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Impacts of Interpolating Methods on Soil Agri-Environmental Phosphorus Maps Under Corn Production in Eastern Canada

Jeff D. Nze Memiaghe[1,2], Athyna N. Cambouris[1], Noura Ziadi [1], Marc Duchemin[1], and Antoine Karam[2]

[1]Agriculture and Agri-Food Canada, Quebec Research and Development Centre, 2560 Hochelaga Boulevard, Quebec City, QC, G1V 2J3 (Canada). [2]Soils and Agri-Food Engineering Department, Université Laval, 2425, rue de l'Agriculture, Quebec City (Canada).

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Abstract. *Phosphorus (P) is an essential nutrient for crop production including corn. However, the excessive P application tends to P accumulation at the soil surface under crop systems. This may increase water and groundwater pollution by surface runoff. Understanding spatial variability of P will improve the economic and rational use of P fertilizers, promote the profitability and sustainability of agricultural companies, while reducing P losses. The objective of this study was to compare two methods of interpolation (kriging vs spline) for sustainable P_2O_5 recommendations in Eastern Canada. To achieve this, the kriging interpolation approach was the reference method used. However, this interpolation method requires a high sampling density (more than 100 sampling points), which is not economically practical for the producers. Other interpolation methods, such as the spline method, could be used to set up maps with more precision. Two commercial fields under conventional tillage (CT; 10.8 ha) and no-tillage (NT; 9.5 ha), were managed under corn–soybean rotation since 1994. Soil samples were collected in fall 2014 in regular 35-m by 35-grids, at 0–5 cm depth, providing 141 and 134 georeferenced points for CT and NT fields, respectively. Five sampling densities, referred as 100%, 80%, 60%, 40%, and 20%*

of the georeferenced sampling points, were used to interpolate map with the spline methods. Available P and Aluminum (Al) were analyzed by Mehlich-3 extraction (M3), and the P saturation index $(P/Al)_{M3}$ was calculated. Data were analyzed using descriptive statistics, geostatistics, and geographic information system (GIS) tools. Intensity of variation of soil P ranged from moderate to high (32–52%) in both fields. A reduced soil sampling density had little impacts on variability of soil P while modifying substantially spatial structure of soil P (24–93%) under both contrasted fields. The use of spline up to 60% and 40% may be recommended for sustainable P_2O_5 recommendations in both contrasted fields. There would be a potential for using the spline interpolation for maintaining an acceptable level of information related to the spatial variation of agri-environmental P index in Eastern Canada.

Keywords: *P extracted Mehlich-3 (P_{M3}); $(P/Al)_{M3}$ index; geostatistics; soil sampling strategy; tillage, kriging, spline, precision agriculture*.

Introduction

Phosphorus (P) is an essential nutrient for crop production including corn. However, the excessive P application tends to P accumulation at the soil surface under crop systems. This may contribute to increase water and groundwater pollution by surface runoff. To prevent this undesired impact, an agri-environmental soil P index, $(P/Al)_{M3}$ was developed for Eastern Canada (Khiari et al., 2000; Pellerin et al., 2006; CRAAQ, 2010) and the Mid-Atlantic USA (Sims et al., 2002). This index aims to estimate soil P saturation for accurate P fertilizer recommendations, while integrating agronomical aspects and environmental risks. In Eastern Canada, the critical environmental threshold for soil P corresponds to a $(P/Al)_{M3}$ value of 8% for fine-textured soils (MDDELCC, 2017), indicating that $(P/Al)_{M3}$ values higher than this value can result in water contamination. Thus, it is important to have a better understanding of spatial variability of P in agricultural fields for improving the economic and rational use of P fertilizers, promoting the profitability and sustainability of agricultural companies, while reducing P losses.

To achieve this aim, geostatistical interpolation methods were used in soil science studies aiming to understand better and reproduce the model of spatial variability of soil properties (Trangmar et al. 1985). Kriging interpolation approach is the reference method currently used for interpolating soil properties (Shao-qing et al., 2011, Quenum et al., 2012). However, this approach requires a high sampling density (more than 100 sampling points), which is not economically practical for the producers. Other interpolation methods, such as the spline method, could be used to set up soil P spatial maps with less sampling points.

Many studies were carried out on comparison of different spatial interpolation methods for mapping soil available P in various regions (Kravchenko and Bullock, 1999; Gao et al., 2011; Patil et al., 2011; Shao-qing et al., 2011; Shen et al., 2019; Zhao et al., 2021). Shao-qing et al. (2011) compared three interpolation approaches (kriging, inverse distance weighted, and spline) for determining hot-spots of soil available P in a hilly area. The authors found that the kriging method was the best interpolation method (lowest mean error=0.06) in predicting spatial variability of soil available P. Inversely, Gao et al. (2011) reported that spline methods (spline tension and regularized) were the best interpolation methods (r=0.91; r=0.81) for predicting soil available P based on 81 soil samples collected from Chaohu Lake watershed.

However, to our knowledge, no field-scale studies have been conducted on the use of spline method for mapping soil available P in Eastern Canada. Thus, the main objective of our study was to compare two methods of interpolation (kriging vs spline) to ensure optimal P fertilization recommendations and sustainability in agriculture production. The specific objectives were to (1) compare two methods of interpolation (kriging vs spline) on the precision and the reliability of the $(P/Al)_{M3}$ maps obtained with a decrease of soil sampling density, and to (2) evaluate the current

P_2O_5 fertilizer recommendations (kg P_2O_5 ha^{-1}) using prescription maps of spatial values of $(P/Al)_{M3}$ in two commercial corn fields in Eastern Canada.

Materials and methods

Site description and soil sampling

The study was conducted in the Montérégie region (Quebec, Canada). Two commercial fields were selected, representing two contrasted soil tillage practices. One field was located at Saint-Marc-sur-Richelieu (45°42′N; 73°14′W; 10.8 ha, established in 1994), referred to as Conventional Tillage (CT) field, and the second field was located at La Présentation (45°36′N; 73°02′W; 9.5 ha, established in 1994), referred to as No-Till (NT) field (Figure1). Both fields belong to the same soil texture group (i.e., fine-textured soils with clay > 30%) and were poorly drained. The soils on the fields were classified as Orthic Humic Gleysols and presented similar soil series (St-Urbain and Kierkoski) (Nolin and Lamontagne, 1990). The mean annual temperature and total annual precipitation are 6°C and 973 mm, respectively, at Saint-Marc-sur-Richelieu. The mean annual temperature and total annual precipitation are 5.9°C and 984 mm, respectively, at La Présentation. These fields were managed under corn (*Zea mays* L.) production. At seeding, the NPK fertilizers were band applied similarly under the two tillage systems. The P and potassium (K) were both applied at the seeding stage, while nitrogen (N) was applied by a twice fractionation: at the seeding stage, and during the 6–8 leaf stage using commercial fertilizer, following local recommendations for the province of Quebec (CRAAQ, 2010).

An intensive soil sampling was performed on November 2014 using a grid design with a sampling interval of 35 m × 35 m, providing 141 and 134 georeferenced sampling points for the CT and NT fields, respectively (Figure 1). A composite soil sample of four cores was taken within a radius of 1 m around each sampling point at the soil depth (0–5 cm) using a 5 cm-diameter Dutch auger. Soil samples were analyzed for available P and aluminum (Al) by the Mehlich-3 method (M3) and the $(P/Al)_{M3}$ index was calculated. Five sampling density points, (100%, 80%, 60%, 40%, 20% of the georeferenced sampling points), were used to interpolate agri-environmental $(P/Al)_{M3}$ index at the field scale. These sampling densities were generated using the "Create random points" ArcGIS tool (Figure 1).

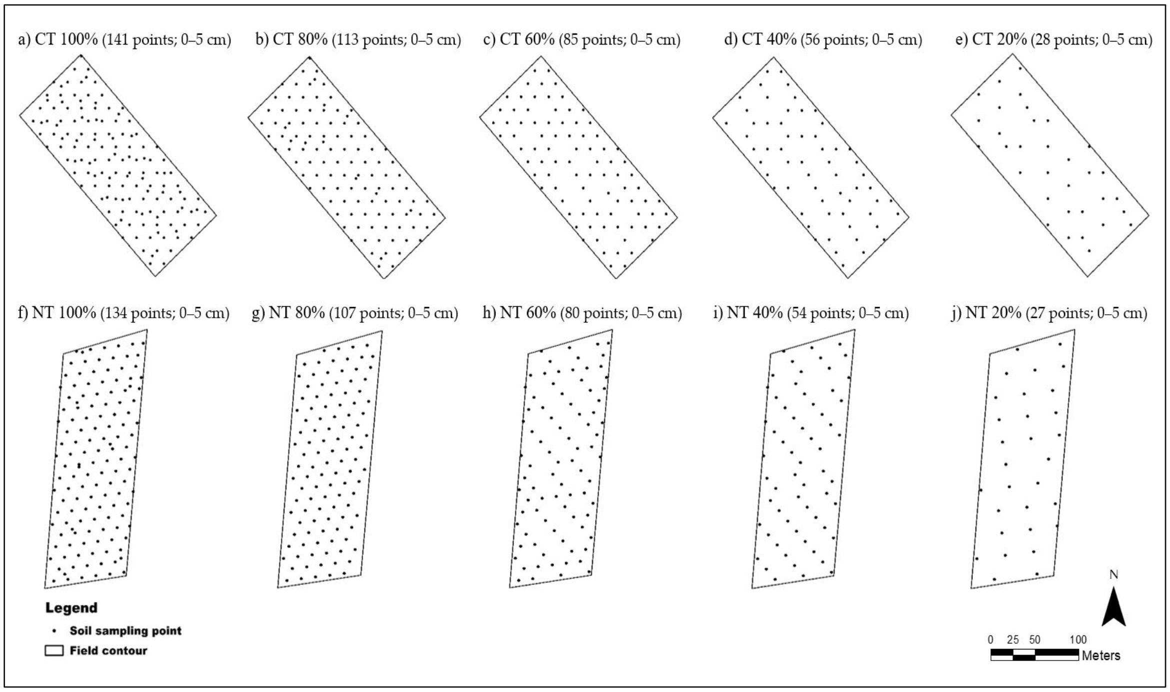

Fig 1. Sampling strategy grids for different sampling densities in the 0–5 cm soil layer in the conventional tillage and no-tillage fields.

Statistical and geostatistical analyses

Data were analyzed using descriptive statistics and geostatistics. Means and coefficient of variation (CV) values were estimated using the SAS software version 9.4 (SAS Institute, 2010). The CV of intensity soil P values was classified based on the approach of Nolin and Caillier (1992) as follow: (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 analyses (parameters calibrations, geostatistical computations, and model validations) were performed to determine spatial structures of soil P using GS+ version 9 (Robertson, 2008) and ArcGIS software. The spatial structure of soil P was evaluated via isotropic and anisotropic semivariograms. Semivariogram parameters for each theoretical model (spherical and exponential) were generated. The corresponding nugget (C_0), partial sill (C), sill (C_0+C), and range values of the best-fitting theoretical model were determined. The partial sill ratio [$C/(C_0 + C)$] was calculated to determine the spatial structure of the soil P for both fields. Semivariograms with a partial sill ratio of <25%, 25% to 40%, 40% to 60%, 60% to 75%, or >75% were considered to have a low, low moderate, moderate, strong moderate, or strong spatial structure, respectively (Whelan and McBratney, 2000). The range indicates the maximum distance at which sample points are correlated (Vieira et al., 1983).

Interpolation methods and spatial correlations

Kriging and spline interpolation methods were used to spatialize (map) soil agri-environmental P index, $(P/Al)_{M3}$ using ArcGIS tools. Kriging interpolation method was performed with 100% sampling density using the "Geostatistical Wizard" ArcGIS tool. Spline method was performed with the five sampling densities (100%, 80%, 60%, 40%, 20%) using "Spline with barriers" ArcGIS tool. Then, the kriged and splined resulting maps were converted into raster maps using the "GA

Layer to Grid” ArcGIS tool. These raster maps were circumscribed to the field contours using the “Extract by mask” ArcGIS tool. The spatial resolution of the resulting raster maps was 1 m^2.

A spatial correlation approach of five sampling density raster maps (100%, 80%, 60%, 40%, 20%) from the spline method relative to the 100% sampling density of the kriging method was performed on soil $(P/Al)_{M3}$ index for both fields using the “Band collections statistics” ArcGIS tool. This correlation analysis aimed to establish correspondence between both interpolation methods. Spatial correlation values higher than 0.6 can be considered as acceptable level for maintaining spatial information related to the estimation of spatial variation of soil $(P/Al)_{M3}$ index. Future P prescription maps will be also completed. Finally, P fertilizer recommendations (kg P_2O_5 ha^{-1}) were developed for corn for a sustainable management of P in these different agro- ecosystems studied.

Results and Discussion

Soil $(P/Al)_{M3}$ accumulation was observed with NT (7.9%) at the 0–5 cm soil layer (Table 1). In Province of Quebec, the national critical environmental threshold for P saturation for fine-textured soils is 8% (MDDELCC, 2017), indicating that $(P/Al)_{M3}$ values higher than this can result in water contamination.

The CVs of soil $(P/Al)_{M3}$ ranged from moderate to high (32–52%) in both contrasted fields (Table 1). A high CV of soil P has implications for developing future agronomic strategies for sustainable management of P based on delineating management zones or variable rate applications for accurate P recommendations in precision agriculture.

In the CT field, a more reduced sampling density corresponds generally to a higher variability of soil P (46–52%). In the NT field, a more reduced sampling density corresponds generally to a relative low variability of soil P (32–34%). Thus, a reduced sampling density had little impacts on CV of soil P under intensive contrasted tillage activities. Radocaj et al (2021) observed also a similar tendency through a close range of CV values for soil P under different sampling densities.

In the CT field, CV of soil P ranged from high to very high (46–52%). In the NT field, CV of soil P ranged from moderate to high (32–34%). Thus, in this field-scale study, reduction of soil P variability was observed under both contrasted tillage practices. Jia et al. (2011) reported a large decrease in the CV of soil P from 151% to 55% after 25 years of intensive farming practices.

Table 1. Descriptive statistics of the soil $(P/Al)_{M3}$ for the soil layer (0–5 cm) in the conventional tillage and no-tillage fields.

	Units	n	Mean	Min	Max	STD	CV (%)
		----------0–5 cm----------					
Conventional tillage							
100-$(P/Al)_{M3}$	(%)	141	2.8	0.6	7.4	1.3	46
80-$(P/Al)_{M3}$	(%)	113	2.7	0.6	7.4	1.4	52
60-$(P/Al)_{M3}$	(%)	85	2.8	0.6	7.4	1.4	50
40-$(P/Al)_{M3}$	(%)	56	2.9	0.6	7.4	1.5	52
20-$(P/Al)_{M3}$	(%)	28	2.5	0.6	6.3	1.2	48
No tillage							
100-$(P/Al)_{M3}$	(%)	134	7.9	2.5	17.5	2.6	33
80-$(P/Al)_{M3}$	(%)	107	8.2	2.5	17.5	2.6	32
60-$(P/Al)_{M3}$	(%)	80	8.0	2.5	17.5	2.7	34
40-$(P/Al)_{M3}$	(%)	54	8.2	2.5	17.5	2.8	34
20-$(P/Al)_{M3}$	(%)	27	7.7	3.4	15.2	2.5	32

Soil available P was mainly fitted with spherical models in both contrasted fields (Table 2). Previous studies reported that soil available P was best modeled using spherical models (Jiang et al., 2012; Metwali et al., 2019). Spatial structure of soil P varied from low to strong (24–93%) in both contrasted fields (Table 2). Spatial ranges varied between 45 and 153 m, extended beyond the 35 m × 35 m sampling grid.

Table 2. Geostatistical properties of the soil $(P/Al)_{M3}$ for the soil layer (0–5 cm) in the conventional tillage and no-tillage fields.

	---0–5 cm---		
	Model[1]	**Sill ratio[2] (%)**	**Range[3] (m)**
Conventional tillage			
100-$(P/Al)_{M3}$	Sph	45	57
80-$(P/Al)_{M3}$	Sph	65	53
60-$(P/Al)_{M3}$	Exp	31	45
40-$(P/Al)_{M3}$	Sph	43	56
20-$(P/Al)_{M3}$	Sph	30	55
No tillage			
100-$(P/Al)_{M3}$	Sph	45	60
80-$(P/Al)_{M3}$	Sph	24	60
60-$(P/Al)_{M3}$	Sph	54	70
40-$(P/Al)_{M3}$	Sph	29	60
20-$(P/Al)_{M3}$	Sph	93	153

[1]Semivariogram model: Exp: exponential, Sph: spherical; [2] Sill ratio (%) =$[C/(C_0+C)]$ x100; this ratio measures spatial dependence or structure according to Whelan and McBratney (2000); [3] Distance at which a semivariance becomes constant.

In the CT field, spatial structure of soil P varied from low moderate to moderate (24–65%), corresponding to a more reduced sampling density (Table 2). Fu et al. (2013) observed similar results with the same tendency. Spatial range varied from 45 to 57 m. In the NT field, spatial structure of soil P varied from low to strong (24–93%), corresponding generally to a more reduced sampling density with a spatial range up to 153 m (Table 2). Other studies observed strongest spatial structures of soil P (up to 98%) with a reduced soil density (2 samples by ha) (Shi et al., 2000). As reported by Fu et al. (2013), the amount of soil samples impacted on revealing spatial structure of soil P. Thus in this field-scale study, soil sampling density modified substantially the spatial range and structure of soil P under contrasted tillage practices. Moderate spatial structure for soil P was observed in many previous field-scale studies (Whelan et McBratney, 2000; Dalchiavon et al., 2017; Metwally et al., 2019; Nze Memiaghe et al., 2021). Consequently, an optimal sampling grid should be optimized for each field.

In the CT field, spatial values of $(P/Al)_{M3}$ ranged from 0.5–6.5% and were similar to those estimated by interpolation methods selected (kriging vs spline up to 60% sampling density) (Figure 2). Moreover for other interpolation methods such as spline 40% and 20% sampling density, spatial values of $(P/Al)_{M3}$ ranged from 0.5–8.0% and 0.5–5.0%, respectively (Figure 2). Consequently, we can infer that spatial distribution values of $(P/Al)_{M3}$ were not affected by kriging and spline interpolation methods up to 60% of sampling density. In the NT field, spatial values of $(P/Al)_{M3}$ ranged from 4–12% for kriging (100%). These $(P/Al)_{M3}$ values were different from those performed using spline methods (Figure 3). Indeed, spatial values of $(P/Al)_{M3}$ ranged from 0–20% and were similar for spline up to 40%. Spatial values of $(P/Al)_{M3}$ ranged from 0–16% for spline 20% (Figure 3). Consequently, we can infer that spatial distribution values of $(P/Al)_{M3}$ were affected by interpolation methods selected (kriging vs spline up to 40%).

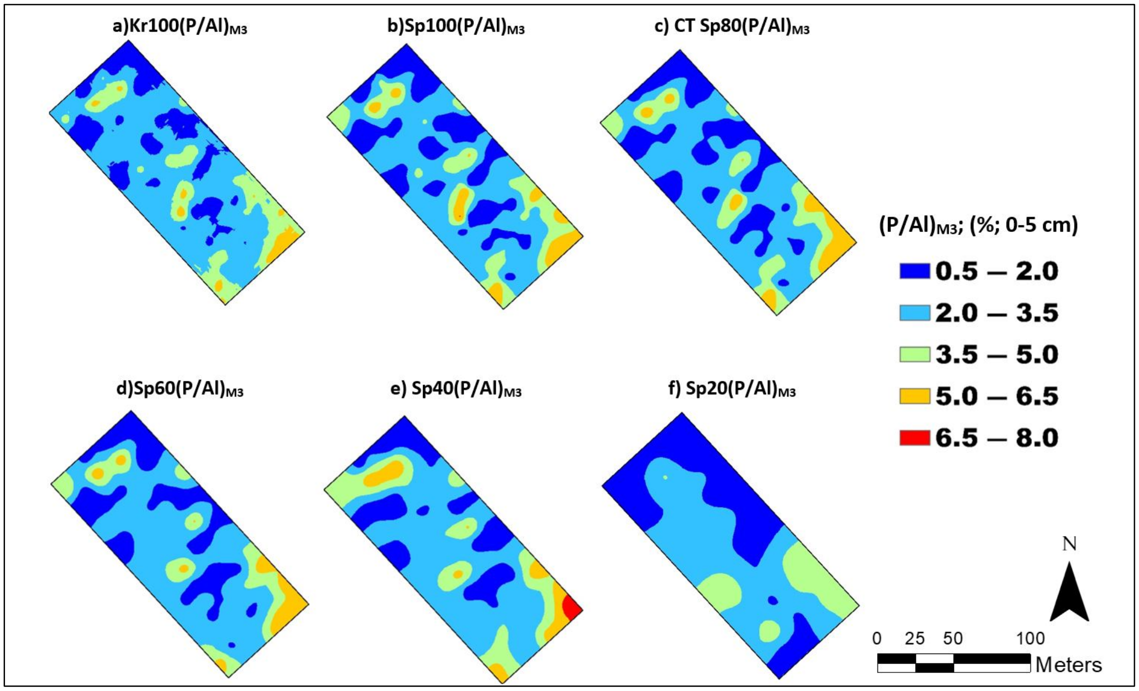

Fig 2. Spatial distribution maps of $(P/Al)_{M3}$ performed using Kriging (Kr) and Spline (Sp) interpolation methods for different sampling densities in the 0–5 cm soil layer in the conventional tillage field.

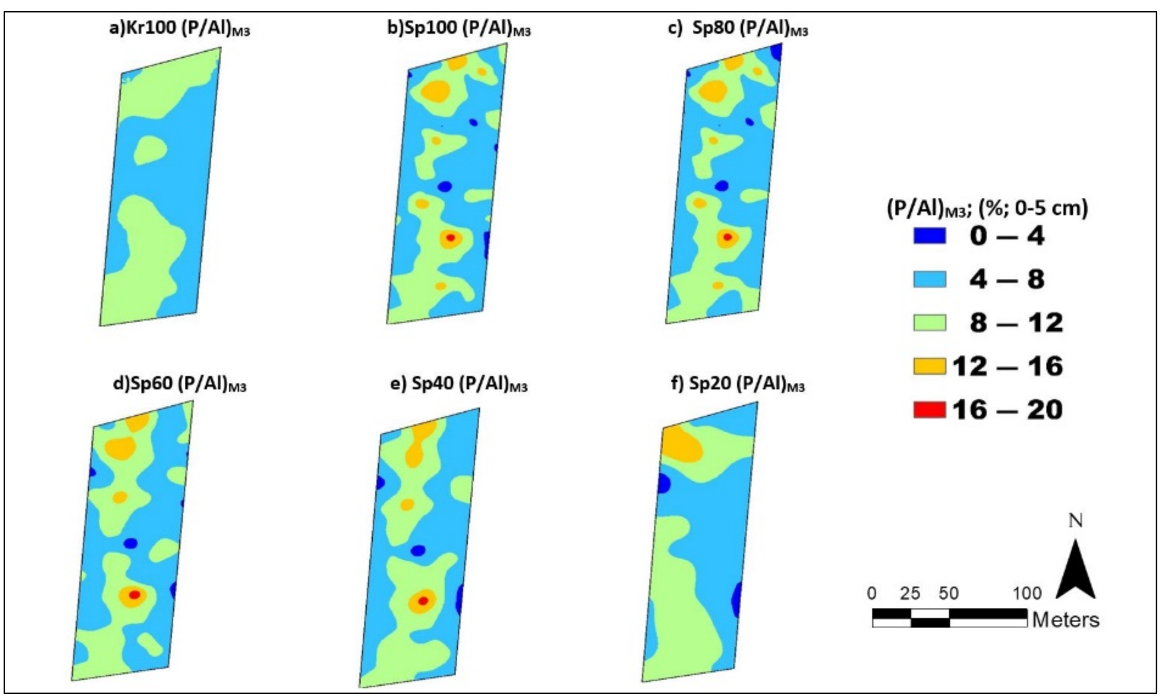

Fig 3. Spatial distribution maps of $(P/Al)_{M3}$ performed using Kriging (Kr) and Spline (Sp) interpolation methods for different sampling densities in the 0–5 cm soil layer in the no-tillage field.

Pearson correlation coefficients between these interpolation methods were generally higher in CT soil layer compared to the NT soil layer (0–5 cm) (Table 3). Results revealed also a more reduced sampling density impacted on decrease of effectiveness of spatial correlations between spline methods (100%, 80%, 60%,40% and 20%) and the kriging method (100%) in both contrasted fields (Table 2).

Table 3. Pearson correlation of the five sampling density maps using spline method in relationship with the kriging map for soil $(P/Al)_{M3}$ for the soil layer (0–5 cm) in the conventional tillage and no tillage fields.

	Conventional tillage		No tillage	
	$Kr100(P/Al)_{M3}$		$Kr100(P/Al)_{M3}$	
$Sp100(P/Al)_{M3}$	0.96	***	0.84	***
$Sp80(P/Al)_{M3}$	0.93	***	0.79	***
$Sp60(P/Al)_{M3}$	0.87	***	0.73	***
$Sp40(P/Al)_{M3}$	0.82	***	0.68	***
$Sp20(P/Al)_{M3}$	0.47	***	0.58	***

Significance of correlation indicated by *** are equivalent to *p*-value < 0.001

A high CV of soil $(P/Al)_{M3}$ indicates that the uniform P fertilizer recommendations currently applied for corn are not suitable for large (10 ha) fields following local recommendations. Soil variability and potential yield differences in a given field are responsible for large field-scale heterogeneity in the distribution pattern of soil nutrients, such as P (Nze Memiaghe et al., 2021; Cambouris et al., 1999). Consequently, accurate P fertilizer recommendations (kg P_2O_5 ha^{-1}) were developed for both fields planted with corn taking into account (1) spatial distribution values for soil P resulting from high soil P variability in these large fields and (2) the corresponding Quebec agronomic P recommendations for corn (Figure 4).

In the CT field, three specific P_2O_5 recommendations (80, 60 and 40 kg P_2O_5 ha^{-1}) were generated for corn from five interpolation maps, including kriging (100%) and four sampling density spline methods (100%, 80%, 60%, 40%). In addition, two specific P_2O_5 recommendations (80 and 60 kg P_2O_5 ha^{-1}) were generated from spline 20%. In the NT field, three specific P_2O_5 recommendations (60, 40 and 20 kg P_2O_5 ha^{-1}) were generated from kriged spatial map (100%). Furthermore, four specific P_2O_5 recommendations (80, 60, 40 and 20 kg P_2O_5 ha^{-1}) were generated based on five interpolation maps from the five spline methods (100%, 80%, 60%, 40%, and 20%). Thus, the selected interpolation method from a specific sampling density may impact on P_2O_5 fertilizer recommendations under contrasted tillage practices.

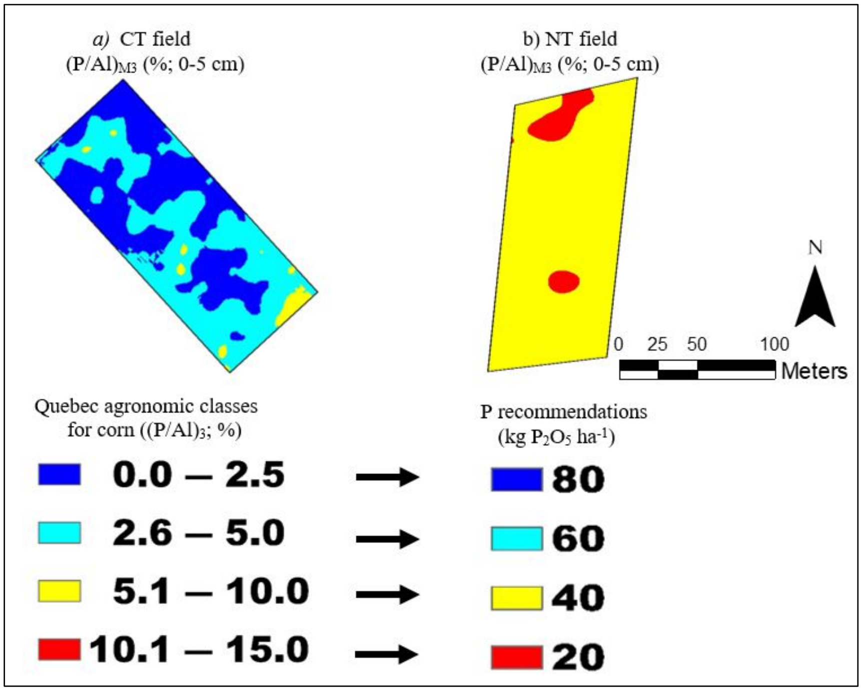

Fig 4. Quebec agronomic classes of soil $(P/Al)_{M3}$ and the corresponding accurate P recommendations (kg P_2O_5 ha^{-1}) for corn in the conventional tillage and no-tillage fields.

Geostatistics helps to determine the amount of soil samples to be collected according to the range, tillage system, and soil property to be analyzed (Mc Bratney and Webster 1983; Malvezi et al., 2019). From all observed results, we recommend use of the spline up to 60% (85 sampling points) and 40% (54 sampling points) in the CT and NT fields, respectively for sustainable P_2O_5 recommendations for corn. These sampling density values may represent up to 8 samples ha^{-1} compared to kriging method (141 points, 13 samples ha^{-1}) and 6 samples ha^{-1} compared to kriging method (134 points, 14 samples ha^{-1}), respectively in both contrasted fields. Furthermore, Pearson correlation values between spline methods in relation with the kriging map were significantly higher than 0.87 and 0.68 under both contrasted fields, which can be acceptable. Thus, there would be a potential for using the spline interpolation method aiming to reduce sampling density while maintaining an acceptable level of information related to the estimation of spatial variation of soil agri-environmental P index in Eastern Canada.

Conclusions

This study aimed to compare two interpolation methods (kriging vs spline) for sustainable P_2O_5 recommendations in Eastern Canada. The results revealed that a reduced sampling density had little impacts on the variability of soil P (32–52%) while modifying substantially spatial structure of soil P (24–93%) under both contrasted fields. Consequently, an optimal sampling grid should be optimized for each field. Interpolation methods impacted on the spatial values of $(P/Al)_{M3}$ in the CT field (spline up to 60%) and the NT field (kriging vs spline up to 40%). The sampling density impacted on the effectiveness of spatial correlations between interpolation methods. The interpolation method (Kriging vs Spline) from a specific sampling density may affect P_2O_5 rate recommendation under intensive contrasted tillage practices. In keeping with the results of this study, we recommend the spline interpolation method up to 60% and 40% for sustainable P_2O_5 recommendations in the CT and NT fields, respectively.

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