Soil texture influences on soil health scoring functions in Ontario agricultural soils: a possible framework towards a provincial soil health test

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Abstract

Since soil health is impacted by inherent soil properties, it is, therefore, challenging to apply the same soil health frameworks across multiple regions and soil types. Here, we examined the effect of soil textural group (coarse, medium, and fine) on four soil health indicators of soils sampled from diverse agricultural systems across Ontario. Scoring functions were developed by calculating cumulative normal distributions, using the mean and standard deviation of each soil health indicator, for three or five soil textural groups. For each soil health indicator, soil health scoring values were provided using the "more is better" approach, where greater soil health scores implied better soil health. Soil health indicators were significantly affected by three but not all five soil textural groups. Evolved NH_3 and CO_2, and potentially mineralizable N had stronger associations with each other as revealed by correlation and principal component analysis. Our results also suggested that mean separation of the tested soil health indicators was more consistent with three soil textural groups (coarse, medium, and fine) than five soil textural groups (clays, clay loams, loams, sandy loams, and sand); therefore, we recommend using three soil textural groups to develop soil health scoring functions. The findings of this study lay a groundwork for future soil health assessment involving a larger number of samples across Ontario and more soil indicators, which will facilitate the regional interpretation of soil health.

Key words: region-specific, microbial activity, organic matter, soil quality, carbon

1. Introduction

Soil health, defined as the ability of the soil to function and support ecosystem services, is an integral component to sustain agricultural productivity and resiliency (Bünemann et al. 2018; USDA-NRCS 2020). Soil health is impacted by inherent (soil texture and mineralogy), environmental (climate and topography), and anthropogenic factors (Andrews et al. 2004; Idowu et al. 2009; Libohova et al. 2018). It is, therefore, important to consider soil as a living and dynamic system (Doran and Zeiss 2000). Adoption of poor agricultural management practices coupled with the intensification of agricultural production systems has significantly aggravated the decline in soil health, loss of soil organic matter (SOM), and erosion of topsoil (Fine et al. 2017; Amsili et al. 2021). There has been a global pursuit for soil health assessments (Janzen et al. 2021; Powlson 2021) including Ontario where a report by the Environmental Commissioner of Ontario (ECO 2016) emphasized the need to build a "wide-scale soil health focus" for agriculture.

Soil health assessment has emerged as a promising strategy to identify the soil constraints which limit agroecosystem productivity and contributes to improved decision-making by land managers (Moebius-Clune et al. 2016; Hargreaves et al. 2019; Amsili et al. 2021). Assessment of soil health involves the quantification of soil health indicators (physical, chemical, and biological properties), which are generally sensitive to changes in land management practices, easy to measure, and cost-effective (Idowu et al. 2008). To provide an inclusive understanding of soil health status, several soil health indices have been developed (Andrews et al. 2004; Idowu et al. 2009; Congreves et al. 2015; Haney et al. 2018; Chahal and Van Eerd 2019; Marshall et al. 2021), including the comprehensive assessment of soil health (CASH) developed in the USA (Schindelbeck et al. 2008). These frameworks are useful to quantify soil health indicators, identify the soil constraints limiting agroecosystem functioning, and provide appropriate management strategies to improve soil health and minimize environmental degradation (Idowu et al. 2009; Chahal and Van Eerd 2019; Wu and Congreves 2022). However, in some instances, these frameworks have less applicability and sensitivity when developed in one region but evaluated elsewhere (Fine et al. 2017; Roper et al. 2017), which suggests the need for a regional approach.

The soil management assessment framework (SMAF; Andrews et al. 2004) and CASH (Schindelbeck et al. 2008) use cumulative normal distribution scoring functions to standardize the measured laboratory value and derive the unitless soil health score of each indicator ranging between 0 and 100 (Fine et al. 2017). Unitless values, provided by the scoring functions, represent the soil health indicator status relative to a threshold value or a regional dataset consisting of measured values of soil health indicators (Nunes et al. 2021). Typically, nonlinear scoring functions have been demonstrated to be more sensitive to the agronomic management effects than linear functions, and hence are commonly used to calculate the individual soil health indicator scores (Bilgili et al. 2017; Fine et al. 2017; Nunes et al. 2021; Wu and Congreves 2022).

Assessment and interpretation of soil health indicator scores is challenging mainly due to the complex interactions of the soil health indicators with the inherent soil characteristics, land management practices, and environmental conditions. Among the numerous factors of variability, soil texture is one of the most significant inherent soil properties impacting the soil health indicators (Idowu et al. 2008). Soil health studies by Fine et al. (2017), Mbuthia et al. (2015), Nunes et al. (2020, 2021), Stott et al. (2013), and Zobeck et al. (2015) have demonstrated a large effect of soil sampling depth, texture, or other inherent properties (Wu and Congreves 2022) on soil health indicators and have reported issues in using the same soil health scoring functions across different regions and soil textures. Development of regional soil health scoring functions, therefore, is recommended to better understand and improve the soil health interpretation (Congreves et al. 2015; Roper et al. 2017; Chahal and Van Eerd 2019; Chu et al. 2019; Marshall et al. 2021; Wu and Congreves 2022). For example, the Ontario Agricultural Soil Health and Conservation Strategy (OASHCS) set variable targets for SOM content in agricultural soils based on soil texture, grouping the 13 textural classes of the Canadian texture triangle into five groups (Ontario Ministry of Agriculture, Food, and Rural Affairs 2018).

Using a large dataset consisting of mineral topsoil samples collected from commercial grain, horticultural, and pasture lands across Ontario, we investigated and compared the differences in soil health indicators due to soil texture. The objectives of this study were to (*i*) quantify and compare the effect of soil texture on soil health indicators (potentially mineralizable N (PMN), evolved NH_3, evolved CO_2, and SOM) in Ontario and (*ii*) develop regional (Ontario) soil health scoring functions to account for the inherent factors. Consistent with the criteria related to soil health indicator selection outlined by Bünemann et al. (2018) and Nunes et al. (2021), the soil health indicators selected in this study were previously found to be sensitive to changes in production system management, easy to measure, and played a key role in soil functioning and processes. Hence, the indicators selected in this study were expected to be useful in detecting differences in soil health. The research findings aim to better inform soil health interpretation and serve as an approach to develop a regional soil health test. This study provides an opportunity to apply and expand the knowledge gained through soil health research commonly conducted at small plots to a regional scale in Ontario.

2. Materials and methods

2.1 Soil sampling

Topsoil samples for this study were collected on mineral soils (i.e., <300 mg·g^{-1} SOM) through two distinct programs: the Ontario Topsoil Sampling Program (OTSP) and the Ontario Soil Survey (OSS). The OTSP is a collaborative project between the Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA) and the School of Environmental Sciences, University of Guelph, with the goal to characterize soil physical, chemical, and biological properties in the surface layer of targeted agricultural soils across southern Ontario, Canada (Fig. 1), to better understand soil health. The OSS, on the other hand, is an OMAFRA program primarily designed for the production of digital soil maps, with ongoing projects in Peterborough County and Ottawa (Fig. 1). In both programs, the Ap (horizon disturbed by human activity, also called plough layer; Canadian System of Soil Classification (Agriculture and Agri-Food Canada 1998)) horizons were sampled, but in the OTSP, sampling depth was terminated at 30 cm. Sampling design for both programs are described briefly below.

Sample locations for the OTSP were selected using a conditioned Latin hypercube sampling (cLHS) approach (Minasny and McBratney 2006), which seeks to generate a maximally stratified sampling plan across a set of given environmental covariates for the area of interest. Given the goal of understanding soil health, a combination of covariates to ensure stratification of the sampling locations across topographic (e.g., digital elevation model (DEM), curvature, slope gradient, topographic position index, topographic wetness index, deviation from maximum elevation), environmental (e.g., soil series, gamma-radiometric (potassium, thorium, uranium), biodiversity (i.e, ecodistricts), and agricultural (e.g., annual crop inventory (Agriculture and Agri-Food Canada 2018)) characteristics of southern Ontario was selected. The source DEM was the provincial DEM for Ontario at 30 m spatial resolution (Ontario Ministry of Natural Resources and Forestry 2021). All covariates not generated from the DEM were resampled to match the grid of the DEM using either bilinear (continuous) or nearest neighbour (categorical) interpolation. Sample size specified to the cLHS algorithm was 500, and these locations were named "seed points". For each seed point, three samples were collected to represent upper, mid, and lower slope positions in landscapes with sloping terrain. In level landscapes, three samples were collected with a minimum 50 m separation between samples. Samples were collected by excavating a small soil pit (30 cm by 30 cm) to the base of the topsoil and sampling from all sides of the soil pit with a soil knife, which was cleaned between soil pits. Sampling was restricted to either the depth of the topsoil, or a maximum depth of 30 cm for sites where the topsoil exceeded 30 cm (see Fig. S1 for distribution of topsoil sampling depth). Soil was homogenized by hand and a subsample put into a cooler during transportation and immediately refrigerated at 4 °C until processed in

Fig. 1. Map of the Ontario Topsoil Sampling Program, the Ottawa soil survey, and the Peterborough soil survey study areas with sampling locations. Topographic base maps courtesy of the Ontario GeoHub, Ontario Ministry of Natural Resources and Forestry. Map projection: MNR Lambert Conformal Conic, GCS North America 1983.
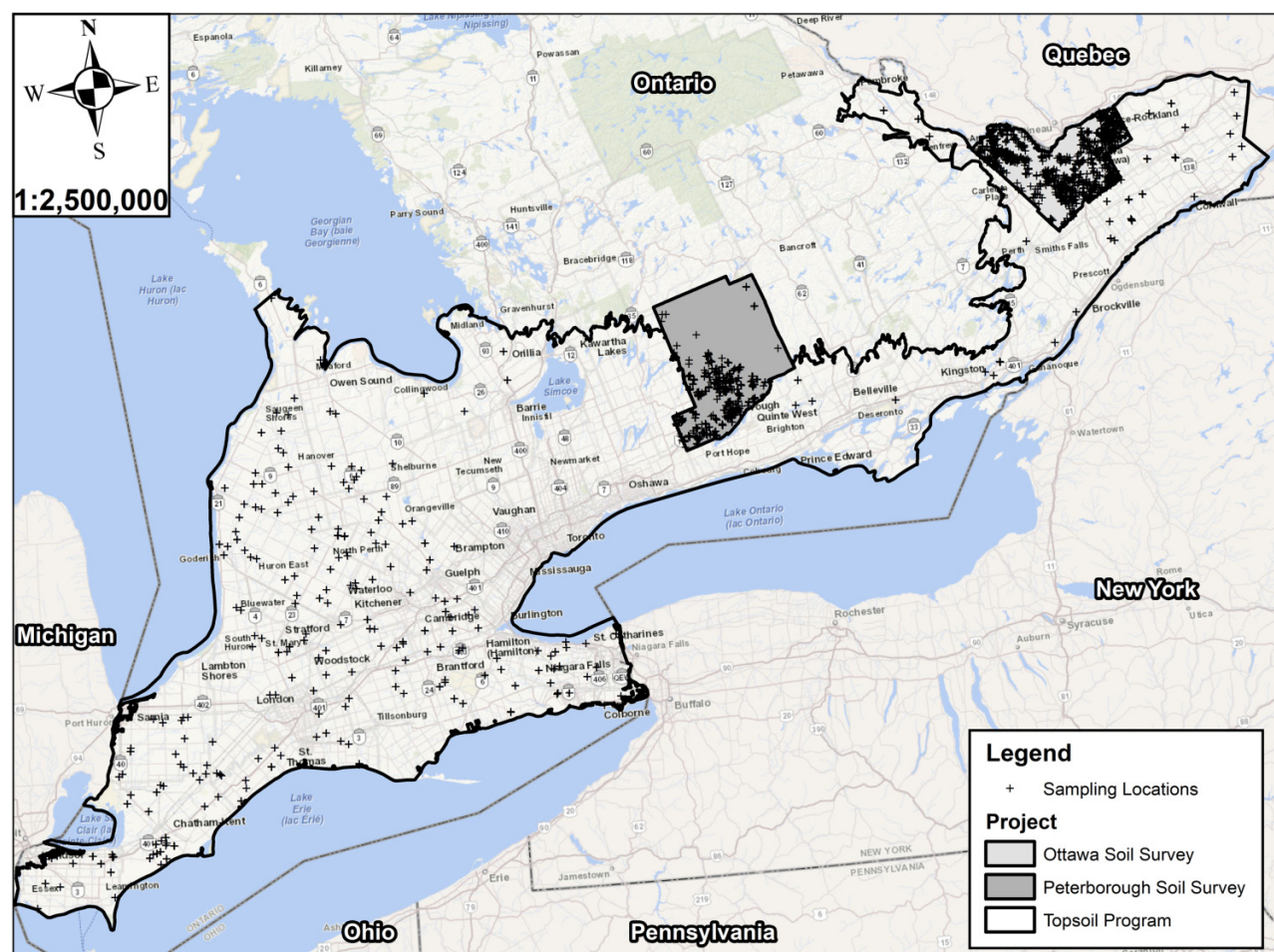
the laboratory for evolved CO_2 and NH_3 analyses (see the detailed methodology in Section 2.2). The OTSP is ongoing; soil sampling occurred in 2019–2022, with about 50% of samples collected during summer 2019. Only samples collected in 2019 and 2020 were included in our analysis at this time (largely due to uncertainty of soil sampling at the time of statistical analysis and lack of additional funding in 2021). For this study, soil analyses of interest were particle size, evolved CO_2 and NH_3, PMN, and SOM (see the detailed methodology in Section 2.2).

Sample locations for the OSS were also selected using the cLHS algorithm from covariates representing topographic, environmental, and agricultural characteristics of the study areas. In the case of the OSS, the study areas are much smaller than the OTSP; therefore, covariates were all generated at 10 m spatial resolution. Since the soil survey activities were not limited to topsoil sampling of agricultural fields, only Ap horizons were extracted from the OSS datasets for this analysis. Topsoil samples for the OSS were collected in the months of May to November over a 4-year period (2016–2019). Unlike the OTSP, sampling of topsoil horizons in the OSS was not limited to the upper 30 cm when such horizons were thicker

than 30 cm (see Fig. S2 showing distribution of Ap horizon depth). Samples were collected from all sides of the soil pit and homogenized. The OSS project is not a soil health project; particle size analysis and SOM are routine analyses for soil survey activities and were utilized in this study on soil health indicators (see details on methodology in Section 2.2).

2.2 Soil analyses

Solvita CO_2-burst and Solvita labile amino N (SLAN), commercially available soil health tests, are indicators of soil microbial activity. Evolved CO_2, as measured by Solvita CO_2-burst, was evaluated following the updated protocol released in 2019 by the Woods End® Laboratories Inc., Mt. Vernon, ME. Briefly, a 30 cc scoop (about 25–35 g) of 2 mm sieved and oven-dried (40 °C) soil subsample was used (Brinton 2019). Each soil subsample was transferred to a 50 mL plastic vial. Depending on the weight of the soil subsample, 9–10 mL of distilled water was added to each vial with a transfer pipette (Brinton 2019). Solvita CO_2-burst paddles (Woods End® Laboratories Inc., Mt. Vernon, ME) were inserted into each soil subsample. The vials (consisting of soil and paddles) were placed in 475 mL glass jars; jars were sealed and left undisturbed for

24 h at room temperature (22 °C). Using a digital colorimeter reader, evolved CO_2 was recorded and expressed as mg CO_2–C kg^{-1} soil.

For evolved NH_3, as measured by SLAN, a 4 g subsample of 2 mm sieved and oven-dried soil was used; the soil subsample was added to plastic vials containing 10 mL of 2N NaOH. The vials, along with soil subsample and SLAN paddles (Woods End® Laboratories Inc., Mt. Vernon, ME), were transferred to 250 mL glass jars. Like evolved CO_2, glass jars were sealed and left undisturbed for 24 h at room temperature (22 °C). Evolved NH_3 was recorded using the digital colorimeter reader and expressed as mg NH_3–N kg^{-1} soil.

Soil organic carbon was determined as the difference between total carbon and inorganic carbon. Prior to quantification of inorganic carbon, soil samples were combusted at 475 °C for 3 h. Using the dry combustion method (LECO 828 Series Carbon/Nitrogen Analyzer), total carbon and inorganic carbon were determined. As described by Pribyl (2010), SOM was determined by multiplying soil organic carbon values using the conversion factor of 1.724, commonly known as the "van Bemmelen factor", which assumes that organic matter is 58% carbon. Particle size analysis was done using the pipette method with hydrogen peroxide pretreatment to remove SOM as described in Sheldrick and Wang (1993).

PMN was determined following the procedures outlined in the Cornell University CASH Laboratory Standard Operating Procedures by Schindelbeck et al. (2016). Briefly, a fresh soil sample (8 g) sieved through 2 mm is anaerobically incubated for 7 days (Schindelbeck et al. 2016). Nitrogen mineralization potential is estimated by taking the difference between the preincubation and postincubation ammonium–N concentration (Schindelbeck et al. 2016; Rogers et al. 2018). This 7-day anaerobic incubation was added to this study after its initial conception. As a result, fresh soil samples were not available for all sampling locations; however, air-dried soil samples were available. To allow an adjustment to the PMN results for the air-dried samples, an experiment was conducted on 30 samples to calculate a correction factor for converting PMN-dry to PMN-fresh basis. PMN was determined for the 30 soil samples in both fresh and air-dry conditions, and a linear regression was developed with y intercept set to zero, and all samples adjusted according to PMN-fresh = PMN-dry × 0.352 ($R^2 = 0.89$, $P < 0.0001$; Fig. 2). Hereafter, only the fresh-basis PMN data are reported and discussed.

2.3 Scoring functions

For all the tested soil health indicators, a "more is better" approach was used to provide a scoring value, where high score values indicate greater soil health (Fine et al. 2017; Wu and Congreves 2022). Soil health scores were categorized into ratings of very low (0–20), low (20–40), medium (40–60), high (60–80), and very high (80–100) classes, and to facilitate interpretation, a five-color scale consisting of red, orange, yellow, light green, and dark green was applied to each rating (Fine et al. 2017). Scoring functions were determined for each soil health indicator using the following procedures. First, data outliers were removed using the interquartile range (IQR) technique. For each soil property, the IQR of the data was

Fig. 2. Linear regression of potentially mineralizable N (PMN) determined on soil samples in both air-dry and fresh conditions used to establish a correction factor from dry- to fresh-basis PMN.
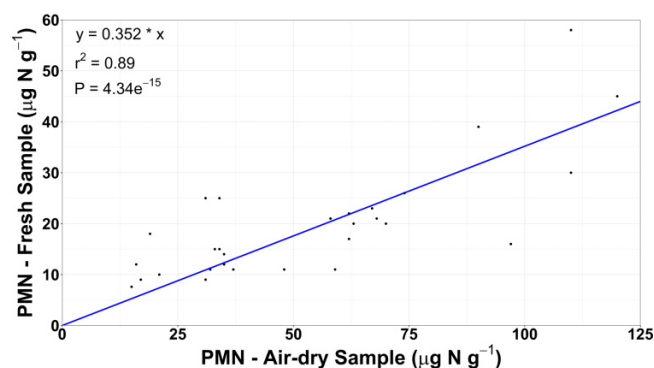

Table 1. Textural groups of the soil groups investigated in the Ontario's Agricultural and Soil Health Conservation Strategy (OASHCS) and Comprehensive Assessment of Soil Health (CASH).

Textural group	OASHCS group	CASH group
Heavy clay		
Silty clay	Clays	
Clay		Fine
Sandy clay		
Silty clay loam		
Clay loam	Clay loams	
Sandy clay loam		
Loam		
Silt loam	Loams*	Medium
Silt		
Sandy loam	Sandy loams	
Loamy sand		Coarse
Sand	Sands	

*Very fine sandy loam is grouped with loams in the OASHCS.

calculated as the difference between the 75th and 25th percentiles. The upper limit of the data to be retained for further analysis were calculated as 75th percentile + 1.5 × IQR and the lower limit as 25th percentile − 1.5 × IQR, also known as Tukey's inner fences (Hoaglin 2003). Once the outliers were removed, the individual observations were grouped based on two different systems (Table 1): (*i*) into one of three soil textural groups (coarse, medium, or fine) as outlined in CASH (Moebius-Clune et al. 2016) and (*ii*) into one of five soil textural groups (clays, clay loams, loams, sandy loams, and sands) based on the OASHCS recommendations (Ontario Ministry of Agriculture, Food, and Rural Affairs 2018). The nonparametric Kruskall–Wallis (Kruskal and Wallis 1952) rank sum test was used to detect an effect of texture group, as it is commonly used as the alternative to a one-way analysis of variance for nonparametric data (Brunner et al. 2020), followed by the post hoc Dunn's test (Dunn 1961) with

Bonferroni *P*-value adjustment to determine which texture groups differed significantly. Brunner et al. (2020) showed that unequal sample sizes can result in erroneous results from the Kruskal–Wallis rank sum test when comparing more than two groups, and that an alternative is to use pseudo-ranks. The pseudo-ranks technique was therefore applied using the "pseudorank" package (Happ et al. 2020) in R version 4.1.0 (R Core Team 2020). Where the Kruskal–Wallis and Dunn's tests confirmed significant differences between texture groups, the scoring functions were developed by texture groups, which were significantly different. If no significant differences existed between texture groups, the data were combined. Scoring functions were determined by calculating the mean and standard deviation of the data and generating a cumulative normal distribution, which becomes the scoring function (Moebius-Clune et al. 2016) and assigns a score ranging from 0 to 100.

2.4 Data visualization and correlation analysis

Regardless of soil textural groups, a principal component analysis (PCA) was conducted in SAS (SAS Institute version 9.4, Cary, NC, USA) on the measured values (without outliers) of the soil health indicators. Based on the scree plots, the first two PCs were selected; the eigenvalues of the soil health indicators within the first two PCs were visualized in two-dimensional plots to understand the interdependence among soil health indicators and better summarize the trends of variation in the dataset. Moreover, Pearson correlation analysis (at $P < 0.05$) was conducted to further examine the relationship between the soil health indicators.

3. Results and discussion

Our results of evolved CO_2, PMN, and SOM (Table 2) were comparable with the previous studies conducted in Ontario (Chahal et al. 2021) and elsewhere (Amsili et al. 2021; Wu and Congreves 2022); hence, it is confirmed that the dataset used for developing soil health scoring functions was representative of the soil health studies conducted in North America. For instance, Chahal et al. (2021) reported a mean concentration of evolved CO_2 as 70.4 mg CO_2–C kg^{-1} from a long-term crop rotation and tillage experiment at Elora, Ontario, which was similar to our study (76 mg CO_2–C kg^{-1} with the outliers and 74.5 mg CO_2–C kg^{-1} without the outliers). Likewise, soil health research by Wu and Congreves (2022) in a native prairie grassland in Saskatchewan reported mean PMN as 14.5 μg N g^{-1}, which was comparable with our study (18.5 μg N g^{-1} with the outliers and 17 μg N g^{-1} without the outliers). Similarly, Fine et al. (2017) found a mean SOM of 37.8 mg·g^{-1} (comparable with our results of SOM with (41 mg·g^{-1}) and without (37 mg·g^{-1}) the outliers). In contrast, evolved NH_3 concentration (252.7 mg NH_3–N kg^{-1} with the outliers and 255.3 mg NH_3–N kg^{-1} without the outliers) measured by SLAN was greater in our study than the previously published research in Ontario (e.g., 103.3–121.4 mg NH_3–N kg^{-1} (Chahal and Van Eerd 2018; Chahal et al. 2021)) and elsewhere (Chatterjee and Acharya 2018; Moore et al. 2019*a*, 2019*b*). In addition to depth of soil sampling (surface 15 cm vs. topsoil ∼25 cm (Fig. S1)), the differences in soil textures, crop-

ping history, use of amendments, and agronomic management factors across sites might have contributed to the observed differences in evolved NH_3 concentration between the present study and the previously published research. Since SLAN is an indicator of soil microbial activity, high evolved NH_3 concentration is an indicator of greater soil health (Brinton 2019); hence, there are no negative implications of high evolved NH_3 values on soil functioning and processes.

The soil health indicators selected in this study represented a combination of labile and stable indicators of soil carbon and nitrogen. For instance, SOM is a key indicator of soil health; however, it is difficult to measure changes in SOM in the short term (Simonsson et al. 2014). On the other hand, labile indicators of soil carbon and nitrogen such as evolved NH_3, evolved CO_2, and PMN are more sensitive to detect changes in soil health due to agronomic management practices in the short term (Luo et al. 2015; Miller et al. 2019) and are valuable indicators of monitoring early changes in soil health. Therefore, these four soil health indicators were used as a starting point to evaluate the framework approach to select appropriate soil health indicators on a regional scale (i.e., Ontario).

The number of samples is considerably larger for the SOM data due to the addition of the OSS samples (1976 samples). The removal of outliers from the datasets resulted in the removal of 29, 20, 38, and 135 observations for evolved NH_3, evolved CO_2, PMN, and SOM, respectively. The effect of the outlier removal process is variable when looking at the mean values (Table 2). For example, the effect of outlier removal was negligible for evolved NH_3 (252.7–255.3 mg NH_3–N kg^{-1}), whereas the mean SOM decreased from 41 to 37 mg·g^{-1}.

More importantly and obviously, with the removal of the outliers, a decrease in the standard deviation is observed; this is critical given that the scoring functions are cumulative normal distributions calculated from the mean and standard deviation, and the cumulative normal distributions are more heavily influenced by the standard deviation. With the removal of outliers, the scoring curves were generally flatter. In effect, the result is that with the removal of outliers, greater indicator concentrations would be needed at the low rating categories (very low to low) to get the same soil health score than if outliers were included (Fig. 3). But the opposite was true at the high rating categories (high to very high). For example, to achieve a score of 80, the PMN concentration would need to be about 5 μg N g^{-1} greater when using the scoring curve with outliers (∼28 μg N g^{-1}) than without outliers (∼23 μgN g^{-1}; Fig. 3). A change in rating from high to very high (or very low to low) is unlikely to affect the management decision a farmer might make. It is expected that scoring functions will be routinely revised as more soils are added to the database.

3.1 Effect of soil texture on soil health indicators

Due to the known effects of texture on soil parameters, each dataset was subdivided into soil textural groups based on three (i.e., the same textural groups as CASH) or five groups (as recommended by OASHCS). Regardless of the

Table 2. Sample size, mean, and standard deviation (SD) for the chemical and biological indicators of soil health sampled from topsoil in Ontario.

Indicator	All data			Outliers removed		
	n	Mean	SD	n	Mean	SD
Evolved NH_3 (mg NH_3–N kg^{-1})	768	252.7	88.3	739	255.3	79.0
Evolved CO_2 (mg CO_2–C kg^{-1})	777	76.0	29.0	757	74.5	26.3
Potentially mineralizable N (μg N g^{-1})	752	18.5	9.4	714	17.0	7.0
Organic matter (mg·g^{-1})	2781	41	21	2646	37	12

Fig. 3. Scoring functions plot showing the empirical cumulative distribution function (ECDF) for potentially mineralizable N and the cumulative normal distributions (CND) developed from the mean and standard deviation of the data with outliers and with outliers removed.
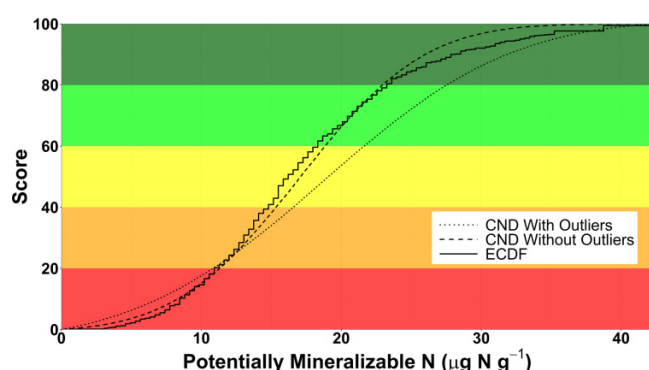
number of textural groupings (three or five), our results demonstrated a significant effect of soil texture on all the tested soil health indicators ($P < 0.05$; Tables 3, 4, S1, and S2), which was consistent with other jurisdictions (Stott et al. 2013; Fine et al. 2017; Nunes et al. 2021).

For evolved NH_3, evolved CO_2, and SOM concentration, all three textural groupings (i.e., CASH approach) were significantly different from each other (Table 3), whereas for PMN concentration, significant differences were observed between coarse and medium, and coarse and fine textural groups but no differences were detected between medium and fine textural groups (Table 3). In fact, this aligns with CASH, where the PMN soil health indicator was evaluated based on a single scoring function curve because no significant differences were observed in PMN between the three texture groups (Moebius-Clune et al. 2016).

The multiple comparison of means showed that the trends across five texture groups differed, and the trends were inconsistent between the soil health indicators (Table 4). For example, evolved NH_3 mean values for clay and clay loam groups were not significantly different from each other but were significantly different from the loam and sandy loam groups; however, the sandy group was not significantly different from any of the other four soil textural groups. A somewhat similar trend was observed for the PMN indicator, with clay, clay loam, and loam not being significantly different from one another but being significantly different from the sand group (Table 4). In addition, for PMN, the sandy loam

group only differed significantly from the loam and sand groups. The difficulty in separating the sands from the other soil texture groups is likely a result of the relatively small sample size for the sandy group (ranging from 17 to 24) for the evolved NH_3, evolved CO_2, and PMN indicators where the sample size is an order of magnitude smaller than the other texture groups. For the SOM indicator, clay and clay loam groups were not significantly different, but loam, sandy loam, and sand groups were all significantly different from one another (Table 4). In the present study, the dataset for SOM was larger ($n = 2781$) than the other indicators ($n = 752$–777). Regardless, the SOM concentration was not different between clay (440 samples) and clay loam (593 samples; Tables 4 and S2), which suggests that there was no need for five texture groups. Lastly, when looking across all four indicators, the five texture groupings recommended by OASHCS generally indicated that the clay and clay loam groups were similar, as were the sandy loam and sand groups. When considering how the textures are grouped (Table 1), mean separation of the five texture grouping is remarkably similar to the three texture groups; hence, scoring functions were developed using three texture groupings (i.e., CASH) and forms the basis of further results and discussion.

All the soil health indicators, except PMN, followed the pattern of a decrease in mean values with an increase in the coarseness of soil, which is consistent with Amsili et al. (2021), Nunes et al. (2018), Fine et al. (2017), and van Es and Karlen (2019). As expected, greater concentration of SOM in fine soils compared to coarse soils reflects the increased potential of soil carbon retention in fine-textured soils (von Lutzow et al. 2006; Samson et al. 2020; Amsili et al. 2021). Likewise, high concentration of evolved CO_2 and NH_3 from fine-textured soils indicates a greater microbial activity with the fineness of soil texture, which is perhaps related to greater soil carbon in fine-textured soils (Amsili et al. 2021). Unlike all other indicators, concentration of PMN was 5.2% greater in medium- than fine-textured soils (Table 3). It is unclear why the PMN trend contrasts with the other indicators but Bechtold and Naiman (2006) observed a higher fraction of mineralizable and labile nitrogen in medium- than fine-textured soils.

3.2 Scoring functions

We developed scoring functions for each soil health indicator using three soil textural groups (Fig. 4). Like CASH, we used a cumulative normal distribution function, based on the mean and standard deviation of the soil health indicator, to

Table 3. Sample size, mean, and standard deviation (SD) for the chemical and biological indicators of soil health sampled from topsoil within three soil textural groups in Ontario.

Indicator	Soil textural group	n	Mean*	SD
Evolved NH_3 (mg NH_3–N kg^{-1})	Fine	338	276a	76.0
	Medium	273	245b	76.0
	Coarse	128	221c	77.2
Evolved CO_2 (mg CO_2–C kg^{-1})	Fine	339	82.0a	82.0
	Medium	280	72.5b	25.0
	Coarse	138	60.2c	23.0
Potentially mineralizable N (μg N g^{-1})	Fine	319	17.2a	17.2
	Medium	252	18.1a	6.40
	Coarse	143	14.7b	6.30
Organic matter (mg·g^{-1})	Fine	981	41.0a	41.0
	Medium	1123	37.0b	11.0
	Coarse	542	32.0c	11.0

*For each soil health indicator, different letters indicate statistically significant differences ($P < 0.05$) between soil textural groups per Kruskal–Wallis and Dunn's tests.

Table 4. Sample size, mean, and standard deviation (SD) for the soil chemical and biological indicators of soil health sampled from topsoil within five soil textural groups in Ontario.

Indicator	Soil textural group	n	Mean*	SD
Evolved NH_3 (mg NH_3–N kg^{-1})	Clays	154	283a	81.8
	Clay loams	200	271a	69.6
	Loams	257	243b	76.7
	Sandy loams	111	220c	71.6
	Sand	17	229abc	109.5
Evolved CO_2 (mg CO_2–C kg^{-1})	Clays	152	85.0a	25.9
	Clay loams	203	79.0ab	25.9
	Loams	264	72.5b	25.1
	Sandy loams	116	62.1c	23.1
	Sand	22	50.2c	19.9
Potentially mineralizable N (μg N g^{-1})	Clays	143	17.7ab	8.2
	Clay loams	192	16.8ab	6.6
	Loams	236	18.2a	6.5
	Sandy loams	119	15.4b	6.3
	Sand	24	11.3c	4.5
Organic matter (mg·g^{-1})	Clays	440	42.0a	12
	Clay loams	593	40.0a	12
	Loams	1071	37.0b	11
	Sandy loams	461	33.0c	11
	Sand	81	27.0d	10

*For each soil health indicator, different letters indicate statistically significant differences ($P < 0.05$) between texture groups per Kruskal–Wallis and Dunn's tests.

provide a soil health score and rating for each indicator evaluated in this study. Our results showed very little overlap in scoring function curves among soil textural groups (Fig. 4), which confirmed that separate scoring functions by each soil textural group should be developed for each soil health indicator. This contrasted with previous CASH research where soil respiration and PMN were not different among soil textural groups; hence, the same scoring functions for all the soil textural groups were used (Fine et al. 2017; Amsili et al. 2021). This discrepancy might be due to methodological differences, such as depth of soil sampling (surface 15 cm vs. topsoil ~25 cm (Fig. S1)) and incubation time to measure

Fig. 4. Cumulative normal distribution scoring functions developed using the mean and standard deviation of evolved CO_2 (*a*), evolved NH_3 (*b*), potentially mineralizable N (*c*), and soil organic matter (*d*) sampled from topsoil in Ontario. Points represent the empirical cumulative distribution function while lines represent the cumulative normal distributions.
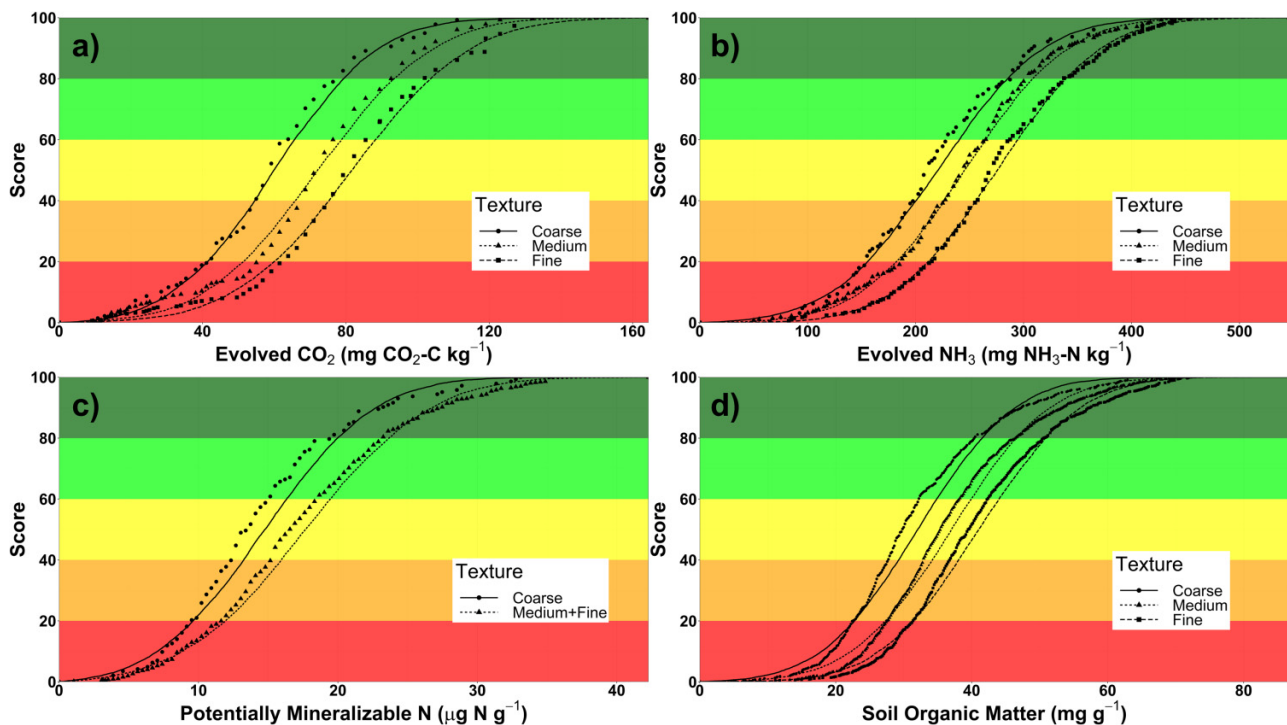
evolved CO_2 (i.e., 4 days with CASH compared to 1 day in our study).

As expected, the soil health scoring and ratings varied with the soil textural group (Table 5). For instance, evolved NH_3 rating was very low when concentrations ranged from 154 (coarse texture) to 211 mg NH_3–N kg^{-1} (fine texture; Table 5). For SOM, measured values between 42 (coarse texture) and 51 mg·g^{-1} (fine texture) represented high ratings (Table 5). Very low to low soil health ratings are expected to indicate a constraint in soil functioning and identify the need to make appropriate soil and crop management decisions to improve soil health (Fine et al. 2017); thus, it is important to have soil health scoring and ratings based on soil texture and regionally (i.e., Ontario) specific.

3.3 Relationship among indicators

Based on the scree plots, two principal components (PCs) were selected, which explained 68.9% of the total variability in the dataset. About 50% of the variance was accounted for by PC1, where the eigenvectors of the soil health indicators followed the order of evolved NH_3 > PMN > evolved CO_2 > SOM (Table 6). On PC2, which explained 18.6% of the variance, SOM had the greatest eigenvector whereas PMN had the least (Table 6). Typically, each PC is represented by soil physical, chemical, or biological indicators (Fine et al. 2017; Wu and Congreves 2022). In our study, the biological soil health indicator, evolved NH_3, had the greatest influence on soil health assessment in PC1, whereas the chemical soil health indicator SOM was the most important on PC2 (Table 6). Unlike our study, previous findings by Fine et al. (2017) and Zebarth et al.

(2019) indicated a high influence of soil respiration (biological) and SOM (chemical) on PC1. A soil health study by Chahal and Van Eerd (2019) found a high influence of soil respiration on PC1 and SOM on PC2. Furthermore, no clear groups among the soil textures were observed between PC1 and PC2 (Fig. 5a). Among the three soil textural groups, the two-dimensional plots revealed a high degree of overlap (Fig. 5a).

Across all soils, biplots of the eigenvectors of soil health indicators on PC1 and PC2 indicated two distinct groups: (i) evolved CO_2, PMN, and evolved NH_3 and (ii) SOM (Fig. 5b). Although SOM and evolved CO_2 fell into the same quadrant in the biplot, evolved CO_2 was more closely associated with evolved NH_3 and PMN than SOM. Similar results were observed by the correlation analysis, where the correlation coefficient of evolved CO_2 with evolved NH_3 ($r = 0.35$, $P < 0.0001$) and PMN ($r = 0.33$, $P < 0.0001$) was greater than with SOM ($r = 0.29$, $P < 0.0001$). Contrary to Marshall et al. (2021), our study results suggest that the amount of readily available soil nitrogen has a greater influence on soil respiration (soil microbial activity) than the amount of substrate (represented by SOM), which is consistent with Zhu et al. (2016). As expected, a positive relationship of evolved NH_3 with PMN ($r = 0.44$, $P < 0.0001$) was observed, further confirming PMN as an indicator of soil microbial activity and soil health (Sharifi et al. 2007). From the correlation and PCA, SOM had a positive but weak relationship with evolved NH_3 ($r = 0.30$, $P < 0.0001$), evolved CO_2 ($r = 0.29$, $P < 0.0001$), and PMN ($r = 0.28$, $P < 0.0001$). Although weak but positive association of SOM with PMN, evolved NH_3 and CO_2 confirm the multifaceted role of SOM in influencing mineralization

Table 5. Soil health scores, ratings, and the corresponding chemical and biological soil health indicator values sampled from topsoil within three soil textural groups in Ontario.

Indicator	Score	Rating*	Value[†] Fine	Value[†] Medium	Value[†] Coarse	Value[†] All
Evolved NH_3 (mg NH_3–N kg^{-1})	0–20	Very low	0–211	0–184	0–154	0–189
	>20–40	Low	211–258	>184–228	>154–201	>189–235
	>40–60	Medium	258–295	>228–266	>201–242	>235–275
	>60–80	High	295–339	>266–311	>242–286	>275–321
	>80	Very high	>339	>311	>286	>321
Evolved CO_2 (mg CO_2–C kg^{-1})	0–20	Very low	0–60.2	0–51.7	0–40.8	0–52.3
	>20–40	Low	>60.2–75.8	>51.7–66.4	>40.8–54.1	>52.3–67.7
	>40–60	Medium	>75.8–88.7	>66.4–79	>54.1–65.6	>67.7–81.2
	>60–80	High	>88.7–104	>79–93.4	>65.6–79.4	>81.2–96.9
	>80	Very high	>104	>93.4	>79.4	>96.9
Potentially mineralizable N (μg N g^{-1})	0–20	Very low	0–10.8	0–12.8	0–9.5	0–11.2
	>20–40	Low	>10.8–15.3	>12.8–16.5	>9.5–13.1	>11.2–15.2
	>40–60	Medium	>15.3–19.1	>16.5–19.8	>13.1–16.3	>15.2–18.8
	>60–80	High	>19.1–23.5	>19.8–23.6	>16.3–20	>18.8–22.8
	>80	Very high	>23.5	>23.6	>20	>22.8
Organic matter (mg·g^{-1})	0–20	Very low	0–31	0–27	0–22	0–27
	>20–40	Low	>31–38	>27–34	>22–29	>27–34
	>40–60	Medium	>38–44	>34–40	>29–35	>34–41
	>60–80	High	>44–51	>40–47	>35–42	>41–48
	>80	Very high	>51	>47	>42	>48

*Using cumulative normal distribution scoring function for each soil textural group, measured value of a soil health indicator is transformed to a soil health rating.
[†]Represents the measured value of a soil health indicator.

Table 6. Eigen analysis of chemical and biological soil health indicators sampled from topsoil in Ontario.

Indicator	Eigenvectors Principal component 1	Eigenvectors Principal component 2
Evolved NH_3 (mg NH_3–N kg^{-1})	0.533	−0.343
Evolved CO_2 (mg CO_2–C kg^{-1})	0.488	0.056
Potentially mineralizable N (μg N g^{-1})	0.522	−0.425
Organic matter (mg·g^{-1})	0.452	0.835

Note: For the principal component analysis, soil health indicator values were not separated into soil textural groups.

and soil microbial activity (Maestrini et al. 2014; Marshall et al. 2021).

Although simplified soil health assessments are promoted as cost- and time-efficient, comprehensive assessments consisting of a suite of soil health indicators might be informative. For instance, in our study, despite the correlations among the soil health indicators, the degree of orthogonality revealed by PCA indicates an independent effect of the indicators other than evolved NH_3 and PMN. We did not assess any soil physical indicator in this study, which is a limitation. It is expected that adding other indicators to the soil health database might provide additional information related to soil functioning and contribute to improving soil health interpretation. Most soil health assessments sample surface soil to 15 cm depth but we were interested in characterizing topsoil (median depth was approximately 25 cm). One might ex-

pect greater concentrations in soil sampled from shallower depth soils (i.e., 15 cm), especially in no-till systems, but this is not always the case (Wu and Congreves 2022). This study is not promoting (nor excluding) any commercially available soil health test. Our goal is to enhance understanding of soil health assessment and to facilitate the process and development of a provincial soil health test.

4. Conclusions

With the goal to better inform soil health interpretation in Ontario, we quantified four indicators of soil health from about 700 mineral topsoil samples collected from agricultural fields. Our results suggested interpretation of soil health depended on topsoil texture. Except PMN, values of evolved NH_3, evolved CO_2, and SOM increased with an

Fig. 5. Principal component (PC) analysis demonstrating the variability in the dataset between soil textural groups (*a*) and factor groupings (*b*) of chemical and biological soil health indicators, sampled from topsoil in Ontario, on PC1 and PC2. PMN, potentially mineralizable N; SOM, soil organic matter.
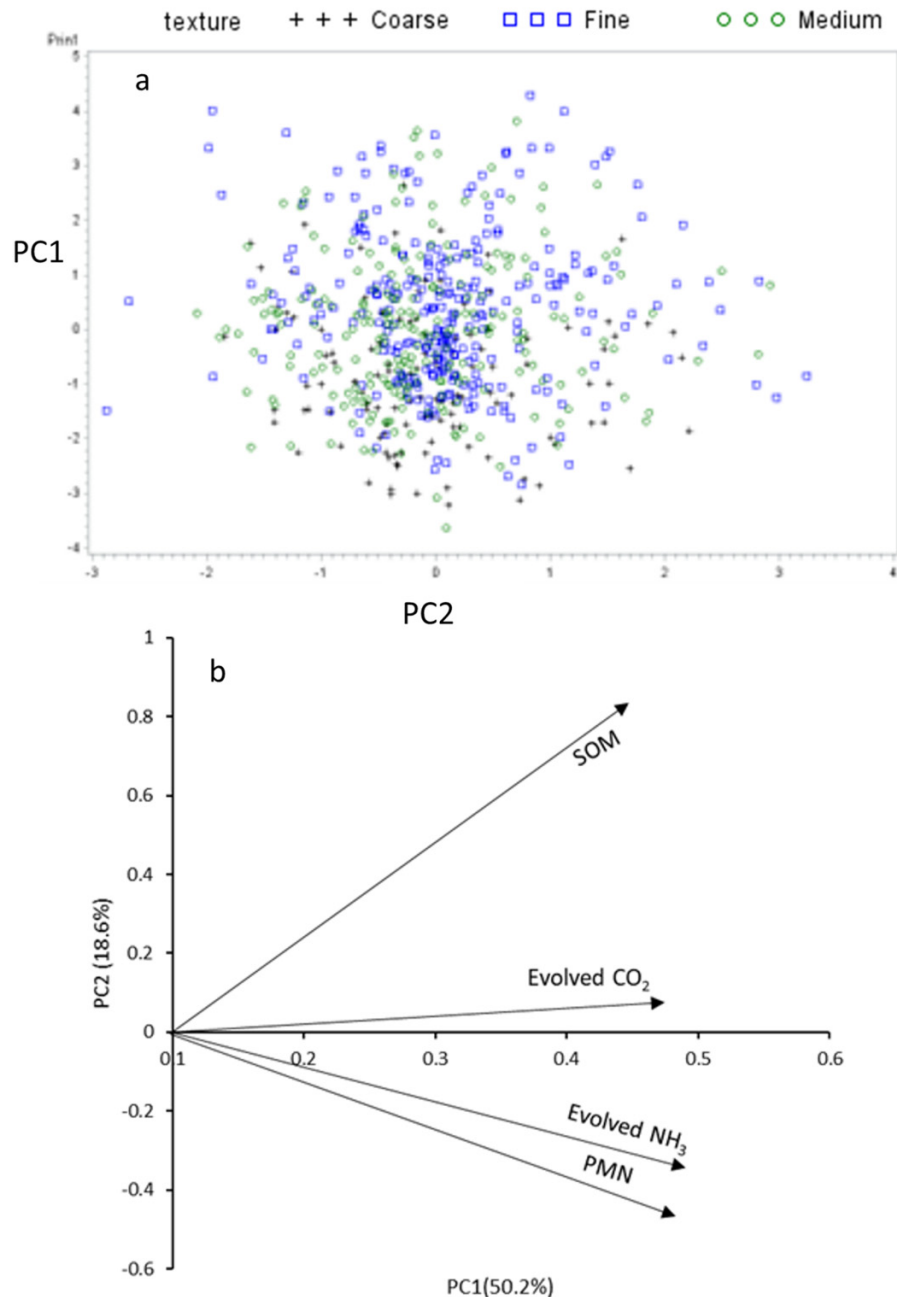
increase in fineness of soil texture. Based on our analyses, we recommend the use of three (fine, medium, and coarse) instead of five textural groups to develop scoring functions to quantify soil health. Here, we provide Ontario soil health ratings and scoring functions for four indicators (PMN, evolved NH_3, evolved CO_2, and SOM), which can be used by (*i*) crop advisors to explain soil health concepts to their clients, (*ii*) by analytical laboratories as a means of providing interpretation of soil health tests to clients, (*iii*) by government agencies actively working on soil health initiatives, and (*iv*) by

producers to compare their soil health results relative to agricultural land in southern Ontario and perhaps most importantly modify soil management practices to enhance soil health.

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Notes

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Copyright

Data availability

Data generated or analyzed during this study are not publicly available due to confidentiality agreement with participating land-owners but are available from the co-authors on reasonable request.

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Competing interests

The authors declare there are no competing interests.

Supplementary material

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