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Benchmarking soil health in glaciated soils under grain and oilseed production

J.A. Bower[a,*], D. Liptzin[a], R. Carlow[b], P.G.R. Smith[b], D.D. Saurette[c], J. Munroe[c], L.L. van Eerd[d], C.L.S. Morgan[a]

[a] Soil Health Institute, Morrisville, NC 27560, USA
[b] Greenbelt Foundation, Toronto, Ontario M6G 1A5, Canada
[c] Ontario Ministry of Agriculture, Food, and Agribusiness, Guelph, Ontario N1G 4Y2, Canada
[d] School of Environmental Sciences, University of Guelph Ridgetown Campus, Ridgetown, Ontario N0P 2C0, Canada

A R T I C L E I N F O

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A B S T R A C T

Quantifying soil health on agricultural lands has become a global priority, yet it remains unclear how much management practices have improved soil functioning on commercial farms, or how much potential for improvement remains. Reference-based benchmarking, by comparing row-cropped soils to undisturbed perennial soils, offers one approach for addressing this. Our objectives were to (1) determine the maximum soil health potential for soils under row crop production, (2) quantify the effects of management practices, and (3) assess progress toward soil health potential under improved management. We sampled 262 soils from the Greater Golden Horseshoe region in Ontario, Canada: 160 from grains and oilseeds, and 102 from perennials undisturbed by cultivation (> 10 years) to represent references. Soil measurements included texture, pH, organic carbon, aggregate stability, and potentially mineralizable carbon. Multiple linear regression was used to evaluate effects of management and inherent soil properties on soil health indicators, and logistic regression was used to estimate the probability of reaching a hypothetical goal relative to the potential for each indicator. Decreased soil disturbance, cover crops, and presence of winter wheat (*Triticum aestivum* L.) in rotation were the factors that improved aggregate stability. Manure additions and cover crops were the factors that improved potentially mineralizable carbon. The probability of approaching a goal of 75% of the reference aggregate stability value increased from 0.36 (conventional) to 0.76 (no-till and cover crops). By comparing management with respect to soil, our approach quantifies progress achieved by farmers and the potential for improvement to enable soil health interpretations.

1. Introduction

Healthy soil ecosystems support much of the world's biodiversity (Anthony et al., 2023) and are essential for sustaining crop production. Quantifying soil health on agricultural lands has therefore become a priority for farmers, their advisors, scientists, and policymakers globally (Costantini and McBratney, 2025; Falcão et al., 2024; Karlen et al., 2019) and within Canada (Cerkowniak et al., 2016; Falcão et al., 2024; OMAFA, 2018; Senate of Canada, 2024; van Eerd et al., 2021). Several frameworks have been developed to quantify soil health, such as the Comprehensive Assessment of Soil Health (CASH), the Ontario Soil Health Assessment and Plan (SHAP), and the Soil Health Institute's benchmarking approach (Bagnall et al., 2023; Chahal et al., 2023; Looker et al., 2025; Moebius-Clune et al., 2016; OMAFA, 2024, 2023), Yet, establishing reliable, interpretable benchmarks that allow producers to understand current soil health and set realistic goals for improvement remains a central challenge for soil health assessment.

Despite progress in developing soil health indicators and assessment frameworks, a gap remains in our understanding of how soil health is expressed on commercial farms, specifically how much soil health management practices have improved soil functioning, and how much room for improvement remains. Reference-based benchmarking offers one such approach. By comparing human-disturbed (e.g., row-cropped) soils to reference (e.g., undisturbed perennial) soils that theoretically express the upper range of soil function for each soil type, reference benchmarking provides a way to quantify the potential for improvement

* Corresponding author.
E-mail address: jbower@soilhealthinstitute.org (J.A. Bower).

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(Droogers and Bouma, 1997; Maharjan et al., 2020; Matson et al., 2024; Román Dobarco et al., 2021). This approach aligns with other soil assessment frameworks that compare degraded soils with soils that maximize soil function, notably soil capacity and condition (McBratney et al., 2014) and the genoform/phenoform concept (Droogers and Bouma, 1997; Rossiter and Bouma, 2018).

Despite its conceptual appeal, on-farm applications of reference-based benchmarking remain limited. In many regions, we lack quantitative, soil-specific estimates of how close soils on commercial farms are to their functional potential or how different management practices influence progress toward that potential. This gap limits producers' ability to interpret soil health indicator values and limits the scalability of soil health assessment. Recent efforts have attempted to set soil health goals or performance thresholds for producers using non-reference-based, distributional approaches. For example, Drexler et al. (2022) proposed threshold values that are based on land use types and inherent soil properties, and Amsili (2020) and Amsili et al. (2023) developed percentile-based scores that compare a given soil to soils with similar texture under similar cropping systems. These approaches define progress relative to other agricultural soils and incorporate the regional prevalence of practices. However, the definition of "good" can shift as management trends shift (e.g., a soil scoring at 80% may not score as high in 10 years as soil health management increases regionally). In contrast, reference benchmarking uses undisturbed perennial systems to define an upper bound of soil function for each soil type, enabling explicit quantification of the soil health gap attributable to management practices.

Beyond management, soil health expression is influenced by inherent soil properties such as texture, mineralogy, and drainage, which arise from pedogenic processes and are reflected in soil morphology and classification, with landscape position playing a role in their development (Congreves and Wu, 2024; Kirsten et al., 2021; Liptzin et al., 2022; Nunes et al., 2024; Sun et al., 2018). For meaningful comparisons, it is essential to stratify soils by their major inherent properties (Das et al., 2024). Stratification improves regional inference by accounting for inherent soil properties and isolating management effects that would otherwise be obscured, while reducing the needed number of samples and associated expense (Devine et al., 2021; Saurette et al., 2025; Svoray et al., 2015). Soils can be additionally stratified by management, to quantify the influence of soil health promoting practices (or beneficial management practices; e.g., reduced tillage, cover cropping, and organic amendments) through space-for-time substitutions, where management-induced differences across locations are used to as proxies for temporal change (e.g., Blair et al., 2024; Han et al., 2023; Yang et al., 2022).

The overall goal of this work was to investigate changes in soil health indicators resulting from management practices that promote soil health in row crop agriculture. To achieve this, we evaluated how management practices influence soil health on grain and oilseed farms in temperate, glaciated soils. Our objectives were to (1) measure the soil health potential for the predominant soils under row crop agriculture, after accounting for variation in inherent soil properties, (2) assess the relative effects of different management practices employed by commercial growers on soil health, and (3) evaluate the progress achieved by these management practices in row-cropped soils relative to the maximum soil health potential. By integrating soil stratification, on-farm management information, and reference-based benchmarking, this study provides a quantitative, soil-specific assessment of both progress and remaining potential on working farms. This approach is expected to directly support soil-specific goal setting, something recognized as essential yet rarely implemented at regional scales (Matson et al., 2024), and offers a transferable framework that can strengthen soil health monitoring and interpretation efforts in other crop-growing regions of the world.

2. Materials & methods

2.1. Study area

The study was conducted in the Greater Golden Horseshoe of Ontario, Canada, excluding the Canadian Shield, and within the Mixedwood Plains Ecozone. The Greater Golden Horseshoe region was chosen to support the partnership with the Greenbelt Foundation and to leverage existing connections with farmers and farming organizations in this area. Mean annual temperature ranged from 6.3 to 9.7 °C and mean annual precipitation ranged from 851 to 1096 mm. The major soil types sampled included Luvisols, Cambisols, and Gleysols (Table 1; IUSS Working Group WRB, 2022). Parent materials are predominantly glacial in origin and include calcareous and non-calcareous glaciofluvial and glaciolacustrine sediments, fluvial and lacustrine sediments, and till (Table 1).

2.2. Site selection

To identify sampling locations on the common agricultural soils of the region, dominant map unit components from the Ontario Soil Survey Complex were first stratified by surface texture and drainage class into soil sampling groups (OMAFA GIS, 2019). Texture classes were based on the family level particle size classes, except fine-clayey and very-fine-clayey were combined into one class, and the component-level drainage class was simplified from seven to four classes (Soil Classification Working Group, 1998; Table 1).

Soil groups were selected based on their relative abundance under grain and oilseed production, which is the dominant cropping system in the region. We intersected a raster of the soil groups with a raster representing the area in grains and oilseeds in six out of the 12 years prior to sampling (2011–2022) produced from the Annual Crop Inventory, and removed isolated groups of pixels smaller than 0.5 ha (Agriculture and Agri-Food Canada, 2022). We focused on seven common soil groups to target in our soil sampling campaign. The seven sampling groups represent more than 75% of the cropped area: well drained coarse-loamy, moderately well/imperfectly drained coarse-loamy, moderately well/imperfectly drained fine-loamy, moderately well/imperfectly drained fine-silty, moderately well/imperfectly drained clayey, well drained fine-loamy, and well drained fine-silty (Fig. 1). Poorly drained coarse-loamy soils were not included in sampling due to their presence in lower topographic positions, where a goal of sampling was to minimize the effects of topographic variability by sampling backslope topographic positions.

In 2023, producers were voluntarily recruited from the regional municipalities of Hamilton, Halton, Peel, and surrounding areas that had fields with the targeted soil groups (central regions; Fig. 2). In 2024, producers were voluntarily recruited from Niagara, York, Durham, and surrounding areas (northern and southern regions; Fig. 2). Fields spring-planted with grains and oilseeds on the selected soil groups were prioritized for soil sampling, with soybeans (*Glycine max* [L.] Merr.) and corn (*Zea mays* L.) being the predominant crops. We sought to sample equal numbers of fields that were growing with and without soil health management practices. Reference soils with perennial vegetation and no disturbance for at least 10 years were sampled in both regions. The sampled references included 75 fencerows and conservation areas, ten hayfields, nine grazed pastures, and eight fruit orchards. While some reference sites (e.g., hayfields, grazed pastures, and fruit orchards) experience low levels of anthropogenic disturbance, all were selected to represent the maximum expression of soil health principles, including continuous living roots, minimal soil disturbance, and soil cover, for the dominant agricultural soils in this region. Restricting references to a single land use type (e.g., native forest) would have risked excluding some of the dominant agricultural soil types targeted in this study, as soil type and land use are often correlated in this landscape.

Management data for the row-cropped sites included the (a) timing,

Table 1
Soil taxonomic classifications of sampled soils according to the Ontario Soil Survey Complex and approximate correlation to the World Reference Base, along with parent materials, surface particle size classes, and drainages sampled according to Canadian System of Soil Classification (IUSS Working Group WRB, 2022; Ontario Ministry of Agriculture, 2019; Soil Classification Working Group, 1998).

Principal Qualifier	Reference Soil Group	Parent Material	Surface Particle Size Classe	Drainage	Sites
Calcaric	Luvisol	Fluvial, glaciofluvial, glaciolacustrine, lacustrine, till	Coarse-loamy, clayey, fine-loamy, fine-silty	Well, moderately well	123
Gleyic Calcaric	Luvisol	Fluvial, glaciolacustrine, lacustrine, till	Coarse-loamy, fine-loamy, clayey, fine-silty	Well, imperfectly	84
Calcaric	Cambisol	Fluvial, till	Coarse-loamy, fine-loamy	Well	31
Mollic Calcaric	Gleysol	Glaciolacustrine, lacustrine, till	Coarse-loamy, clayey, fine-loamy	Poorly	22
Gleyic Calcaric	Cambisol	Fluvial, till	Coarse-loamy	Imperfectly	2

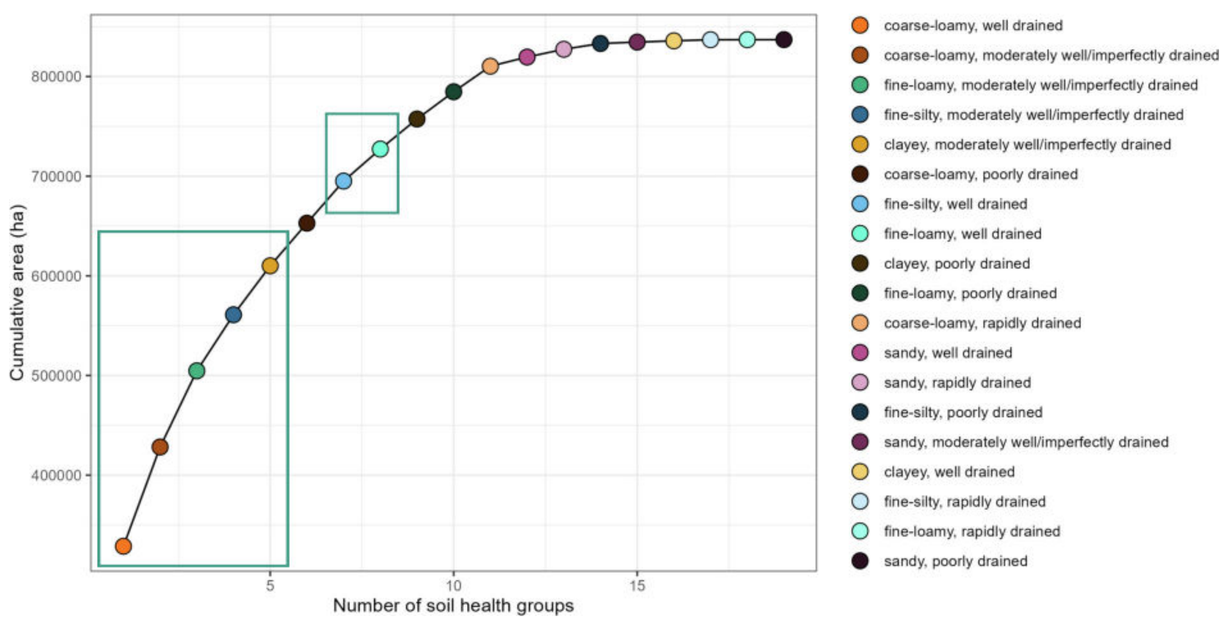

Fig. 1. Cumulative area in our sampling region (hectares) planted in grains and oilseeds on the soil groups identified through stratification. The area outlined by the boxes represents over 75% of the area and the soil groups that were targeted for sampling. Poorly drained coarse-loamy soils were excluded because they occurred on different landscape positions than and were therefore less comparable to the other soils.

depth, number of passes, and implement type of tillage, (b) the species, planting dates, and harvest dates of row crops, (c) the species, planting dates, and termination information for cover crops, (d) the species, planting dates, harvest frequency, and termination information for forage/biomass crops (e.g., alfalfa [*Medicago sativa* L.], silage corn) if applicable, (e) the application dates and types of organic amendments, and (f) any non-tillage soil disturbances in the past five years (e.g., land leveling or tile drainage installation). For reference sites, information on the type of perennial vegetation, harvest type and frequency if applicable, grazing records, and history of management changes over ten years were collected.

Tillage information was used to calculate a generalized tillage intensity rating (GTIR) for each tillage event using tillage depth, area disturbed, and the tillage implement type, and the maximum GTIR for each year was averaged over five years ($GTIR_{max}$; Dada et al., in press; Fig. S1). Using preliminary management data, row-cropped fields were first assigned to one of two categories, “baseline” and “soil health management system” (SHMS) according to the intensity and frequency of soil disturbance (baseline = $GTIR_{max}$ of 12 or more; SHMS = $GTIR_{max}$ less than 12) and the inclusion of cover crops and winter wheat (*Triticum aestivum* L.) in the rotation. Fields were reassigned after collecting the five-year management history if needed (e.g., if a field described as no-till was disced before corn). The SHMS category was defined to include all no-till fields and reduced/rotational tillage fields (except for one, which was moldboard plowed). The common rotations and management practices are given in Table 2.

2.3. Field sampling

The field sampling methodology was designed to fulfill criteria in the Ontario SHAP protocol as well as the standard operating procedures for soil sampling used by the Soil Health Institute (OMAFA, 2023; SHI, 2024). A total of 285 soil samples were collected from locations in the targeted soil health groups and management classes during the last week of May to July in 2023 and 2024. Soils were sampled from 2 to 6 weeks after planting the row crop. To minimize the effect of topographic variation on soil properties, backslope topographic positions in each field and reference area were prioritized for sampling. Visibly eroded areas and areas with high traffic, such as headlands, were avoided. Soil samples composited from 20 holes collected using a 2.9-cm-diameter push probe were collected from 0 to 15 cm in a 10-m radius. Aggregates that were approximately 5 to 9 mm in diameter were collected for measuring aggregate stability were handpicked from soil collected from the top 6 cm next to the bulk density core location. Supplemental observations (e.g., photos, evidence of soil crusting), sample coordinates, bulk density depth information, and notes were collected at the time of sampling using iPads in the field and Survey123 (Esri, 2023).

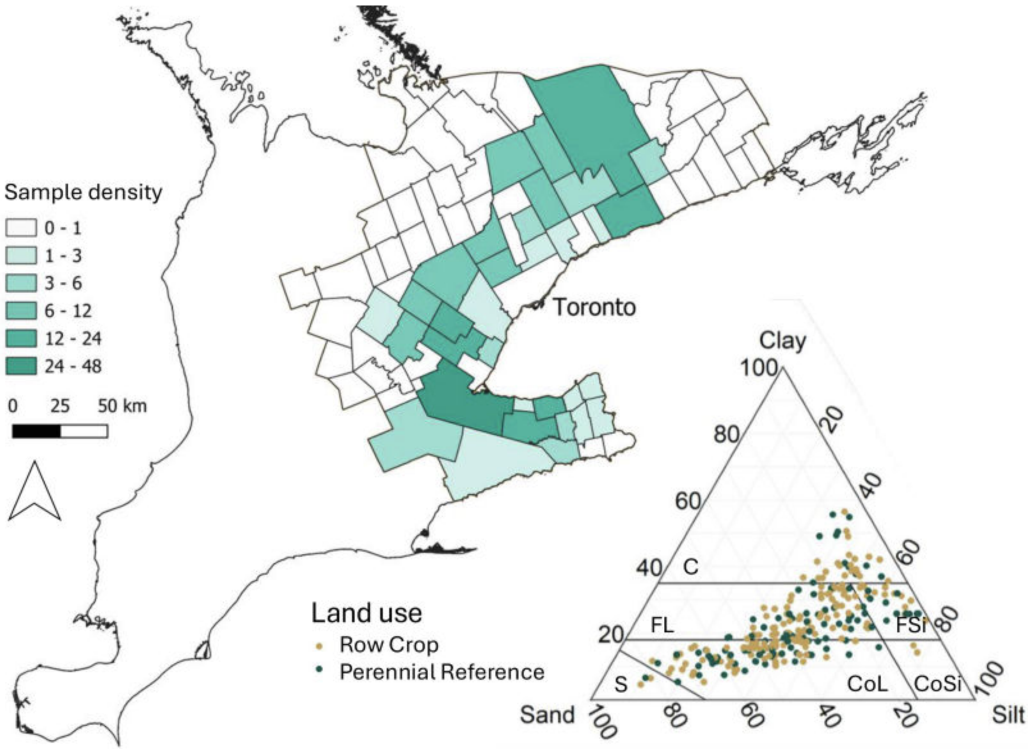

Fig. 2. (left) Choropleth of sample density by municipality in the Greater Golden Horseshoe area, Ontario, Canada, with the area clipped to remove soils in the Canadian Shield. (right) Sampled soil textures represented on a soil texture triangle with particle-size classes demarcated by solid lines (C = clayey; FL = fine-loamy; FSi = fine-silty; CoSi = coarse-silty; CoL = coarse-loamy; S = sandy).

Table 2
Rotations and approximate management practices sampled in this study. Management categories identified as SHMS are italicized and baseline are non-italicized.

Tillage	Corn-soy	Corn-soy-wheat	Corn-soy-wheat-cover crops	Corn-soy-alfalfa	Sum
No-till	*6*	*2*	*29*	*5*	**42**
Reduced/ rotational	*1*	*6*	*22*	*7* 1	**37**
Annual	25	20 *1*	24 *2*	9	**81**
Sum	**32**	**29**	**77**	**22**	**160**

2.4. Laboratory analyses

The soil health indicators were analyzed according to the indicators specified by SHAP as well as SHI's essential indicators (Bagnall et al., 2023; OMAFA, 2023). During the first year of sampling (2023), soil analysis was split between two laboratories, American Agricultural Laboratory (AAL) in McCook, Nebraska, USA and the Agriculture and Food Laboratory (AFL) in Guelph, Ontario, CA. Texture, total carbon, inorganic carbon, and aggregate stability were analyzed at AAL, and 96-hour respiration and pH were measured at AFL. In the second year (2024), all analyses were performed at AFL. For all analyses except aggregate stability, soil was air-dried, homogenized, and sieved (2 mm).

The following analyses were performed on composite samples from 0 to 15 cm. The moisture content correction factor was measured at 105° C to report mass-based measurements on an oven-dried basis. In the first year, clay was measured by hydrometer for clay and wet sieving for sand (United States Department of Agriculture, 2014). In the second year, the pipette method was used for particle size analysis (United States Department of Agriculture, 2014). Total carbon (TC) and nitrogen (TN) were measured by dry combustion. Inorganic carbon (IC) was measured using a modified pressure calcimeter (Fonnesbeck et al., 2013). Soil organic carbon was calculated as the difference between total carbon and inorganic carbon and expressed as a percent. Carbon mineralization potential of rewetted air-dried soil was measured by incubating soil over 96 h and measuring CO_2 concentration with a 0.5 M potassium hydroxide trap using methods modified from Haney and Haney (2010) and Zibilske (1994) and expressed as ppm CO_2-C. Soil pH was measured using the saturated paste method with a soil to water ratio of 1:1. Aggregate stability was measured by image analysis of slaking of three intact, air-dried aggregates per petri dish in triplicate (nine total aggregates) using the SlakeItEasy package (Fajardo et al., 2016; Looker, 2023), and expressed as the geometric mean of the aggregate stability index (unitless). Two samples were not measured for aggregate stability: one row-cropped sample was too sandy to collect aggregates, and one reference aggregate sample was lost during transport.

2.5. Data processing and statistical analyses

After evaluating the management data, twenty-one fields that did not meet the criteria of the project were classified as "other" and excluded from analysis. These sites included young hayfields (disturbed within 10 years), a few market vegetable fields, and fields with an anomalous soil disturbance in the past 5 years (e.g., deep ripping or new tile drainage installation). Two row-cropped fields for which management data could not be obtained due to lack of farmer response were excluded from analysis. This left 262 samples.

Fields were assigned to one of three management categories for analysis: baseline (79 soil samples); soil health management system (SHMS; 81 soil samples); or reference (102 soil samples). Most fields with annual or intensive tillage were classified as baseline, except three fields with annual tillage were classified as SHMS because of high living roots from use of winter wheat in the rotation and cover cropping. Two fields in the corn-soybean rotation and two fields in corn-soybean-alfalfa included cover crops. One or two years of additional grain crops, e.g. triticale (x *Triticosecale* Wittmack), canola (*Brassica napus* L.), and barley

(*Hordeum vulgare* L.) were present in some corn-soybean-wheat and corn-soybean rotations. The proportion of sites applying manure was relatively even across baseline and SHMS management groups (~40%; Fig. S2).

The following predictors were investigated through correlation analysis and evaluated during the model selection process. Mean annual temperature (MAT; degrees Celsius) and precipitation (MAP; mm) for point locations were extracted from DAYMET 30-year annual averages (Thornton et al., 2022; Wieczorek and Signell, 2023). Terrain predictors, including slope, mean curvature, and deviation from mean elevation, were generated using processing tools in the R package whitebox (Lindsay, 2016; Wu and Brown, 2022) from best-available lidar-derived digital elevation models and digital terrain models downloaded using the terrainr R package where coverage allowed and the Ontario GeoHub where 3DEP coverage was absent (Mahoney et al., 2022; OMNRF, 2025; Posit team, 2025). Laboratory-analyzed clay, laboratory-analyzed sand, laboratory-analyzed pH, drainage class from soil survey, management category without accounting for manure (baseline, SHMS, and reference), and management category accounting for manure (baseline, SHMS, manure, and reference) were also evaluated as predictors. In the case of continuous predictors, the distribution of values in row-cropped and reference soils was visually confirmed to be similar before inclusion. Prior to model fitting, all soil health indicators were log-transformed.

Candidate models with all combinations of predictors were created and compared using the Bayesian Information Criterion (BIC) and adjusted r^2. For each soil health indicator, the adjusted r^2 of the model with the lowest BIC value was compared to the adjusted r^2 of reduced models containing fewer predictors. If the difference in explanatory power was less than 0.05, the full model was discarded in favor of the reduced model. If multiple reduced models met this criterion, the model with the fewest predictors was retained. If models containing clay and sand differed in adjusted r^2 by less than 0.05, clay was retained instead of sand. Throughout this process, potential collinearity of predictors was considered with correlation analysis, as well as mechanistic knowledge of pedologic relationships between predictors and soil health indicators. Once final models were selected, differences between management groups were evaluated through pairwise comparisons using the emmeans R package, with statistical significance assessed at $p < 0.1$ using the Tukey method of adjusting for multiple comparisons (Lenth, 2025; Posit team, 2025).

To compare management practices, a second, modified approach was employed which used management practices as predictors within row-cropped soil models. In this case, the inherent soil properties identified in the previous step were used, and instead of the management categories, the following predictors were included: manure (applied at least once in five years [n = 64] vs. not applied [n = 96]), winter wheat (WW; grown at least once in five years [n = 110] vs. not grown [n = 50]), winter wheat and cover crops (WW + CC; combination grown at least once in five years [n = 81] vs. not grown [n = 79]), and $GTIR_{max}$ (continuous). Interactions were allowed between management predictors during model evaluation. In this case, the model with the lowest Aikake Information Criterion (AIC) was selected. If the model with management predictors improved the adjusted r^2 of the basic model with inherent properties by less than 0.05, the basic model was retained. After models were created, effect sizes were plotted with the dotwhisker package (Solt et al., 2024). Continuous coefficients were rescaled using the by_2sd function to ease comparison with binary predictors.

2.6. Goal setting

To evaluate soil health performance across row-cropped fields, we determined which soils met or exceeded a goal and which remained below it using the following approach. For each soil under row-cropped management, each soil health indicator value was divided by the modeled reference value at the same inherent soil property values (e.g., 20% clay, using the model predictors in Table 4), yielding a proportion between zero and one for each sample. The median of these proportions across all row-cropped soils was then used as a benchmark goal for each indicator (soil organic carbon = 0.63; aggregate stability = 0.75; potentially mineralizable carbon = 0.51). The median was chosen to increase model accuracy and in accordance with the sampling design, which had roughly equal numbers of baseline and SHMS fields. This could be considered a realistic, rather than aspirational, goal for row-cropped fields, acknowledging that the maximum soil health potential of these soils (e.g., reference soil values) may not be achievable under row-crop production. Model terms from the row-cropped multiple linear regression models were used within binomial logistic regression to estimate the probability of reaching the median proportion of the reference soil health indicator value achieved by row-cropped soils.

3. Results

3.1. Relationship of soil health indicators to inherent soil properties

Soil samples spanned a broad range in percent clay (~5 to 57%) and pH (~4.7 to 8.0), whereas they encompassed a smaller range of MAT and MAP (~4 °C and 250 mm, respectively). Row-cropped and reference soils had similar means and ranges of clay, pH, MAT, and MAP, as well as similar representation in drainage classes, which was a goal of the sampling design. The distributions and relationships of soil health indicators and inherent soil properties are presented in Fig. S3 and Fig. S4.

All soil health indicators were significantly correlated with clay, with soil organic carbon and aggregate stability having the strongest correlations. Potentially mineralizable carbon was strongly correlated with clay in reference soils and weakly correlated with clay in row-cropped soils. In addition, potentially mineralizable carbon was strongly correlated with soil pH in row-cropped soils but had a weak, opposite relationship in reference soils.

3.2. Soil health potential and management effects

Clay was identified as a significant predictor for soil organic carbon, aggregate stability, and potentially mineralizable carbon (reference soils only; Table 3). pH was a predictor for potentially mineralizable carbon (row-cropped soils only). Management was a predictor for all three indicators.

The multiple linear regression models identified through the model selection process are presented in Table 3 and visualized in Fig. 3. Because of the different relationship between potentially mineralizable carbon and pH and clay in references and row-cropped soils, we modeled them separately. Model selection statistics are given in Table S1.

Considering the range of each predictor modeled through linear regressions, high clay content soil (57% clay) had 1.92 times greater predicted soil organic carbon than low clay content soil (5% clay; Fig. 3). Low clay content soil had 1.62 times greater predicted aggregate stability than high clay content soil. In row-cropped soils, high pH (8) resulted in 2.28 times greater predicted potentially mineralizable carbon than low pH (4.7), whereas in reference soils, high clay content soil resulted in 2.11 times greater predicted potentially mineralizable carbon than low clay content soil.

Table 3
Multiple linear regression models identified for log-transformed soil health indicator variables.

Indicator	Model	Adjusted r^2
Soil Organic Carbon	Management + Clay	0.44
Aggregate Stability	Management + Clay	0.52
Potentially Mineralizable Carbon (row crop)	Management + pH	0.25
Potentially Mineralizable Carbon (reference)	Clay	0.23

Table 4
Relative differences between management groups obtained using estimated marginal means, or least-squares means, from the regression models in Table 3 and Fig. 3, respectively. Asterisks indicate significant differences adjusted for multiple comparisons ($p < 0.1$). A range of ratios is given for potentially mineralizable carbon because separate models were developed for row-cropped and reference soils due to differing relationships with soil properties. This range reflects comparisons across combinations of high and low clay and high and low pH within each model.

Indicator	SHMS: Baseline	Reference: SHMS	Reference: Baseline
Soil Organic Carbon	1.07	1.55*	1.67*
Aggregate Stability	1.15*	1.30*	1.49*
Potentially Mineralizable Carbon	1.12*	*1.06–5.53*	*1.21–6.29*

All soil health indicators increased in the following order of management groups (note: the model for aggregate stability included the management term without a manure category): Baseline < SHMS < Reference (Fig. 3). Using estimated marginal means, we found that means of references ranged from 1.21 to 6.29 times greater than baseline means and were significantly greater than estimated means for SHMS for all indicators. Estimated SHMS means ranged from 1.07 to 1.15 times greater than baseline means (Table 4). These differences were significant for aggregate stability and potentially mineralizable carbon (Fig. 3). The ratios between management groups are in Table 4.

3.3. Management practices driving observed effects

Model coefficients for the management practices identified as predictors in models for row-cropped soils (rescaled to allow for comparing the relative magnitude between continuous and binary predictors) are

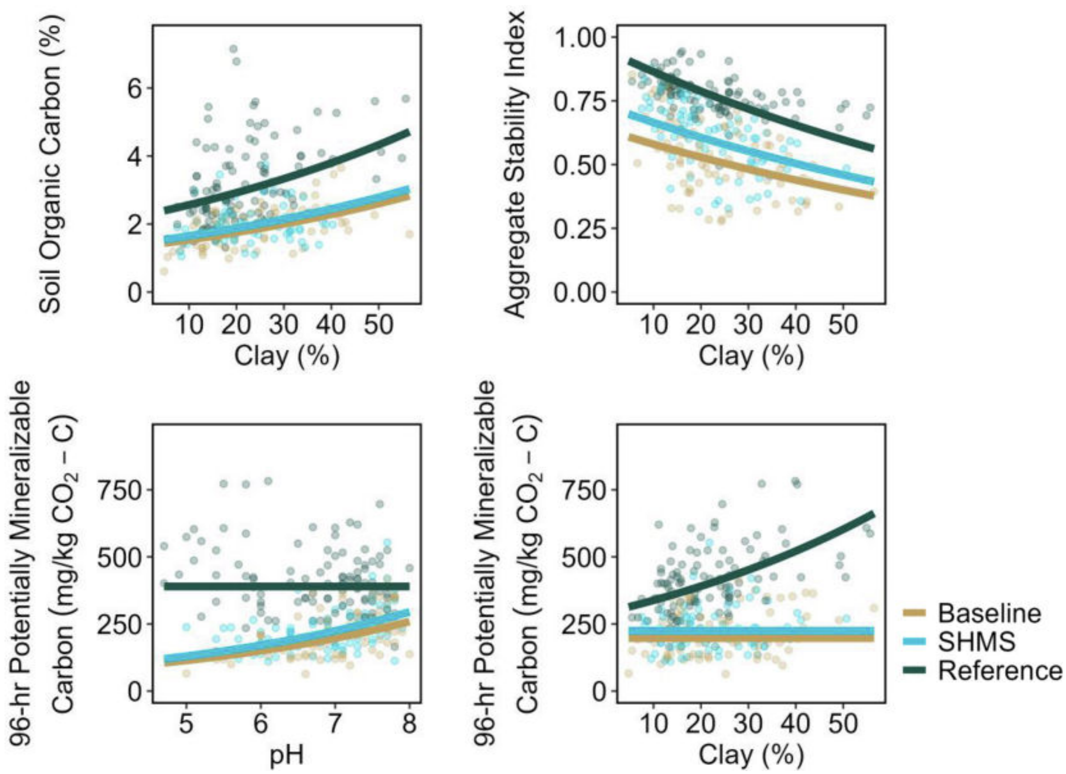

Fig. 3. Relationships with soil inherent properties and management for each of the soil health indicators. Lines represent fitted linear regressions, which are curved due to the log transformation of response variables.

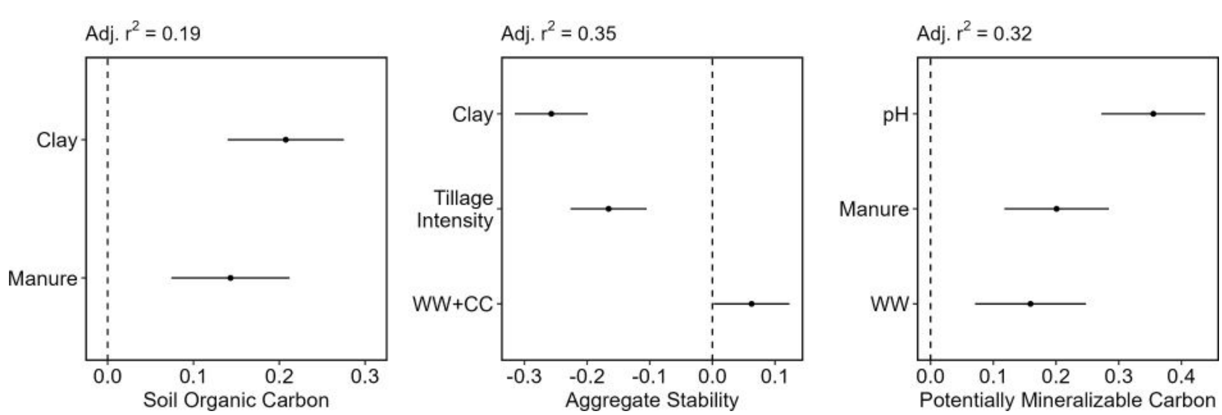

Fig. 4. Relative coefficient estimates and 90% confidence intervals for predictors included in multiple linear regression models for row-cropped soils. Zero on the x-axis is indicated with a dotted line. Inherent properties (clay, pH) were included based on models in Table 4.

given in Fig. 4. Model selection statistics (BIC and AIC) for the selected models are provided in Table S1. The rescaled coefficient estimates in Fig. 4 represent the effect sizes for management and inherent soil property predictors. After accounting for inherent soil properties, manure had a positive effect on the carbon soil health indicators but not for aggregate stability. Manure was the sole predictor identified for soil organic carbon (Fig. 4; Fig. S5).

Winter wheat and cover crops positively influenced aggregate stability and potentially mineralizable carbon (Fig. 4; Fig. S5). Aggregate stability was 1.06 times greater in fields with winter wheat and cover crops (WW + CC) and potentially mineralizable carbon was 1.17 times greater in fields with winter wheat (with or without cover crops; WW).

Tillage intensity was negatively associated with aggregate stability (Fig. 4; Fig. S5). Every one-unit decrease in GTIR was predicted to increase aggregate stability by 1.01. This represented an increase of 1.09 when transitioning from annual to reduced tillage, an increase of 1.06 when transitioning from reduced tillage to continuous no-till, and an increase of 1.16 when transitioning from annual tillage to continuous no-till.

3.4. *Relating progress achieved to predicted soil health potential*

Soil health indicators for row-cropped soils were compared to predicted indicator values for reference soils to evaluate progress toward achieving the maximum soil health potential for a given soil. We set the median proportion of the modeled reference as a goal for row-cropped soils (soil organic carbon = 0.63; aggregate stability = 0.75; potentially mineralizable carbon = 0.51). The probability of achieving the median of the predicted reference for soil organic carbon increased from 41% to 62% with manure additions. For fields without cover crops, the probability of achieving the goal for aggregate stability increased from 36% under annual tillage to 53% under reduced tillage and 64% under continuous no-till (Fig. 5). For fields with winter wheat and cover crops, the probability of achieving the goal increased from 50% under annual tillage to 66% under reduced tillage and 76% under continuous no-till (Fig. 5). The probability of achieving the median of the predicted reference potentially mineralizable carbon in fields without manure increased from 33% to 53% when winter wheat was added (Fig. 5). In fields with manure, the probability increased from 54% to 72% (Fig. 5).

4. Discussion

4.1. *Role of inherent properties*

The transition from till and glaciofluvial deposits in the upper part of the Greater Golden Horseshoe to glaciolacustrine deposits in Hamilton and Niagara contributed to the broad range of soil textures and pH located in a narrow range of temperature and precipitation (Fig. 2; Fig. S2). Considering this and given the established relationship of clay to many soil health indicators (e.g., Amsili et al., 2021; Chahal et al., 2022), it was expected that the soil health indicators would correlate to clay content. Although clay influenced potentially mineralizable carbon in reference sites, in alignment with work by Balogh et al. (2011), potentially mineralizable carbon at row-cropped sites was only weakly correlated to clay, while having a strong correlation to pH. The connection between pH and potentially mineralizable carbon is demonstrated by Looker et al. (2025), Rousk et al. (2009), and Liptzin et al. (2022). In row-cropped soils, application of lime and nitrogen fertilizers influences pH, which is well known to control microbial community dynamics (Fierer and Jackson, 2006).

4.2. *Role of management*

This work underscores the value of measuring multiple soil health indicators to capture the multifunctionality of soils (Lehmann et al., 2020). We found that different soil health indicators responded to different management practices, as also found in Looker et al. (2025). For instance, aggregate stability, which is connected to water storage, infiltration, and erosion susceptibility (Rabot et al., 2018), was improved by decreasing tillage and increasing living roots through winter wheat and cover crops, but was unaffected by manure, in line with findings from Das et al. (2023) and Rieke et al. (2022). Potentially mineralizable carbon responded to manure and increased living roots, but no influence of tillage was detected, coinciding with findings from Liptzin et al. (2022). During modeling evaluation, we identified potential interactions between tillage and manure as well as tillage and winter wheat/cover crops for potentially mineralizable carbon (Fig. S6). These interactions did not meaningfully change the direction of observed trends and did not improve the models by more than 5% but suggested that the manure and increased living roots can partly compensate for the negative influence of intensive tillage. We found a small but non-significant increase in the surface enrichment of organic carbon in soils with low disturbance compared to soils with higher disturbance (Fig. 3). We detected no significant effects of decreased tillage or increased living roots on soil organic carbon. This is surprising in the case of tillage, given the average duration since first use of soil health promoting practices (92% of producers who provided this information had implemented practices for 10 or more years). The influence of current and legacy manure applications in this region may have overshadowed the effects of decreased tillage and increased living roots for this indicator, as observed in Northeast Ohio by Bridges et al. (2023). Adding manure is well-known to significantly raise soil organic carbon

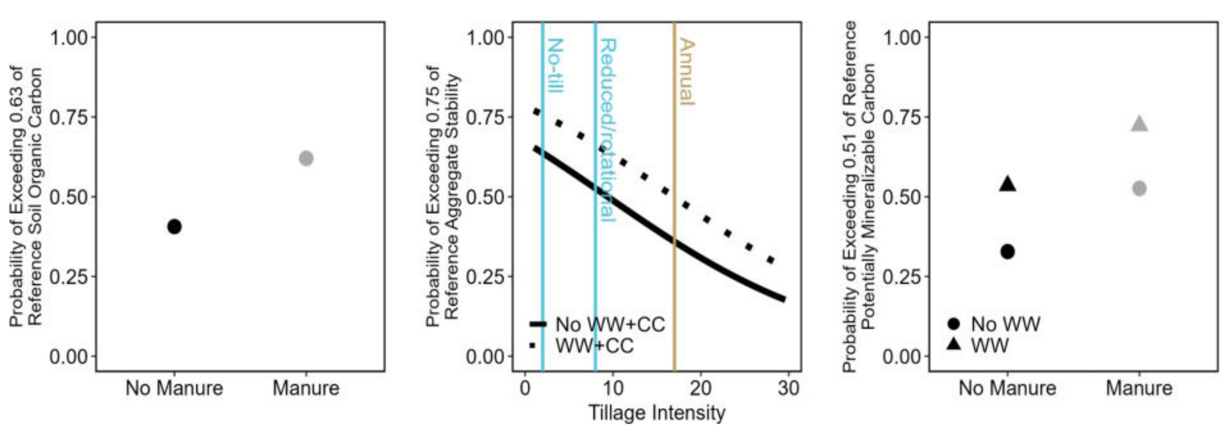

Fig. 5. Probability of exceeding the goal (i.e., median proportion of row-cropped soils relative to the modeled reference value; 0.63, 0.75, and 0.51 for soil organic carbon, aggregate stability, and potentially mineralizable carbon, respectively) for all three indicators, according to the dominant practices influencing soil health. Three common tillage categories are shown with colored lines in the aggregate stability plot.

concentration in agricultural soils (Han et al., 2016; VandenBygaart et al., 2003). Although our results only describe indicator effects in the upper 0–15 cm of soil, the small and non-significant enrichment of organic carbon we observed under decreased soil disturbance should be interpreted with caution, as the effects of no-till on shallow organic carbon do not necessarily reflect net gains across the full soil profile (Haddaway et al., 2017). The combined effects of organic amendments and no-till are not necessarily additive, as a *meta*-analysis of 101 studies identified a small increase in soil organic carbon stocks in manured annual tillage systems compared to manured reduced tillage systems (Gross and Glaser, 2021).

The strength of our interpretation is constrained by the voluntary nature of producer enrollment, which may include more producers already interested in soil health, who may use more soil health promoting practices or for longer than the broader population. This suggests that the true potential for improvements from use of soil health promoting practices could be greater than detected in this study. This would mean that our selection of the median proportion of reference in this study as an "achievable" goal could be less practical than intended, if it represents the median of relatively progressive farmers rather than an even distribution. Still, despite increasing use of soil health promoting practices, modelling of soil organic matter trends nationally and corroborating data suggest declining soil organic matter levels in much of Ontario and eastern Canada over five decades (Cerkowniak et al. 2016).

In addition, temporal changes in management practices are likely influencing trends in soil health. For example, over the last five decades, tillage declined until recently, soybean acreage expanded, winter wheat acreage fluctuated, cover crop use increased, and the overall row crop acreage expanded (Shirriff et al., 2022; Smith, 2015; Statistics Canada, 2021, 2016, 2011). This has been accompanied by decreases in access to organic amendments, rotation diversity, livestock, and area of hay lands and pasture (Chen et al., 2025; Gaudin et al., 2015; Wright and Wimberly, 2013). Because manure applications had a larger effect on soil organic carbon than adding either winter wheat or cover crops, continued reductions in organic amendments and livestock could drive regional decreases in both organic carbon and potentially mineralizable carbon, even with increased cover–crop use and reduced tillage. Such decreases could also occur at the farm scale if manure applications cease on a farm with a long history of organic amendments, even if the farmer introduces other soil health promoting practices. Finally, although some soil–health–promoting practices may be becoming more common in row–crop systems, others may be declining, and the ongoing conversion of pasture and hay lands into row crops continues, so a provincial analysis of regional trends in soil health practices is needed (OMAFA, 2018; Smith, 2015).

In the study sample, rotation largely predicted the use of cover crops, where 95% of cover crops occurred in corn-soybean-winter wheat rotations. Most instances of cover crops in this rotation involved underseeding winter wheat with red clover (*Trifolium pratense*) in early spring, which added around 75 to 90 more days of living roots in that year. Spread out over a three-year rotation, the inclusion of winter wheat combined with red clover added 30–60% more days with living roots compared to a corn-soy rotation. Hence, in our study, treating rotation and cover cropping as an integrated system yielded more insight than considering either practice in isolation. Our finding that winter wheat and cover crops improve two key indicators of soil health reflects the effect of living roots on soil health. In temperate climates, it is difficult to establish significant cover crop biomass in the other potential window for cover crops in a corn-soybean-winter wheat rotation, after corn harvest. Future improvement in soil health may hinge on cover crop practice innovations such as planting green and interseeding in corn (e.g., Belfry and Van Eerd, 2016).

We can contrast the effect sizes identified in this on-farm study to the effect sizes of rotations, cover crops, tillage treatments, and manure within long-term research trials on similar soils. Information about individual Ontario long-term experiments is provided in Norris et al. (2022). Congreves et al. (2015) identified a 47% increase in aggregate stability by wet sieving between conventional tillage and no-till at a long-term (36 year) experiment on a loam soil in Elora, Ontario. We found a 15% increase between baseline and SHMS groups, although a different aggregate stability method was used. Decreased tillage resulted in 26% (chisel plow to no-till) and 40% (conventional to no-till) greater aggregate stability by wet sieving in a loamy sand in southwestern Ontario, higher than our estimate of 15%, although a different aggregate stability method was used and no effect of cover crops was observed (Ball-Coelho et al., 2000). Higher soil organic carbon was identified between conventional tillage and no-till at the Ridgetown, Ontario and Elora, Ontario experiments, although neither included organic amendments (Chahal et al., 2021). The magnitude of these effects varied from 2 to 25%, encompassing our finding of 7% higher soil organic carbon (non-significant) between baseline and SHMS groups. Aggregate stability by wet sieving increased 16–25% at Ridgetown when comparing corn-soy rotations to corn-soybean-winter wheat and soybean-winter wheat (van Eerd et al., 2014), and potentially mineralizable carbon increased at Woodslee 29% when comparing corn-soy to corn-soybean-winter wheat (Agomoh et al., 2021). These increases were higher than the increases observed in this study (6% and 17%, respectively). Increases in soil organic carbon and microbial activity were observed under repeated manure inputs in temperate long-term experiments in South Dakota and Nebraska (Mikha et al., 2015; Ozlu et al., 2019), mirroring our finding that fields with a history of manure inputs had greater soil organic carbon and higher potentially mineralizable carbon, although the different climate and variable manure rates in this study limit comparability. Considered together, these results from long-term experiments reinforce the direction of management effects observed in our on-farm study. In contrast to controlled experiments, the duration of management practices used in this study varied widely, from under five to over forty years. Still, our findings indicate that the same practices shown to improve soil health in controlled trials can produce comparable improvements on working farms.

4.3. Evaluating soil health progress and setting reference-based goals

By evaluating soil health improvements in row-cropped soils relative to undisturbed perennial references, we constrained soil health progress against a soil property-adjusted quantitative maximum. The definition of "baseline" as used within this study, representing the maximum-intensity set of farming practices in a region, has changed over time, with deep, frequent tillage such as moldboard plowing becoming less common (Smith, 2015). Using the definition of baseline from 70 years ago, most of the practices in this study could be considered progressive because of a shift from moldboard plowing to vertical tillage methods. Due to this, comparing progress to reference sites allows us to understand current impacts of row-cropping on soils despite a shifting baseline. Our selection of reference sites from a variety of land uses means that maximum soil health may be somewhat underestimated, given that certain land uses (e.g., pastures, orchards, hayfields) in our dataset are agriculturally managed with fertilizer inputs and infrequent soil disturbance. Future work could compare inter-reference variation where possible (and where soils are similar) in order to quantify the potential gap between managed and unmanaged references.

Additionally, grouping soils from different taxonomic classes into management categories may introduce residual variation not captured by clay and pH covariates. Cultivation homogenizes surface soil properties through physical mixing (Dyck and Kachanoski, 2011), whereas undisturbed soils tend to retain more pedogenic differentiation. We expect differences in taxonomic classes to therefore most strongly influence the reference samples. Additionally, pooling across soil types may mask soil-type-specific responses. For example, management effects on potentially mineralizable carbon could differ between Luvisols and Gleysols due to differences in drainage and organic matter. As sample sizes allow, analyses within individual soil classes or soil-climatic zones, and pairing references with managed soils within narrower taxonomic units (e.g., Gasser et al., 2023), would help determine whether soil-type-specific management effects differ from grouped estimates and further isolate management from pedogenic variation.

This study sampled a range of land use types that represented our definition of undisturbed perennial references, including fencerows, conservation lands (including forests and young prairies), woodlots, pastures, hayfields, and orchards. There is existing evidence that soil organic carbon, potentially mineralizable carbon, and aggregate stability vary between land use types (e.g., Adhikari et al., 2019; Li et al., 2023; Sharma et al., 2025; Toh et al., 2020). In addition, land use history is likely to contribute to variation, as identified elsewhere by Das et al. (2024). Still, the range of references was selected to include the common land use types for soils in this region that maximize soil health principles, including time with living roots, minimal disturbance, above-ground diversity, and maintaining soil cover (van Eerd et al., 2021). Sampling a multitude of references was necessary to capture a similar range of soil parameters as row-cropped soils. Going forward, additional resources such as the Ontario Ecological Land Classification could link reference soils with vegetation community to further characterize soil health variation in references as has been proposed using similar information in the USA (Das et al., 2024).

Dividing soil health indicator results for row-cropped soils by predicted reference values at the same inherent soil property value (e.g., at 23% clay) provided an actionable measure of progress relative to potential. Our finding that the median organic carbon value for row-cropped soils was 0.63 of the modeled organic carbon of reference soils is in line with work by Powlson et al. (2022) and reflects an achievable goal based on the balanced sampling design of this study. This probability-based goal framework offers a way for farmers and their advisers to set soil-tailored goals. Rather than interpreting soil health values in isolation, producers can use the management-explicit probabilities in Fig. 5 to understand the likelihood of meeting a benchmark under their current practices and the potential gain from adopting new soil health promoting practices. This translates our research into practice-specific guidance that can support on-farm decision-making. One potential limitation of this approach is that our work did not evaluate the time needed to reach the benchmark, which could be the focus of future work. Lastly, a few row-cropped sites reached the predicted reference values for individual indicators, but no sites reached the predicted reference value for more than one indicator. This reinforces the need for multiple indicators to evaluate soil health progress. Further work remains to understand how much improvement is possible from soil health promoting practices in row crop agriculture relative to reference soils.

5. Conclusions

Our study demonstrates gains in soil health from improved soil health management of row-cropped fields once inherent soil properties are accounted for. Reduced tillage disturbance, increased living roots through winter wheat and cover crops, and manure additions were associated with higher aggregate stability, potentially mineralizable carbon, and soil organic carbon. These improvements occurred across diverse soils and management types, underscoring that measurable progress is already being achieved on many commercial farms. Producers and their advisers can use these findings to adopt soil health promoting practices (e.g., reduced tillage, no-till, cover crops, rotating with overwintering crops, and/or organic amendments) based on their soil health goals and unique on-farm needs. Non-farmer stakeholders can use aggregated reports to better understand how implementing soil health principles improve soil health in this region and by soil type.

Reduced disturbance, increased living roots, and manure additions each advanced soils toward their modeled potential, although different practices improved different indicators. The reference-based framework presented here offers a transparent, quantitative means of evaluating both the progress achieved and remaining potential, adjusted to soil type. This approach provides producers, advisers, and regional programs with a realistic basis for setting goals and serves as a transferable model for soil health assessment in Ontario and elsewhere.

CRediT authorship contribution statement

J.A. Bower: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **D. Liptzin:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Data curation. **R. Carlow:** Writing – review & editing, Resources, Project administration, Data curation. **P.G.R. Smith:** Writing – review & editing, Project administration, Methodology, Funding acquisition, Conceptualization. **D.D. Saurette:** Writing – review & editing, Resources, Methodology, Data curation, Conceptualization. **J. Munroe:** Writing – review & editing, Validation, Methodology, Conceptualization. **L.L. van Eerd:** Writing – review & editing, Supervision, Methodology, Conceptualization. **C.L.S. Morgan:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Jennifer Bower reports financial support was provided by Weston Family Foundation. 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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.geoderma.2026.117806.

Data availability

Data will be made available on request.

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