A soil health scoring framework for arable cropping systems in Saskatchewan, Canada1

Authors: Wu, Qianyi, and Congreves, Kate A.

Source: Canadian Journal of Soil Science, 102(2) : 341-358

Published By: Canadian Science Publishing

URL: https://doi.org/10.1139/CJSS-2021-0045

Canadian Science Publishing

ARTICLE

A soil health scoring framework for arable cropping systems in Saskatchewan, Canada[1]

Qianyi Wu and Kate A. Congreves

Abstract: Farmers are looking for appropriate tools for assessing and interpreting the health status of their soils; however, there is no standardized and prairie-based soil health scoring framework. Accordingly, we focused on developing one for arable cropping systems in Saskatchewan. In 2018, soil samples (0–15, 15–30, and 30–60 cm depths) were collected from 55 arable fields across Saskatchewan, along with native prairie samples. Various soil chemical, physical, and biological attributes were measured (23 attributes in total). Based on the data distribution for each attribute, we developed scoring functions. The results from multivariate analyses were used to determine the weighting factors needed to integrate the individual scores from each soil attribute into a single Saskatchewan Assessment of Soil Health score. Soil carbon (C) and nitrogen (N) indices (soil organic C, active C, total N, and soil protein) and total phosphorus produced the highest weighting factors. We also tested if there were linkages between the soil health and crop productivity by assessing the cereal yields for the past 10 years as reported from the same rural municipalities where the soil samples were collected. A positive relationship between soil health and yields was most apparent during dry years; thus, we recommend further research to explore this linkage at a finer scale. Overall, this research forms the foundation of a promising framework that can be built upon, and in due course, lead to the development of a tool for producers who are interested in tracking soil health and using the results to inform management.

Key words: soil health, prairie cropping systems, soil–crop, nitrogen, carbon.

Résumé : Les agriculteurs cherchent des outils appropriés pour évaluer la vitalité de leurs sols et interpréter les résultats obtenus. Malheureusement, il n'existe aucun cadre normalisé pour coter la vitalité des sols particuliers aux prairies. Pour y remédier, les auteurs en ont élaboré un applicable aux systèmes culturaux sur les sols arables de la Saskatchewan. En 2018, ils ont prélevé des échantillons de sol (à 0–15, 15–30 et 30–60 cm de profondeur) dans 55 champs arables de la Saskatchewan ainsi que des prairies naturelles. Cela fait, ils ont mesuré diverses propriétés chimiques, physiques et biologiques du sol (23 paramètres en tout). Ensuite, ils ont élaboré des fonctions de notation d'après la répartition des données pour chaque paramètre. Les résultats des analyses à variables multiples ont permis d'établir les facteurs de pondération nécessaires pour intégrer les notes individuelles de chaque paramètre et en faire un barème de la vitalité des sols de la Saskatchewan. Les indices du C et du N du sol (C organique, C actif, N total et protéines du sol) et la concentration totale de P donnent les facteurs de pondération les plus importants. Les auteurs ont aussi vérifié s'il existait un lien entre la vitalité du sol et la productivité des cultures en évaluant le rendement céréalier des 10 dernières années, tel que rapporté par les municipalités rurales où les sols ont été échantillonnés. La corrélation positive entre la vitalité du sol et le rendement est plus évidente les années de sécheresse. Les auteurs proposent qu'on étudie ces liens davantage, à une échelle plus fine. Dans l'ensemble, ces travaux forment la base d'un cadre prometteur qu'on pourra développer et qui, éventuellement, débouchera sur un outil pour les producteurs qui aimeraient suivre la vitalité du sol et se servir des résultats pour mieux le gérer. [Traduit par la Rédaction]

Mots-clés : vitalité du sol, systèmes culturaux des Prairies, sol-culture, azote, carbone.

Received 14 April 2021. Accepted 8 July 2021.

Q. Wu and K.A. Congreves. Department of Plant Sciences, University of Saskatchewan, Saskatoon, SK S7N 5A8, Canada.

Corresponding author: Kate A. Congreves (email: kate.congreves@usask.ca).

[1]This paper is part of a Special Issue entitled "Soil Health Evaluation: Methods and Directions".

Introduction

Soil degradation limits agricultural productivity, resulting in economic and environmental losses, and contributes to food insecurity. On the Canadian Prairies, one of the historic drivers of soil degradation was wind erosion, exacerbated by periods of drought and frequent tillage operations that exposed the soil to loss and resulted in the Dust Bowl of the 1930s. Since then, soil conservation practices have been adopted in this region to protect the soil and increase agricultural productivity — with (70%) of the cultivated Canadian prairies under no-till management and only 5% summer fallowed (Clearwater et al. 2016). In Saskatchewan, the risk of soil erosion is now considered very low (Clearwater et al. 2016). This history clearly demonstrates how improved soil management can minimize the risk of soil degradation. However, there are new concerns on the horizon which are largely brought about by climate change and the intensification of agricultural production. Moving forward, we must continue to identify the soil constraints and work towards supporting the continued functioning of agroecosystems.

Soil health is defined as "the capacity of soil to function as a vital living system, within the ecosystem and land-use boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and promote plant and animal health" (Doran and Zeiss 2000). By fulfilling complex functions, soil contributes to ecosystem services and highlights the linkages between soil health and human health. As such, monitoring the soil health status over time will aid in identifying soil constraints and in adapting management practices for sustained soil functioning. To do this, however, robust soil health tests are needed.

Farmers and scientists are looking for an appropriate tool to interpret soil health status, so a comprehensive assessment should be developed to provide a foundation for soil management. No single measurement can quantify soil health, but holistic measures of soil health are challenging because one must integrate biological, chemical, and physical properties, processes, and interactions (Karlen et al. 1997). Ideally, the selected soil indicators should be conceptually related to soil function and ecosystem processes, practical to sample and measure, responsive to changes in management, and comparable to a baseline for a meaningful interpretation (Bünemann et al. 2018).

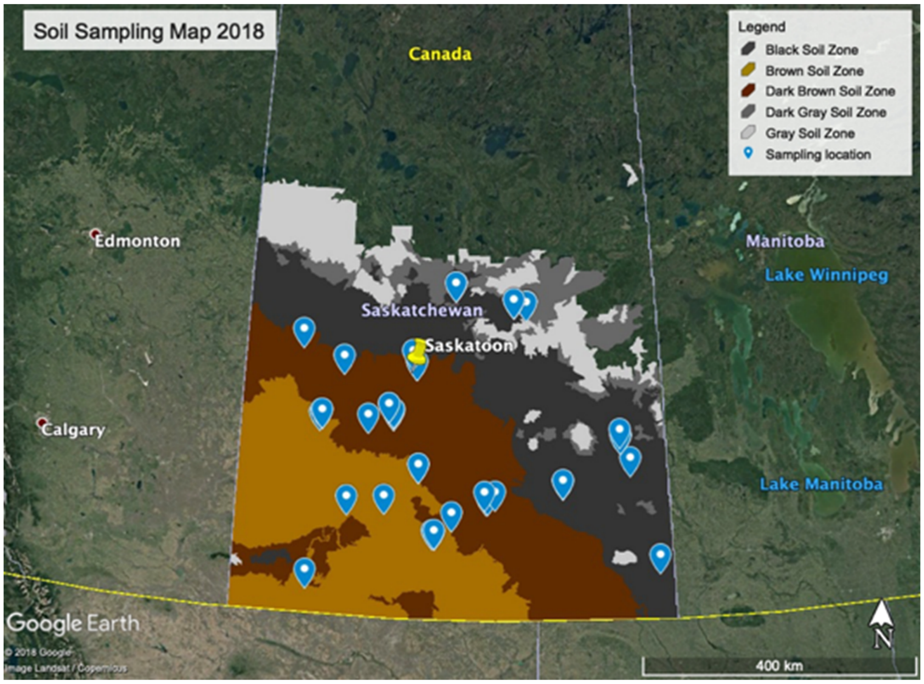
Currently, various soil health tests are in widespread use in many countries including the USA (Moebius-Clune et al. 2016), China (Li et al. 2013), Turkey (Karaca et al. 2021), the UK (Cooper et al. 2020), and India (Purakayastha et al. 2019). One of the most comprehensive soil health tests was developed in the USA at Cornell University (Moebius-Clune et al. 2016). Their Comprehensive Assessment of Soil Health (CASH) provides standardized information about the soil's physical and biological constraints, covering approximately 15 soil attributes that include the biological, physical, and chemical properties. Each attribute is scored, and the overall score reflects the soil health status (0–100). The CASH provides a useful framework for integrating soil attributes into an easily interpretable soil health score. Currently, farmers and researchers are using CASH to estimate their soil health status and improve their management decisions. Research showed that CASH scores were sensitive to various management practices in New York State (Idowu et al. 2008). However, the current CASH scoring functions are not always suitable for regions where the soil is different from those used to develop the scoring system used by CASH (i.e., soils outside the northeast, midwest, and mid-Atlantic region of the USA — Fine et al. 2017). For example, when used in locations outside the region of development, the CASH scores were less sensitive across distinct management practices with soil from the southeast region of the USA (Roper et al. 2017). Other times, soil attribute values but not scores are sensitive to management (van Es and Karlen 2019). Climate, parent material, and time are major factors that affect the soil formation, and using the soil test developed from other regions may lose its meaning when applied to other regions. Numerous researchers recommend regional interpretations of soil health tests to gain the most meaningful information on soil health and functioning (Congreves et al. 2015; Roper et al. 2017; Frost et al. 2019; Chu et al. 2019).

On the Canadian prairies — an agriculturally important region of Canada — there is no standardized prairie-based soil health scoring framework. Our objective is to develop a soil health scoring framework, tailored to Saskatchewan soils — one that integrates biological, physical, and chemical indicators; transforms soil attribute values into meaningful scores; and uses a relevant weighting system to calculate the overall soil health score.

Materials and Methods

Soil samples were collected after harvest from 55 fields (26 sites) across Saskatchewan in September and October 2018 (Fig. 1). The sampling area spanned four soil zones including 4 from the Gray zone, 13 from the Black zone, 21 from the Dark Brown zone, and 17 from the Brown zone. At each site, a composite soil sample (5–7 individual samples) was collected using a 3″ closed bucket auger from the 0–15, 15–30, and 30–60 cm depths. The selected sites represented various Agri-Arm sites, producer fields, and Agriculture and Agri-Food Canada long-term sites. Soil samples were air-dried and sieved (2 mm) prior to all analyses described below. The sampling sites were representative of Saskatchewan agriculture: in the year of sample collection, most sites were producing canola (44%) and wheat (29%), some sites (15%) were producing pulse crops (such as lentil, field pea, chickpea, or soybean), and a minority

Fig. 1. Soil sampling locations across Saskatchewan. The points were created based on the GPS coordinates. The soil sampling map was overlaid with Saskatchewan soil zones. The map resource was retrieved from https://open.canada.ca/data/en/dataset/ac6a1e51-9c70-43ab-889f-106838410473.



of sites were producing flax, barley, or potato (one site each), and green manure (three sites). Native prairie grassland and woodland (one site each) were also included.

Soil chemical attributes

Soil pH and electrical conductivity

Soil pH and electrical conductivity (EC) were determined by 1:2 soil water slurry, where 10 g of soil was mixed with 20 mL of deionized water and analyzed using a pH meter (AE 150; Fisher Scientific™) and EC meter (HI763100; Hanna Instrument).

Soil nutrient and carbon (C) concentrations

Soil total concentrations of phosphate, potassium, sodium, magnesium, calcium, manganese, iron, copper, zinc, boron, and sulfur were measured by the Natural Resources Analytical Laboratory (Edmonton, AB, Canada). Briefly, 0.7 g of soil was digested with HNO_3 at 185 °C for 10 min, and dissolved metals were analyzed by inductively coupled plasma optical emission spectroscopy (Thermo iCAP 6000 series).

Soil nitrate (NO_3^-) and ammonium (NH_4^+) were extracted using 25 mL 2.0 M potassium chloride from 5 g of soil, shaken for 30 min at 160 r·min^{-1}, and filtered by Whatman No. 42 filter papers (Maynard et al. 2007). The filtered extracts were stored at −20 °C until analysis, whereupon the extracts were thawed to room temperature and subsamples (~1 mL) were analyzed for NO_3^- and NH_4^+ concentrations using air-segmented, continuous-flow colorimetric method with a SEAL AA3 HR chemistry analyzer (SEAL Analytical, Kitchener, ON, Canada).

To determine soil organic C (SOC), soil subsamples were ball-ground for 3 min to achieve a powdery texture, and 0.8 g of soil was placed in a nickel boat liner inside a ceramic combustion boat. Boats were placed on top of a heater, with a temperature lower than 70 °C. Approximately 1 mL of deionized water was added to each boat to moisten the sample. Samples were pretreated to remove carbonates, following the method of Skjemstad and Baldock (2007); briefly, 6% sulfurous acid was added to each boat until no effervescence was observed, at which point an additional 1 mL of 6% sulfurous acid was added to confirm complete carbonate removal. Thereafter, samples were dried in an oven at 60 °C for 48 h. The carbonate-free samples were analyzed for organic C (%) using a C632 LECO Carbon Analyzer at 1440 °C.

Total C (TC) and total N (TN) were determined by dry combustion (Rutherford et al. 2007; Skjemstad and Baldock 2007). Subsamples of the ball-ground soil (1 g) were placed in a nickel liner inside of a ceramic combustion boat and analyzed for TC and TN by a TruMac CNS analyzer (LECO) at 1350 °C.

Potentially mineralizable N

Potentially mineralizable N (PMN) was determined via anaerobic incubation (Curtin and Campbell 2007). Subsample of soil (5 g) was incubated with 10 mL of

Table 1. Different scoring functions as assigned to each soil attribute.

Indicator	Attribute	Scoring function
Chemical	Soil organic carbon and total carbon	More is better
	Soil total nitrogen	More is better
	Inorganic nitrogen (nitrate and ammonium)	Optimum is best
	Total phosphorous, potassium, sulfur, calcium, sodium, magnesium, manganese, iron, and zinc	Optimum is best
	pH	Optimum is best
	Electrical conductivity	Less is better
Biological	Active carbon	More is better
	Soil respiration (CO_2)	More is better
	Soil nitrous oxide (N_2O)	Less is better
	Potentially mineralizable nitrogen	More is better
	Soil extractable protein	More is better
Physical	Texture (sand, silt, and clay)	Optimum is best
	Wet aggregate stability	More is better
	Field capacity	Optimum is best

distilled water and placed in an incubator for 7 d at 37 °C. Then, NH_4^+ was extracted with 15 mL of potassium chloride (3.33 mol·L^{-1}) and shaken for 30 min at 120 r·min^{-1}. The extracts were filtered by Whatman No. 42 filter papers and stored at −20 °C until analysis. The amount of PMN is determined by subtracting the pre-incubation (initial) ammonium levels from that determined at the end of the incubation.

Soil physical attributes

Soil texture

Soil texture was determined by using the hydrometer method (Kroetsch and Wang 2007). Briefly, 25.0 g of soil was soaked overnight with 100 mL of 0.082 mol·L^{-1} sodium hexametaphosphate solution and 250 mL of deionized water. In the morning, the solution was mixed to complete the dispersion. Buoyancy readings were recorded after mixing at 40 s and 6 h and 52 min.

Field capacity

Field capacity (FC) was determined using a modified long column method (Reynolds and Topp 2007). Soil samples (5 g) were packed in a column (5.5 ± 0.3 cm tall; 0.17 cm diameter) and wetted to saturation by placing the column in a beaker filled with water (the water level in the breaker was equal to the soil surface in the column). Once saturated, the soil-filled column was placed on a fine sand bed and allowed to drain by gravity for 24 h until drainage stopped, indicating FC. At this point, the weight of the soil and water inside the column was determined by recording the moist weight and dry weight of the soil inside the column (after oven-drying at 105 °C for 24 h). The FC was expressed as percent by weight.

Wet aggregate stability

Wet aggregate stability (WAS) was measured by using a Wet Sieving Apparatus (Eijkelkamp Soil and Water), operating under the principle that unstable aggregates break down easier and faster than stable aggregates in water. Briefly, 4 g of soil was placed on a sieve and enclosed inside a container filled with distilled water. The apparatus moved up and down for 3 min, and the unstable aggregates were collected in the enclosed container. The unstable aggregates were collected and placed in a sieve enclosed inside a new clean water-filled container. The material which remained inside the sieve were considered stable aggregates, disrupted by an Ultra Sonic Probe (Branson Sonifer 250), collected, oven-dried overnight at 120 °C. The proportion of water-stable aggregate was determined using the dry weight of the stable and unstable aggregates (Angers 2007).

Soil biological attributes

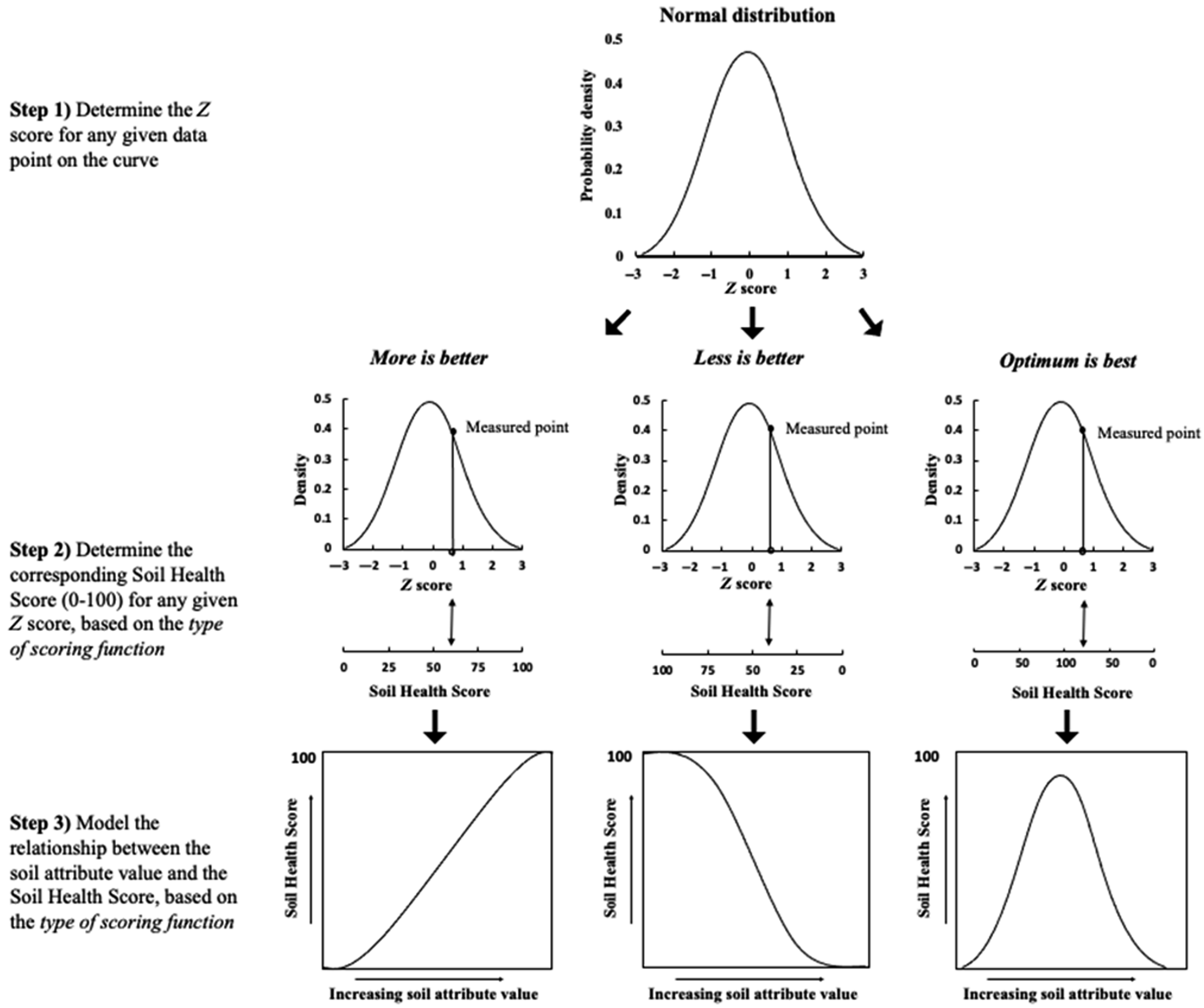
Soil protein

Soil protein was extracted and quantified according to the bicinchoninic acid (BCA) assay (Hurisso et al. 2018). Briefly, 1 g of soil was extracted with 8 mL 20 mmol·L^{-1} sodium citrate (pH = 7), shaken at 120 r·min^{-1} for 5 min, autoclaved at 121 °C and 15 psi for 30 min, cooled to room temperature, and thereafter centrifuged at 10 000g for 5 min. Subsequently, 25 μL of the supernatant was pipetted into microplate wells (96-well flat-bottomed microplate), and 200 μL of the BCA working reagent was added. After a 30 min incubation in the dark at 37 °C (followed by a 15 min cooling period), an absorbance reading was recorded at 562 nm using a microplate spectrophotometer (Epoch™ 2; Bio Tek). Soil extraction and analytical replication were conducted in duplicate for each soil sample.

Active C

Soil active C was measured using the permanganate oxidization approach (Weil et al. 2003). Soil subsamples (2.5 g) were mixed with 18 mL deionized water and 2 mL 0.2 mol·L^{-1} potassium permanganate solution. The

Fig. 2. Graphical depiction of the development of the Saskatchewan Soil Health Score.



mixture was shaken for 2 min at 120 r·min^{-1} and left to settle for 8 min. The supernatant was collected, and a 0.5 mL aliquot was diluted with 49.5 mL of deionized water. The amount of active C was calculated after the solution was analyzed by a spectrophotometer at 550 nm.

Soil respiration and nitrous oxide production

A modified "burst" test was conducted to determine soil respiration (CO_2) and nitrous oxide (N_2O) production. Plastic Petri dishes with 53 mm of diameter and 13 mm of height were filled with dry soil samples, and moisture was adjusted to 75% water-filled pore space by adding deionized water, the amount of which was calculated from the targeted gravimetric moisture. The Petri dish with moist soil was immediately placed in a 1 L mason jar and sealed. The sealed soil sample was incubated at 22 ± 1 °C in the laboratory for 24 h, upon which a 20 mL of gas sample was collected and analyzed for CO_2 and N_2O by gas chromatography (Rochette and Bertrand 2007).

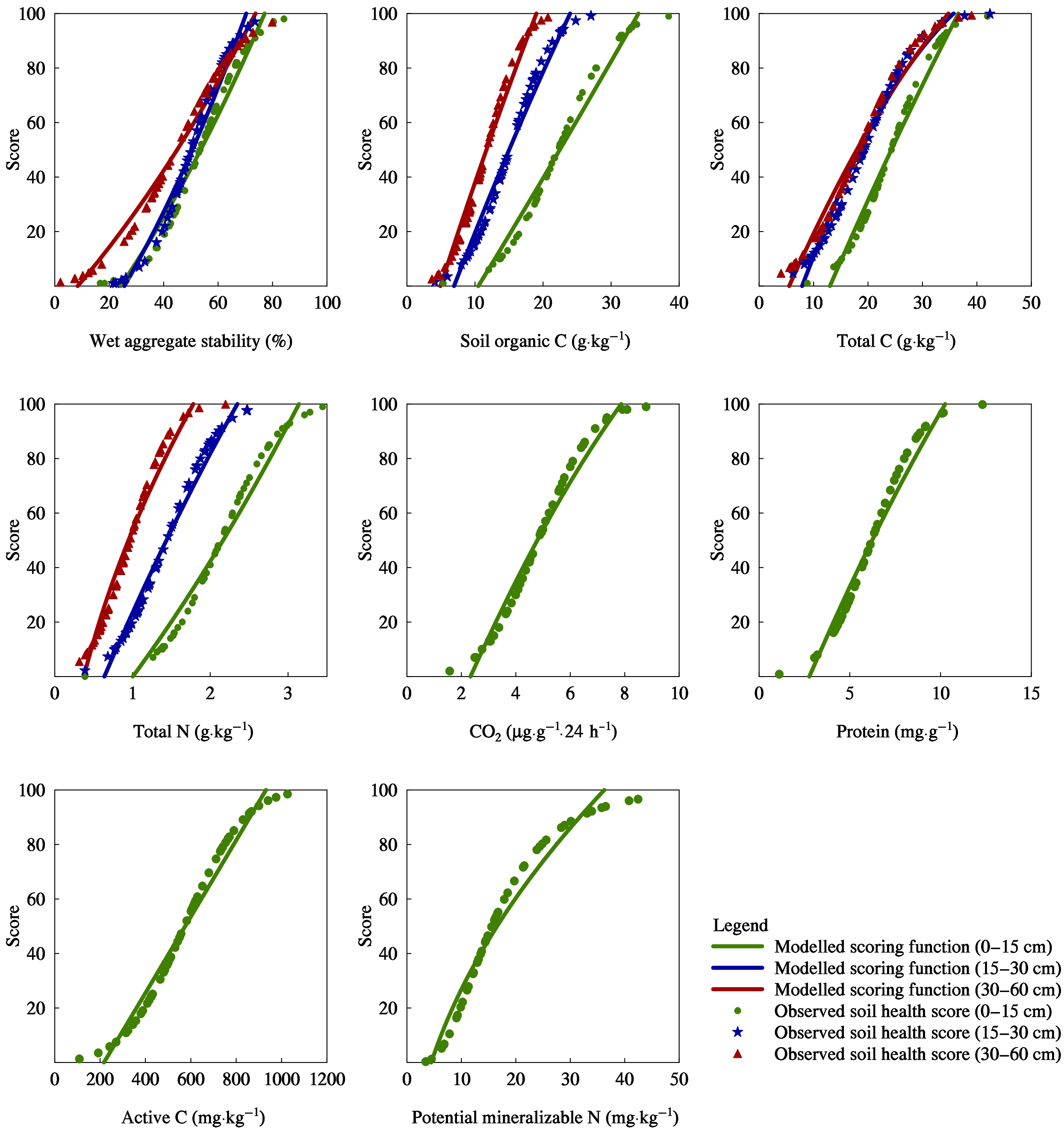
Data analysis and development of scoring functions

Data were analyzed using SAS (SAS Institute, Inc. Cary, NC, USA). PROC MEANS was used for descriptive statistics, PROC UNIVARIATE for testing normality, and PROC CORR for evaluating correlations among variables. Data were visualized using R studio (R Core Team 2020) and CoPlot (version 6.45).

Transformations

A Shapiro–Wilk's test was conducted in SAS to determine if the data were normally distributed for each soil attribute. There were several cases where the data were not normally distributed; yet, achieving a normal distribution for each soil attribute was a prerequisite for computing the soil health scores. A log transformation resulted in normality for all cases,

Fig. 3. The soil health scores for indicators following a "more is better" function (0–15, 15–30, and 30–60 cm depth). The coloured symbol indicates the observed soil health score, and the coloured line represents the modelled score.



except for pH and sand which were subjected to a square-root transformation to achieve normality (Supplementary Table S1[2]). The data of Fe from 30–60 cm depth failed to reach normality via any transformation (be it log, ln, square root, etc.); thus, Fe in 30–60 cm depth was not included in the soil health scoring. Outliers were removed if detected by the interquartile range (IQR) where the value is out of the range from (quartiles 1 − 1.5 × IQR) to (quartile 3 + 1.5 × IQR).

Scoring functions for individual soil attributes

Three different types of soil scoring functions were used: (*i*) more is better, (*ii*) optimum is best, and (*iii*) less is better. Each soil attribute was assigned to a scoring

[2]Supplementary data are available with the article at https://doi.org/10.1139/cjss-2021-0045.

function type, based on previous literature as well as author consensus (Table 1).

Standardized scoring functions were developed to express the score for each soil attribute on a scale of 0–100 (Fig. 2). The mean, standard deviation, and Z scores from the normal distribution of each soil attribute were used to develop these scoring functions, following the logic: for any normally distributed dataset, Z values range from −3 to 3, and a Z value of 0 corresponds to the observed mean. Therefore,

(*i*) for the more is better shape, the health scores are positively related to the Z scores; the score is highest when Z value is 3, and lowest when Z value is −3;
(*ii*) for the less is better shape, the health scores are negatively related to the Z scores; the score is highest when Z value is −3, and lowest when Z value is 3;
(*iii*) for the optimum is best shape, the health scores are positively related to the Z scores between the Z values of −3 and 0, and thereafter, negatively related to the Z scores between Z values of 0 and 3. As such, the health score is highest when Z value is 0, and lowest when the Z value is −3 or 3.

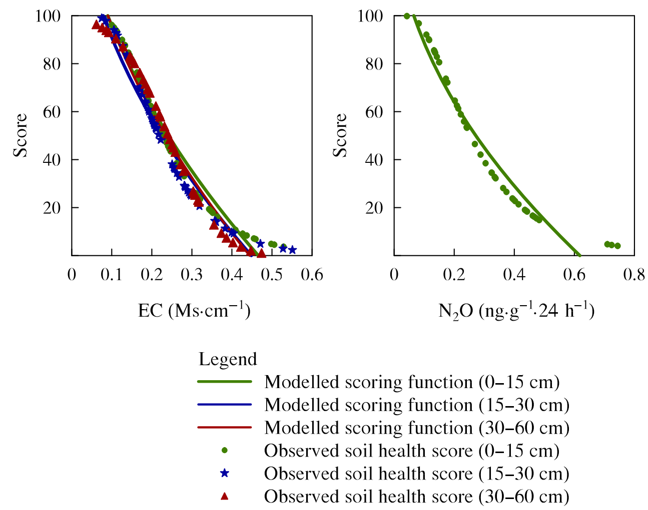
Once the scores were computed for each soil attribute, predictive models were also developed based on the relationship between the soil attribute measurement and score. To do this, several non-linear regressions were tested to determine the best-fit between the measurement and scores, including a second-order polynomial regression with and without intercepts, power regression, inverse power regression, square-root regression, Hoerl's model, logarithmic regression, and a first-order polynomial regression. The R square (R^2) and root-mean-square error were used to select the best-fit regression, with one additional criterion: the model must not have an inflection point that underestimated the scores at the high-end of the scale, which would have erroneously predicted the top score (Supplementary Tables S2 and S3[2]).

Overall soil health scoring

The individual soil health scores were combined into a single overall soil health score using a weighted average approach. Weighting factors were developed by analyzing the patterns in our large dataset, via principal component analysis (PCA). The PCA was conducted using "FactoMineR" package from R studio; data were grouped by soil depth. Soil attributes which explained more variation in the dataset were assigned greater weights, using principal component (PC) eigenvalues, eigenvectors, and the percentage of variance explained. We used this information to develop the weighting factors (w) or each attribute, and treated each depth increment separately (eq. 1):

$$(1)\qquad \text{Weighting factor}(w) = \sum_{1}^{k}(e_k \times p_k)$$

Fig. 4. The soil health scores for indicators following a "less is better" function (0–15, 15–30, and 30–60 cm depth). The coloured symbol indicates the observed soil health score, and the coloured line represents the modelled score.



where the e is the eigenvector of the soil attribute on each PC (k); and where p_k is the proportion of explained variance. We considered all PCs up until the cumulative percent variance reached over 80% and p_k reached over 1. Negative weighting factors were set to zero. The overall soil health score was computed according to eq. 2, separately for each depth increment:

$$(2)\qquad \text{SASH score} = \frac{\sum_1^k (s_k \times w_k)}{\sum_1^k (w_k)}$$

where s represents the soil health score (0–100) for each individual soil attribute and w is the corresponding weighting factor. Then, the score for the three depth increments was averaged for a single, overall Saskatchewan Assessment of Soil Health (SASH) score. The SASH score was normalized from 0 to 100, and the higher SASH score expresses a better soil health status.

Relationship between soil health score and crop yields

Regional yield data for wheat and canola crops collected from the Saskatchewan AGR RM yield database (http://applications.saskatchewan.ca/agrrmyields) for each of the last 10 years from 2009 to 2019, and we also computed the 5 and 10 year average yields. The yields derived from the rural municipalities were matched to the same rural municipalities where the soil samples were collected, and a correlation test was conducted.

Results

Data distributions

The distribution for each individual soil attribute is summarized in the Supplementary Material

Fig. 5. The soil health scores for indicators following a “optimum is best” function (0–15, 15–30, and 30–60 cm depth). The coloured symbol indicates the observed soil health score, and the coloured line represents the modelled score.

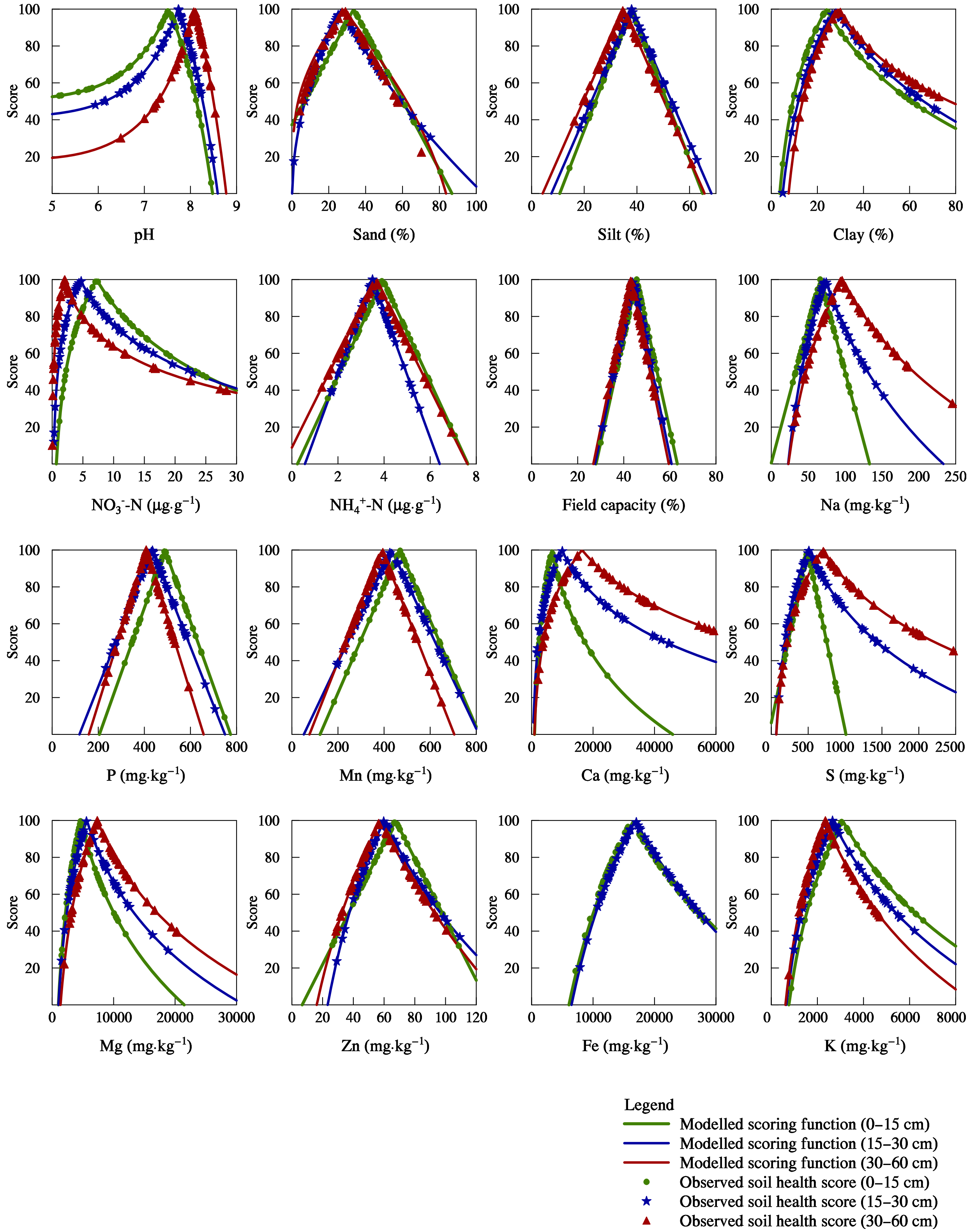


Table 2. The correlation between individual soil health indicators of surface soil and average crop yields obtained from rural municipalities from 2009 to 2018 regardless of crop types.

Indicators	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	5 year	10 year
pH	−0.25	−0.03	−0.30	−0.12	−0.13	−0.09	−0.20	−0.25	**−0.45***	**−0.53***	**−0.36***	**−0.32***
WAS	−0.23	0.03	−0.26	0.14	0.05	−0.16	−0.13	−0.20	−0.26	−0.14	−0.21	−0.16
FC	0.05	0.02	−0.08	0.19	0.13	0.03	0.07	0.07	−0.03	0.05	0.05	0.07
Sand	0.18	−0.12	0.06	−0.20	−0.15	0.05	0.06	0.12	0.15	0.17	0.13	0.05
Silt	0.00	−0.15	0.17	−0.09	−0.03	−0.03	0.21	−0.02	0.19	0.05	0.08	0.04
Clay	−0.17	0.20	−0.15	0.24	0.16	−0.03	−0.17	−0.11	−0.24	−0.19	−0.17	−0.07
Total N	**0.37***	−0.12	0.11	0.06	0.07	−0.05	0.30	0.15	**0.32***	**0.39***	0.26	0.21
Total C	**0.33***	−0.19	0.02	−0.01	0.01	−0.08	**0.31***	0.11	0.29	**0.40***	0.24	0.16
SOC	**0.35***	−0.18	0.07	0.00	0.03	−0.06	**0.32***	0.15	**0.33***	**0.43***	0.27	0.20
CO_2	0.16	−0.02	0.04	0.22	0.12	0.00	−0.03	0.12	0.10	0.10	0.08	0.11
N_2O	0.27	0.00	0.27	0.13	0.22	0.10	**0.33***	0.10	**0.38***	**0.35***	0.28	0.27
Nitrate-N	0.12	0.12	0.24	−0.01	0.16	0.16	0.02	0.07	0.20	−0.09	0.08	0.12
Ammonium-N	0.01	0.10	0.29	0.13	**0.37***	0.09	0.18	0.02	0.28	−0.01	0.12	0.18
EC	−0.09	0.00	0.05	−0.08	0.14	0.01	0.16	−0.06	0.03	−0.13	−0.01	0.00
Protein	**0.35***	−0.10	0.20	0.05	0.05	0.03	**0.38***	0.22	**0.43***	**0.55***	**0.37***	0.29
P	**0.57***	0.07	0.25	0.23	0.19	0.22	**0.39***	0.28	**0.42***	**0.36***	**0.38***	**0.38***
K	−0.10	0.28	−0.10	**0.34***	0.29	0.12	−0.12	−0.01	−0.22	−0.19	−0.10	0.02
S	0.02	−0.18	−0.18	−0.10	−0.14	−0.14	0.06	−0.16	−0.08	−0.04	−0.09	−0.12
Na	0.24	0.10	0.29	0.15	0.21	0.14	**0.32***	0.12	**0.33***	**0.35***	0.28	0.28
Fe	−0.13	0.23	−0.08	0.28	0.21	0.02	−0.10	−0.04	−0.18	−0.13	−0.10	0.00
Mg	−0.19	0.24	−0.28	0.20	0.11	0.04	−0.17	−0.19	**−0.38***	**−0.34***	−0.25	−0.15
Ca	−0.23	−0.10	**−0.42***	−0.14	−0.21	−0.13	−0.19	**−0.34***	**−0.38***	**−0.32***	**−0.33***	**−0.33***
Mn	−0.11	0.10	−0.16	0.15	0.22	−0.02	−0.10	−0.08	−0.15	−0.11	−0.11	−0.04
Zn	0.06	0.23	0.06	0.27	0.28	0.16	0.07	0.10	0.05	0.07	0.10	0.16
Active C	**0.38***	−0.20	0.00	−0.06	0.09	0.00	**0.40***	0.16	**0.31***	**0.42***	0.29	0.20
PMN	0.03	−0.23	−0.16	−0.15	−0.14	−0.25	−0.12	−0.16	−0.03	−0.04	−0.14	−0.15

Note: Significant correlations are bolded and indicated at $p < 0.05$ (*). WAS, wet aggregate stability; FC, field capacity; N, nitrogen; C, carbon; SOC, soil organic carbon; EC, electrical conductivity; P, phosphorus; K, potassium; S, sulfur; Na, sodium; Fe, iron; Mg, magnesium; Ca, calcium; Mn, manganese; Zn, zinc; PMN, potentially mineralizable N.

Table 3. The correlation between the Saskatchewan Assessment of Soil Health (SASH) score and average cereal crop yields obtained from rural municipalities from 2009 to 2019.

Year	Correlation between cereal crop yield and soil health (Pearson's coefficient)		Crop yields ($Mg \cdot ha^{-1}$) (min, median, max)	Precipitation (mm) (annual, April–June)
	SASH score (0–15 cm)	SASH score (0–60 cm)		
2009	**0.64***	**0.63***	1.7, 2.4, 3.0	389.6, 108.6
2010	0.09	0.13	2.1, 2.3, 2.7	550.3, 242.0
2011	−0.28	−0.08	2.0, 2.7, 3.3	409.7, 162.7
2012	0.22	0.21	1.8, 2.4, 3.5	446.6, 207.8
2013	0.24	0.26	2.6, 3.6, 3.8	372.8, 139.9
2014	0.37	0.34	2.1, 2.7, 3.2	443.9, 205.4
2015	**0.47†**	**0.65***	2.0, 2.6, 3.2	373.7, 69.0
2016	0.34	0.29	2.3, 3.3, 4.0	478.6, 144.8
2017	0.28	0.21	2.4, 2.9, 3.9	310.0, 108.5
2018	**0.43‡**	0.32	1.7, 2.8, 3.9	319.0, 104.7
5 year (2014–2018)	**0.47†**	**0.44‡**	2.4, 2.7, 3.4	385.2, 126.5
10 year (2009–2018)	**0.41‡**	**0.41‡**	2.2, 2.8, 3.1	409.5, 149.3

Note: Significant correlations are bolded and indicated at $p < 0.05$ (*), $p < 0.1$ (†), and $p < 0.15$ (‡). Cereal crop yield and precipitation data are included for each year.

(Supplementary Figs. S1–S3[2]) and forms the foundation of the scoring functions, which is presented next. Where the raw data were not normality distributed, transformations ensured normality (Supplementary Table S1[2]).

Scoring functions for individual soil attributes

The soil health scores following the more is better, less is better, and optimum is best scoring functions are shown in relation to the individual soil attribute measurements along with the predictive models of best fit (Figs. 3–5, respectively). The formula and threshold limits for each model are also presented herein (Supplementary Table S4[2]).

Towards an overall soil health score

Principal component analysis

The first seven PCs accounted for over 80% of the total variation in the raw dataset from 0 to 15 cm depth, whereas the first five PCs reached this same criterion for the deeper depths (15–30 and 30–60 cm) (Supplementary Table S5[2]). The weighting factors (w) determined using eq. 1 are presented in Fig. 7 and Supplementary Table S5[2].

For the 0–15 cm soil depth, the PC1 accounted for 30% of the total variation which was predominantly explained by six different soil attributes (i.e., attributes with high positive eigenvectors), including TC, SOC, TN, WAS, FC, and Zn. The PC2 represented 21% of the total variance, and the following attributes had relatively high positive eigenvectors: protein, SOC, and active C. The PC3 contributed 11% towards the total variation, with Ca, S, pH, and Mg showing high eigenvectors. The remaining PCs each contributed <10% of the total variance. Generally, it is observed that different PCs are predominantly explained by indicator type. For example, in the top 15 cm of soil PC1 appears to be explained by soil chemical and physical attributes, whereas PC2 more so by soil biological attributes. Considering all relevant PCs for the 0–15 cm depth, the attributes with the greatest weight (and therefore, the most influence on the soil health score) include P, TC, active C, SOC, TN, and N_2O as the top six (Fig. 7 and Supplementary Table S5[2]).

For the deeper soil depths of 15–30 and 30–60 cm, the first PC accounted for 39% and 25% of the total variance, respectively. Major drivers for this first dimension were clay, Fe, Zn, K, and FC. The PC2 accounted for 20% ± 1% of total variance, predominantly explained by S, Ca, Total C, Mg, and pH. The PC3 explained 11% of the total variance, attributed to TN, SOC, and P. Overall, both soil chemical and physical attributes appeared equally important in these depths (note that biological attributes were not measured in these depths). Taking all relevant PCs for the 15–30 cm depth into account, the attributes that have the most influence on the soil health score are TC, SOC, FC, P, TN, and WAS (Fig. 7 and Supplementary Table S5[2]). For the 30–60 cm depth SOC, FC, Mn, TN, Zn, and TC have the greatest influence.

The Saskatchewan Assessment of Soil Health score

The SASH score averaged 56.97% in the 0–15 cm depth and was lower compared with the 15–30 and 30–60 cm depths, which had average scores of 63.88% and 64.33%, respectively (Fig. 8A). With scores ranging from 26% to 88% and a CV of 20%, the top 15 cm soil also had more variation than the deeper depths (with CVs of 15% and 13%, respectively).

The overall SASH score for the 0–60 cm ranged from 41.24% to 77.05% — the highest score belonging to the native prairie soil. The overall SASH score for the 0–60 cm depth did not differ across soil zones, and median of overall SASH score was 60.17%, 65.68%,

Table 4. Example application of the Saskatchewan Assessment of Soil Health (SASH) test to three sites (0–15 cm soil): native prairie grassland (Brown soil zone), farm 1 (arable crops rotated with summer cover crops in the Black soil zone), and farm 2 (intensive potato production in the Black soil zone).

		Native prairie		Farm 1		Farm 2	
		Measured value	Score category	Measured value	Score category	Measured value	Score category
Physical	WAS (%)	59.14	Sufficient	66.55	Optimal	52.85	Sufficient
	FC (%)	48.35	Optimal	45.17	Optimal	37.56	Sufficient
	Sand (%)	43.07	Optimal	47.40	Optimal	42.88	Optimal
	Silt (%)	44.72	Optimal	33.46	Optimal	34.34	Optimal
	Clay (%)	12.21	Sufficient	19.14	Optimal	22.78	Optimal
Chemical	pH	7.51	Optimal	7.58	Optimal	7.79	Optimal
	EC ($mS{\cdot}cm^{-1}$)	0.22	Sufficient	0.79	Constrained	0.77	Constrained
	TN ($g{\cdot}kg^{-1}$)	**2.98**	**Optimal**	**2.75**	**Optimal**	**1.71**	**Constrained**
	TC ($g{\cdot}kg^{-1}$)	**33.41**	**Optimal**	**36.12**	**Optimal**	**33.02**	**Optimal**
	SOC ($g{\cdot}kg^{-1}$)	**31.70**	**Optimal**	**31.44**	**Optimal**	**23.50**	**Sufficient**
	NO_3^--N ($\mu g{\cdot}g^{-1}$)	3.55	Optimal	15.58	Sufficient	37.33	Sufficient
	NH_4^+-N ($\mu g{\cdot}g^{-1}$)	4.14	Optimal	3.24	Optimal	4.22	Optimal
	P ($mg{\cdot}kg^{-1}$)	**540.3**	**Optimal**	**591.7**	**Sufficient**	**563.6**	**Optimal**
	K ($mg{\cdot}kg^{-1}$)	3052	Optimal	2233	Optimal	1900	Sufficient
	S ($mg{\cdot}kg^{-1}$)	511.2	Optimal	1058	Constrained	1264	Constrained
	Na ($mg{\cdot}kg^{-1}$)	39.24	Sufficient	52.97	Optimal	107.4	Sufficient
	Fe ($mg{\cdot}kg^{-1}$)	13 187	Optimal	12 170	Optimal	11 562	Sufficient
	Mg ($mg{\cdot}kg^{-1}$)	3892	Optimal	5306	Optimal	10 074	Sufficient
	Ca ($mg{\cdot}kg^{-1}$)	5806	Optimal	17 250	Sufficient	41 360	Constrained
	Mn ($mg{\cdot}kg^{-1}$)	418.1	Optimal	541.9	Optimal	478.1	Optimal
	Zn ($mg{\cdot}kg^{-1}$)	55.48	Optimal	41.9	Sufficient	45.20	Sufficient
Biological	CO_2 ($\mu g{\cdot}g^{-1}{\cdot}24\ h^{-1}$)	11.85	Optimal	7.92	Optimal	3.06	Constrained
	N_2O ($ng{\cdot}g^{-1}{\cdot}24\ h^{-1}$)	0.24	Sufficient	0.29	Sufficient	0.15	Optimal
	Protein ($mg{\cdot}g^{-1}$)	**9.18**	**Optimal**	**6.13**	**Sufficient**	**4.77**	**Constrained**
	Active C ($mg{\cdot}kg^{-1}$)	**789.9**	**Optimal**	**763.2**	**Optimal**	**512.1**	**Sufficient**
	PMN-N ($\mu g{\cdot}g^{-1}$)	14.47	Sufficient	56.03	Optimal	9.31	Constrained
	SASH overall score		76		70		48

Note: For each attribute, the measured value is shown alongside a score category: Optimal, Sufficient, and Constrained. Scores higher than 70 are considered optimal; scores between 30 and 70 are considered sufficient; scores equal or less than 30 are considered constrained. Bolded rows are attributes with the highest weighting factors. WAS, wet aggregate stability; FC, field capacity; EC, electrical conductivity; TN, total nitrogen; TC, total carbon; SOC, soil organic carbon; P, phosphorus; K, potassium; S, sulfur; Na, sodium; Fe, iron; Mg, magnesium; Ca, calcium; Mn, manganese; Zn, zinc; PMN, potentially mineralizable N.

62.92%, 61.02% in Gray, Black, Dark Brown, and Brown soil zone, respectively.

Linking the SASH score to crop yields

Based on the historic yield data from the same rural municipalities where the soil samples were collected, there were some linkages between soil attributes and yields — but most apparent in 2018 and 2017, closer to when the soil samples were collected in 2018 (Table 2). Soil TN and TC, SOC, soil respiration, soil protein, active C were positively related to crop yields; whereas soil pH, Mg, and Ca were negatively correlated to crop yields (Table 2).

For the most part, cereal crop yields were not well correlated to the SASH score; however, there were two cases in the past 10 years — 2009 and 2015 — where a positive correlation was detected at $p < 0.05$ (Table 3). In both 2009 and 2015, not only were crop yields on the lower end, but precipitation tended to be low as well — especially during the early part of the growing season (Table 3). At $p < 0.1$ or $p < 0.15$, the SASH score was positively correlated to 5 or 10 years average yields (Table 3).

Case study example

As a case study, the SASH was applied to three contrasting sites: one native grassland site and two sites producing arable crops (Table 4). Soil from native prairie grassland site had an overall score of 76% SASH (Table 4). In comparison, farm 1 was in the Black soil zone, and it had an overall SASH score of 70%; whereas, farm 2 (also in the Black soil zone) had a much lower score of 48%. Interestingly, farm 1 had historically produced arable crops under no-till, and

Fig. 6. The correlation of variables on the first two dimensions of the principal component analysis for the 0–15 cm depth. The colour of the variables indicates the contribution (contrib.) to the first two dimensions (Dim).

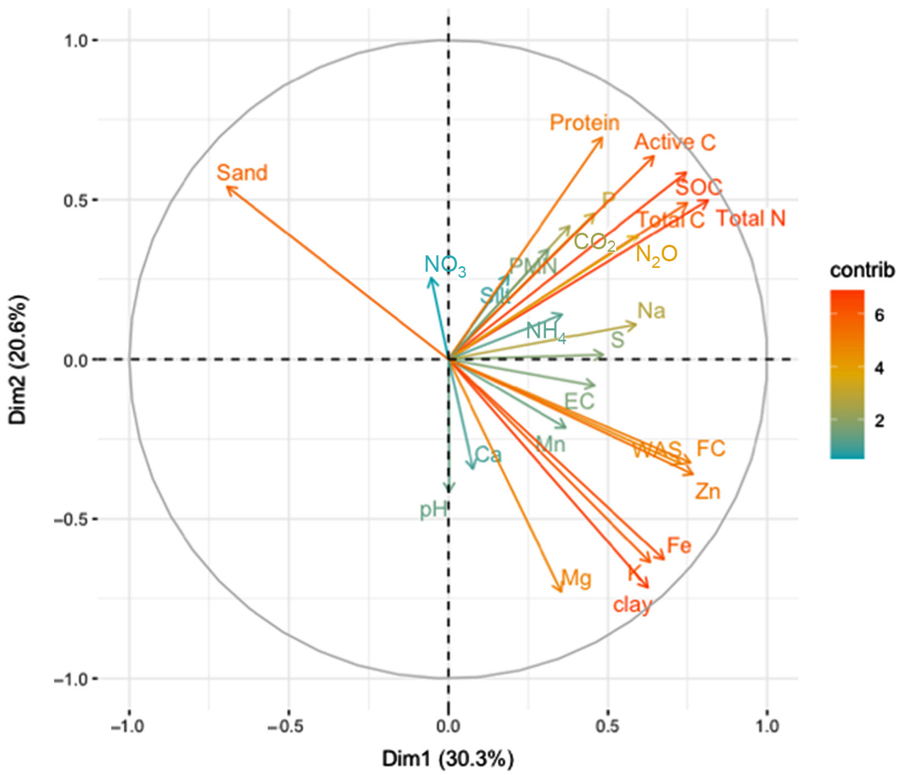
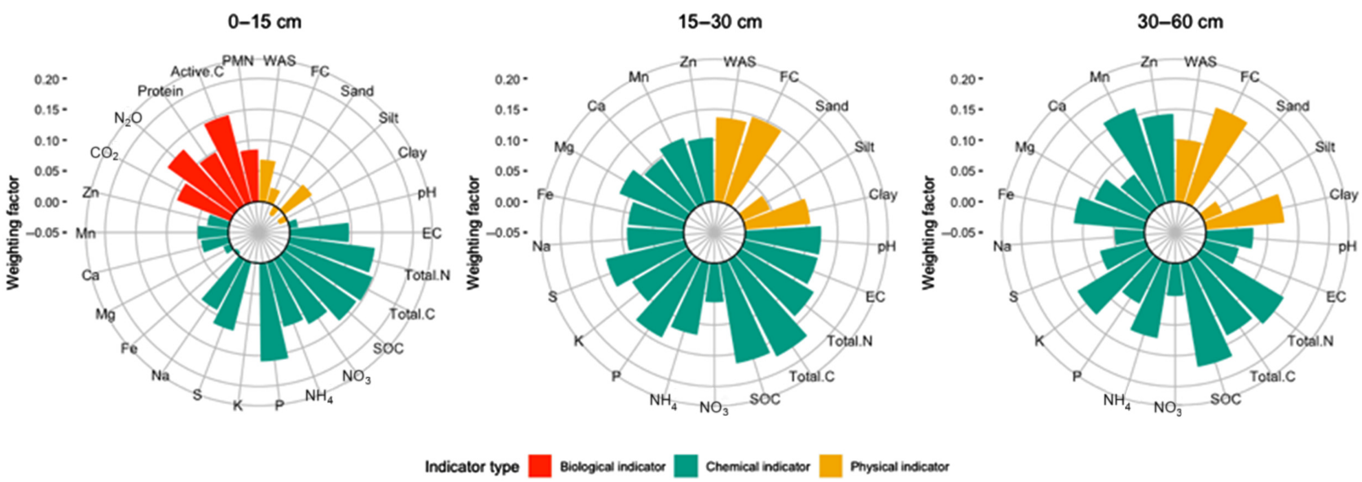


Fig. 7. The weighting factor for each soil attribute in the Saskatchewan Assessment of Soil Health for the 0–15, 15–30, and 30–60 cm depths, respectively.



in rotation with a cover crop mixture which was periodically grazed. Farm 2, in contrast, had been under intensive potato production with frequent tillage operations.

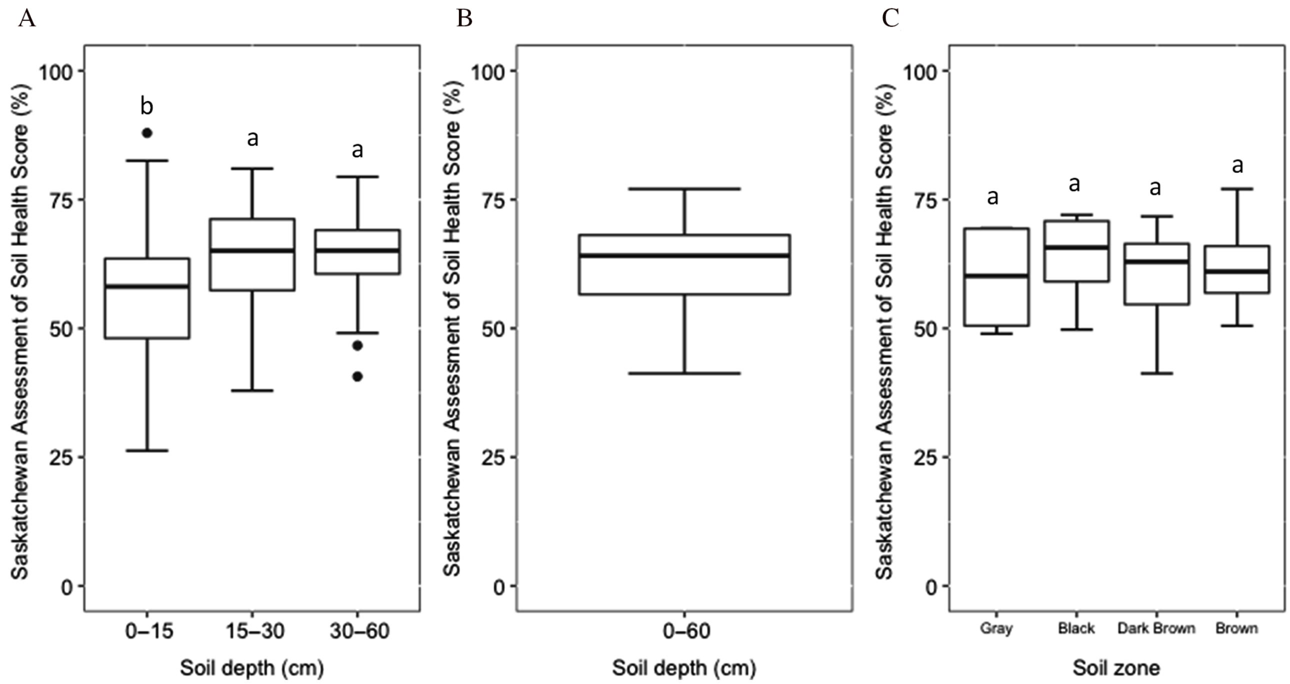
Discussion

Carbon, nitrogen, and phosphorous are key regulators of soil health

Soil protein, active C, TN and TC, and SOC explained the greatest amount of variance in the dataset. Both C and N are key constituents of soil organic matter, which is critical for the functioning of several ecosystem services such as nutrient supply and cycling, water supply and cycling, climate regulation, and supporting plant growth (Lal 2016). By having C- and N-based attributes highly weighted in the SASH framework, the scoring system demonstrates an encouraging linkage to soil ecosystem functioning.

Saskatchewan soils hold great potential for C sequestration and storage (McConkey et al. 2003); however,

Fig. 8. The Saskatchewan Assessment of Soil Health score (A) by soil depth increment, (B) for the full 0–60 cm, and (C) by soil zone (0–60 cm depth). Boxplots with the same letters are not significantly different ($p > 0.05$) according to Tukey's multiple means comparison. For panel (A), note that the scoring framework is different for each depth increment, i.e., different weights for each depth increment (Fig. 7).



changes in soil organic matter or SOC may only be detected in the long term, 5–10 years or more (Simonsson et al. 2014). The conundrum is that the soil organic matter is a crucial metric for soil health, but it is a difficult metric to interpret changes in soil health in the short term. The labile C indicators are included to work as the early detector of the effect of management practice (Luo et al. 2015; Bongiorno et al. 2019; Miller et al. 2019). By representing both the labile (active C and soil protein) and more stable measures of soil organic matter (TC and TN, SOC), the SASH framework might offer a more useful metric to detect early changes, rather than relying on soil organic matter measures alone.

Nitrogen is a crucial element for both crop production and the soil ecosystem. Total N represents long-term N supply in the soil, whereas shorter-term N supply metrics can be gleaned from soil protein, potential minimizable N estimates (Geisseler et al. 2019), or inorganic N (NO_3^- and NH_4^+). In our study, different N attributes were not only included to help capture N cycling from different angles but also to better understand which N metrics might be most useful in determining soil health — to that end, soil TN and protein estimates had the greatest weighting factors.

Total P concentration also produced among the highest weights. Typically, more than 50% of total P is in the organic P form in agricultural soils (Nash et al. 2014), and unsurprisingly, total P was positively correlated to total N, active C, and SOC. Total P might be viewed as a broad indicator of soil P levels for soil health, but we recommend that future research explore the inclusion of extractable P or organic P forms to the soil health scoring framework.

Consideration of soil depths beyond 0–15 cm

The SASH framework not only includes the 0–15 cm depth but also the 15–30 and 30–60 cm depths. Rather than applying the same weighting factors for the 0–15 cm depth to the subsurface depths, the SASH considers each depth increment independently (i.e., weighting factors are different for each depth increment, as shown in Fig. 7 and Supplementary Table S5[2]). If a score for subsurface soil is computed using the same weighting factors as the 0–15 cm depth, the result could mislead users by implying that the subsurface soils "are not as healthy" — when in fact, subsurface functions are simply different than those of surface soil. For example, the weighting factors varied by soil depth increment (Fig. 7). Noticeably, the physical attributes of WAS and FC were more highly weighted in the 15–30 and 30–60 cm depths than the 0–15 cm depth (Fig. 7). If deeper depth increments were not included in the soil health test, then perhaps key information subsurface soil functions, predominantly related to water dynamics, might have been lost.

The results shown in Fig. 8 — where surface soil had lower scores than subsurface soil — must be carefully interpreted, acknowledging that each soil depth increment has its own weighing system. The surface soil is arguably the most weathered and impacted by agricultural management after the conversion from native grassland to arable cropland; in this view, it makes sense that the surface soil health score is more variable and numerically lower than the subsurface soils (Fig. 8A). This result implies that there is more room for improvement in the surface soil layer than deeper depths, and that management practices aimed at ameliorating the surface conditions such as no-till and crop residue retention might go a long way towards improving soil health overall (Kinoshita et al. 2017).

How the SASH scoring framework compares with others

For meaningful interpretation of soil health and functioning, it is recommended that soil health tests and interpretation thereof are regionally adapted (Frost et al. 2019). Herein, scoring functions and weighting systems were tailored to Saskatchewan soils — and this soil health test is a distribution type of test. There are pros and cons when using a distribution type of soil health test. For example, an advantage of applying the distribution type of scoring system to the region it was developed from is that the scoring functions and overall scores are representative of the area, hence, meaningful for the region. But on the downside, a distribution type of scoring function might produce a rather narrow range of scores because the data are required to fit a normal distribution theory. Measured values that are out of the range are directly assigned as 100 or 0 based on this type of scoring function. Accordingly, a rather narrow range of soil health scores might make it difficult to achieve a stellar score (i.e., even the native grassland soil results were in the mid-70s not 90% or higher).

An additive approach is the most common and simplest method to integrate each attribute to an overall score, as used by the Comprehensive Assessment of Soil Health (Moebius-Clune et al. 2016) and Soil Management Assessment Framework (Andrews et al. 2004). However, assigning equal weight to each attribute may oversimplify the complex relationship between soil attributes and service in the ecosystem. The Haney test (Haney et al. 2018) also functions similar to an additive index by summing several attributes but only consisted of three soil attributes. Other methods integrate several attributes via a weighted average approach. Principal component analyses are often used to reduce attribute numbers in a large set of attributes but retain most information in the database (Andrews and Carroll 2001; Bi et al. 2013; Purakayastha et al. 2019; Karaca et al. 2021). However, it could also inform the relative contribution that different attributes could contribute to an overall score. This approach involves measuring many different soil attributes, prior to integrating them into a single score. If only a small number of indicators are included in a soil health test, the capacity to detect the soil health conditions from different practices may be limited (Chu et al. 2019).

The SASH may not only help to inform management decisions on-farm but also provide supplementary information when assessing soil capability for agricultural use. For example, soil capability information systems indicate the soil's capacity for agriculture use — classified based on climate, soil type, and landscape characteristics (Shields et al. 1968). Agricultural capacity classification is a useful tool to gain the general information of a land and its inherent properties, resulting from soil-forming factors like climate, topography, and parent material. The potential for crop production is a function of the soil capability classes, but the soil health status remains changeable over time, requiring routine soil tests to inform management decisions.

The link between soil health and crop productivity might be most apparent during suboptimal conditions

Crop yield is one of the most crucial considerations for farmers when deciding on management practices. In our case, weak correlations between soil health and crop yields were expected, given that the average yield data captures a larger area than the specific field where the soil sample was collected. Nonetheless, detecting a positive correlation between SASH scores and crop yields during dry years opens a promising avenue for future research. Quantitatively linking soil health to crop yield has been an elusive goal (Garland et al. 2021). Soil health scoring is aimed at capturing the *capacity of soil to function*; however, supporting crop growth is just one of several functions provided by soil—this likely contributes to the difficulty in determining an authoritative linkage between soil health scores and crop yields. Despite the challenges, researchers have found relationships between soil health indicators and crop yields, for example, higher soil biological activity (reflected from active C, SOC, and soil protein) corresponded to greater corn yields in the rainfed corn belt region of United States (Wade et al. 2020). Furthermore, corn and soybean yield were positively associated with soil active C, protein, respiration, and Mn in the United States; van Es and Karlen (2019) concluded that the labile organic matter — C- and N-based indices — is a central for linking soil health and crop productivity. Likewise, our SASH framework prioritizes soil C- and N-based attributes and showed promise for linking soil health scores to crop yield (Table 3). In agreement with others (Lal 2016; Garcia et al. 2018; van Es and Karlen 2019), our results indicate that soil TN, TC, SOC, protein, active C, and N_2O are correlated to crop yield (Table 2). Also, total concentration of nutrients (P, Na, Mg, and Ca) showed a promising link with crop yield.

Certain regions may show tighter relationships between crop yields and organic matter than others (Wood et al. 2018). For example, a global meta-analysis found crop yield positively correlated with SOC when SOC was less than 2%, but the relationship was less clear

Published by Canadian Science Publishing

when SOC was above 2% (Oldfield et al. 2019). Climate and environment play a major role in driving this relationship. The positive relationship between yields and SOC was more apparent in arid regions but less consistent in semi-arid and humid regions (Sun et al. 2020). Saskatchewan is a semi-arid region, and this may help explain why the soil health scores were positively correlated to crop yields *only* during years with lower than usual precipitation (Table 3). It is possible that soil health offers some resiliency for crop production during suboptimal growing conditions. Further research is recommended to link soil health scores to crop yields at a finer scale (i.e., field scale), improving upon the regional-scale portrait of crop yield linkages to soil health as presented herein. This would offer more precise information about how different management practices influence soil health scores across Saskatchewan.

Soil management for improved soil health

The SASH system was able to detect differences between native grassland and two farms under very dissimilar management practices. Farm 1 produced cereal and oilseed crops in rotation with a summer cover crop mixture and periodically rotated livestock onto the field to graze the cover crop. Most of the soil attributes on farm 1 were considered optimal, with generally high organic C, aggregate stability, and active microbial activity. Although the soil EC was in the high range relative to regional soils, the value had not reached a level that would be considered saline, but the SASH system flagged EC as an attribute that would require careful monitoring. Soil S concentrations were also relatively high compared with other soils in the region, so the fertilization plan for future crops should take the total S pool into account. Overall, the soil at farm 1 may considered as an example of a healthy soil, and where the current practices are helping to maintain soil health. In contrast to farm 1, soil health at farm 2 was scored much lower — likely due to the nature of intensive potato production. The constraining attributes at farm 2 were mainly chemical and biological, including EC, TN, S, Ca, soil respiration, protein, and PMN. This indicates a potentially weak capacity for nutrient cycling and supporting soil biological activity. As such, management practices that restore the biological activity and support nutrient cycling should be considered at this site. We recommended the future agronomic research should be aimed at improving soil health and functionality to increase the sustainability of intensively produced crops. Implementing practices aimed at improving soil health may require time before a change in the soil health score results, but a healthy soil should eventually benefit both farmers and the environment.

Inherent and manageable components of soil health

Some soil health components can be manageable, whereas others are more inherent to soil formation. Interestingly, two clusters are observed when evaluating the PCA results: one was dominated by C and N indices, and another consisted of mainly physical indicators like textural components (Fig. 6). Thus, the PCA results point towards groupings of biological vs. physical indicators of soil health (both of which were blended in with chemical indicators) and possibly also indicate the more manageable vs. inherent component of soil health. The manageable attributes are of greater importance when planning agronomic practices to improve soil health, but the inherent attributes like texture are useful when designing methods to maximize agronomic efficiency and profitability (i.e., best strategies to improve soil health on a clayey soil will be different than those on a sandy soil). Moving forward with a practical tool for farmers to assess soil health, researchers may wish to focus on the more manageable components.

Different soil zones in Saskatchewan inherently have differences in soil attributes, primarily due to soil formation and climate factors. Although variation in individual soil attributes by soil zone was observed (i.e., differences in soil organic C by soil zone, Supplementary Fig. S1A[2]), there was no significant difference among soil zones when comparing the overall soil health scores across zones (Fig. 8C). On one hand, further research is recommended to refine the scoring functions by soil zones due to the differences in individual soil attributes among soil zones (and perhaps different soil zones would have different weighting systems); on the other hand, because the overall soil health score did not dramatically differ by zone, it appears to be a suitable starting place for a provincial soil health test for arable cropping systems.

Limitations and future research needs

No scoring approach is without limitations. It is acknowledged that the SASH does not consider disease, nor are there any direct measurements of plant germination and growth — factors that we recommend considering in future efforts to improve soil health scoring. Further, many of the nutrient attributes considered in the SASH are total concentration, rather than available nutrient concentration. On one hand, assessing available nutrient concentrations will be more suitable from the perspective of crop production and would be readily analyzed in local soil testing laboratories — but on the other hand, total nutrient concentrations provide a more stable metric that is linked to the potential nutrient supply for crops (less fluctuation due to environmental conditions and timing of soil sampling). Some specialists want to see extractable nutrients in a soil health test, whereas others prefer total concentrations. In our test, nitrogen is a good example for where we investigated the extractable and the total form — and in the end, the soil TN resulted in a higher weighting factor than the extractable forms. To build upon this research, we recommend investigating the inclusion of extractable vs. total nutrient concentrations and addressing other limitations such as linking soil health to plant health metrics (susceptibility to disease, weeds, insects, and vulnerability to abiotic stress).

Expanding the database across the Canadian prairies will improve the data distributions and scoring functions. Although our work provides a foundation and a proof-of-concept for how to develop a soil health test for Saskatchewan, it will undoubtedly benefit from more soil samples and a larger dataset. Also, we recommend expanding the number of soil samples for each soil zone and investigating and (or) refining the scoring functions to provide zone-specific information to growers from different regions. This initiative may help to tease a part of the inherent and manageable components of soil health, as soil zones are a function of soil formation and climate.

Whereas our research indicated that healthier soil may improve crop resiliency during suboptimal (dry) conditions, we recommend investigating this relationship on a finer scale (spatially and temporally) and via a priori experimental designs. Research of such nature would provide more robust information about the linkage between soil and crops, and it would continue to improve the collective understanding of how soil health regulates crop and economic factors in addition to environmental factors.

The SASH framework herein encompasses a wide range of soil attributes, but future researchers may wish to reduce the number of soil attributes as a means of increasing the practicality and reducing the cost of a soil health test. To work towards a minimum dataset for assessing soil health, we recommend focusing on the attributes which produced the highest weighting factors (Fig. 7), such as soil C- and N-indices and soil P (for the 0–15 cm) and WAS and FC (for the 15–30 or 30–60 cm depths).

Conclusions

Maintaining and improving soil health are central to mitigating the adverse impacts of changing climate on agricultural production, and soil health tests are valuable tools to measure and track soil health over time. Soil health tests can provide the scientific information needed to inform management decisions. The CASH framework provides a roadmap and standardized approach to access soil health status by integrating soil biological, physical, and chemical attributes, but the scoring functions have not been tailored to Saskatchewan soils — until now. Herein, we present a soil health scoring framework for arable cropping systems in Saskatchewan (the SASH). Our results show that soil C- and N-indices and total P primarily drive soil health differences. Management decisions aimed at supporting biogeochemical cycling, C and N sequestration, and P retention may also improve soil health scores. It is possible that healthier soils may help to safeguard crop yields during suboptimally dry growing seasons, but further research is recommended to explore this linkage more closely. The SASH testing protocol and scoring functions provide a foundation for building upon the framework, and in due course developing extension tools that can transform farmers' routine soil test data into a soil health score. Ultimately, a grower-friendly online tool which outputs the SASH from laboratory results would be valuable to producers and industry.

Acknowledgements

We are grateful to the Saskatchewan Ministry of Agriculture (Agriculture Development Fund), Western Grains Research Foundation, Saskatchewan Canola Development Commission, and the Saskatchewan Wheat Development Commission for providing financial support. Thanks to Jamie Taylor and Darin Richman for contributions to the field and laboratory activities, as well as the Prairie Environmental Agronomy Research Lab for the soil sample collection and analysis help. Special thanks Dr. Rich Farrell, Dr. Diane Knight, and Dr. Melissa Arcand for valuable input throughout the project.

References

Andrews, S.S., and Carroll, C.R. 2001. Designing a soil quality assessment tool for sustainable. Ecol. Soc. Am. **11**: 1573–1585. doi:10.2307/3061079.

Andrews, S.S., Karlen, D.L., and Cambardella, C.A. 2004. The soil management assessment framework: a quantitative soil quality evaluation method. Soil Sci. Soc. Am. J. **68**: 1945–1962. doi:10.2136/sssaj2004.1945.

Angers, D.A. 2007. Aggregate stability to water. Pages 845–854 in M.R. Carter and E. Gregorich, eds. Soil sampling and methods of analysis. CRC Press.

Bi, C.J., Chen, Z.-L., Wang, J., and Zhou, D. 2013. Quantitative assessment of soil health under different planting patterns and soil types. Pedosphere, **23**: 194–204. doi:10.1016/S1002-0160(13)60007-7.

Bongiorno, G., Bünemann, E.K., Oguejiofor, C.U., Meier, J., Gort, G., Comans, R., et al. 2019. Sensitivity of labile carbon fractions to tillage and organic matter management and their potential as comprehensive soil quality indicators across pedoclimatic conditions in Europe. Ecol. Indic. **99**: 38–50. doi:10.1016/j.ecolind.2018.12.008.

Bünemann, E.K., Bongiorno, G., Bai, Z., Creamer, R.E., De Deyn, G., de Goede, R., et al. 2018. Soil quality — a critical review. Soil Biol. Biochem. **120**: 105–125. doi:10.1016/j.soilbio.2018.01.030.

Chu, M., Singh, S., Walker, F.R., Eash, N.S., Buschermohle, M.J., Duncan, L.A., and Jagadamma, S. 2019. Soil health and soil fertility assessment by the Haney soil health test in an agricultural soil in West Tennessee. Commun. Soil Sci. Plant Anal. **50**: 1123–1131. doi:10.1080/00103624.2019.1604731.

Clearwater, R.L., Martin, T., and Hoppe, T. 2016. Environmental sustainability of Canadian agriculture. Agri-Environmental Indicators Report Series.

Congreves, K.A., Hayes, A., Verhallen, E.A., and Van Eerd, L.L. 2015. Long-term impact of tillage and crop rotation on soil health at four temperate agroecosystems. Soil Tillage Res. **152**: 17–28. doi:10.1016/j.still.2015.03.012.

Cooper, R.J., Hama-Aziz, Z.Q., Hiscock, K.M., Lovett, A.A., Vrain, E., Dugdale, S.J., et al. 2020. Conservation tillage and soil

health: lessons from a 5-year UK farm trial (2013–2018). Soil Tillage Res. **202**: 104648. doi:10.1016/j.still.2020.104648.
Curtin, D., and Campbell, C.A. 2007. Mineralizable nitrogen. Pages 599–606 in M.R. Carter and E.G. Gregorich, eds. Soil sampling and methods of analysis. CRC Press.
Doran, J.W., and Zeiss, M.R. 2000. Soil health and sustainability: managing the biotic component of soil quality. Appl. Soil Ecol. **15**(1): 3–11. doi:10.1016/S0929-1393(00)00067-6.
Fine, A.K., van Es, H.M., and Schindelbeck, R.R. 2017. Statistics, scoring functions, and regional analysis of a comprehensive soil health database. Soil Sci. Soc. Am. J. **81**: 589–601. doi:10.2136/sssaj2016.09.0286.
Frost, P.S.D., van Es, H.M., Rossiter, D.G., Hobbs, P.R., and Pingali, P.L. 2019. Soil health characterization in smallholder agricultural catchments in India. Appl. Soil Ecol. **138**: 171–180. doi:10.1016/j.apsoil.2019.02.003.
Garcia, C., Nannipieri, P., and Hernandez, T. 2018. The future of soil carbon. Pages 239–267 in C. Garcia, P. Nannipieri, and T. Hernandez, eds. The future of soil carbon: its conservation and formation. Elsevier Inc. doi:10.1016/B978-0-12-811687-6.00009-2.
Garland, G., Edlinger, A., Banerjee, S., Degrune, F., García-Palacios, P., Pescador, D.S., et al. 2021. Crop cover is more important than rotational diversity for soil multifunctionality and cereal yields in European cropping systems. Nat. Food, **2**: 28–37. doi:10.1038/s43016-020-00210-8.
Geisseler, D., Miller, K., Leinfelder-Miles, M., and Wilson, R. 2019. Use of soil protein pools as indicators of soil nitrogen mineralization potential. Soil Sci. Soc. Am. J. **83**(4): 1236–1243. doi:10.2136/sssaj2019.01.0012.
Haney, R.L., Haney, E.B., Smith, D.R., Harmel, R.D., and White, M.J. 2018. The soil health tool — theory and initial broad-scale application. Appl. Soil Ecol. **125**: 162–168. doi:10.1016/j.apsoil.2017.07.035.
Hurisso, T.T., Moebius-Clune, D.J., Culman, S.W., Moebius-Clune, B.N., Thies, J.E., and van Es, H.M. 2018. Soil protein as a rapid soil health indicator of potentially available organic nitrogen. Agric. Environ. Lett. **3**(1): 180006. doi:10.2134/ael2018.02.0006.
Idowu, O.J., van Es, H.M., Abawi, G.S., Wolfe, D.W., Ball, J.I., Gugino, B.K., et al. 2008. Farmer-oriented assessment of soil quality using field, laboratory, and VNIR spectroscopy methods. Plant Soil, **307**: 243–253. doi:10.1007/s11104-007-9521-0.
Karaca, S., Dengiz, O., Demirağ Turan, İ., Özkan, B., Dedeoğlu, M., Gülser, F., et al. 2021. An assessment of pasture soils quality based on multi-indicator weighting approaches in semi-arid ecosystem. Ecol. Indic. **121**: 107001. doi:10.1016/j.ecolind.2020.107001.
Karlen, D.L., Mausbach, M.J., Doran, J.W., Cline, R.G., Harris, R.F., and Schuman, G.E. 1997. Soil quality: a concept, definition, and framework for evaluation (A guest editorial). Soil Sci. Soc. Am. J. **61**: 4. doi:10.2136/sssaj1997.03615995006100010001x.
Kinoshita, R., Schindelbeck, R.R., and van Es, H.M. 2017. Quantitative soil profile-scale assessment of the sustainability of long-term maize residue and tillage management. Soil Tillage Res. **174**: 34–44. doi:10.1016/j.still.2017.05.010.
Kroetsch, D., and Wang, C. 2007. Particle size distribution. Pages 713–725 in M. Carter and E. Gregorich, eds. Soil sampling and methods of analysis, 2nd ed. CRC Press. doi:10.1201/9781420005271.
Lal, R. 2016. Soil health and carbon management. Food Energy Secur. **5**: 212–222. doi:10.1002/fes3.96.
Li, P., Zhang, T., Wang, X., and Yu, D. 2013. Development of biological soil quality indicator system for subtropical China. Soil Tillage Res. **126**: 112–118. doi:10.1016/j.still.2012.07.011.
Luo, S., Zhu, L., Liu, J., Bu, L., Yue, S., Shen, Y., and Li, S. 2015. Sensitivity of soil organic carbon stocks and fractions to soil surface mulching in semiarid farmland. Eur. J. Soil Biol. **67**: 35–42. doi:10.1016/j.ejsobi.2015.01.004.
Maynard, D.G., Kalra, Y.P., and Crumbaugh, J.A. 2007. Nitrate and exchangeable ammonium nitrogen. Pages 71–80 in M. Carter and E.G. Gregorich, eds. Soil sampling and methods of analysis, 2nd ed. CRC Press.
McConkey, B.G., Liang, B.C., Campbell, C.A., Curtin, D., Moulin, A., Brandt, S.A., and Lafond, G.P. 2003. Crop rotation and tillage impact on carbon sequestration in Canadian prairie soils. Soil Tillage Res. **74**: 81–90. doi:10.1016/S0167-1987(03)00121-1.
Miller, G.A., Rees, R.M., Griffiths, B.S., Ball, B.C., and Cloy, J.M. 2019. The sensitivity of soil organic carbon pools to land management varies depending on former tillage practices. Soil Tillage Res. **194**: 104299. doi:10.1016/j.still.2019.104299.
Moebius-Clune, B., Moebius-Clune, D.J., Gugino, B., Idowu, O., Schindelbeck, R., Ristow, A., et al. 2016. Comprehensive assessment of soil health the Cornell Framework Manual, 3rd ed. Cornell University, Ithica, NY, USA. [Online]. Available from: http://www.scs.cals.cornell.edu [7 Nov. 2016].
Nash, D.M., Haygarth, P.M., Turner, B.L., Condron, L.M., McDowell, R.W., Richardson, A.E., et al. 2014. Using organic phosphorus to sustain pasture productivity: a perspective. Geoderma, **221**: 11–19. doi:10.1016/j.geoderma.2013.12.004.
Oldfield, E.E., Bradford, M.A.M.M., and Wood, S.A. 2019. Global meta-analysis of the relationship between soil organic matter and crop yields. Soil Biol. Biochem. **5**: 15–32. doi:10.5194/soil-5-15-2019.
Purakayastha, T.J., Pathak, H., Kumari, S., Biswas, S., Chakrabarty, B., Padaria, R.N., et al. 2019. Soil health card development for efficient soil management in Haryana, India. Soil Tillage Res. **191**: 294–305. doi:10.1016/j.still.2018.12.024.
R Core Team. 2020. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. [Online.] Available from https://www.R-project.org/.
Reynolds, W.D., and Topp, C.G. 2007. Soil water desorption and imbibition: long column. Pages 999–1006 in E.G. Gregorich and M.R. Carter, eds. Soil sampling and methods of analysis, 2nd ed. Boca Raton, FL, USA.
Rochette, P., and Bertrand, N. 2007. Soil-surface gas emissions. Pages 885–896 in M.R. Carter and E.G. Gregorich, eds. Soil sampling and methods of analysis. CRC Press.
Roper, W.R., Osmond, D.L., Heitman, J.L., Wagger, M.G., and Reberg-Horton, S.C. 2017. Soil health indicators do not differentiate among agronomic management systems in North Carolina soils. Soil Sci. Soc. Am. J. **81**: 828. doi:10.2136/sssaj2016.12.0400.
Rutherford, P.M., McGill, W.B., Arocena, J.M., and Figueiredo, C.T. 2007. Total nitrogen. Pages 267–278 in M. Carter and E. Gregorich, eds. Soil sampling and methods of analysis. CRC Press.
Shields, J.A., Clayton, J.S., and Rostad, H.P.W. 1968. A guide to soil capability and land inventory maps in Saskatchewan. Saskatchewan Institute of Pedology, University of Saskatchewan.
Simonsson, M., Kirchmann, H., Magid, J., and Kätterer, T. 2014. Can particulate organic matter reveal emerging changes in soil organic carbon? Soil Sci. Soc. Am. J. **78**: 1279–1290. doi:10.2136/sssaj2013.12.0533.
Skjemstad, J., and Baldock, J. 2007. Total and organic carbon. Pages 253–266 in M. Carter and E. Gregorich, eds. Soil sampling and methods of analysis. CRC Press.
Sun, W., Canadell, J.G., Yu, L., Yu, L., Zhang, W., Smith, P., et al. 2020. Climate drives global soil carbon sequestration

and crop yield changes under conservation agriculture. Glob. Chang. Biol. **26**: 3325–3335. doi:10.1111/gcb.15001. PMID:31953897.

van Es, H.M., and Karlen, D.L. 2019. Reanalysis validates soil health indicator sensitivity and correlation with long-term crop yields. Soil Sci. Soc. Am. J. **83**: 721–732. doi:10.2136/sssaj2018.09.0338.

Wade, J., Culman, S.W., Logan, J.A.R., Poffenbarger, H., Demyan, M.S., Grove, J.H., et al. 2020. Improved soil biological health increases corn grain yield in N fertilized systems across the Corn Belt. Sci. Rep. **10**: 1–9. doi:10.1038/s41598-020-60987-3.

Weil, R.R., Islam, K.R., Stine, M.A., Gruver, J.B., and Samson-Liebig, S.E. 2003. Estimating active carbon for soil quality assessment: a simplified method for laboratory and field use. Am. J. Altern. Agric. **18**: 3–17. doi:10.1079/AJAA2003003.

Wood, S.A., Tirfessa, D., and Baudron, F. 2018. Soil organic matter underlies crop nutritional quality and productivity in smallholder agriculture. Agric. Ecosyst. Environ. **266**: 100–108. doi:10.1016/j.agee.2018.07.025.