Assessment of spatial variability of soil phosphorus, potassium, and aluminum using a portable VIS-NIRS Soil Probe for On-Farm Precision Experimentation

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Abstract.

Assessing spatial variability of soil properties represents an important issue for on-farm sustainable management due to the high cost of sampling to obtain representative soil map. Traditional methods of soil property measurement are based on conventional soil sampling of one sample per ha, followed by laboratory analysis, requiring different soil extraction processes with harmful chemicals. Nevertheless, this conventional laboratory analysis does not allow the exploration of spatial variation of soil properties at a desired fine spatial scale. Thus, sustainable management of soil elements calls for implementation of new devices enabling the measurement of edaphic properties for agri-environmental purposes.

Currently, there are several newly developed and commercially available probes for soil sampling. They can provide rapid, reliable, non-destructive, and low-cost measurements of soil properties directly in the field. Most use soil reflectance measurements that do not require further analysis in a wet lab, making them ideal for on-farm experiment research. However, the impacts of these new data acquisition techniques for measuring soil chemical properties remain unknown. Therefore, the main objective of our study was to compare spatial maps of soil properties generated via two methods (i.e. conventional laboratory analysis vs a novel in situ VIS-NIRS soil probe) in two commercial fields located in Eastern provinces of Canada using descriptive statistics and geostatistical tools.

To address this, around 50 georeferenced soil sampling points were collected in each field using a Dutch auger (conventional laboratory method) and measured with the VIR-NIRS probe (in situ VIR-NIRS portable device) having the same diameter. Geostatistical parameters (nugget, range, partial sill, sill ratio) and fitting statistics (RMSE, RMSES) were calculated with ArcGIS and used to adjust variogram models and evaluate the differences between both measurement methods. Likewise, spatial maps of soil properties were created for each method. Finally, maps illustrating the differences (i.e. difference between laboratory and VIR-NIRS probe values) in the spatial distribution of soil properties were produced.

Preliminary results suggest that spatial distribution of soil P/Al ratio and K content differed notably between traditional laboratory analysis and in situ VIR-NIRS probe data. Discrepancies in mean, median, range, and coefficient of variation (CV) values between the two methods were significant, with inconsistencies observed across different fields and spatial patterns. No general trend could be detected to explain or to correct the difference observed in the dataset. The fertilization maps showed important differences between the reference and the probe methods. Once more, these differences varied inconsistently from the fields, leading to areas being either under or over-fertilized.

These preliminary observations further raise several questions: How to use these probes in research projects? How can we link these new tools results with past laboratory results? How can we adjust the values from the in situ VIR-NIRS probe to reproduce the values from the conventional laboratory method as best as possible? Finally, how can these probes be integrated in producer field management in the context of the new digital agriculture paradigm?

Keywords.
Variable rate application map, P/Al ratio, laboratory methods, in situ VIR-NIRS portable device, spatial comparison.

Introduction

Measuring soil chemical properties such as phosphorus (P) and potassium (K) is essential for crop production, and their concentrations are used to guide fertilizer applications. Moreover, assessing the spatial variability of these soil properties represents an important issue for on-farm sustainable management related to the high cost of soil sampling densities. Conventional methods of soil property measurement are mainly based on traditional soil sampling, followed by laboratory analyses, requiring many soil extraction processes with harmful chemicals. These conventional laboratory analyses restrict the exploration of the variations in spatial soil properties at a desired fine spatial scale. Wherever possible, the use of proximal soil sensing is expected to replace conventional laboratory methods due to their gains in time efficiency and reduced labor-intensive operations during soil sampling and analysis (Adamchuk et al. 2018). Nowadays, several connected commercial probes are available for soil sampling and offer the potential of rapid, reliable, non-destructive, and low-cost measurements of soil properties directly in the field. These *in situ* reflectance measurements, in the VIS-NIRS spectrum offered by these device, are correlated to soil properties using machine learning algorithms. Thus, they do not require analysis in a wet laboratory, making them ideal for On-Farm Experiment (OFE) research. Yet, the effects of these novel measurement techniques on the reliability of experimental findings and their comparison to conventional soil property measurements remain largely unknown. Therefore, the main objective of our exploratory study was to compare spatial variability of P, K, aluminum (Al) and P/Al ratio maps of soil properties generated via two methods (i.e. conventional laboratory analysis vs a novel *in situ* VIS-NIRS soil probe) in two commercial fields using descriptive statistics and geostatistical tools. Additionally, P and K quantities estimated by these two methods will be calculated according to fertilization classes (CRAAQ, 2010) and compared spatially.

Methodology

Fields studied

This study was conducted on two agricultural fields located in the provinces of Quebec (QC; 8.3 ha) and New Brunswick (NB; 12.9 ha) in Eastern Canada. (Fig. 1). The QC field was under a soya-corn rotation, whereas the NB field was under a cereal-potato rotation. In 2022, corn was sown in the QC field, while potatoes were planted in the NB field. The average soil texture in the QC field was Sandy Loam, whereas in the NB field, it was Loam. A georeferenced point grid of 25 m x 25 m was implemented in the QC field, while a point grid of 50 m x 50 m was implemented in the NB field. Thus, a total of 53 and 52 sampling points were collected for the QC and NB fields, respectively.

Soil sampling and analysis

The soil physicochemical characteristics were obtained using the conventional method (referred as Lab) and *in situ* VIR-NIRS reflectance measurement (referred as Probe). Each soil sample was a composite of four soil cores taken in a 1.5 m radius, and the VIR-NIRS reflectance was measured in the same four holes using an *in situ* VIR-NIRS portable device. Conventional soil sampling method was performed using a Dutch auger (diameter 2.5 cm; sampling depths 0-20 cm at QC field and 0-15 cm at NB field). For the conventional method, soil samples were air-dried, grounded and sieved through a 2 mm sieve. Soils were extracted with a soil solution ratio of 1:10 using Mehlich-3 solution (Ziadi and Tran 2008), and the concentrations (mg kg^{-1}) of P, K, and Al in the extract were determined by inductively coupled plasma optical emission spectroscopy (ICP–OES; Model 4300DV, PerkinElmer, Shelton, CT, USA). The phosphorus saturation index (PSI: P/Al %) was also calculated:

$$PSI\ (\%) = [P\ (mg\ kg^{-1}) / Al\ (mg\ kg^{-1})] \times 100 \quad (1)$$

For the *in situ* VIR-NIRS portable device, reflectance measurements were transferred directly to the company's web portal for soil parameters determination by artificial intelligence. The Probe data was then retrieved from the company website to be integrated into our database.

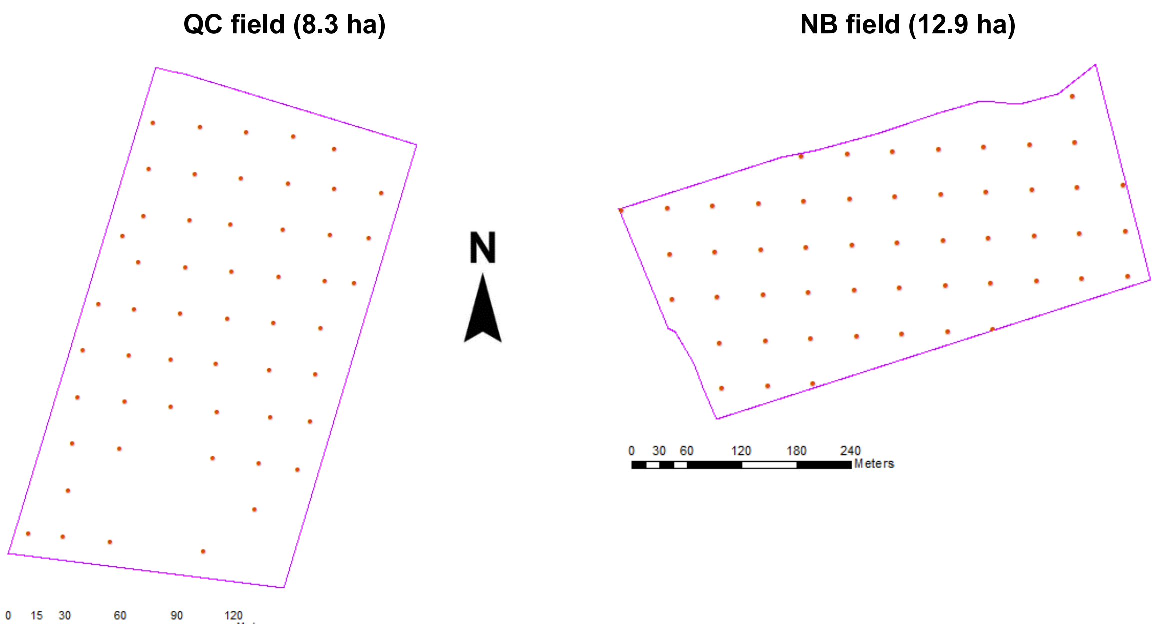

Fig 1. Grid sampling at Quebec field (QC) and New Brunswick field (NB) (Red dot: sampling point location).

Statistical and geostatistical analysis

Descriptive statistics (minimum, maximum, mean, median, standard deviation (STD), and coefficient of variation (CV) were calculated for each parameter at each field using SigmaPlot software. The CVs of soil chemical properties were classified based on the approach of Nolin and Caillier (1992) as follows: (1) low (CV < 15%); (2) moderate (15% < CV < 35%); (3) high (35% < CV < 50%); (4) very high (50% < CV < 100%); and (5) extremely high (CV > 100%). Geostatistical analysis was performed using ArcGIS software (Geostatistical Analyst Tool) to illustrate the field-scale spatial distribution of parameters. Cleaning of each parameter's database was carried out to contain the data within an interval of mean ± 3 standard deviations. The ordinary kriging method was chosen to interpolate the soil physicochemical characteristics in each field. The fitting of the variogram models was obtained by optimizing geostatistical parameters (range, nugget, and partial sill) through examining statistical parameters such as root mean square error (RMSE, optimal value = 0) and root mean square error standardized (RMSES; optimal value = 1). A spatial dependence index was calculated for each adjustment according to Cambardella et al. (1994) dependency criteria. Thus, the spatial distribution of each soil property was obtained in each field by kriging the Lab and Probe data. The kriged maps were transformed into rasters (1m x 1m resolution).

Spatial comparisons

A comparison (Lab vs Probe) of the spatial distribution of each soil properties was generated for each field. A geostatistical analysis procedure was developed using ArcGIS (Model Builder Tool) to automate the steps leading to the calculation of the differences between the spatial distributions associated to the Lab and Probe data (Fig. 2). Maps illustrating the differences (Lab – Probe) in the spatial distribution pattern of the parameters were thus obtained for each field.

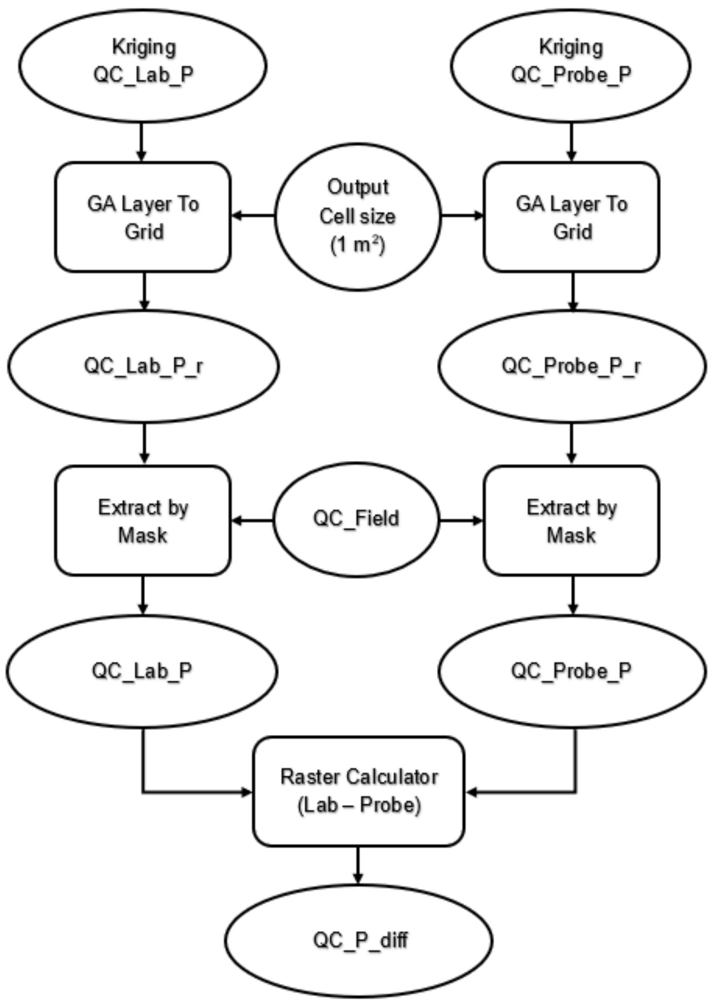

Fig 2. Model Builder calculation procedure in ArcGIS [example for phosphorus (P) at the QC field].

Variable application maps of phosphorus and potassium fertilizer

For both fields, variable rate application maps of P and K were determined based on the fertilization recommendation rates for the Quebec province for corn and potato crops (CRAAQ, 2010), respectively, using the Lab and Probe database. Then, calculations were carried out to optimize the P_2O_5 and K_2O total quantities to apply on each field, from each method (i.e. Lab, Probe).

Results and discussion

Descriptive statistics

Descriptive statistics of each dataset revealed significant differences between these two methods (Table 1). In the QC field, Lab mean and median values were lower than those obtained with the Probe measurements. Furthermore, the Lab STD and CV values were higher than those of the Probe method. In the NB field, P and P/Al Lab means and medians were twice as high as those from the Probe. For K and Al, mean and median values were quite similar. In general, the Lab CV values were also higher but still remained in the same class (i.e., moderate: 15% < CV < 35%), except for P classified as high in the QC Field. This suggests that the range of sensitivity of the probe sensor measurements was lower compared to the Lab methods. In terms of fertilization applications for P and K, this could bring significant differences for agronomic recommendations.

Table 1. Descriptive statistics of the datasets obtained by the conventional (Lab) and in situ VIR-NIRS reflectance measurement (Probe) methods for QC and NB fields.

Parameter	Method	n	Median	Mean	Min	Max	STD	CV %
QC Field								
P (ppm)	Lab	53	42	46	18	100	20	43
	Probe	53	69	73	43	113	18	24
K (ppm)	Lab	53	59	65	43	124	18	28
	Probe	53	123	122	47	173	28	23
Al (ppm)	Lab	53	717	746	576	1225	128	17
	Probe	53	952	965	814	1207	92	10
(P/Al) (%)	Lab	53	5.7	6.1	2.7	12.6	2.3	38
	Probe	53	7.7	7.6	5.1	11.1	1.5	20
NB Field								
P (ppm)	Lab	52	205	204	89	346	52	25
	Probe	52	85	93	63	140	19	21
K (ppm)	Lab	52	164	167	92	299	44	26
	Probe	52	152	152	103	234	29	19
Al (ppm)	Lab	52	1337	1329	1039	1674	138	10
	Probe	52	1313	1333	912	1762	188	14
(P/Al) (%)	Lab	52	14.4	15.5	7.0	28.4	4.1	26
	Probe	52	6.7	7.0	5.4	10.6	1.3	18

Geostatistical analysis

Gaussian, spherical, and exponential models were the best fit with the experimental semi-variograms for soil physicochemical properties in both fields (data not shown). Spatial ranges varied from 42 m to 94 m and 112 m to 420 m in the QC and NB fields, respectively (Table 2) indicating that the grid sampling intensity used to characterize spatial variability of soil properties was appropriate for each field.

Table 2. Geostatistical parameters adjustment of the datasets obtained by the conventional (Lab) and in situ VIR-NIRS reflectance measurement (Probe) methods for QC and NB fields.

Parameter	Method	Model	Range (m)	Nugget C_0	Partial Sill C	Spatial dependence index (%)	Spatial dependence class	RMSE	RMSES
QC Field									
P (ppm)	Lab	Gauss	48	12.513	407.289	3.0	H	13.32	0.951
	Probe	Gauss	94	157.361	157.471	50.0	M	13.95	0.972
K (ppm)	Lab	Spher	42	10.349	213.375	4.6	H	14.15	0.983
	Probe	Spher	71	119.281	584.451	16.9	H	20.07	0.965
Al (ppm)	Lab	Gauss	56	4699.191	17681.39	21.0	H	102.20	0.950
	Probe	Gauss	73	3679.032	4599.097	44.4	M	70.16	0.963
P/Al (%)	Lab	Gauss	50	0.8694	3.553	19.7	H	1.62	0.969
	Probe	Gauss	56	1.209	0.6837	63.9	M	1.27	0.965
NB Field									
P (ppm)	Lab	Gauss	420	2237.265	844.147	72.6	M	46.75	0.947
	Probe	Gauss	303	122.921	363.953	25.2	M	13.00	1.036
K (ppm)	Lab	Expo	106	1883.939	96.497	95.1	L	43.22	0.929
	Probe	Expo	181	492.587	370.2	57.1	M	29.15	1.030
Al (ppm)	Lab	Gauss	224	13634.33	6550.665	67.5	M	130.05	1.021
	Probe	Gauss	112	25415.26	1632.249	94.0	L	169.96	1.001
P/Al (%)	Lab	Expo	142	6.978	9.987	41.1	M	3.83	0.983
	Probe	Spher	126	0.3104	1.156	21.2	H	0.97	0.951

Note: Model: variogram model selected; Gauss = Gaussian, Expo = exponential, Spher = spherical; Range: distance at which semi-variance reach the sill (m); Nugget C_0: random semi-variance; Partial sill C: difference between the sill (C_0+C) and nugget (C_0) semi-variances; Spatial dependence index: (random semi-variance / total semi-variance) × 100 = [C_0 / (C_0+C)] × 100; Spatial dependence class: H = high spatial dependence (<25%); M = moderate spatial dependence (25–75%); L = low spatial dependence (>75%) [Cambardella et al., 1994]; RMSE : root mean square error (optimal value = 0); RMSES : root mean square error standardized (optimal value = 1)

The RMSES for each semivariogram model was close to the optimal value (RMSES = 1). The spatial dependence classes were generally different between the two methods. For the QC field, the spatial soil parameter dependence determined with the Lab dataset was generally higher for the Lab method compared to those obtained with the Probe method. For the NB field, moderate spatial dependence classes were obtained with the Lab method, while the spatial dependence of the Probe method was lower (Table 2).

In general, visual distribution of the soil property maps obtained with the Lab compared to the Probe method showed important differences (Figs. 3 and 4) while only few maps showed similar patterns (e.g. Fig. 3 A3 and B3 for Al). The interpretation legend of the maps (Figs.3 and 4 C1, C2, C3, C4; Difference (∆) = Lab – Probe) indicated different ranges and when the inferior limit was negative this indicated that the Probe method showed higher value than the Lab method and *vice versa*. The smaller the range of the legend and the more centered to zero, resulted in a lower difference between the two methods.

In the QC field, regardless of the soil properties, the patterns of the maps were quite different and the difference map (Lab - Probe) reflected the pattern of the longer distribution of values obtained in the Lab dataset. In the NB field, even though we observed a smaller distribution of values in the dataset (median, mean and CV), the pattern of the Difference (∆) = Lab-Probe maps also showed high differences.

Variable rate application maps of phosphorus and potassium fertilizer

Application rates of P_2O_5 and K_2O for corn and potato production were calculated based on the specific area from each fertilization class following Quebec recommendations (CRAAQ, 2010; Fig. 5). Unsurprisingly, the obtained Lab and Probe maps was quite different and reflected the previous observations concerning the mean, CV and STD values. The quantities (kg) of recommended fertilizer in QC field determined by the Probe method were < 12% and < 30% of those recommended with the Lab method for P_2O_5 and K_2O, respectively (Table 3).

In the NB field, the recommended fertilization quantities determined by the Probe method were > 68% and > 23% of those recommended with the Lab method for P_2O_5 and K_2O, respectively (Table 4).

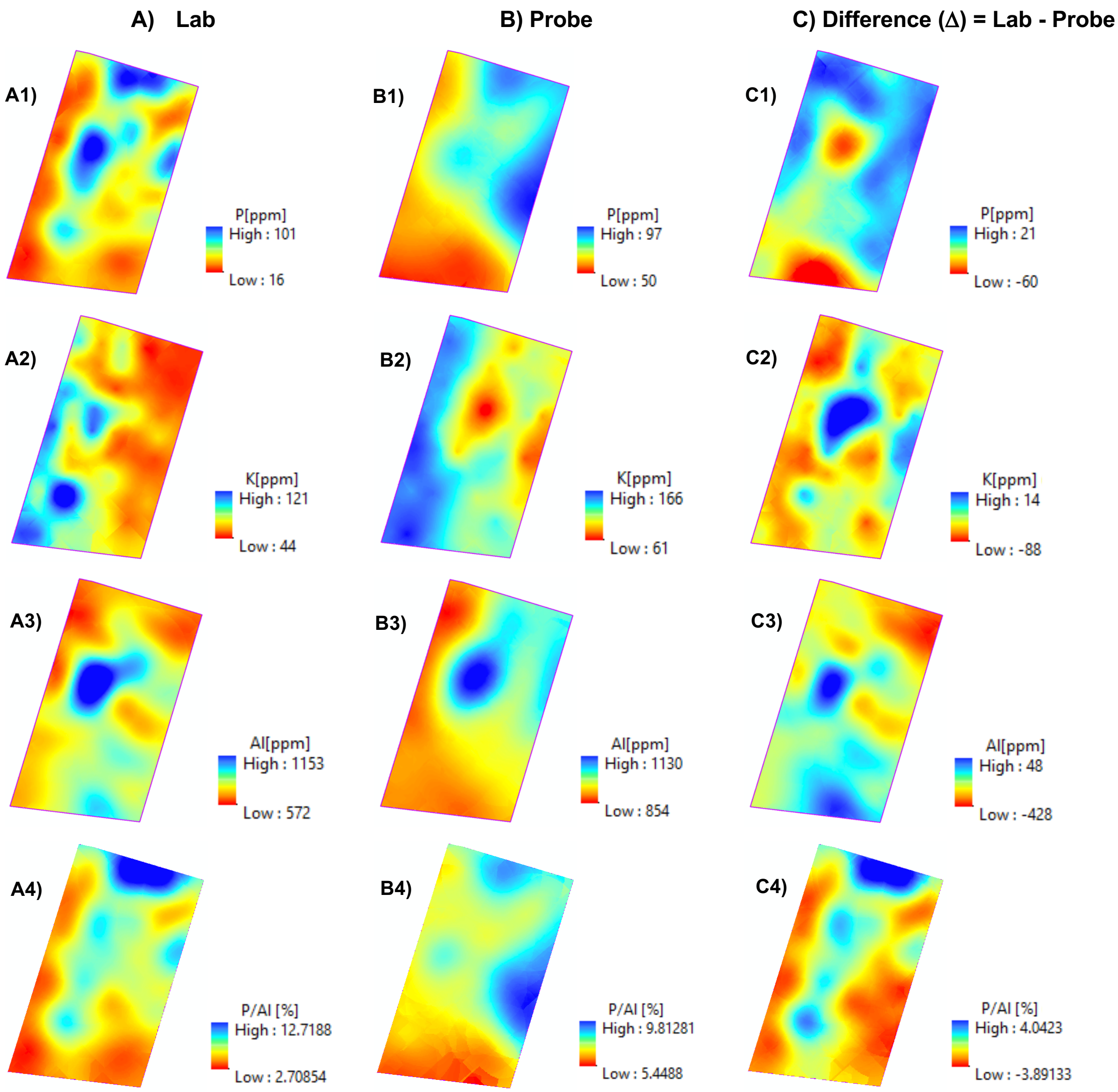

Fig 3. Spatial distribution maps of phosphorus (P), potassium (K), aluminum (Al) and P/Al ratio obtained by the conventional (Lab; A1, A2, A3, A4) and in situ VIR-NIRS reflectance measurement (Probe; B1, B2, B2, B4) methods and the difference (Δ) between the two methods (C1, C2, C3, C4) at the QC field.

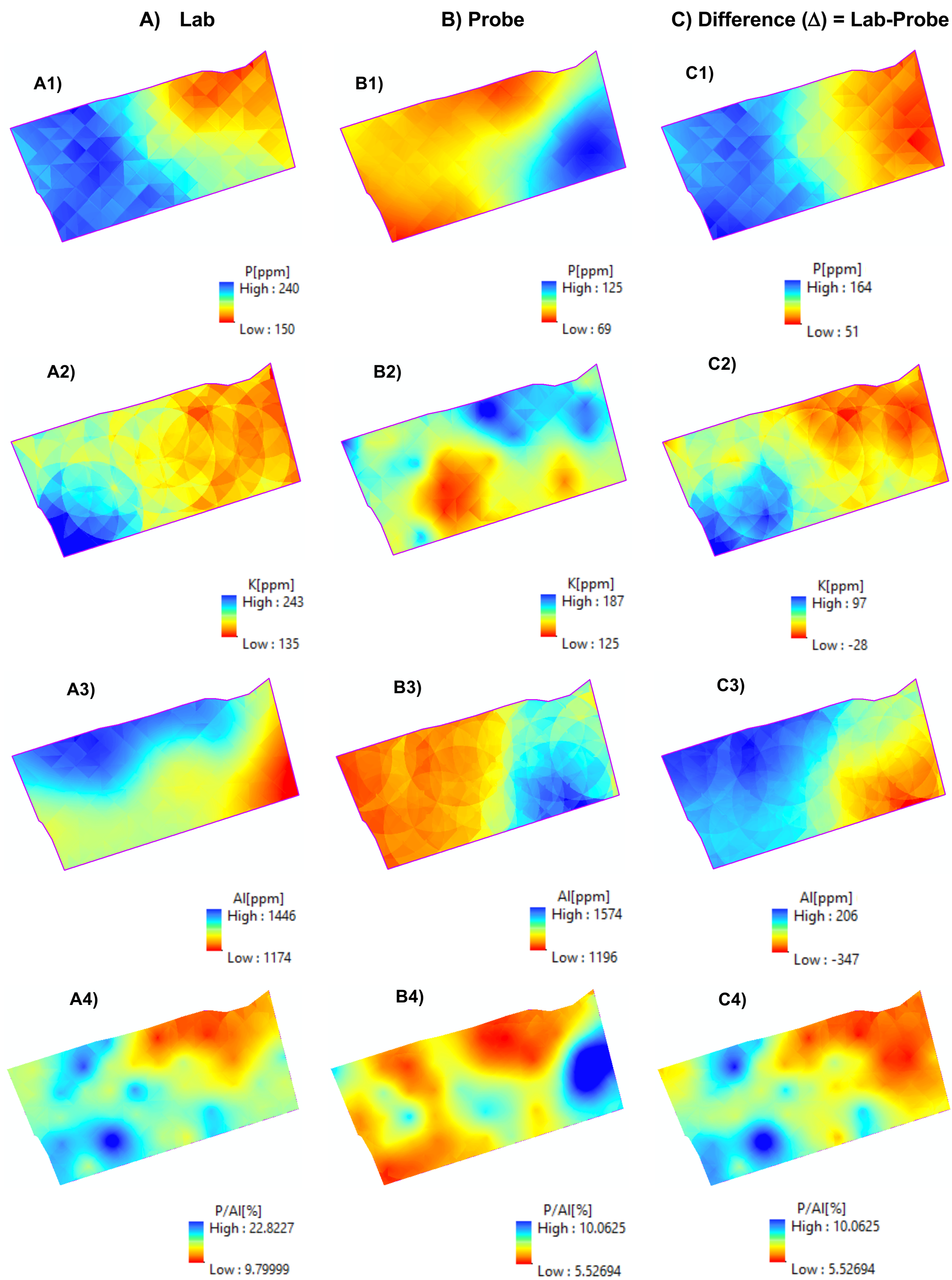

Fig 4. Spatial distribution maps of phosphorus (P), potassium (K), aluminum (Al) and P/Al ratio obtained by the conventional (Lab; A1, A2, A3, A4), and in situ VIR-NIRS reflectance measurement (Probe; B1, B2, B2, B4) methods and the difference (Δ) between the two methods (C1, C2, C3, C4) at the NB field.

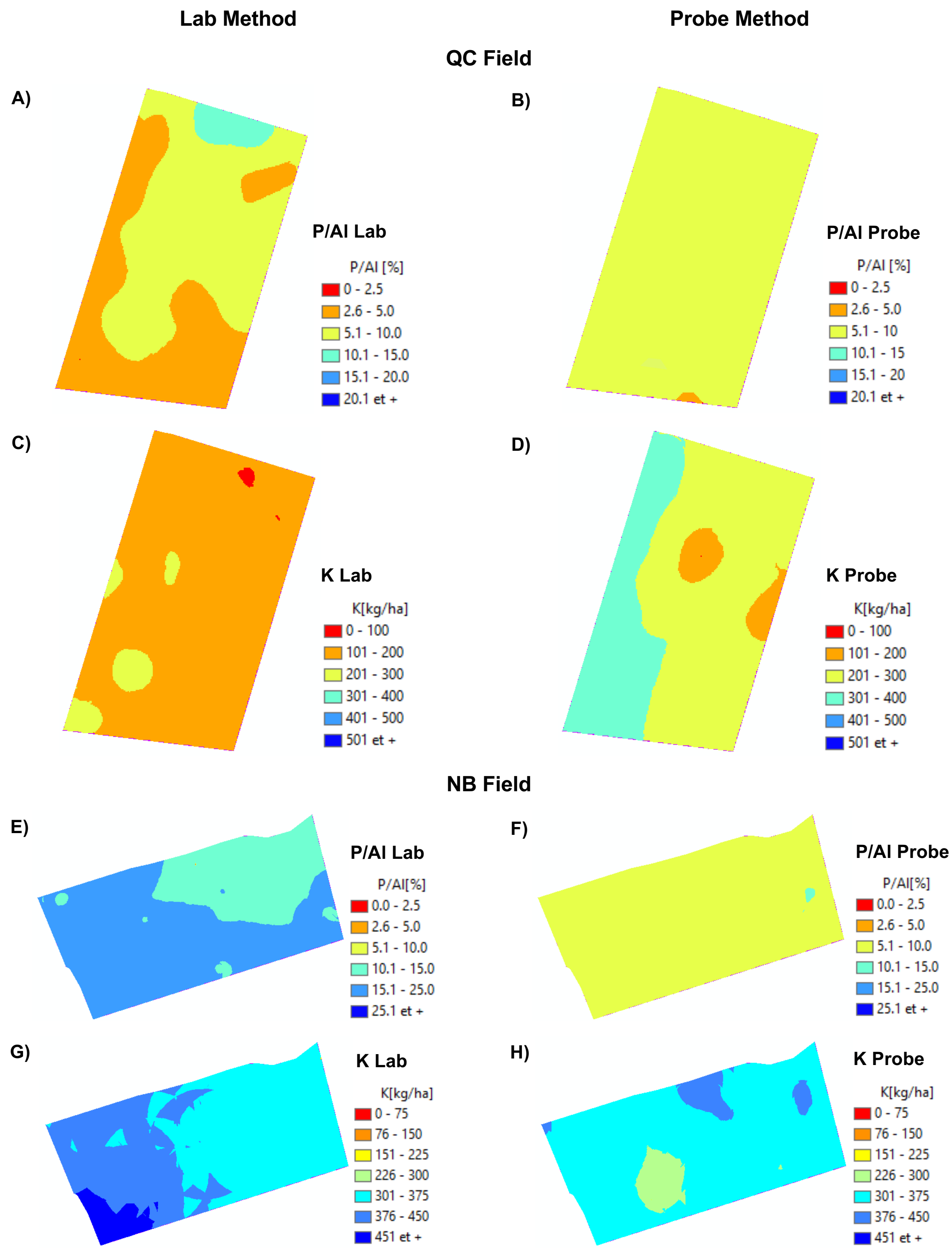

Fig 5. Spatial distribution maps based on the Quebec fertilization recommendation classes based on soil content of P/Al and K obtained by Lab and Probe methods for QC (A,B,C,D) and NB fields (E,F,G,H).

Table 3. Quantity of P_2O_5 and K_2O (kg) for corn production based on soil P/Al ratio or soil K content, area and application rates for each class in the QC corn field.

Fertilization Class[1]	Methods					
	Lab			Probe		
	Area	Rate applied	Quantity area^{-1}	Area	Rate applied	Quantity area^{-1}
P/Al (%)	(ha)	P_2O_5 (kg ha^{-1})	P_2O_5 (kg)	(ha)	P_2O_5 (kg ha^{-1})	P_2O_5 (kg)
0 - 2.5	0.00	80	0	0.00	80	0
2.6 - 5.0	2.69	60	162	0.00	60	0
5.1 - 10.0	5.19	40	208	8.27	40	331
10.1 - 15.0	0.39	20	8	0.00	20	0
15.1 - 20.0	0.00	20	0	0.00	20	0
20.1 et +	0.00	0	0	0.00	0	0
Total quantity apply in the entire field			**378**			**331**
	Area	Rate applied	Quantity area^{-1}	Area	Rate applied	Quantity area^{-1}
K (kg ha^{-1})	(ha)	K_2O (kg ha^{-1})	K_2O (kg)	(ha)	K_2O (kg ha^{-1})	K_2O (kg)
0 -100	0.04	80	3	0.00	80	0
101 - 200	7.72	60	463	0.53	60	32
201 - 300	0.51	40	21	5.28	40	211
301 - 400	0.00	40	0	2.46	40	98
401 - 500	0.00	40	0	0.00	40	0
501 et +	0.00	0	0	0.00	0	0
Total quantity apply in the entire field			**487**			**341**

[1]Quebec recommendations based on the soil content of P/Al ratio and K and the recommended application rate for corn.

Table 4. Quantity of P_2O_5 and K_2O (kg) for potato production based on soil P/Al ratio or soil K content, area and application rate for each class in the for NB potato field.

Fertilization Class[1]	Methods					
	Lab			Probe		
	Area	Rate applied	Quantity area^{-1}	Area	Rate applied	Quantity area^{-1}
P/Al (%)	(ha)	P_2O_5 (kg ha^{-1})	P_2O_5 (kg)	(ha)	P_2O_5 (kg ha^{-1})	P_2O_5 (kg)
0 - 2.5	0.00	200	0	0.00	200	0
2.6 - 5.0	0.00	150	0	0.00	150	0
5.1 - 10.0	0.00	150	0	12.85	150	1927
10.1 - 15.0	4.35	120	522	0.04	120	5
15.1 - 25.0	8.54	75	641	0.00	75	0
25.1 et +	0.00	50	0	0.00	50	0
Total quantity applied in the entire field			**1163**			**1962**
	Area	Rate applied	Quantity area^{-1}	Area	Rate applied	Quantity area^{-1}
K (kg ha^{-1})	(ha)	K_2O (kg ha^{-1})	K_2O (kg)	(ha)	K_2O (kg ha^{-1})	K_2O (kg)
0 -75	0.00	240	0	0.00	240	0
76 - 150	0.00	215	0	0.00	215	0
151 - 225	0.00	160	0	0.00	160	0
226 - 300	0.00	120	0	0.93	120	112
301 - 375	7.41	80	593	11.16	80	893
376 - 450	4.68	50	234	0.80	50	40
Total quantity applied in the entire field			**843**			**1045**

[1]Quebec recommendations based on the soil content of P/Al ratio and K and the recommended application rate for potato.

Summary

The OFE research needs to assess the variation in soil properties to improve soil nutrient management. This requires a high density of soil sampling and analysis that could not be afforded using conventional techniques. In this study, we compared both conventional method for soil properties analysis and a novel *in situ* VIS-NIRS soil probe in two commercial fields with different crops using descriptive statistics and geostatistical tools. The descriptive data showed important differences in terms of mean, median, CV values between both methods. Furthermore, the differences were inconsistent for the P, K, Al and P/Al ratio as well as when we compared one field data values to another. Unsurprisingly, the comparison of spatial pattern for each soil property between the two methods were also inconsistent. No general trend can be detected to explain or to correct the difference observed in the dataset of the Probe method compared to Lab method. The spatial maps based on recommended fertilization classes for P_2O_5 or K_2O application rates showed substantial differences between the Lab and the Probe methods and resulted into under- and over-fertilized areas.

The preliminary observations still lead us to consider several key inquiries: What methodologies should we adopt for incorporating these probes into research projects? How can we correlate the outcomes from these cutting-edge tools with historical data? Additionally, how do we seamlessly integrate these probes to investigate soil properties and their spatial variations within the framework of the emerging digital agriculture paradigm?

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