$; $0.01 < {}^{**}P \le 0.05$; $0.001 \le {}^{***}P \le 0.01$; PRP – perpendicular co-planar; HCP – horizontal co-planar during Samplings 3 and 4. The collected data were used to develop calibrations and validations.

The location of sampling points was recorded using an RTK-GPS (Gatineau, Canada) for geo-referencing purposes. The θ, HCP and PRP readings were collected four times over the growing season of 2017 (sampling 1 was during the potato plantation in middle of May; sampling 2 was conducted during middle of July (at the stage of 60 days after plantation); sampling 3 was taken up during the early August (at the stage of 80 days after plantation); and sampling 4 was in late August (at the stage of 100 days after plantation) at each sampling location. The period from May through August in Atlantic Canada is generally mild summer. The same was true during this study year. The data were collected in cloud-free days during 10:00 am and 2:00 pm when the days were bright and clear in all study sites with no hill shades on the fields.

Statistical analysis. Statistical analysis of collected data was performed using Minitab 17 (Minitab Inc., State College, USA) statistical software. Summary statistics were made to determine standard deviation (SC) and coefficient of variation (*CV*) for the measured values of HCP, PRP, and θ. Regression analysis was performed to develop calibrations for predicting θ from DualEM-II sensor data. Linear and quadratic models of regression were evaluated to find the best fitted model to predict θ. The performance of these models was verified through the coefficient of correlation (r), coefficient of determination (R^2) and root mean square error. The actual and predicted θ were regressed to evaluate the prediction potential of the DualEM-II sensor.

RESULTS AND DISCUSSION

Relationship between soil moisture content and co-planar values. Results of the correlation matrix revealed that the HCP and PRP were significantly correlated with θ (Table 2). Generally, the HCP was found to be correlated better with θ than PRP for selected sites. Nonetheless a pattern of correlation was similar for all four sampling, a better correlation between PRP and θ (r: 0.64–0.83) was calculated than between HCP and θ (r: 0.41–0.79).

Lower θ were observed during these sampling periods when compared with earlier samplings (Table 3). Field 3 was found to have a consistently higher correlation for all four sampling events. Mean θ in this field was slightly lower when compared to other fields (Table 3), likely due to different soil texture, structure,

Table 3. Summary statistics of horizontal coplanar geometry (HCP, mS/m), perpendicular coplanar geometry (PRP, mS/m), and soil moisture content (θ, %) for experimental Fields 1 and 2 in New Brunswick and Fields 2 and 3 in Prince Edward Island

Field	Sampling	Parameter	Min.	Max.	Standard deviation	S.V (%)
1	1	HCP	1.78	7.04	4.41	1.26
		PRP	3.14	8.48	5.31	1.28
		θ	16.0	30.4	23.9	2.76
	2	HCP	4.10	10.9	7.26	1.60
		PRP	5.10	13.0	8.44	4.37
		θ	10.3	28.9	18.9	4.37
	3	HCP	1.90	15.3	6.96	3.53
		PRP	1.32	9.22	4.30	1.66
		θ	11.1	33.4	20.2	5.93
	4	HCP	2.74	10.5	5.67	1.88
		PRP	1.99	9.24	4.84	1.75
		θ	7.94	24.4	13.5	4.00
2	1	HCP	3.80	6.48	5.05	0.65
		PRP	3.40	6.90	4.81	0.83
		θ	11.0	41.6	20.2	7.03
	2	HCP	3.80	9.84	6.16	1.66
		PRP	2.70	10.6	5.38	2.22
		θ	10.2	38.7	20.4	7.35
	3	HCP	4.30	9.82	6.86	1.17
		PRP	6.46	12.2	8.30	1.22
		θ	10.64	32.3	19.2	4.91
	4	HCP	3.04	7.46	5.32	1.03
		PRP	1.40	6.56	4.35	1.09
		θ	7.00	19.0	12.4	3.58
3	1	HCP	3.94	13.1	8.65	2.45
		PRP	2.68	11.2	7.10	2.08
		θ	11.0	25.9	18.7	4.44
	2	HCP	2.43	11.6	7.15	2.44
		PRP	1.05	9.55	5.42	2.01
		θ	7.11	21.8	14.6	4.30
	3	HCP	3.12	11.6	7.47	2.37
		PRP	1.81	9.58	5.45	1.84
		θ	3.11	18.5	10.6	4.32
	4	HCP	1.51	10.7	5.93	2.45
		PRP	1.09	8.86	4.77	1.91
		θ	3.90	18.6	11.4	4.29
4	1	HCP	4.83	11.5	7.69	1.84
		PRP	3.53	8.55	5.56	1.18
		θ	12.5	26.9	20.1	3.94
	2	HCP	4.70	11.6	7.73	1.83
		PRP	3.20	9.20	6.41	1.73
		θ	9.30	24.3	16.5	3.93
	3	HCP	3.42	9.78	6.99	1.75
		PRP	2.50	8.08	5.67	1.35
		θ	6.30	18.4	12.1	3.32
	4	HCP	3.70	8.60	6.42	1.38
		PRP	2.82	6.82	4.57	0.92
		θ	5.14	18.6	11.1	4.13

and organic matter levels. The coefficient of variation (*CV*) revealed that the HCP, PRP, and θ were moderate to highly variable within selected fields (Table 3). Summary statistics reported higher θ values for samplings 1 and 2 when compared with 3 and 4 for monitoring sites (Table 3). Higher θ in samplings 1 and 3 were supported by the precipitation data, indicating lower rainfall in the later months of July and August.

Other researchers have evaluated the relationships between electromagnetic induction readings and θ for different crops, and reported varying results (Sudduth et al. 2005, Rodríguez-Pérez et al. 2011, Farooque et al. 2012). They also showed prediction fluctuations within selected fields for different crops. Farooque et al. (2012) found a positive relationship between HCP/PRP and volumetric θ in soil at the root zone of wild blueberry crops. Rodríguez-Pérez et al. (2011) evaluated the relationship between sensor based ground conductivity and volumetric θ showing fluctuating *r* at different sampling depths. Sudduth et al. (2005) reported that the relationship between EC_a and θ was variable between different states in the USA. Some of the states showed significant correlations, while others showed non-significant correlations, which might be due to different soil types and climatic variations within the states of USA. Overall, HCP was significantly correlated with θ within selected fields, indicating significant prediction potential using DualEM-II sensors in a non-destructive and rapid fashion.

Linear regression models between θ and HCP were computed for each field and the best-fitted models are presented in Figure 3. Results showed significant correlations between HCP and θ with R^2 ranging from 0.60 to 0.69 (Figure 3). These results agree with the correlation coefficients (Table 2). The range of R^2 between HCP and θ coincided with the findings of other studies (Sudduth et al. 2005, Rodríguez-Pérez et al. 2011). Sudduth et al. (2005) considered $R^2 < 0.40$ of low accuracy and $R^2 \geq 0.55$ of reasonable accuracy. Regression between θ and HCP were of reasonable accuracy for samplings 1 and 4 in Field 1, samplings 2, 3, and 4 in Field 2, all samplings in Field 3, and samplings 2 and 3 in Field 4 (Figure 3). Results of the correlation matrix and regression analysis showed that the HCP provided better predictions than PRP, which might be due to a greater sensing depth of HCP. Schumann and Zaman (2003) suggested that the greater sensing of the HCP component (3 m) was the reason for better correlations with HCP. Results were different between sampling times and locations may be due to differences in environmental conditions (Rodríguez-

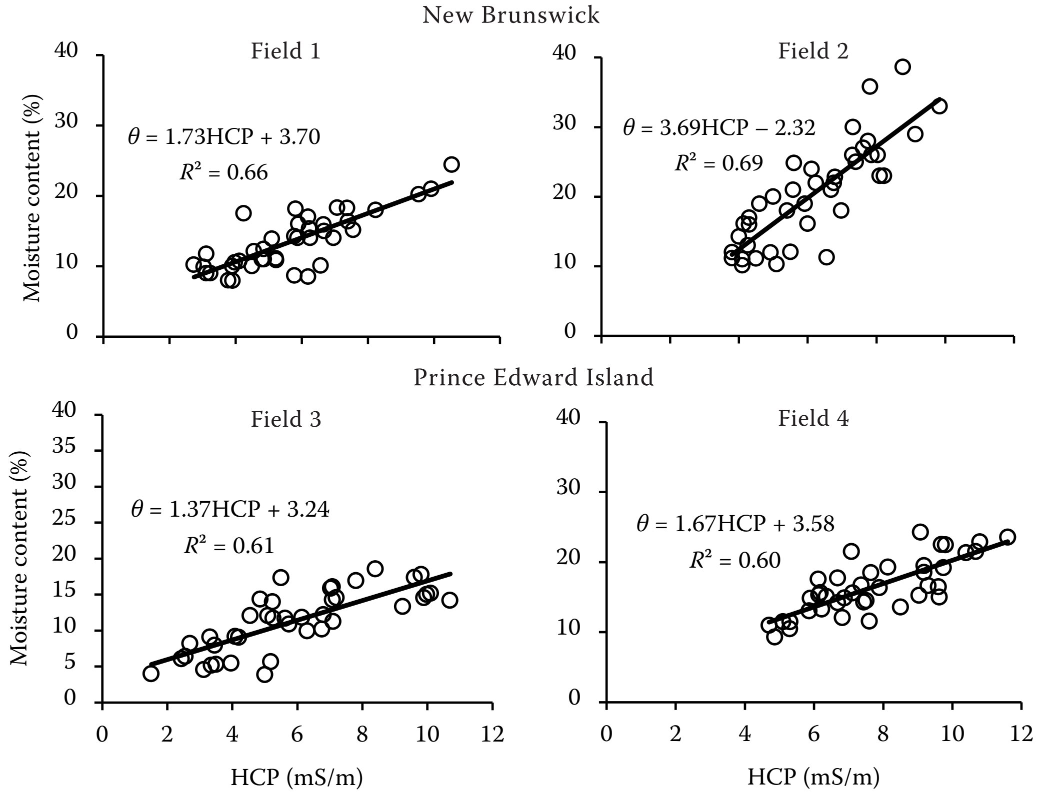

Figure 3. Linear regression between horizontal coplanar geometry (HCP) and soil moisture content

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Table 4. Linear regression equation between predicted (θ_P) and measured (θ_M) soil moisture content (%)

Field		Relationship	R^2	RMSE
1	NB	$\theta_P = 0.66\ \theta_M + 4.65$	0.66	2.32
2		$\theta_P = 0.69\ \theta_M + 6.27$	0.69	4.02
3	PEI	$\theta_P = 0.61\ \theta_M + 4.45$	0.61	2.65
4		$\theta_P = 0.60\ \theta_M + 6.58$	0.60	2.45

NB – New Brunswick; PEI – Prince Edward Island; RMSE – root mean square error

Pérez et al. 2011) between the two provinces due to geographical locations of New Brunswick, which is surrounded with mainland Canada on its northern and western sides and the Prince Edward Island is surrounded by Atlantic Ocean. Some studies found that soil temperature influences EC_a measurements (Sudduth et al. 2005, Robinson et al. 2004, McKenzie and Woods 2006). However, Sudduth et al. (2005) showed that the temperature effect did not cause significant difference in EC_a regression results. Collectively, regression analysis in conjunction with correlation matrix revealed significant relationships between HCP and θ, indicating great potential for a DualEM-II sensor to sense variations in θ to facilitate irrigation scheduling for site-specific irrigation within potato fields in Atlantic Canada.

Cross validation of regression equations across the fields. In order to further strengthen and assess the prediction accuracy of θ using a DualEM-II sensor, cross validations were performed. Results of regression plots between actual and predicted θ showed significant correlations with R^2 ranging from 0.60 to 0.69 within selected fields (Table 4). The RMSE ranged from 2.45% to 4.02%, suggesting significant prediction accuracy of the DualEM-II sensor. Results showed over-and-under prediction for θ within selected fields, which might be due to variations in precipitation, uncontrolled drainage, soil temperature, management practices, and other environmental conditions. The EC_a measurements are affected by the variation in θ under too wet or too dry conditions (Kitchen et al. 1999). In this study, θ varied between too wet and too dry during the growing season (Figure 2). This likely caused variations in sensor responses, resulting in over-and-under predictions of θ within the potato fields. Rhoades et al. (1989) reported that electromagnetics induction measurements are influenced by soil moisture and Kachanoski et al. (1988) suggested that θ might be the main factor affecting electromagnetics induction measurements. They also reported that the relationship between electromagnetics induction and θ can be affected by time and location. These conclusions support the findings of this study, since these experiments were conducted in different geographic locations. Sensing θ under appropriate conditions (not too dry or wet) can improve prediction accuracy. Significant R^2 in conjunction with lower RMSE suggested that the DualEM-II sensor can be used to estimate and map variations in θ to facilitate site-specific irrigation within potato fields. Additionally, the sensed information can be used to design an optimal drainage system.

In conclusion, the performance of DualEM-II sensor, as a non-destructive technique to measure and predict θ was evaluated under Atlantic Canadian agricultural and environmental conditions. Four potato fields were selected for experimentation; two in New Brunswick and two in Prince Edward Island. The DualEM-II sensor-measured conductivities of horizontal as well as vertical coplanar geometries had a significant correlation with TDR-measured θ (r: 0.41–0.83). These models were used to predict θ that closely related with the values of θ measured using TDR (R^2: 0.60–0.69; RMSE: 2.32–4.02) confirm-

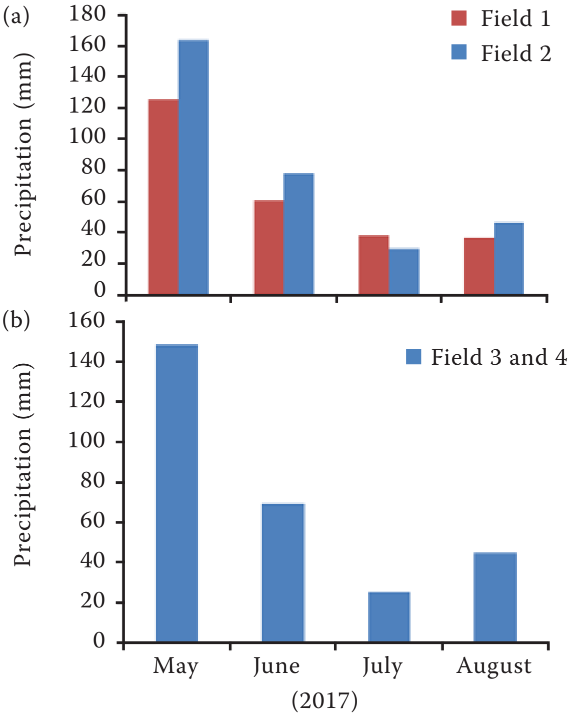

Figure 2. Total precipitation from May to August in 2017: (a) Fields 1 and 2 in New Brunswick, (b) Fields 3 and 4 in Prince Edward Island

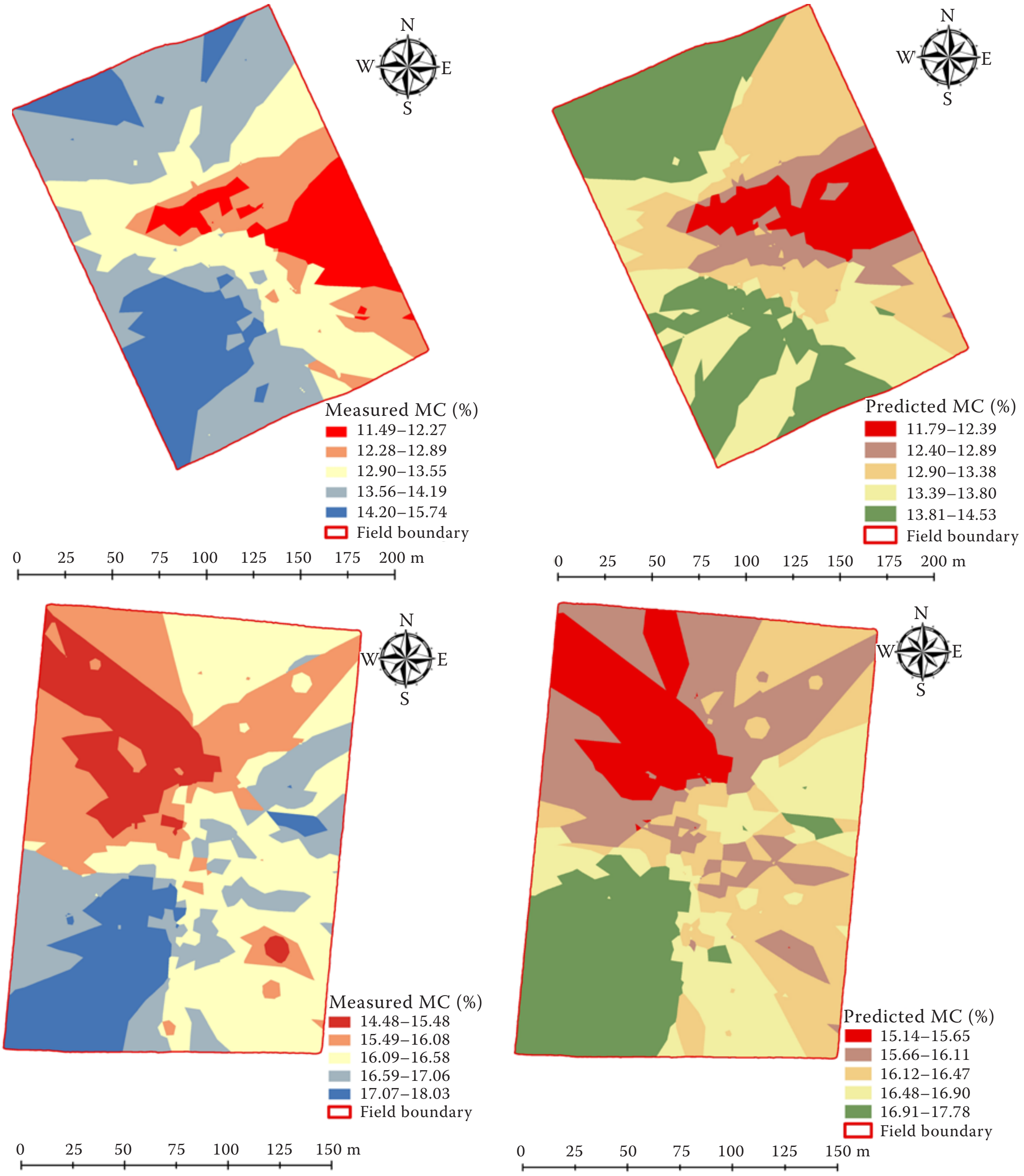

Figure 4. Representative maps of interpolated measured and predicted moisture content (MC, %) for Field 1 in New Brunswick (top) and for Field 4 in Prince Edward Island (bottom). Due to space constraint maps of Fields 2 and 3 are not presented here

ing the reliability of the electromagnetic induction technique to measure θ. This technique may be helpful in precision farming of potatoes in agricultural fields with highly variable θ and land characteristics (elevation and slope). The tested technique is advantageous over the conventional gravimetric methods of estimating θ that are laborious, time-consuming, and destructive to agricultural fields.

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REFERENCES

Agriculture and Agri Food Canada (2017): Potato Marketing and Cost of Productions. Ottawa, Agriculture and Agri-food Canada. Available at http://www.agr.gc.ca/eng/industry-markets-and-trade/canadian-agri-food-sector-intelligence/horticulture/horticulture-sector-reports/potato-market-information-review-2015-2016/?id=1500402297688#a1.1 (accessed on May 27, 2019)

Bogena H., Herbst M., Huisman J.A., Rosenbaum U., Weuthen A., Vereecken H. (2010): Potential of wireless sensor networks for measuring soil water content variability. Vadose Zone Journal, 9: 1002–1013.

Council W.P. (2003): Potato Market Information Review, 2015–2016. Ottawa, Government of Canada.

Callegary J.B., Ferré T.P.A., Groom R.W. (2007): Vertical spatial sensitivity and exploration depth of low-induction-number electromagnetic induction instruments. Vadose Zone Journal, 6: 158–167.

Elzner P., Jůzl M., Kasal P. (2018): Effect of different drip irrigation regimes on tuber and starch yield of potatoes. Plant, Soil and Environment, 64: 546–550.

Escuredo O., Seijo-Rodriguez A., Rodríguez-Flores M.S., Míguez M., Seijo M.C. (2018): Influence of weather conditions on the physicochemical characteristics of potato tubers. Plant, Soil and Environment, 64: 317–323.

Fares A., Alva A.K. (2000): Evaluation of capacitance probes for optimal irrigation of citrus through soil moisture monitoring in an entisol profile. Irrigation Science, 19: 57–64.

Farooque A.A., Zaman Q.U., Schumann A.W., Madani A., Percival D.C. (2012): Response of wild blueberry yield to spatial variability of soil properties. Soil Science, 177: 56–68.

Government of Canada (2018): Monthly Climate Summaries. Gatineau, Environment and Climate Change Canada. Available at: http://climate.weather.gc.ca/prods_servs/cdn_climate_summary_e.html

Huang J.Y., McBratney A.B., Minasny B., Triantafilis J. (2017): Monitoring and modelling soil water dynamics using electromagnetic conductivity imaging and the ensemble Kalman filter. Geoderma, 285: 76–93.

Kachanoski R.G., Van Wesenbeeck I.J., Gregorich E.G. (1988): Estimating spatial variations of soil water content using noncontacting electromagnetic inductive methods. Canadian Journal of Soil Science, 68: 715–722.

Kerry R., Oliver M.A. (2003): Variograms of ancillary data to aid sampling for soil surveys. Precision Agriculture, 4: 261–278.

Kitchen N.R., Sudduth K.A., Drummond S.T. (1999): Soil electrical conductivity as a crop productivity measure for claypan soils. Journal of Production Agriculture, 12: 607.

Kodikara J., Rajeev P., Chan D., Gallage C. (2013): Soil moisture monitoring at the field scale using neutron probe. Canadian Geotechnical Journal, 51: 332–345.

Le T., Pék Z., Takács S., Neményi A., Helyes L. (2018): The effect of plant growth-promoting rhizobacteria on yield, water use efficiency and Brix Degree of processing tomato. Plant, Soil and Environment, 64: 523–529.

Lynch D.R., Foroud N., Kozub G.C., Fames B.C. (1995): The effect of moisture stress at three growth stages on the yield, components of yield and processing quality of eight potato varieties. American Potato Journal, 72: 375–385.

Martini E., Wollschläger U., Kögler S., Behrens T., Dietrich P., Reinstorf F., Schmidt K., Weiler M., Werban U., Zacharias S. (2015): Spatial and temporal dynamics of hillslope-scale soil moisture patterns: Characteristic states and transition mechanisms. Vadose Zone Journal, 14: 16.

McKenzie C., Woods S.A. (2006): Potential of precision farming with potatoes. In: Srinivasan A. (ed.): Handbook of Precision Agriculture: Principles and Applications. New York, Food Products Press, 379–391.

McNeill J.D. (1980): Electromagnetic Terrain Conductivity Measurement at Low Induction Numbers. Mississauga, Technical Note TN-6. Geonics Ltd.

Rhoades J.D., Manteghi N.A., Shouse P.J., Alves W.J. (1989): Soil electrical conductivity and soil salinity: New formulations and calibrations. Soil Science Society of America Journal, 53: 433.

Robinson D.A., Lebron I., Lesch S.M., Shouse P. (2004): Minimizing drift in electrical conductivity measurements in high temperature environments using the EM-38. Soil Science Society of America Journal, 68: 339.

Rodríguez-Pérez J.R., Plant R.E., Lambert J.-J., Smart D.R. (2011): Using apparent soil electrical conductivity (EC_a) to characterize vineyard soils of high clay content. Precision Agriculture, 12: 775–794.

Sadler E.J., Evans R.G., Stone K.C., Camp C.R. (2005): Opportunities for conservation with precision irrigation. Journal of Soil and Water Conservation, 60: 371–378.

Schumann A.W., Zaman Q.U. (2003): Mapping water table depth by electromagnetic induction. Applied Engineering in Agriculture, 19: 675–688.

Singh G., Williard K.W.J., Schoonover J.E. (2016): Spatial relation of apparent soil electrical conductivity with crop yields and soil properties at different topographic positions in a small agricultural watershed. Agronomy, 6: 57.

Sudduth K.A., Kitchen N.R., Wiebold W.J., Batchelor W.D., Bollero G.A., Bullock D.G., Clay D.E., Palm H.L., Pierce F.J., Schuler R.T., Thelen K.D. (2005): Relating apparent electrical conductivity to soil properties across the north-central USA. Computers and Electronics in Agriculture, 46: 263–283.

Terry N., Day-Lewis F.D., Werkema D., Jr J.W.L. (2018): MoisturEC: A New R Program for Moisture Content Estimation from Electrical Conductivity Data. Hoboken, John Wiley and Sons. Available at: https://doi.org/10.1111/gwat.12650

Ward E.R. (1988): Irrigation in relationship to disease incidence and tuber quality after storage. In: Carr M.K., Hamer P.J. (eds.): Irrigation Potatoes. Bedford, Cranfield Press, 41–49.

Wait J.R. (1962): A note on the electromagnetic response of a stratified earth. Geophysics. Available at: https://doi.org/10.1190/1.1439028.

Wraith J.M., Robinson D.A., Jones S.B., Long D.S. (2005): Spatially characterizing apparent electrical conductivity and water content of surface soils with time domain reflectometry. Computers and Electronics in Agriculture, 46: 239–261.

Zrcková M., Capouchová I., Eliášová M., Paznocht L., Pazderů K., Dvořák P., Konvalina P., Orsák M., Štěrba Z. (2018): The effect of genotype, weather conditions and cropping system on antioxidant activity and content of selected antioxidant compounds in wheat with coloured grain. Plant, Soil and Environment, 64: 530–538.

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