



## Research article

# Calibrated SoilOptix<sup>®</sup> estimates of soil pH and exchangeable cations in three agricultural fields in western Canada – implications for managing spatially variable soil acidity

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## ABSTRACT

Spatial variability in soil pH is a major contributor to within-field variations in soil fertility and crop productivity. An improved understanding of the spatial variability of soil pH within agricultural fields is required to determine liming requirements for precision farming. This study with the use of proximal sensors, firstly assessed the spatial pattern of soil pH and how it can be used to determine site-specific, spatially variable lime requirements. Secondly, the effects of soil pH on soil concentrations of nitrate nitrogen (NO<sub>3</sub>-N), phosphorus (P), potassium (K), sulfur (SO<sub>4</sub>-S), calcium (Ca), magnesium (Mg), soil organic matter (SOM), aluminum (Al), and manganese (Mn) were assessed in three study fields in central Alberta, Canada. Soil pH varied between 4.5 and 7.5 across all field sites. The field-scale coefficient of variation (CV %) for soil pH, Al and Mn ranged between 4.39 and 7.50 %, 7.33–13.72 %, and 7.33–13.72 % across the three sites. The other soil properties showed low, moderate, and high variability, with field-scale CVs ranging between 6.39 and 17.70 % for SOM and 24.33–91.39 % for SO<sub>4</sub>-S. Soil pH exhibited positive correlations with both Ca and Mg, across all fields. Negative correlations were observed between soil pH and Al across all fields. A principal component analysis (PCA) was performed for all soil parameters and two principal components accounted for 50 %, 54.9 %, and 76.8 % of the total variance in field 1, field 2, and field 3, respectively. Geostatistical semivariance indicated a strong spatial dependence of all chemical parameters across fields. Large regions within a field were strongly acidic (pH < 5.5) and required lime applications ranging from 0 to 6 t ha<sup>-1</sup>. We conclude that proximal soil sensors can be calibrated to soil properties, enabling variable rate lime recommendations on spatially variable fields for the management of soil acidity.

## 1. Introduction

Soil pH varies spatially across agricultural landscapes [1,2]. Landscape- or field-scale variability of soil properties, including soil

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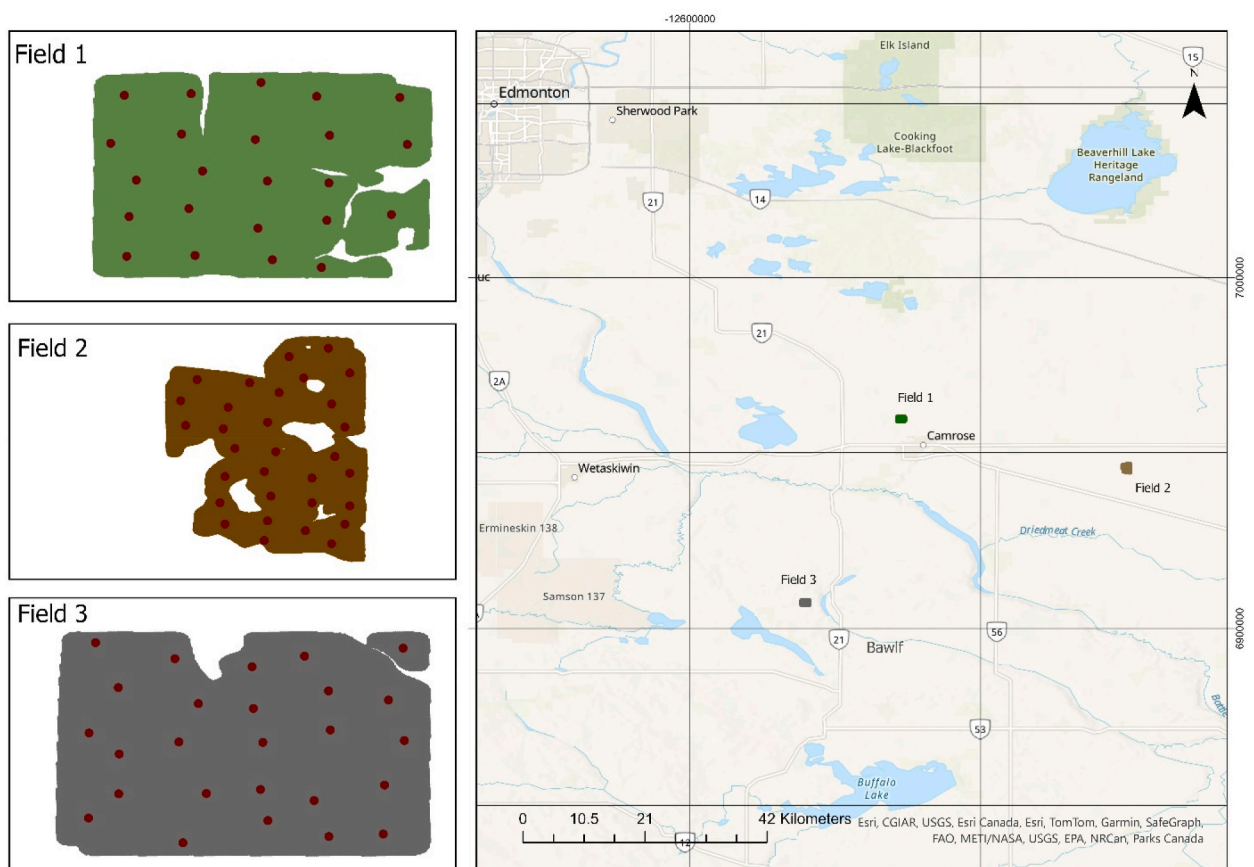
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pH, influences nutrient availability, and microbial diversity, causing within-field variability in crop growth and yields with the same input allocation [3,4]. Soil pH varies in response to inherent factors (topography, geological parent materials and their weathering in response to climate, and management factors), fertilizer applications, removal of harvested plant materials (which influence, biological activities of microorganisms), and soil organic matter levels [5,6]. Information from soil testing supports agricultural management decisions about cost-effective application (rates and placement) of soil amendments and fertilizers that support crop growth and soil fertility [2,7]. A challenge facing crop production in western Canada is the acidification of agricultural soils. Approximately, 2.6 million hectares of arable land are acidic ( $\text{pH} < 6.0$ ), and an additional 3.5 million hectares of arable land have a pH ranging between 6.1 and 6.5 [8]. Decreases in soil pH in this region have been exacerbated by the shift to reduced tillage and increased application rates of nitrogen fertilizers associated with intensive and diverse crop rotations [9]. Excessive and disproportionate use of nitrogenous fertilizers on croplands is known as one of the many ways in which soil acidification can be accelerated.

Previous studies have shown that spatial variations in soil pH can be measured using different sampling approaches, such as grid, adaptive, and random soil sampling techniques in combination with laboratory analysis or “on-the-go” soil sensor information to develop soil maps [10,11]. A major hurdle in conventional sampling approaches is obtaining a sufficient number of representative soil samples for characterizing a specific field. A high number of soil samples is required because using a composite sample neglects variability which would impact the allocation of inputs [11,12]. Collecting many soil samples per field is not financially feasible for crop producers and, as a result, a precise depiction of the variations in soil properties at the field-scale remains unknown [13]. Recently, precision agricultural (PA) techniques have become readily accessible to aid in soil pH management in farmlands [12]. The goal of precision agriculture is to ensure that resource allocation matches the soil and plant requirements according to their spatial distribution within a given field [14]. Precision agricultural management leverages technologies such as geographic information systems (GIS), global positioning systems (GPS), variable rate technology (VRT), remote sensing (RS), yield mapping, high-resolution soil mapping, and weed sensors [15]. Quantification of within-field variability of soil chemical properties allows for the delineation of in-field management zones with agricultural input rates optimized to the soil properties of the zone, potentially improving nutrient use efficiency, crop yields and profitability [16,17].

Soil acidity negatively affects crop productivity, and if issues of low soil pH are not resolved, crop producers will not completely realize the yield advantages offered by breeding and improved management practices [18]. Liming as been reported as an effective



**Fig. 1.** Map showing field sites in Canadian province of Alberta Canada; the location of the studied arable fields (Edmonton). Red dots on the map represents soil sampling points location within a given field. Sources: ArcGISPro (version 3.3.0).

strategy to ameliorate low soil pH [19]. In fields with spatially variable soil pH, variable rate lime application is likely the best strategy for improving crop yields and soil fertility [20]. High resolution maps of soil pH provide the foundation for developing variable rate lime prescriptions [20,21].

Several technologies have been employed to map soil properties. To solve the challenges related to precise input allocations, devices such as proximal soil sensors were designed to map soil parameters at high spatial resolutions [22]. Proximal soil sensors are surface sensors used to measure soil properties [11,23]. Sensor-based soil property estimates are based on calibrations between sensor data and soil property measurements [22]. Several research studies have shown the capacity to obtain high spatial resolution data using sensors and reflectance from soil surfaces, which can be calibrated to a wide range of soil properties such as soil moisture, pH, C, SOM, NO<sub>3</sub>-N, P, Mg, Al, Mn, and Ca [21,24–27]. For example, soil moisture variability at the field scale has been quantified using electromagnetic waves emitted from ground-penetrating radar [28]. Reflectance measurements on cultivated farmlands have been utilized to predict soil physical properties on soil surfaces [26]. Proximal gamma sensors have been used to map soil properties, quantify clay content, pH, and N at high spatial resolution [24,25], and provide quantitative information for the lime requirement in arable soils [21]. Geophysical sensors have been used to predict bulk density, electrical conductivity, and water-holding capacity [27]. These methods are both non-invasive for topsoil analysis and can be used to construct high spatial resolution maps [21,24]. These technologies enable the acquisition of spatially detailed soil information rapidly and precisely to overcome financial and time limitations faced by crop producers. The potential for sensor data to capture a number of relevant soil properties provides a cost-effective means for developing site-specific, variable rate input recommendations [25,27,29].

However, there is a dearth of information on the spatial variability of soil pH within fields and its nutrient availability. This is because most studies provide blanket crop input recommendations on a regional or global scale. Currently, little is known about the extent of within-field pH variation in the prairies of western Canada, its correlation with soil nutrients, and how this information can support site-specific lime requirement.

The objectives of this study were to evaluate: (i) the spatial patterns of soil pH estimated using SoilOptix® gamma sensors, (ii) the relationship between soil pH estimated with the calibrated SoilOptix® sensor and some selected soil properties, (iii) the relationship between soil pH estimated with the calibrated SoilOptix® sensor and field elevation, (iv) The potential of using SoilOptix® for developing soil pH classes. v) The potential of using SoilOptix® for developing variable lime application rates.

## 2. Materials and methods

### 2.1. Site description and management

This study is based on three agricultural fields in Alberta Canada (Fig. 1). Field sizes were 57 ha (field 1), 90 ha (field 2), and 62 ha (field 3). Two of the study sites, field 1 (53°03'39.2"N; 112°51'20.3"W) and field 2 (52°58'54.1"N; 112°31'08.9"W), have clay loam-textured soils that are classified as Haplic Sodic Chernozems. The third study site, field 3 (52°46'39.6"N; 113°00'33.6"W), has silty-clay textured soils that are classified as Mollic Albic Solonetz developed on fine-textured water-laid sediment [30]. All field sites are located within a 50 km radius of the city of Camrose, Alberta, Canada. Typical annual crops grown in this area are wheat (*Triticum aestivum*), canola (*Brassica napus* L), barley (*Hordeum vulgare* L), and field peas (*Pisum sativum* L).

### 2.2. Soil sample collection and mapping

High-resolution soil mapping was facilitated by the SoilOptix® Intelligence System (597112 Hwy 59 Tavistock, Ontario N0B 2R0 Canada). The core of the system is a sensor that measures gamma radiation emitted from the decay of Caesium-137, Uranium-238, Thorium-232, and Potassium-40 emitted from the uppermost soil layer (top 20–30 cm). The gamma sensor is used to estimate soil properties through a proprietary, multivariate calibration algorithm in the SoilOptix® software using lab-measured soil properties from samples taken from locations recommended by the software such that soil samples are taken at locations covering the range of sensor values. Details of this technique can be found in Refs. [21,31]. In this work, the focus is not on how to calibrate the SoilOptix® sensor, but rather on the utility of the SoilOptix® sensor-estimated soil pH and associated properties for agricultural management.

Field mapping and sampling were done before seeding on all fields (i.e., when soils were bare and undisturbed) in May 2022. The sensor was mounted to an off-highway vehicle (OHV) at 80 cm above the soil surface. The survey was conducted at speed of 40 km/h along transects spaced 12 m apart. Approximately 875 spatially referenced data points per ha were collected. Furthermore, soil samples (0–20 cm) were collected from different points within the field, collecting one sample per 3.3 ha for soil analysis and sensor calibration. The number of samples taken is dependent on farm size, resulting in 19 samples in field 1, 30 samples in field 2 and in 21 samples in field 3.

Soil samples are taken at a sampling depth spanning the surface 15–20 cm. The SODL (SoilOptix DataLink) program is a component of SoilOptix's soil mapping technology to help users identify optimal sampling locations in the field, ensuring that the samples reflect the full range of soil conditions, including areas with different radiation levels. During field mapping, soil samples are taken from areas of high and low radiation. While the rest of the samples are spatially distributed. The tool also ensures that the rest of the samples are evenly spread out to cover all radiation levels in the field. These samples collected were used for validation.

The soil samples were analysed for pH (2:1 water), SOM, NO<sub>3</sub>-N, SO<sub>4</sub>-S, Bray1 P, exchangeable K, Ca, Mg, Al, and Mn and CEC at A & L Canada laboratories Inc. Exchangeable cations (Ca, Mg, K, Na, H) and CEC were analysed using the BaCl<sub>2</sub> method [32]. Soil pH was analysed in 0.01 M CaCl<sub>2</sub> (2:1) [33]. Soil organic matter was determined using the dry combustion after treatment with HCl [33]. Nitrate Nitrogen (NO<sub>3</sub>-N) was measured colorimetrically in 2M KCl extracts (2:1), and SO<sub>4</sub>-S was measured turbidometrically in water

extracts (2:1) [33].

Results from soil testing and sensor data were used to create a calibration model using the SoilOptix® Software. The calibration model was then used to create high-resolution maps for detailing the spatial distribution of different soil properties.

### 2.3. Lime rate estimation

A base saturation target of 60–70 % was used to determine lime requirement. Base saturation is calculated as a percentage CEC [34].

$$\text{Base Saturation} = \frac{\sum (Ca, Mg, K, Na)}{CEC} \cdot 100 \quad (1)$$

Where  $\sum (Ca, Mg, K, Na)$  is the sum of exchangeable Ca, Mg, K, and Na and CEC is the cation exchange capacity as cmol of positive charge per kg soil, respectively.

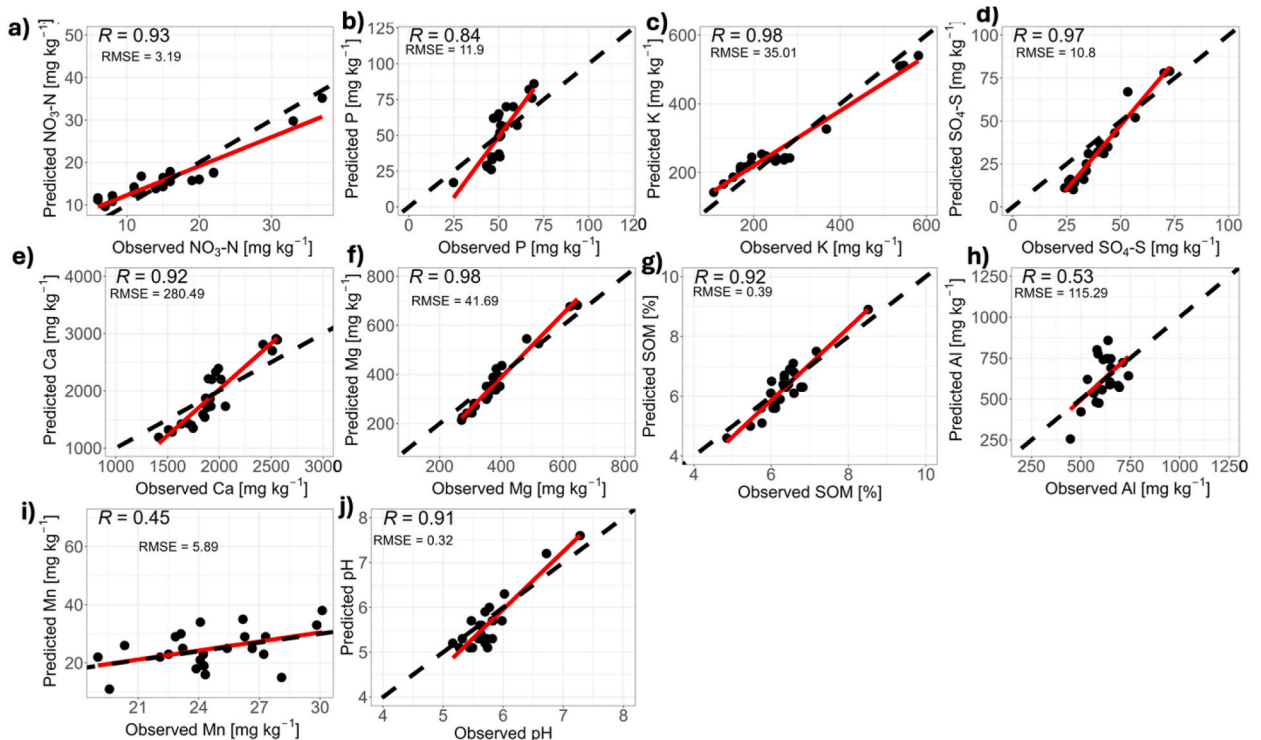
The lime requirement (LR) ( $Mg-CaCO_3 \text{ ha}^{-1}$ ) was calculated by calculating the amount of calcium from  $CaCO_3$  required to change the base saturation from the measured to the target value:

$$LR = \frac{\Delta \text{Base Saturation}}{100} \cdot \frac{1}{q_{Ca}} \cdot M_{Ca} \cdot M_{soil} \cdot \frac{1}{C_{Ca}} \quad (2)$$

Where LR is the lime requirement ( $Mg-CaCO_3 \text{ ha}^{-1}$ ),  $\Delta \text{Base Saturation}$  is the absolute value of the difference between measured and target base saturation,  $q_{Ca}$  is the cmole of positive charges per cmole of exchangeable Ca ( $\text{cmol}(+) \text{ cmol}_{Ca}^{-1}$ ),  $M_{Ca}$  is the molar mass of Ca with units converted to  $Mg-Ca \text{ cmol}^{-1}$ ,  $M_{soil}$  is the specific mass of a soil layer with a thickness equal to the sample on which base saturation was measured ( $\text{kg ha}^{-1}$ ), and  $C_{Ca}$  is the concentration of Ca in  $CaCO_3$  on a dry mass basis ( $Mg-Ca \text{ Mg-CaCO}_3^{-1}$ ). In the case where the liming material is not  $CaCO_3$ , the LR can be adjusted through multiplication with calcium carbonate equivalent (CCE) or changing  $C_{Ca}$  in Eq [2]. to the concentration of Ca in the liming material. In this study, cement kiln dust (CKD) was the intended liming material and CKD rates were estimated based on lab-measured Ca concentrations in the CKD.

### 2.4. Statistical and geospatial analyses

Summary and descriptive statistics including minimum, maximum, mean, median, range, standard deviation, and coefficient of



**Fig. 2.** Correlation between measured and SoilOptix®-predicted soil parameters in field 1. a)  $NO_3-N$ , (b) P, (c) K, (d)  $SO_4-S$ , (e) Ca, (f) Mg, (g) SOM, (h) Al, (i) Mn, and (j) pH. Root mean square error (RMSE) for  $NO_3-N$ , P, K,  $SO_4-S$ , Ca, Mg, SOM, Al, Mn, and pH in field 1. All units are the same for measured and SoilOptix®-predicted values for all soil parameters.



variation (CV), were determined for soil pH, SOM,  $\text{SO}_4\text{-S}$ , Ca, Mg, Al, Mn,  $\text{NO}_3\text{-N}$ , P, and K using the R programming language (R Development Core Team, 2013) and ggplot2 function in R. Pearson correlation between soil pH and other soil chemical properties was performed using the “cor” function. Pearson’s correlation between the SoilOptix® data and measured data was done using the “ggplot2” package. The surface maps of the predicted soil pH generated from the soil optix sensor were produced with ArcGIS. The soil pH data from each field was used to generate soil pH classes. Classified as follows: i) 4.5–5.0 ii) 5.0–5.5 iii) 5.5–6.0 iv) 6.0–6.5 and v) 6.5–7.5. The “geom\_histogram” function was used to create histogram plots to check the normality of the soil pH data across each field site. Boxplots for all the different soil pH classes were generated in R using the “ggboxplot function” and means were calculated using the “fun.y” and “stat\_summary” functions. The spatial dependence of each soil property was evaluated using the “gstat” and “variogram” functions in R. Each soil property was fitted using the “fit.variogram” function spherical semivariogram model. The PCA was done for each Field in R using the “prcomp()” function and the biplots were created to visualize the relationships between the variables using the “biplot” function and “ggplot2” package.

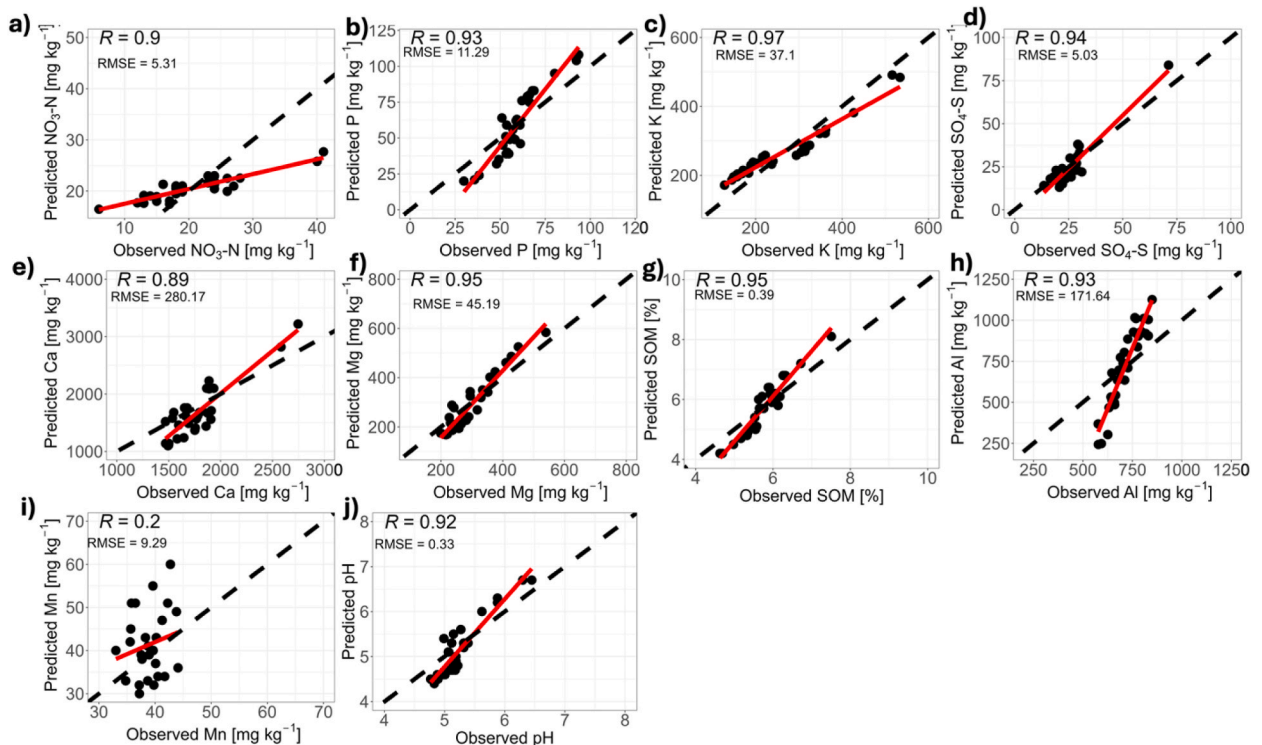
### 3. Results

#### 3.1. Field-Specific calibration of SoilOptix® sensor data

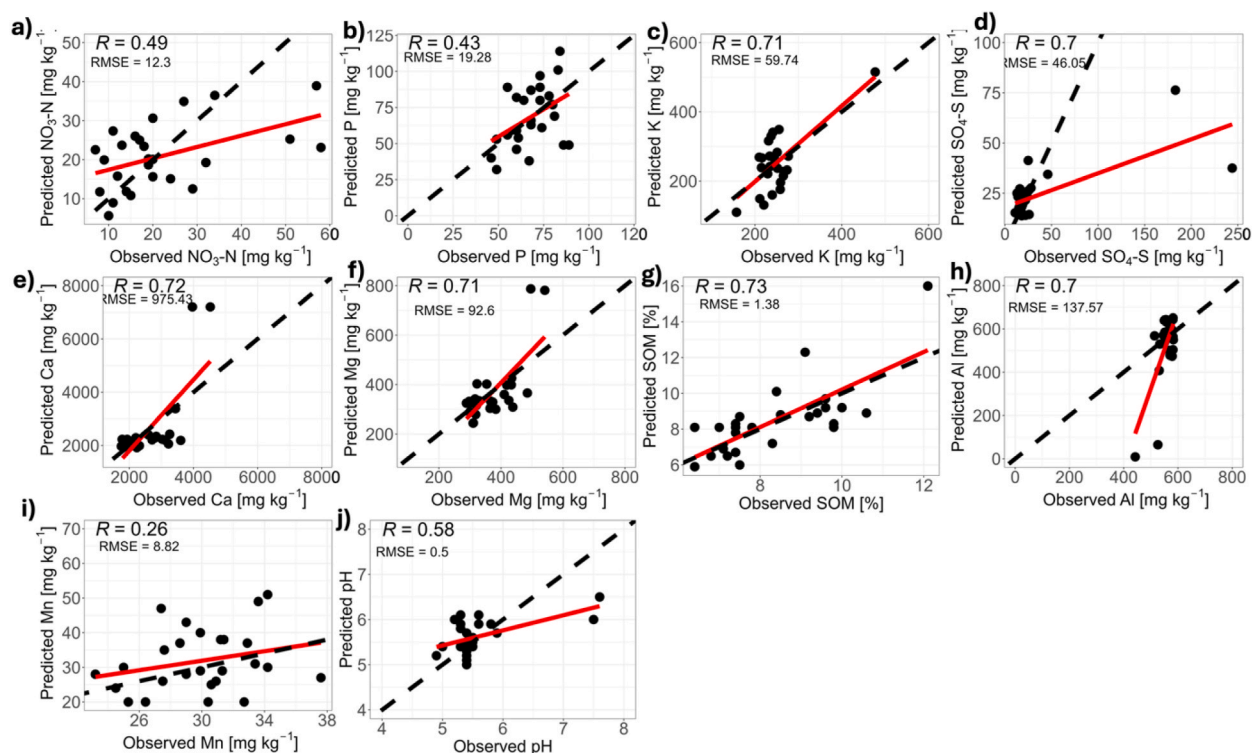
The raw SoilOptix® sensor data at the soil sample locations, and measured soil pH, and soil  $\text{NO}_3\text{-N}$ , P, K,  $\text{SO}_4\text{-S}$ , Ca, Mg, SOM, Al, Mn concentrations were used to calibrate the soil optix sensor using a proprietary, multivariate calibration algorithm such that the sensor response at each spatial location is used to predict multiple soil properties at that location and the “total difference” (specifics are not given by the manufacturer) between predicted and measured soil properties are minimized. The relationship between the measured and SoilOptix®-predicted soil properties are presented in Figs. 2–4. In field 1, high R values were observed for most soil parameters except for Mn ( $R = 0.45$ ) (Fig. 2i). In field 2, the lowest R values were observed for Mn ( $R = 0.2$ ) and for other soil property R values ranged between 0.83 and 0.95 (Fig. 3a–j). In field 3, R values were low for  $\text{NO}_3\text{-N}$  (0.49), P (0.43), and Mn (0.2) while for other soil properties values ranged between 0.56 and 0.76 (Fig. 4a–j).

#### 3.2. Variability in soil pH across field sites

The field maps (Fig. 5a–c) and soil pH distribution (Fig. 6a–c) of all the study areas show that soil pH values ranged between 4.5 and 7.5. In field 1, SoilOptix®-predicted soil pH levels ranged between 4.5 and 5.5 over a large area. Subsequently, the next substantial



**Fig. 3.** Correlation between measured and SoilOptix®-predicted soil parameters in field 2. a)  $\text{NO}_3\text{-N}$ , (b) P, (c) K, (d)  $\text{SO}_4\text{-S}$ , (e) Ca, (f) Mg, (g) SOM, (h) Al, (i) Mn, and (j) pH. Root mean square error (RMSE) for  $\text{NO}_3\text{-N}$ , P, K,  $\text{SO}_4\text{-S}$ , Ca, Mg, SOM, Al, Mn, and pH in field 2. All units are the same for measured and SoilOptix®-predicted values for all soil parameters.



**Fig. 4.** Correlation between measured and SoilOptix®-predicted soil parameters in field 3. a)  $\text{NO}_3\text{-N}$ , (b) P, (c) K, (d)  $\text{SO}_4\text{-S}$ , (e) Ca, (f) Mg, (g) SOM, (h) Al, (i) Mn, and (j) pH. Root mean square error (RMSE) for  $\text{NO}_3\text{-N}$ , P, K,  $\text{SO}_4\text{-S}$ , Ca, Mg, SOM, Al, Mn, and pH in field 3. All units are the same for measured and SoilOptix®-predicted values for all soil parameters.

area showed values within the range of 5.5–6.0. In field 2, a significant portion of the study area recorded pH levels ranging between 4.5 and 5.0, followed by another substantial area with pH levels between 5.0 and 5.5. Only a small portion of the field had pH above 6.0. In field 3, the majority of the area had pH ranging 6.0–6.5 and 5.5–6.0, with only a small portion having pH values between 4.5 and 5.0 (Fig. 5).

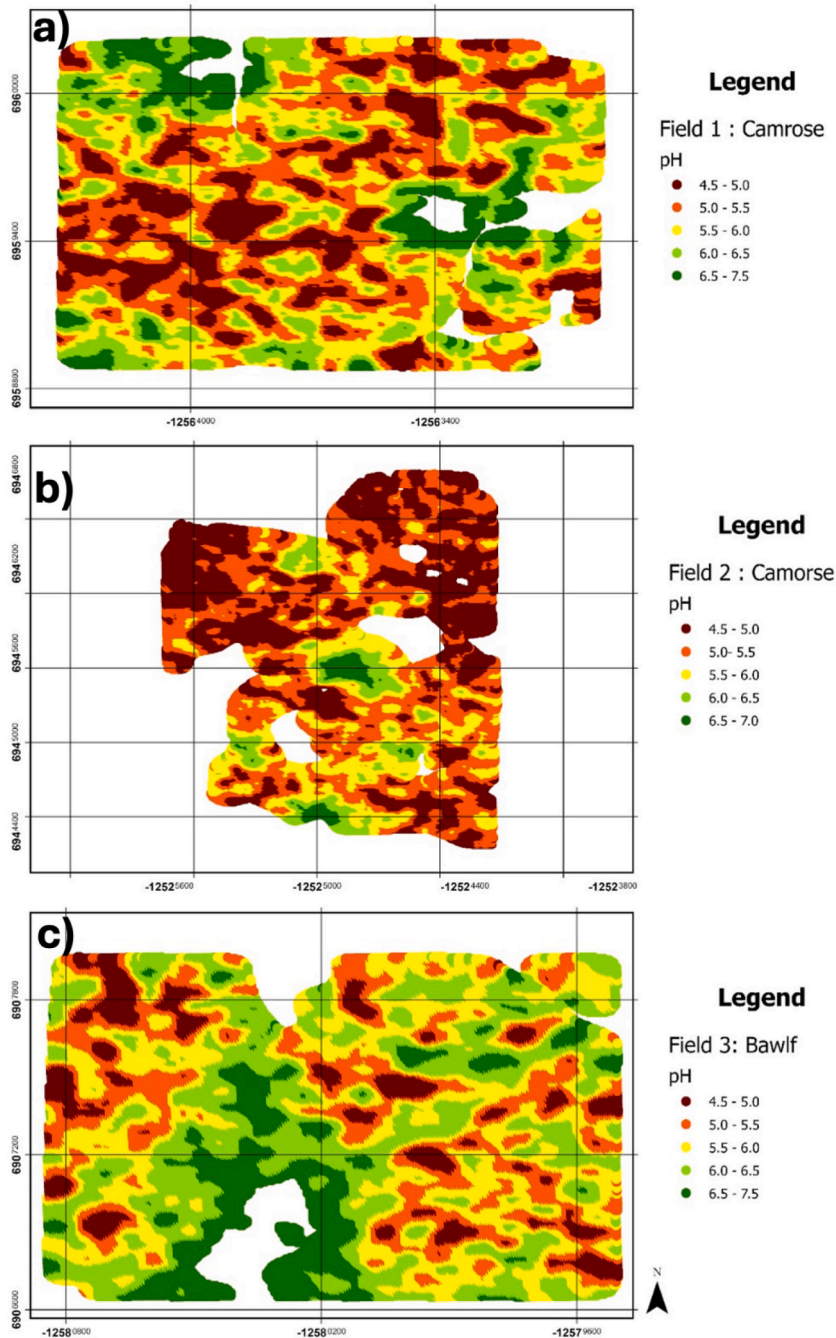
### 3.3. The effect of in-field elevation variability on soil pH

Field elevation values (estimated by GPS) ranged between 740 and 750 m (field 1), 715–720 m (field 2) and 780–810 m (field 3). Soil pH varied with elevation across all fields (Fig. 7a, b & c). More acidic conditions (i.e., lower soil pH) were observed at higher elevations across all fields.

### 3.4. Descriptive statistics of soil properties

The SoilOptix®-predicted soil properties showed low to high variability across the studied fields (Table 1). The categorization system of [35] for the coefficient of variation (CV) was used to describe the variability of the soil chemical properties. CV ranges of CV = 0–15 %, 15–35 %, and >35 % were considered as low, medium, and high variability respectively.

The CV ranges for the predicted soil properties varied between 5.64 (pH) and 91.39 % ( $\text{SO}_4\text{-S}$ ). Despite relatively low variability, pH varied from strongly acidic to neutral with values ranging from 4.5 to 7.5 (Fig. 1 and Table 1). The CV for soil pH was highest in field 3 (CV = 6.80 %), subsequently followed by field 1 (CV = 5.64 %) and finally field 2 (CV = 5.41 %). Field 2 had a lower pH (mean = 5.17) than field 1 (mean = 5.75) and field 3 (mean = 5.57). There was minimal variation ranging from 6.74 % to 14.46 % for the predicted soil Al and Mn concentrations across all fields. Field 3 had greater predicted, average exchangeable Ca ( $7200 \text{ mg kg}^{-1}$ ) and Mg ( $789.70 \text{ mg kg}^{-1}$ ) concentrations than field 2 and 1. Field 1 had the highest exchangeable K ( $596.31 \text{ mg kg}^{-1}$ ) concentrations. The highest predicted, average soil Mn concentrations were observed in field 2 ( $47.15 \text{ mg kg}^{-1}$ ) while the highest predicted, average soil Al concentrations were observed in field 1 ( $981.61 \text{ mg kg}^{-1}$ ). Predicted soil nutrients concentrations such as  $\text{NO}_3\text{-N}$  and P showed moderate to high variability in field 1 (CV = 26.82 % and 26.82 %) and Field 3 (CV = 38.72 % and 19.34 %) respectively, while field 2 exhibited the lowest variability for  $\text{NO}_3\text{-N}$  (CV = 8.37 %) and P (CV = 14.54 %). In field 3, the mean and CV of the predicted soil  $\text{NO}_3\text{-N}$  ( $61.00 \text{ mg kg}^{-1}$ ), P ( $147.00 \text{ mg kg}^{-1}$ ), and  $\text{SO}_4\text{-S}$  ( $255.10 \text{ mg kg}^{-1}$ ) concentrations were greater than the other two sites. Field 3 also had the highest average, predicted SOM content and variability (15.90 %, CV = 17.70), followed by field 1 (9.01 %, CV = 7.44) and field 2 (7.75 %, CV = 6.39). Predicted soil  $\text{SO}_4\text{-S}$  concentrations varied significantly between field sites with CV = 91.39 %, 24.33 %, and 24.33 % for fields 1, 2, and 3 respectively.

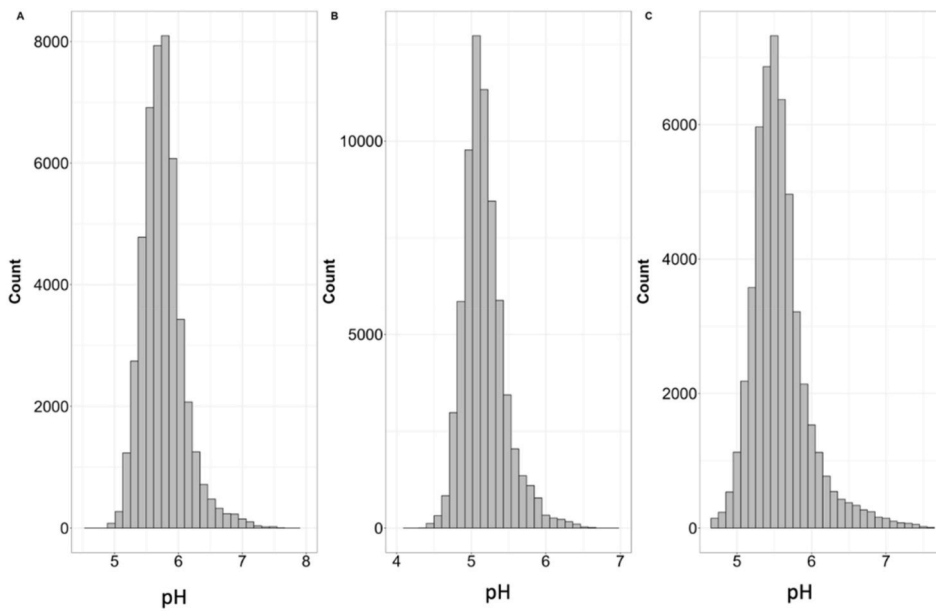


**Fig. 5.** Field-scale spatial variations of SoilOptix<sup>®</sup>-predicted soil pH at different sites. Panel A is field 1 (Camrose), Panel B is field 2 (Camrose) and Panel C is field 3 (Bawlf).

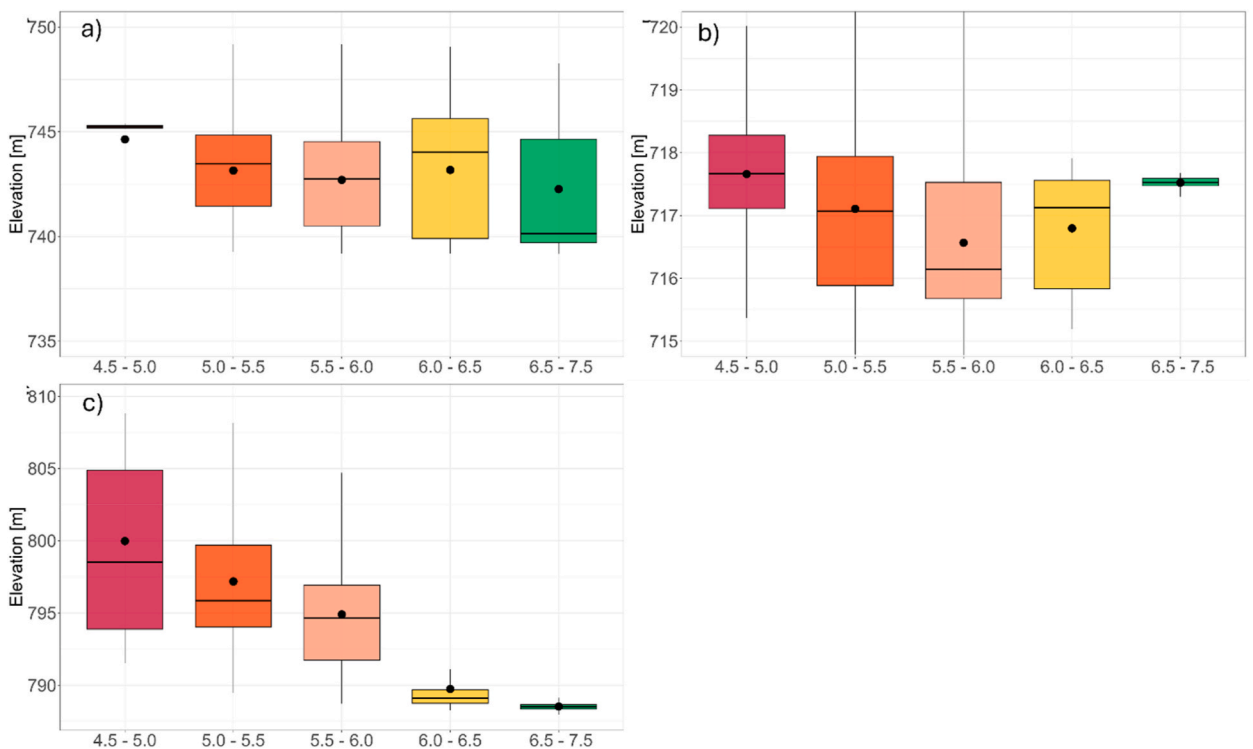
and 47.65 % in fields 3, 2 and 1, respectively.

### 3.5. Variations in soil properties across different soil pH classes

The predicted soil properties varied over the soil pH classes within and across fields (Figs. 8–10). In field 1, the highest soil NO<sub>3</sub>-N concentrations were observed in the slightly acidic soil pH (pH 6.0–6.5) class, followed the moderately acidic (pH 5.5–6.0), neutral (pH 6.5–7.5), strongly acidic (pH 5.5–6.0), and very strongly acidic (pH 4.5–5.0) soil pH classes (Fig. 8a). In fields 2 and 3 (Figs. 9 and 10), the opposite trend was observed for soil NO<sub>3</sub>-N, with higher NO<sub>3</sub>-N concentrations observed in consecutively increasing acidity classes



**Fig. 6.** Frequency distribution of SoilOptix®-predicted soil pH in the three different field site. Panel A is field 1 (Camrose), Panel B is field 2 (Camrose) and Panel C is field 3 (Bawlf).



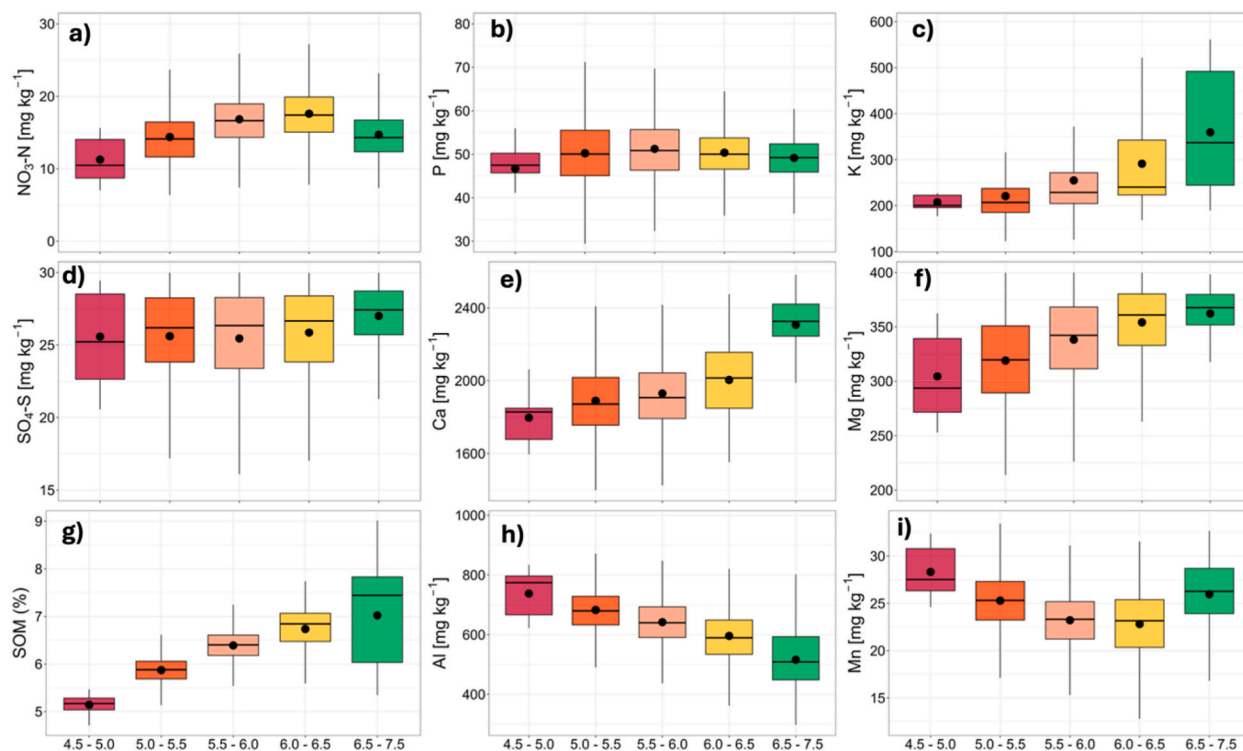
**Fig. 7.** Box plots showing the changes in the distribution of soil pH classes (SoilOptix®-predicted soil pH) with elevation (4.5–5.0, 5.0–5.5, 5.5–6.0, 6.0–6.5, and 6.5–7.5) at three on farm sites in Alberta, Canada. The black dots in the box plots represents mean values of elevation. Panel A (Camrose), Panel B is Field 2 (Camrose) and Panel C is Field 3 (Bawlf).

(Figs. 9a & 10a). In field 1, marginal differences in predicted Bray1 P concentrations were observed between the soil pH classes but the lowest values were observed in the very strongly acidity class (pH = 4.5–5.0; Fig. 8b). Contrasting patterns of predicted Bray1 P concentrations were observed in fields 2 and 3, with the highest values observed the very strongly acidic class (pH = 4.5–5.0), and

**Table 1**

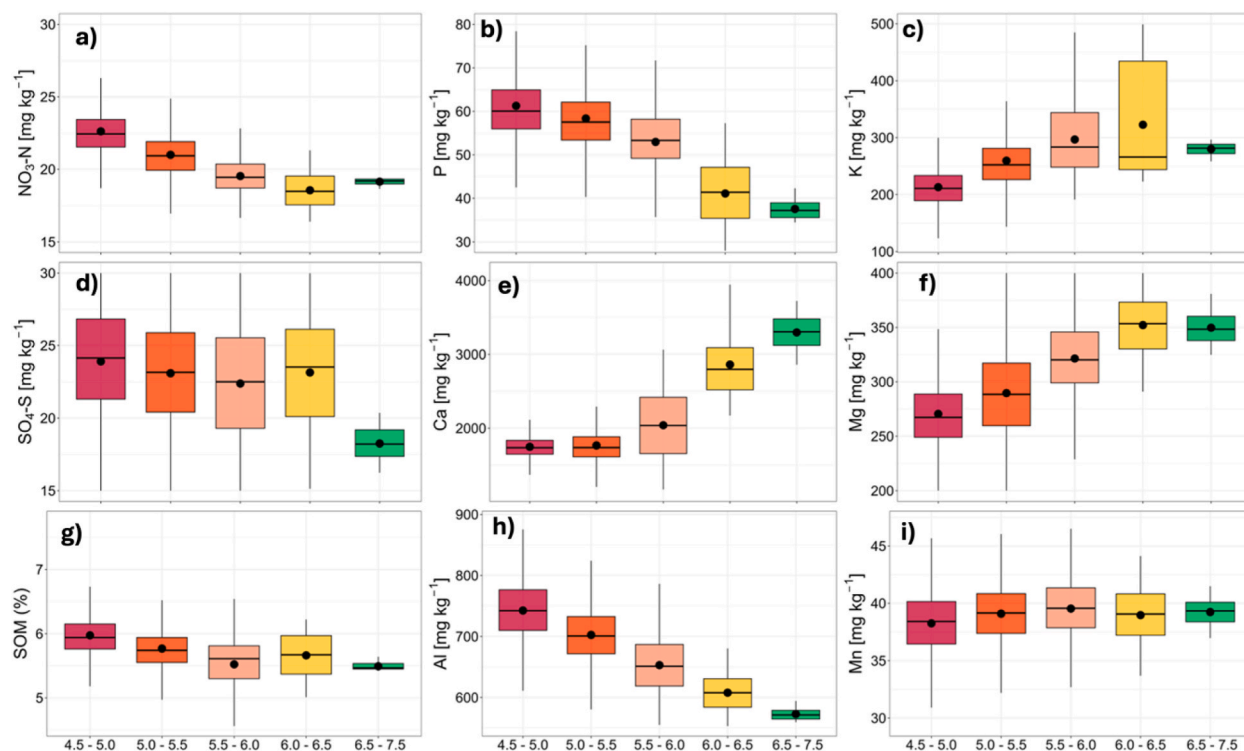
Field-specific descriptive statistics of SoilOptix®-predicted soil pH, soil organic matter and chemical properties. [Field 1, Field 2, and Field 3].

| Soil Properties                           | Sites   | Min     | Max     | Range   | Median  | Mean    | SD     | CV (%) |
|---|---------|---------|---------|---------|---------|---------|--------|--------|
| pH  | Field 1 | 4.90    | 7.56    | 2.66    | 5.73    | 5.75    | 0.32   | 5.64   |
|   | Field 2 | 4.37    | 6.61    | 2.24    | 5.14    | 5.17    | 0.27   | 5.41   |
|   | Field 3 | 4.70    | 7.60    | 2.90    | 5.50    | 5.57    | 0.38   | 6.80   |
| Ca (mg kg <sup>-1</sup> )                 | Field 1 | 1933.35 | 2594.87 | 1195.57 | 48.52   | 1943.35 | 211.52 | 10.88  |
|   | Field 2 | 1155.01 | 4102.08 | 2947.07 | 1749.50 | 1804.49 | 282.75 | 15.66  |
|   | Field 3 | 1153.10 | 7200.00 | 6046.90 | 2362.35 | 2546.35 | 887.12 | 34.80  |
| Mg (mg kg <sup>-1</sup> )                 | Field 1 | 213.88  | 682.03  | 468.14  | 358.84  | 366.72  | 69.52  | 18.95  |
|   | Field 2 | 150.80  | 572.80  | 422.16  | 572.80  | 293.37  | 51.80  | 17.65  |
|   | Field 3 | 211.50  | 789.70  | 578.20  | 347.80  | 363.67  | 80.90  | 22.24  |
| NO <sub>3</sub> -N (mg kg <sup>-1</sup> ) | Field 1 | 6.38    | 42.52   | 36.14   | 16.28   | 16.68   | 4.47   | 26.82  |
|   | Field 2 | 16.39   | 28.46   | 12.07   | 21.17   | 21.24   | 1.77   | 8.37   |
|   | Field 3 | 3.21    | 61.00   | 57.79   | 21.35   | 21.79   | 8.44   | 38.72  |
| P (mg kg <sup>-1</sup> )                  | Field 1 | 24.00   | 80.18   | 56.18   | 50.51   | 50.86   | 7.37   | 26.82  |
|   | Field 2 | 27.97   | 101.51  | 73.54   | 57.74   | 58.33   | 8.48   | 14.54  |
|   | Field 3 | 25.00   | 147.00  | 122.00  | 69.00   | 69.51   | 13.44  | 19.34  |
| K (mg kg <sup>-1</sup> )                  | Field 1 | 122.61  | 596.31  | 472.70  | 228.27  | 256.55  | 88.21  | 34.30  |
|   | Field 2 | 117.04  | 499.04  | 382.00  | 243.41  | 251.92  | 57.91  | 22.98  |
|   | Field 3 | 94.80   | 489.30  | 394.50  | 243.90  | 245.68  | 39.63  | 16.13  |
| SO <sub>4</sub> -S (mg kg <sup>-1</sup> ) | Field 1 | 10.91   | 221.56  | 210.65  | 42.48   | 47.95   | 22.85  | 47.65  |
|   | Field 2 | 9.14    | 74.14   | 65.00   | 23.85   | 24.01   | 5.89   | 24.33  |
|   | Field 3 | 10.40   | 255.10  | 244.70  | 18.5    | 26.70   | 24.4   | 91.39  |
| SOM (%)                                   | Field 1 | 4.71    | 9.01    | 4.30    | 6.34    | 6.35    | 0.47   | 7.44   |
|   | Field 2 | 4.56    | 7.75    | 3.19    | 5.78    | 5.79    | 0.37   | 6.39   |
|   | Field 3 | 5.10    | 15.90   | 10.80   | 8.10    | 8.30    | 1.47   | 17.70  |
| Al (mg kg <sup>-1</sup> )                 | Field 1 | 639.62  | 981.61  | 87.78   | 639.69  | 639.62  | 87.78  | 13.72  |
|   | Field 2 | 553.14  | 888.72  | 335.58  | 706.11  | 706.75  | 51.86  | 7.33   |
|   | Field 3 | 11.52   | 584.21  | 572.69  | 570.51  | 547.76  | 59.58  | 10.83  |
| Mn (mg kg <sup>-1</sup> )                 | Field 1 | 12.10   | 33.73   | 21.63   | 23.75   | 23.64   | 3.09   | 13.08  |
|   | Field 2 | 29.30   | 47.15   | 17.85   | 39.01   | 38.92   | 2.62   | 6.74   |
|   | Field 3 | 16.50   | 45.60   | 29.10   | 30.50   | 30.64   | 4.43   | 14.46  |



**Fig. 8.** Box plots showing SoilOptix®-predicted soil organic matter and soil nutrient concentrations as a function of soil pH class at field site 1, Camrose Alberta, Canada. a) NO<sub>3</sub>-N, (b) P, (c) K, (d) SO<sub>4</sub>-S, (e) Ca, (f) Mg, (g) SOM, (h) Al, and (i) Mn. [The black dot in the box plot represents mean values].





**Fig. 9.** Box plots showing SoilOptix<sup>®</sup>-predicted soil organic matter and soil nutrient concentrations as a function of soil pH class at field site 2, Camrose Alberta, Canada. a) NO<sub>3</sub>-N, (b) P, (c) K, (d) SO<sub>4</sub>-S, (e) Ca, (f) Mg, (g) SOM, (h) Al, and (i) Mn. [The black dot in the box plot represents mean values].

lowest observed in neutral class (Figs. 9b & 10b). In field 1 and 2 (Figs. 8c & 9c), predicted soil exchangeable K levels increased with increasing predicted soil pH levels with the lowest observed in very strongly acidic soil classes (4.5–5.0) while the opposite trend was observed in field 3. Soil SO<sub>4</sub>-S concentrations consistently increased with higher pH in fields 1 and 3 while in field 2 (Fig. 9d), no changes in SO<sub>4</sub>-S concentrations were recorded between the soil pH classes. Ca and Mg as a function of soil pH class showed the same trends in field 1, field 2, and field 3 with higher exchangeable Ca and Mg concentrations associated with higher soil pH. Predicted SOM concentrations increased with higher soil pH in field 1 and 3. Across all the fields, predicted soil Al concentrations consistently increased with lower soil pH. Variations in soil Mn concentrations were inconsistent across fields. The highest Mn values were observed in very strongly acidic soil pH classes (4.5–5.0) in field 1, with no obvious differences between the soil pH classes in field 2 and highest observed values in neutral and very strongly acidic soil zones in field 3.

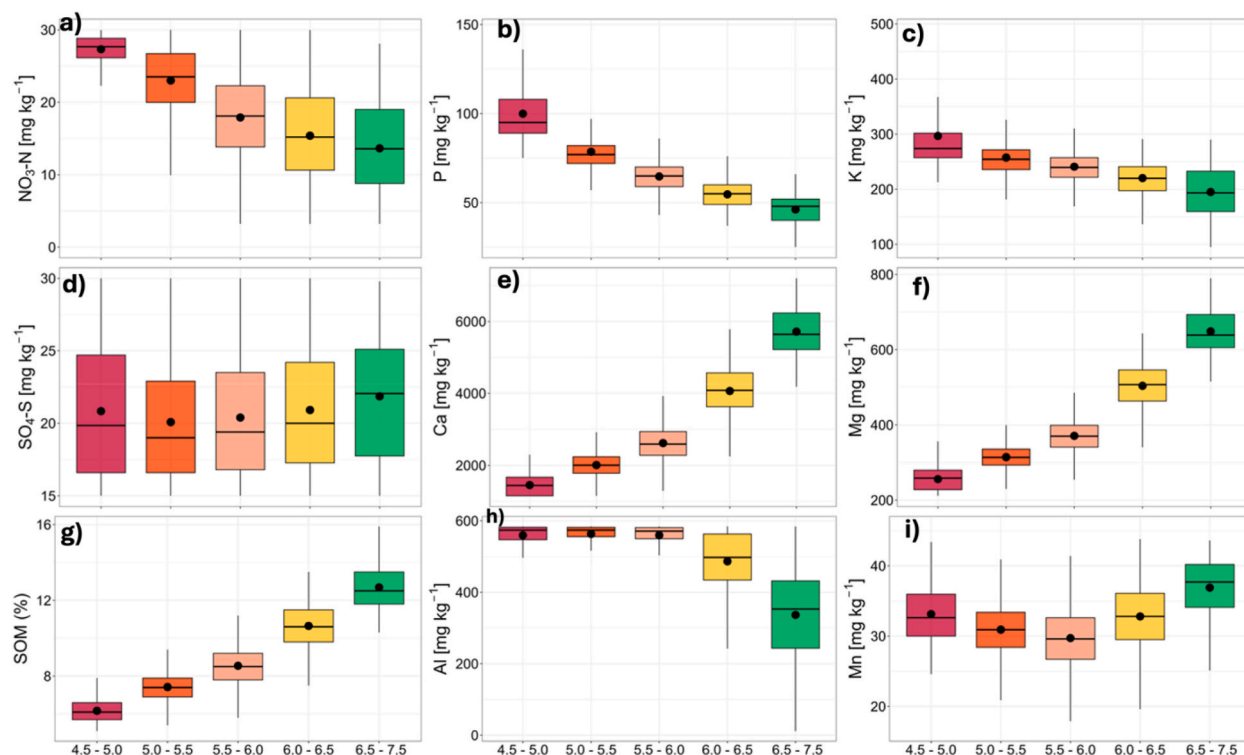
### 3.6. Relationship between soil pH, soil properties and elevation

The correlation analysis shown in Table 2 shows the relationship between SoilOptix<sup>®</sup>-predicted soil properties, elevation and pH. In field 1, there was a significant positive correlation observed between soil pH and soil NO<sub>3</sub>-N (0.20), K (0.34), Ca (0.31) and SOM (0.66) concentrations, showing that higher pH levels are linked with increased concentrations of these nutrients. Additionally, a significant negative correlation was noted between soil pH and exchangeable Al (−0.42) and Mn (−0.15) concentrations.

In field 1, elevation was significantly negatively correlated with soil P (−0.28), K (−0.67), Mg (−0.16), Ca (−0.43), SOM (−0.20), Al (−0.17) and Mn (−0.04) concentrations, indicating that higher elevation areas have lower levels of these soil properties. Furthermore, soil NO<sub>3</sub>-N concentration was significantly positively correlated with P, K, SO<sub>4</sub>-S, SOM and Al, negatively correlated with Mg, Ca and Mn.

In field 2, soil pH was significantly negatively correlated with soil NO<sub>3</sub>-N (−0.60), P (−0.37), SO<sub>4</sub>-S (−0.21) and SOM (−0.36) concentrations, while a significant positive correlation was observed between pH and exchangeable K (0.51), Mg (0.42) and Ca (0.46) concentrations. Elevation was significantly positively correlated with soil NO<sub>3</sub>-N (0.36), P (0.01), SO<sub>4</sub>-S (0.21), Al (0.31) and Mn (0.06) concentrations. Elevation was negatively correlated with pH (−0.28), exchangeable K (−0.52), Mg (−0.57) and Ca (−0.28). Soil NO<sub>3</sub>-N concentration was positively correlated with P, SOM, Al and negatively correlated with pH, exchangeable K, Mg and Ca.

In field 3, a significant negative correlation between soil pH, elevation (−0.53), soil K (−0.42), NO<sub>3</sub>-N (−0.55), P (−0.75) and Al (−0.58) concentrations was observed and positive correlations between pH and soil Ca (0.89), Mg (0.90), Mn (0.14), SO<sub>4</sub>-S (0.61) and SOM (0.84) concentrations. Elevation was positively correlated with soil NO<sub>3</sub>-N (0.27), P (0.56), K (0.33) and Al (0.33) concentrations, but negatively correlated with pH (−0.53), Mg (−0.54), Ca (−0.49), SOM (−0.55), Mn (−0.18) and SO<sub>4</sub>-S (−0.34). Soil NO<sub>3</sub>-N



**Fig. 10.** Box plots showing SoilOptix<sup>®</sup>-predicted soil organic matter and soil nutrient concentrations as a function of soil pH class at field site 3, Bawlf Alberta, Canada. a) NO<sub>3</sub>-N, (b) P, (c) K, (d) SO<sub>4</sub>-S, (e) Ca, (f) Mg, (g) SOM, (h) Al, and (i) Mn. [The black dot in the box plot represents mean values].

concentration was significantly correlated with P, K, and Mn concentrations, but negatively correlated with pH, soil SO<sub>4</sub>-S, Mg, Ca and SOM concentrations. In general, pH was positively correlated with soil Mg and Ca concentrations across all fields. Furthermore, a consistent negative correlation between pH and exchangeable Al was observed across all fields. Elevation was negatively correlated with pH, Ca and Mg consistently across all fields.

### 3.7. Principal component analysis for all soil parameters

Principal component analysis (PCA) was performed to evaluate the association between soil pH and other soil properties and their contributions to overall dataset variance (Fig. 11). The PCA indicated that PC1 contributed 30.5 %, 38.8 % and 54.6 % of the total variance in field 1, field 2, and field 3 respectively (Fig. 11 A, B, & C). PC2 contributed 19.5 %, 16.1 % and 22.5 % of variability in field 1, field 2, and field 3 respectively. In field 1, pH was positively correlated with all variables except with Mn, Al and elevation (Fig. 11 A). In field 2, pH was positively correlated with Mg, Ca and K and negatively correlated with other variables (Fig. 11 B). In field 3, pH was negatively correlated with NO<sub>3</sub>-N, P, K, Al and elevation and negatively associated with all other variables (Fig. 11 C).

### 3.8. Spatial variability of soil pH and soil chemical properties

Semivariogram parameters (i.e., nugget, sill, and nugget: sill) for each SoilOptix<sup>®</sup>-predicted soil property and their spatial dependence are shown in Table 3. A spherical semivariogram model was fit to the estimated variograms of the soil chemical properties for all fields (Table 3). The nugget: sill ratio is a measure used to categorize the spatial dependence of soil properties. Nugget: sill ratio values of <0.25 indicate the variable is spatially autocorrelated, while ratios of 0.25–0.75 and > 0.75 indicate moderate, and weak spatial autocorrelation, respectively [36]. Thus, the smaller the nugget: sill ratio in a dataset, the higher the spatial dependency [7,37]. All the soil chemical nutrients including soil pH were spatially autocorrelated. The nugget: sill ratio across all fields was <0.25, indicating strong spatial dependency. In Field 1, Al (798.85 m) and SO<sub>4</sub>-S (192.97 m) had the greatest range compared to all other properties. In Field 2, Al and P had the greatest range compared to all other properties. In Field 3, Al (373.02 m) and SO<sub>4</sub>-S (174.82 m) had the greatest range compared to all other properties. Generally, soil pH had the shortest soil pH range.

### 3.9. Field specific lime recommendation

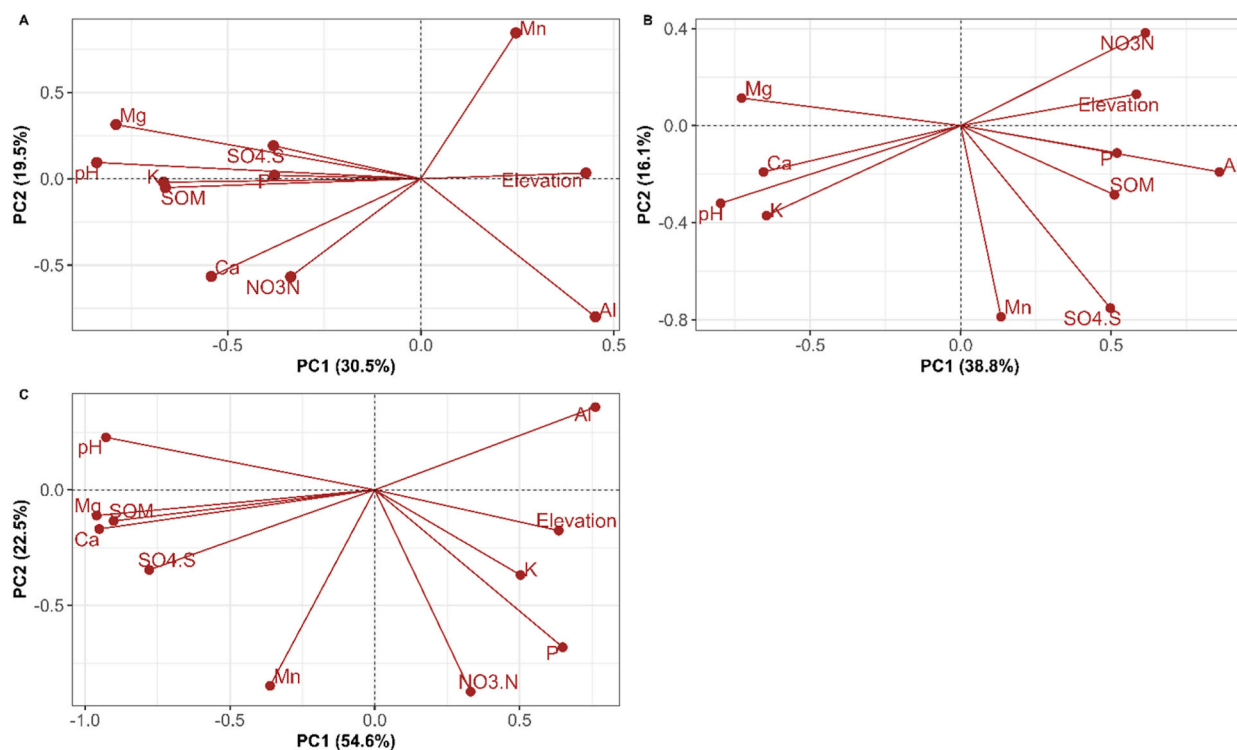
Increasing acidic soil pH in arable lands is facilitated by lime application. The spatial variability in base saturation calculated with

**Table 2**

Pearson's correlation among SoilOptix ®-predicted soil properties for field 1 (Camrose), field 2 (Camrose), and field 3 (Bawlf).

| Site    | pH                 | Elevation    | NO <sub>3</sub> -N | P                       | K            | S            | Mg           | Ca           | SOM          | Al           | Mn           |
|---------|--------------------|--------------|--------------------|-------------------------|--------------|--------------|--------------|--------------|--------------|--------------|--------------|
| Field 1 | pH                 |              |                    |                         |              |              |              |              |              |              |              |
|         | Elevation          | -0.04<br>*** |                    |                         |              |              |              |              |              |              |              |
|         | NO <sub>3</sub> -N | 0.20 ***     | -0.09<br>***       |                         |              |              |              |              |              |              |              |
|         | P                  | -0.01<br>*** | -0.28<br>***       | 0.04 ***                |              |              |              |              |              |              |              |
|         | K                  | 0.34 ***     | -0.67<br>***       | 0.03 ***                | 0.32 ***     |              |              |              |              |              |              |
|         | SO <sub>4</sub> -S | 0.32 ***     | 0.11 ***           | 0.09 ***                | 0.47 ***     | 0.04 ***     |              |              |              |              |              |
|         | Mg                 | 0.58 ***     | -0.16<br>***       | -0.10<br>***            | 0.25 ***     | 0.36 ***     | 0.56 ***     |              |              |              |              |
|         | Ca                 | 0.31 ***     | -0.43<br>***       | -0.40<br>***            | 0.20 ***     | 0.43 ***     | 0.13 ***     | 0.28 ***     |              |              |              |
|         | SOM                | 0.66 ***     | -0.20<br>***       | 0.21 ***                | 0            | 0.24 ***     | -0.23<br>*** | 0.25 ***     | 0.27 ***     |              |              |
|         | Al                 | -0.42<br>*** | 0.17 ***           | 0.32 ***                | -0.21<br>*** | -0.42<br>*** | -0.17<br>*** | -0.71<br>*** | -0.30<br>*** | -0.41<br>*** |              |
|         | Mn                 | -0.15<br>*** | -0.04<br>***       | -0.48<br>***            | -0.25<br>*** | 0.23 ***     | -0.08<br>*** | 0.40 ***     | 0.08 ***     | -0.22<br>*** | -0.50<br>*** |
|         |                    | <u>pH</u>    | <u>Elevation</u>   | <u>NO<sub>3</sub>-N</u> | <u>P</u>     | <u>K</u>     | <u>S</u>     | <u>Mg</u>    | <u>Ca</u>    | <u>SOM</u>   | <u>Al</u>    |
| Field 2 | pH                 |              |                    |                         |              |              |              |              |              |              |              |
|         | Elevation          | -0.28<br>*** |                    |                         |              |              |              |              |              |              |              |
|         | NO <sub>3</sub> -N | -0.60<br>*** | 0.36 ***           |                         |              |              |              |              |              |              |              |
|         | P                  | -0.37<br>*** | 0.01 **            | 0.23 ***                |              |              |              |              |              |              |              |
|         | K                  | 0.51 ***     | -0.52<br>***       | -0.40<br>***            | -0.09<br>*** |              |              |              |              |              |              |
|         | SO <sub>4</sub> -S | -0.21<br>*** | 0.21 ***           | -0.02<br>***            | 0.36 ***     | -0.07<br>*** |              |              |              |              |              |
|         | Mg                 | 0.42 ***     | -0.57<br>***       | -0.45<br>***            | -0.11<br>*** | 0.43 ***     | -0.28<br>*** |              |              |              |              |
|         | Ca                 | 0.46 ***     | -0.28<br>***       | -0.40<br>***            | -0.44<br>*** | 0.23 ***     | -0.05<br>*** | 0.18 ***     |              |              |              |
|         | SOM                | -0.36<br>*** | 0.19 ***           | 0.12 ***                | 0.16 ***     | -0.10<br>*** | 0.40 ***     | -0.35<br>*** | 0.04 ***     |              |              |
|         | Al                 | -0.59<br>*** | 0.31 ***           | 0.36 ***                | 0.64 ***     | -0.41<br>*** | 0.52 ***     | -0.50<br>*** | -0.35<br>*** | 0.43 ***     |              |
|         | Mn                 | 0.16 ***     | 0.06 ***           | 0.01 **                 | -0.04<br>*** | 0.20 ***     | 0.57 ***     | -0.27<br>*** | -0.03<br>*** | 0.06 ***     | 0.18 ***     |
|         |                    | <u>pH</u>    | <u>Elevation</u>   | <u>NO<sub>3</sub>-N</u> | <u>P</u>     | <u>K</u>     | <u>S</u>     | <u>Mg</u>    | <u>Ca</u>    | <u>SOM</u>   | <u>Al</u>    |
| Field 3 | pH                 |              |                    |                         |              |              |              |              |              |              |              |
|         | Elevation          | -0.53<br>*** |                    |                         |              |              |              |              |              |              |              |
|         | NO <sub>3</sub> -N | -0.55<br>*** | 0.27 ***           |                         |              |              |              |              |              |              |              |
|         | P                  | -0.75<br>*** | 0.56 ***           | 0.75 ***                |              |              |              |              |              |              |              |
|         | K                  | -0.42<br>*** | 0.33 ***           | 0.31 ***                | 0.57 ***     |              |              |              |              |              |              |
|         | SO <sub>4</sub> -S | 0.61 ***     | -0.34<br>***       | -0.04<br>***            | -0.23<br>*** | -0.25<br>*** |              |              |              |              |              |
|         | Mg                 | 0.90 ***     | -0.54<br>***       | -0.23<br>***            | -0.50<br>*** | -0.44<br>*** | 0.73 ***     |              |              |              |              |
|         | Ca                 | 0.89 ***     | -0.49<br>***       | -0.18<br>***            | -0.48<br>*** | -0.39<br>*** | 0.73 ***     | 0.98 ***     |              |              |              |
|         | SOM                | 0.84 ***     | -0.55<br>***       | -0.16<br>***            | -0.53<br>*** | -0.33<br>*** | 0.59 ***     | 0.90 ***     | 0.91 ***     |              |              |
|         | Al                 | -0.58<br>*** | 0.33 ***           | 0.02 ***                | 0.21 ***     | 0.24 ***     | -0.99<br>*** | -0.71<br>*** | -0.71<br>*** | -0.57<br>*** |              |
| Mn      | 0.14 ***           | -0.18<br>*** | 0.69 ***           | 0.27 ***                | 0.07 ***     | 0.41 ***     | 0.44 ***     | 0.49 ***     | 0.53 ***     | -0.41<br>*** |              |

Note: Significant at \* $p \leq 0.05$ ; \*\* $p \leq 0.01$ \*\*\*.



**Fig. 11.** PCA analysis for SoilOptix®-predicted Al, Ca, K, Mg, Mn, NO<sub>3</sub>-N, P, pH, SO<sub>4</sub>-S, and SOM determined by the first two principal components for A) Field 1 B) Field 2, and C) Field 3.

the SoilOptix®-predicted exchangeable cations and CEC (Eq. (1)) was used to calculate lime requirements for all study sites according to Eq [1,2], and are shown in Fig. 12. The calculated lime requirements varied across all three fields (Fig. 12a–c). The prescribed lime application rates ranged from 0 to 6 t ha<sup>-1</sup>. In field 2 (Figs. 12b) and 3 (Fig. 12c), a major portion of the field area required 4–6 t ha<sup>-1</sup> of lime while the remaining portion required less. In field 1 (Fig. 12a), lime prescriptions ranged between 3 and 6 t ha<sup>-1</sup> over a large area, with the remaining areas requiring less than 3 t ha<sup>-1</sup> of lime. The lime rate increased as soil pH decreased when compared to the soil pH maps (Fig. 12a–c).

#### 4. Discussion

The identified soil pH classes across all field sites ranged from very strongly acidic to neutral (Figs. 5 and 6). The soil chemical property values varied across all pH classes at all field sites (Figs. 8–10). Low cation concentrations (Ca, Mg, and K) were observed in low soil pH classes, which limits the buffering capacity of soils thus leading to increased solubility phytotoxic elements such as Al and Mn [38]. This has various consequences for soil fertility and plant growth including nutrient imbalances - i.e., imbalance in the uptake of essential nutrients, poor structure due to limited aggregation of soil particles and reduced crop growth [39]. This indicates that under acidic conditions, management practices such as liming, which can increase Ca and Mg levels are particularly critical for raising soil pH to enhance productivity [19]. Soil pH has been effective in partitioning fields into management classes to predict lime requirements in soils that lack carbonate buffering capacity, and to improve soil fertility [40]. In Fields 1 and 2, low K concentrations were observed in low pH classes. Decreases in soil pH can reduce soil cation exchange capacity, thus affecting the ability of the soil to maintain K levels, as observed in our study [41]. The concentration of Al in soils is strongly dependent on soil pH and when this pH drops below 5.0, Al and Mn become soluble, a typical occurrence in acidic soil conditions [42,43], consistent with the observed negative correlation between pH and Al across all field sites in this study (Table 2). Similar occurrences have been observed in studies conducted in Spain and Canada [44,45]. Furthermore, there was a strong negative correlation between soil pH and elevation, indicating the influence of elevation on other soil properties explains, in part, the observed spatial pattern of soil pH (Fig. 7 and Table 2). In all fields, lower soil pH was observed at higher elevations which influenced the concentration of exchangeable cations. These patterns shows that low soil pH due to higher elevation can be linked to the depletion of exchangeable bases from the gradual loss of topsoil due to erosion [46]. In a 5-year study conducted in China, it was reported that topography greatly influenced the spatial pattern of soil pH in arable soils; elevation, slope, valley depth, slope steepness, and organic fertilizer were reported to be the major drivers of soil pH

**Table 3**  
Semivariogram model (Spherical) for SoilOptix®-predicted soil properties at all field sites. NE (Not estimated) due to a poor model fit (spatial trend).

| Sites                     | Soil properties                           | Nugget | Sill    | Nugget: Sill | Range (m) |
|---------------------------|---|--------|---------|--------------|-----------|
| Field 1                   | pH  | 0.01   | 0.11    | 0.12         | 1.21      |
|                           | Ca (mg kg <sup>-1</sup> )                 | 3.39   | 28.44   | 0.12         | 18.90     |
|                           | Mg (mg kg <sup>-1</sup> )                 | 0.37   | 6.97    | 0.05         | 13.88     |
|                           | NO <sub>3</sub> -N (mg kg <sup>-1</sup> ) | 2.91   | 22.25   | 0.13         | 15.96     |
|                           | P (mg kg <sup>-1</sup> )                  | 0.37   | 4.75    | 0.07         | 9.50      |
|                           | K (mg kg <sup>-1</sup> )                  | 0.00   | 13.92   | 0.00         | NE        |
|                           | SO <sub>4</sub> -S (mg kg <sup>-1</sup> ) | 13.32  | 575.66  | 0.02         | 192.97    |
|                           | SOM (%)                                   | 0.02   | 0.22    | 0.11         | 1.73      |
|                           | Al (mg kg <sup>-1</sup> )                 | 115.65 | 7019.48 | 0.01         | 798.85    |
| Mn (mg kg <sup>-1</sup> ) | 0   | 9.42   | 0       | NE           |           |
| Field 2                   | pH  | 0.007  | 0.081   | 0.09         | 1.12      |
|                           | Ca (mg kg <sup>-1</sup> )                 | 0      | 38.41   | 0            | NE        |
|                           | Mg (mg kg <sup>-1</sup> )                 | 0.35   | 4.77    | 0.07         | 9.78      |
|                           | NO <sub>3</sub> -N (mg kg <sup>-1</sup> ) | 0.32   | 3.22    | 0.09         | 6.97      |
|                           | P (mg kg <sup>-1</sup> )                  | 6.46   | 73.57   | 0.08         | 35.41     |
|                           | K (mg kg <sup>-1</sup> )                  | 0.05   | 0.49    | 0.11         | 2.57      |
|                           | SO <sub>4</sub> -S (mg kg <sup>-1</sup> ) | 2.91   | 30.41   | 0.09         | 21.80     |
|                           | SOM (%)                                   | 0.04   | 0.31    | 0.04         | 2.29      |
|                           | Al (mg kg <sup>-1</sup> )                 | 218.84 | 2677.92 | 0.08         | 221.85    |
| Mn (mg kg <sup>-1</sup> ) | 0.99                                      | 6.92   | 0.12    | 8.49         |           |
| Field 3                   | pH  | 0.01   | 0.16    | 0.05         | 2.06      |
|                           | Ca (mg kg <sup>-1</sup> )                 | 2.62   | 83.45   | 0.03         | 62.99     |
|                           | Mg (mg kg <sup>-1</sup> )                 | 0.05   | 0.79    | 0.07         | 4.05      |
|                           | NO <sub>3</sub> -N (mg kg <sup>-1</sup> ) | 0      | 67.11   | 0            | NE        |
|                           | P (mg kg <sup>-1</sup> )                  | 8.27   | 146.04  | 0.05         | 62.14     |
|                           | K (mg kg <sup>-1</sup> )                  | 0.01   | 0.36    | 0.01         | 5.58      |
|                           | SO <sub>4</sub> -S (mg kg <sup>-1</sup> ) | 18.94  | 621.70  | 0.03         | 174.82    |
|                           | SOM (%)                                   | 0.06   | 2.46    | 0.02         | 12.08     |
|                           | Al (mg kg <sup>-1</sup> )                 | 151.89 | 3756    | 0.04         | 373.02    |
| Mn (mg kg <sup>-1</sup> ) | 0   | 18.53  | 0       | NE           |           |

variability [47]. Elevation differences can also alter local temperature and precipitation, with high elevations characterized by low temperatures and high rainfall thus causing leaching of basic cations, which leads to a decline in soil pH [48].

In this study, soil SOM concentrations exhibited low variability, and this agrees with findings of [49,50], who reported that SOM, as a soil property, tends to show more stability and minimal variations within fields with acidic soils in India and Croatia, respectively. Additionally, SOM concentrations increase as soil pH increased in fields 1 and 3 (Figs. 8 and 10). In this study, the variability in SOM may likely be more likely influenced by topographic redistribution of soil and water [51]. Also, the study areas are mostly arable lands and farmers perform minimum tillage practices and hence makes these soils high in SOM. Although lowest SOM was observed in higher soil pH classes in field 2 (Fig. 9), it is known that soils with high SOM can require less lime application to neutralize acidity [18]. This is due to the binding capability of organic matter to form stable organo complexes with H<sup>+</sup> and Al<sup>3+</sup> ions thus lessening their discharge to soil solution [18].

Soil nutrients such as NO<sub>3</sub>-N, P, and SO<sub>4</sub>-S showed the highest CV and inconsistent trends across fields and pH classes. Similarly, moderate to high variability for SOM, P, K, and NO<sub>3</sub>-N has been reported in acid soils [52]. Soil nutrients in the topsoil layers such as N, P, and SO<sub>4</sub>-S are strongly associated with SOM and the cycling of these nutrients is heavily influenced by biological processes and management practices [53]. In our study, NO<sub>3</sub>-N and SOM showed similar trends across the soil pH classes in field 1&2. This may imply that most of the nitrogen present in these fields is in organic form [54]. The negative correlation between NO<sub>3</sub>-N and soil pH in field 2&3 may be due to the organic matter in topsoil layers and the decomposition of organic matter in this layer, leading to the generation of more organic acids and thus lower topsoil pH [55]. Nitrogen in topsoil layers is affected by land management systems and the variability and depletion of N in disturbed land is higher than in natural forest soils [56]. Additionally, agricultural lands (i.e., grasslands) with long histories of cropping and fertilization show variability in soil nutrients within fields [57].

The PCA explained 50 %, 54.9 %, and 76.8 % of the original variance of the data in fields 1, 2, and 3 respectively (Fig. 11). In the biplot analyses, in fields 1, 2, and 3, soil pH was strongly dependent on Ca and Mg levels and these factors should be managed effectively across all fields for precise nutrient management and long-term agricultural sustainability. All the soil chemical nutrients including soil pH showed spatially autocorrelated variation in this study (Table 3). The nugget: sill ratio across all fields was <0.25, indicating strong spatial dependency. Generally, the strong spatial dependence observed can be linked to intrinsic factors such as topography, soil type, mineralogy, climatic conditions, and soil properties, and extrinsic factors such as fertilizer use, tillage practices, crop rotation sequences, and other crop management practices. The higher ranges observed with Al, P, and SO<sub>4</sub>-S suggest that the values of these parameters are more spatially autocorrelated over a larger distance and locations within the fields with similar values are farther apart. The short ranges observed with pH show that they exhibit rapid changes over short distances and are spatially autocorrelated. Also, there is a stronger influence of rainfall and anthropogenic activities on these parameters. This spatial information can be utilized in supporting sampling procedures by farmers, extension agents, and stakeholders for appropriate decision-making



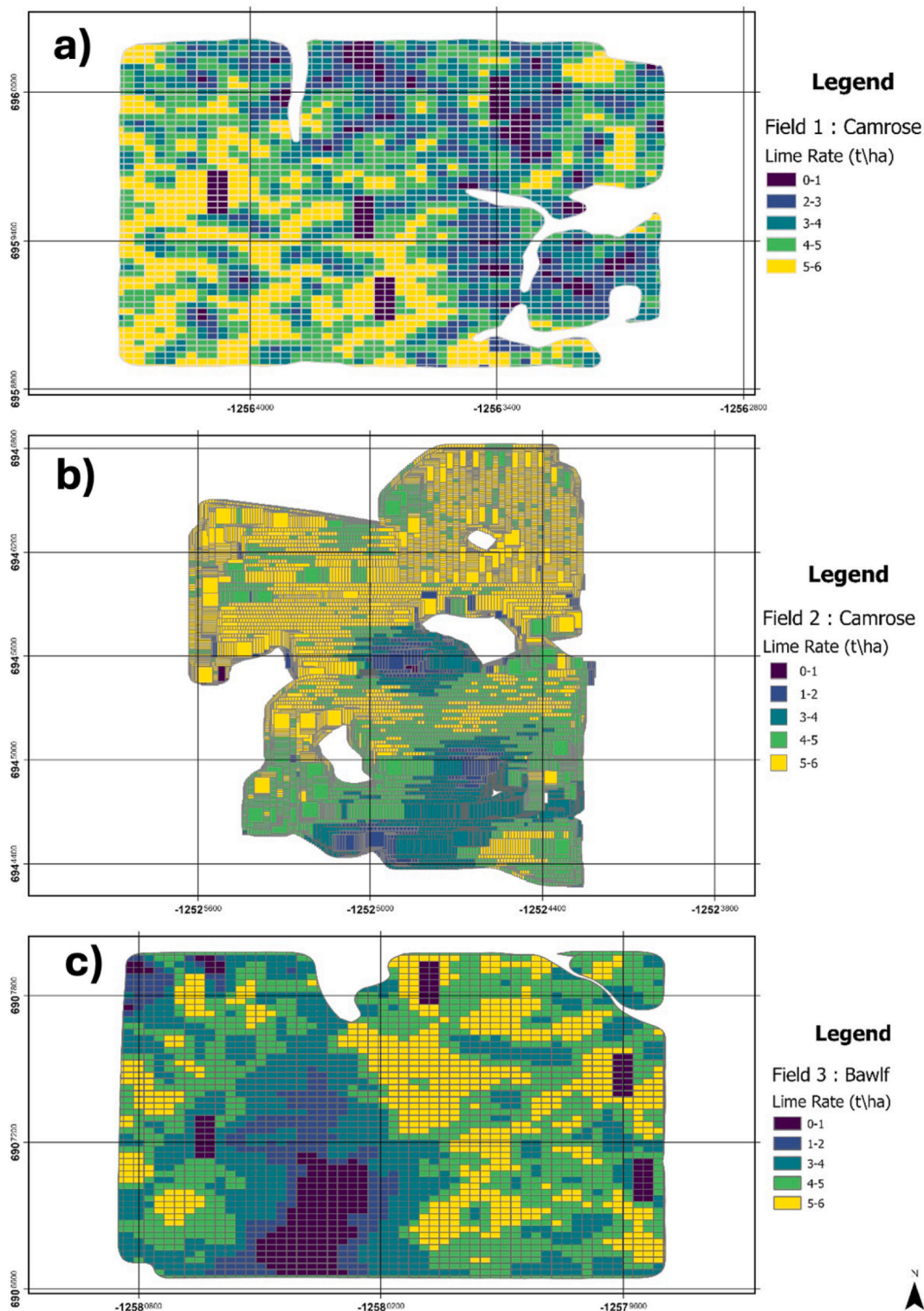


Fig. 12. Field maps of site-specific lime requirements rates ( $t\ ha^{-1}$ ) for soils of all study areas.

[58].

Based on the results, the calibrated SoilOptix<sup>®</sup>-estimated soil properties and associated soil maps are potentially a promising tool for managing soil acidity (Fig. 12), but frequent ground-truthing may be required (i.e., model validation). For the three field sites

presented in this work, low soil pH was associated with low levels of exchangeable Ca and Mg, and high levels of exchangeable Al relative to high soil pH. Therefore, the field maps generated with SoilOptix® data could be used to develop precision liming prescription maps. However, lime applications at rates developed using the SoilOptix-estimated soil properties may not achieve desired changes in soil pH due to uncertainties in the solubility and behavior of non-standard liming products such as cement kiln dust, and also uncertainty and bias that may be introduced during sensor calibration. In addition, researchers and farmers should integrate validation data by soil sampling at random points to allow for comparison against mapped values from SoilOptix® data to improve conclusions and decision-making.

## 5. Conclusions

These results support the importance of precise soil information at high spatial resolution to improve soil health and promote efficient resource utilization that is site-specific. Given the acidic soils in the fields in this study, soil and crop management strategies that ensure sustainable crop production should be considered. The development of field-scale soil liming prescription maps that include soil pH classes could be used to ameliorate soil acidic conditions, reducing the spatial variability in soil pH and improve the profile of exchangeable cations in the soil at the field scale. The use of pH classes for lime application may reduce liming costs, especially if the intent is targeted liming. The success of this approach for precise lime application is presently being studied at different field sites in central Alberta, Canada. This will be verified within the project duration by continuous soil mapping, collection of soil samples and yield assessment.

## Data availability

Data will be made available on request to the corresponding author and other collaborating partners such as crop producers and industry partners after completion of the project.

## CRediT authorship contribution statement

**Rebecca Oiza Enesi:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Formal analysis, Data curation, Conceptualization. **Miles F. Dyck:** Writing – review & editing, Supervision, Conceptualization. **Malinda S. Thilakarathna:** Writing – review & editing, Conceptualization. **Stephen E. Strelkov:** Writing – review & editing. **Linda Yuya Gorim:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Rebecca Enesi reports financial support and article publishing charges were provided by University of Alberta. Rebecca Enesi reports a relationship with University of Alberta that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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