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1. Project title, file numbers, and report author

Developing a soil health assessment protocol for Saskatchewan producers
UnivRS #348811; WGRF AGR 1807; ADF20170151; SWDC 171025-60; SCDC ADF2017-151

Reporting period: Jan 2018-April 2021
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Note: the contents of this report constitute large parts of Ms. Athena Wu's MSc Thesis (2021)

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4. Abstract

Farmers are looking for appropriate tools and methods for assessing and interpreting the health status of their soils; however, for Saskatchewan there is no standardized and prairie-based soil health test available. As such, we focused on developing a soil health testing protocol for arable cropping systems in Saskatchewan by building off of the Comprehensive Assessment of Soil Health (CASH) framework developed in the USA. In Sept and Oct 2018, soil samples (0-15, 15-30, and 30-60 cm depths) were collected from 55 arable fields across Saskatchewan—along with a couple 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 Soil Health Score (SSHS). Soil C and N indices (soil organic C, active C, total N, and soil protein) produced the highest weighting factors. We also tested if there were linkages between the soil health scores 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 tool for Saskatchewan producers who are interested in tracking soil health and using the results to inform management practices.

5. Introduction

Soil degradation limits agricultural productivity, resulting in economic losses and contributing 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 which 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”. This description considers soil as an ecosystem. By fulfilling complex functions, soil contributes to ecosystem services and highlights the linkages between soil health and human health. As such, monitoring and tracking 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 testes are needed in the toolbox.

Farmers and scientists are looking for an appropriate tool to interpret their soil's health status, so the assessment must be comprehensive. 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, a set of comprehensive soil indicators should also 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), UK (Cooper et al.

2020), India (Purakayastha et al. 2019) etc. One on 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 20 soil attributes that include the biological, physical, and chemical properties. Each attribute is scored, and the overall score reflects the 'soil health status' as an unweighted average of all individual indicator's scores. Farmers and researchers are using CASH to estimate their soil health status and improve the management decision. Research showed that CASH was sensitive to various management practices in New York State (Idowu et al. 2008). The CASH provides a useful framework for integrating all the soil attribute into a visualized soil health score. However, the CASH is 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 region of the USA). For example, when used in locations outside the region of development, the CASH lacked consistent responses across the southeast region of the USA (Roper et al. 2017). Climate and parent material are the 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 developing and using a regionally adapted soil health test to gain the most meaningful interpretation of soil health and functioning (Congreves et al. 2015; Roper et al. 2017; Frost et al. 2019; Chu et al. 2019). Since soil is a living ecosystem with its characteristics, a fixed measuring system may not be useful everywhere; rather, a regional soil health test may be most meaningful to farmers.

On the Canadian prairies—an agriculturally important region of Canada—there is no standardized prairie-based soil health test available. Our objective is to develop a soil health testing protocol, 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.

6. Methodology

Soil samples from the 0-15, 15-30, and 30-60 cm depths were collected from 55 fields (26 sites) across Saskatchewan in Sept and Oct 2018 (Fig. 1). The sample from each site was a composite sample (5-7 individual samples) collected using a flat shovel. The selected sites represented various Agri-Arm sites, producer fields, and AAFC long-term sites. Native prairie samples were also collected for comparison. Soil samples were air dried and sieved (2 mm) prior to all analyses described below. The sampling sites were representative of Saskatchewan agriculture. Most sites were previously cropped with wheat (n = 15) or canola (n =21); whereas a few sites had barley (n= 1), chickpea (n = 1), lentil (n =3), field pea (n =1), soybean (n =2) , potato (n = 1), and green manure (n=2).

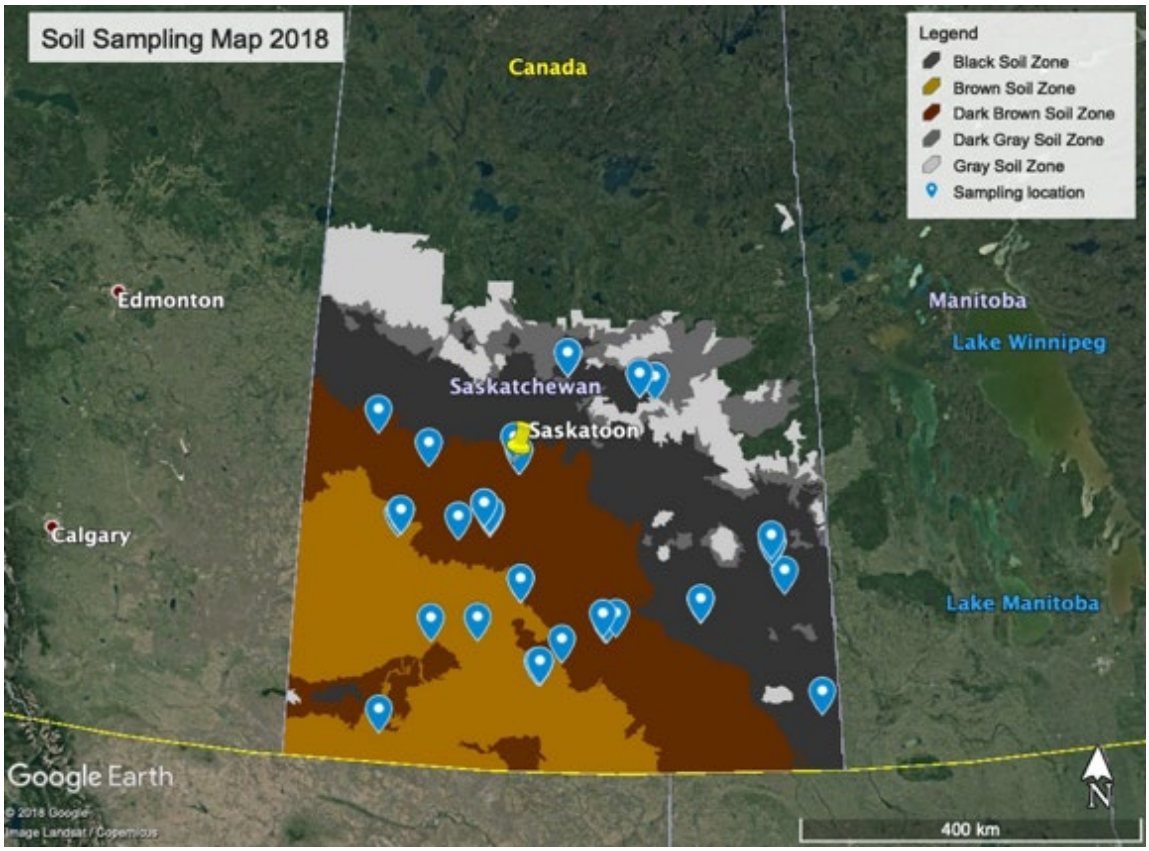


Figure 1 Soil sampling locations across Saskatchewan. The points are created based on the GPS coordinates. The soil sampling map overlay with Saskatchewan soil zones, the map resource retrieved from https://open.canada.ca/data/en/dataset/ac6a1e51-9c70-43ab-889f-106838410473.

Soil chemical attributes

Soil pH and EC

Soil pH and 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 (Fisher Scientific™, AE 150) and EC meter (Hanna Instrument, HI763100).

Soil nutrient and carbon 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). 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 rpm 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 sub-samples (~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 Ontario).

To determine soil organic C, soil sub-samples 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 pre-treated 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 hours. The carbonate-free samples were analyzed for organic C (%) using a C632 LECO Carbon Analyzer at 1440 °C.

Total C and N was determined by dry combustion (Rutherford et al. 2007; Skjemstad and Baldock 2007). Sub-samples of the ball-ground soil (1 g) were placed in a nickel liner inside of a ceramic combustion boat, and analyzed for total C and N 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). Sub-sample of soil (5 g) were incubated with 10 mL of distilled water and placed in an incubator for 7 days at 37 °C. Then, NH_4^+ was extracted with 15 mL of potassium chloride (3.33 M) and shaken for 30 min at 120 rpm. 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 50 mL of 0.082 M sodium hexametaphosphate solution and 200 mL of deionized water. In the morning, the solution was mixed by hand to complete the dispersion. Buoyancy readings of were recorded after mixing at 40 sec and 6:52 hrs.

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 breaker was equal to 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 hrs 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 hrs). 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, as recommended by Wu et al. (*under review*). Briefly, 1 g of soil was extracted with 8 mL 20 mM sodium citrate (pH=7), shaken at 120 rpm for 5 min, autoclaved at 121°C and 15 psi for 30 min, cooled to room temperature, and thereafter centrifuged at 10,000 x g 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 (Bio Tek, Epoch™ 2). Soil extraction and analytical replication was conducted in duplicate for each soil sample.

Active carbon

Soil active C was measured using the permanganate oxidization approach (Weil et al. 2003). Soil sub-samples (2.5 g) were mixed with 18 mL deionized water and 2 mL 0.2 M potassium permanganate solution. The mixture was shaken for 2 min at 120 rpm, 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 ° in the lab for 24 hr, 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., university edition, Cary, NC). PROC MEANS was used for descriptive statistics, PROC UNIVARIATE for testing normality, and PROC CORR for

evaluating correlations among variables. Data was visualized using R studio (R core Team, 2019) and CoPlot (Version 6.45).

Transformations

A Shapiro-Wilk test was conducted in SAS to determine if the data was normally distributed for each soil attribute. There were several cases where the data was 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, except for pH and sand which were subjected to a square root transformation to achieve normality (Supplemental Table S1). 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 were not included in the soil health scoring. Outliers were removed if detected by the interquartile range (IQR) where the value 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 function type, based on previous literature as well as author consensus (Table 1).

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

Indicator	Attribute	Scoring function
Chemical	Soil organic C (SOC) and total C	More is better
	Soil total N	More is better
	Inorganic N (nitrate and ammonium)	Optimum is best
	Total phosphorous, potassium, sulfur, calcium, sodium, magnesium, manganese, iron, zinc,	Optimum is best
	pH	Optimum is best
	Electrical conductivity (EC)	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 (PMN)	More is better
	Soil extractable protein	More is better
Physical	Texture (sand, silt, clay)	Optimum is best
	Wet aggregate stability	More is better
	Field capacity	Optimum is best

Standardized scoring functions were developed to express the score for each soil attribute on a scale of 0 to 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, A) 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. B)

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. C) for the *optimum is best* shape, the health scores are positively related to the Z-scores between the Z-values of -3 to 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.

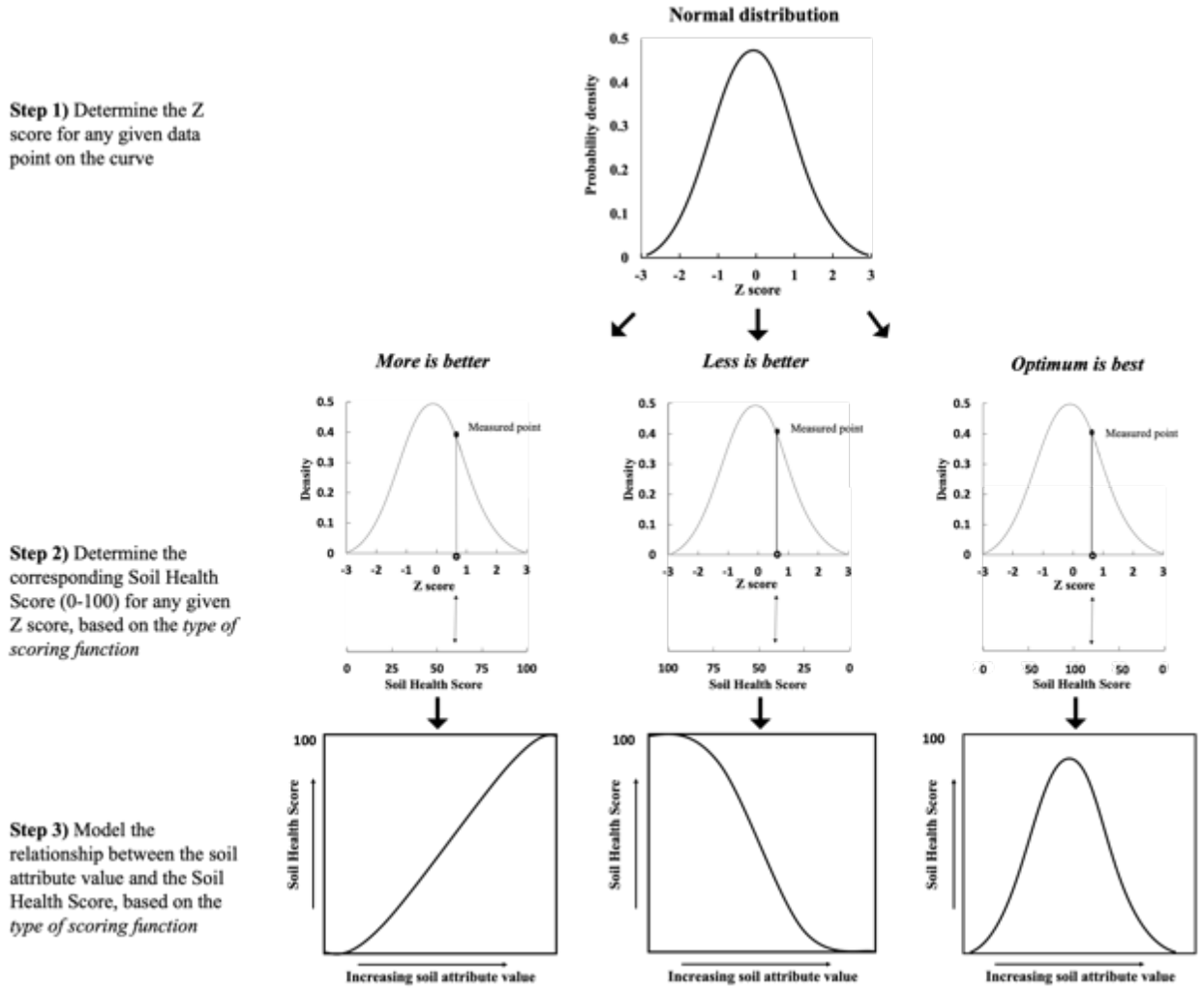


Figure 2. Graphical depiction of the development of the Saskatchewan Soil Health Score.

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 (RMSE) were used to select the best-fit regression, with one additional criterion: the model must not have an inflection point that underestimated scores at the high-end of the scale, which would have erroneously predicted the top score (Supplemental Tables S2 and S3).

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):

$$Weighting\ factor\ (w) = \sum_1^k (e_k \times p_k)$$

(Eq. 1)

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:

$$Saskatchewan\ Soil\ Health\ Score\ (SSHS) = \frac{\sum_1^k (s_k \times w_k)}{\sum_1^k (w_k)}$$

(Eq. 2)

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

Relationship between soil health score and crop yields

Regional yield data for cereal crops (wheat and barley) were collected from the Saskatchewan AGR RM yield database (http://applications.saskatchewan.ca/agrrmyields) for each of the last 10-yrs from 2009 to 2019, and we also computed the 5-year 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.

7. Research accomplishments

Objectives (*Please list the original objectives and/or revised objectives if Ministry-approved revisions have been made to original objective. A justification is needed for any deviation from original objectives)*	**Progress (e.g. completed/in progress)**
a) Identify the soil properties that best characterize soil health in the semi-arid prairies.	Complete – see Results reported below
b) Quantify the effects of medium- and long-term agricultural management (tillage system, crop rotation) on soil health.	Complete — arable cropping systems across Saskatchewan produced an overall soil health score (0-60 cm depths) of 41 to 77%—the highest score belonging to the native prairie soil. See Results reported below.
c) Develop a new producer-oriented manual (soil health assessment protocol) for measuring soil health in Saskatchewan.	Complete — the manual is provided herein. The Materials & Method section here described the instructions for measuring and analyzing each soil attribute, how to produce a score for each attribute, and how to integrate all scores into a single overall soil health score. I am also posting a Webinar to describe the testing protocol on my website, it will be up by May 2021.

Results

Data distributions

The distribution for each individual soil attribute is summarized in the Supplemental Material (Supplemental Figures S1-S3) and form the foundation of the scoring functions—presented next. Where the raw data were not normality distributed, transformations ensured normality (Supplemental Table S1).

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, 4, 5, respectively). The formula and threshold limits for each model are also presented herein (Supplemental Table S4).

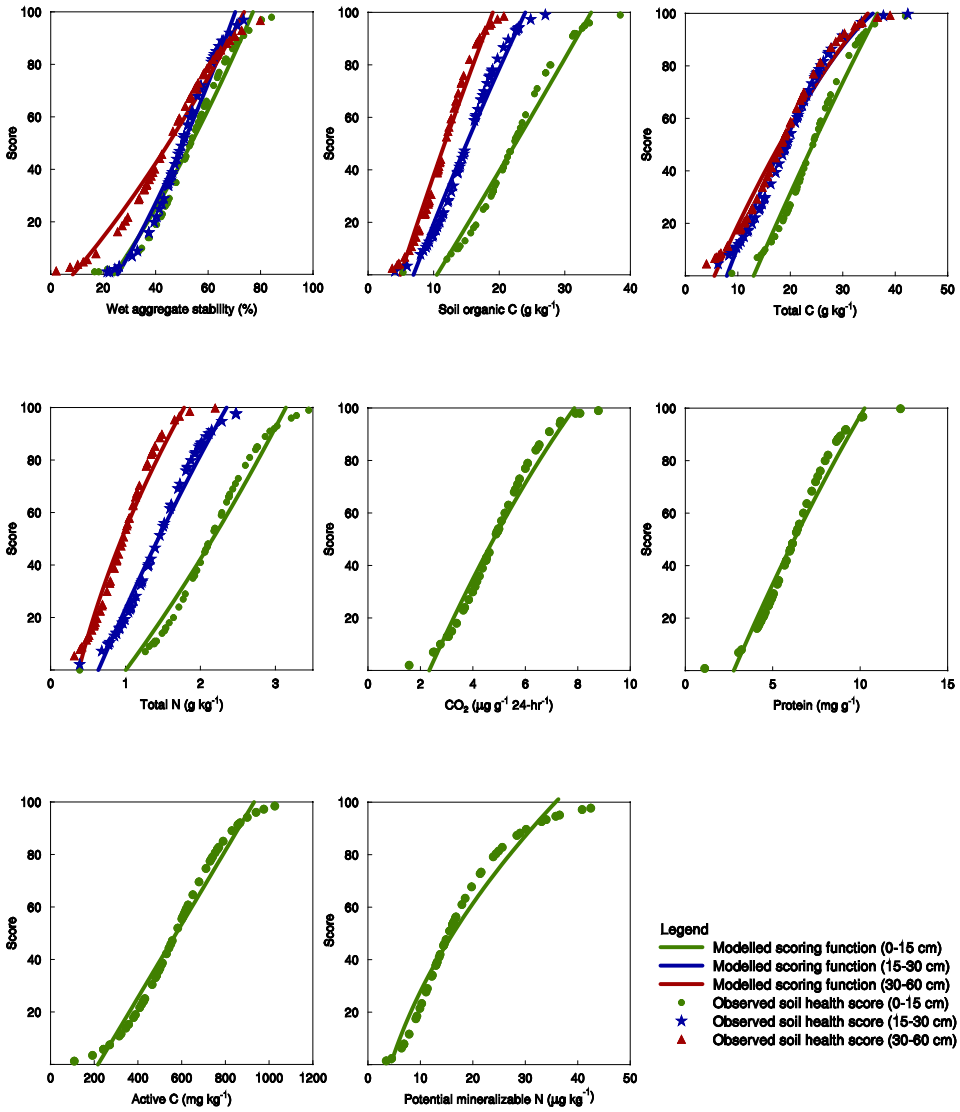


Figure 3. The soil health scores for indicators following a "more is better" function (0-15, 15-30, 30-60 cm depth). The coloured symbol indicates the observed soil health score, and the coloured line represents the modelled score.

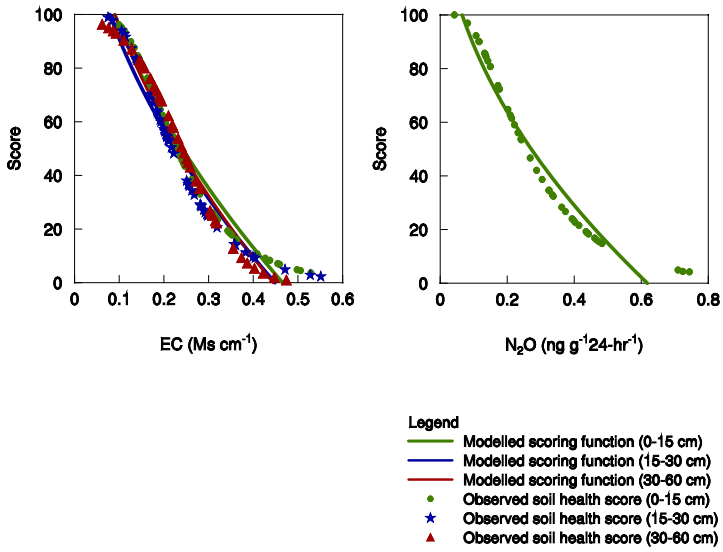


Figure 4. The soil health scores for indicators following a "less is better" function (0-15, 15-30, 30-60 cm depth). The coloured symbol indicates the observed soil health score, and the coloured line represents the modelled score.

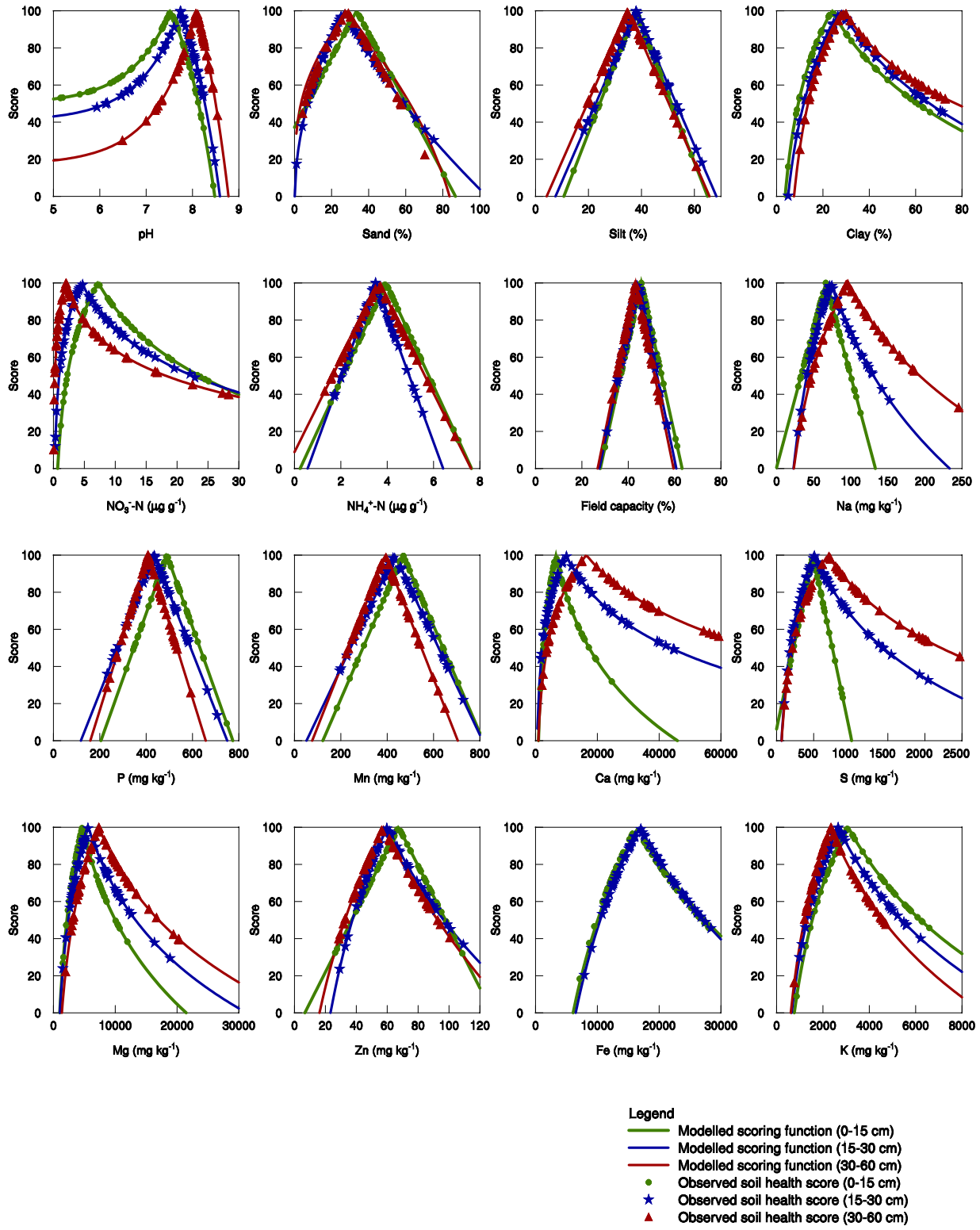


Figure 5. The soil health scores for indicators following a "optimum is best" function (0-15 cm, 15-30, 30-60 cm depth). The coloured symbol indicates the observed soil health score, and the coloured line represents the modelled score.

Towards an overall soil health score

Principal component analysis

The first seven PCs accounted for over 80% of the total variation in the raw data set from 0-15 cm depth, whereas the first five PCs reached this same criterion for the deeper depths (15-30 cm and 30-60 cm) (Table 2). The weighting factors (*w*) determined using Eq. 1 are presented in Table 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, 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 (Table 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$\pm$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: 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 (Table 2). For the 30-60 cm depth SOC, FC, Mn, TN, Zn, and TC have the greatest influence.

Table 2. Summary of the principal component analysis (PCA) and the resulting eigenvectors for each soil attribute.

		0-15 cm depth								15-30 cm depth						30-60 cm depth					
Indicator type	Attribute	PC1	PC2	PC3	PC4	PC5	PC6	PC7	*w*	PC1	PC2	PC3	PC4	PC5	*w*	PC1	PC2	PC3	PC4	PC5	*w*
Chemical	SOC	0.27	0.25	0.08	-0.11	-0.09	-0.1	-0.07	0.14	0.19	0.12	0.47	-0.06	-0.2	0.17	0.09	0.3	0.35	-0.04	0.21	0.17
	Total C	0.27	0.21	0.18	-0.17	-0.09	-0.03	-0.02	0.15	0.16	0.35	0.26	-0.08	-0.19	0.18	0.03	0.42	0.15	-0.07	0.05	0.14
	Total N	0.29	0.22	0.02	-0.1	-0.02	-0.09	-0.09	0.14	0.22	-0.04	0.47	-0.07	-0.18	0.14	0.22	-0.05	0.39	0.11	0.18	0.16
	NO_3^-	-0.02	0.11	0.13	0.38	0.44	0.11	0.21	0.12	-0.09	0.22	0.19	0.4	-0.06	0.06	-0.12	0.09	0.23	0.09	0.62	0.05
	NH_4^+	0.13	0.06	-0.06	0.3	0.51	-0.06	-0.1	0.11	0.21	-0.07	0.02	0.43	0.02	0.12	0.22	0.01	0.02	0.07	0.24	0.12
	P	0.16	0.2	0.13	0.07	0.22	0.34	-0.12	0.16	0.03	0.25	0.38	-0.12	0.31	0.14	-0.08	0.27	0.28	0.21	-0.22	0.08
	K	0.23	-0.27	-0.15	0.04	0.08	0.03	-0.12	0	0.31	-0.09	-0.06	-0.08	-0.05	0.11	0.34	0	0	-0.09	-0.05	0.13
	S	0.17	0.01	0.47	-0.1	-0.01	-0.16	0.13	0.12	0.05	0.46	-0.07	0.09	0	0.13	-0.04	0.4	-0.24	0.14	0.09	0.08
	Ca	0.03	-0.15	0.49	-0.08	-0.04	0.12	0.18	0.05	0.03	0.45	-0.18	-0.01	0.02	0.1	-0.05	0.43	-0.12	-0.1	0	0.07
	Na	0.21	0.05	-0.02	-0.35	0.19	0.28	0.21	0.09	0.19	0.03	-0.24	0.37	0.04	0.09	0.13	0.03	-0.44	0.34	0.11	0.05
	Mg	0.13	-0.31	0.29	-0.03	-0.02	0.12	0.05	0.02	0.17	0.34	-0.24	-0.19	0.06	0.12	0.04	0.43	-0.11	-0.18	-0.08	0.09
	Mn	0.13	-0.09	-0.11	0.32	-0.19	0.44	0.13	0.05	0.28	-0.09	0.02	0	0.01	0.11	0.25	-0.01	0.21	0.15	0.2	0.16
	Fe	0.24	-0.27	-0.17	0	0.02	-0.01	-0.06	0	0.32	-0.14	-0.12	-0.05	-0.06	0.09	0.35	-0.06	-0.06	-0.09	-0.05	0.12
	Zn	0.27	-0.16	-0.13	-0.04	0.14	-0.19	-0.08	0.04	0.32	-0.15	-0.02	-0.04	-0.02	0.1	0.35	-0.04	0.04	0.05	-0.12	0.14
	pH	0	-0.18	0.35	0.2	-0.15	0.09	-0.01	0.02	0.09	0.33	-0.15	-0.05	0.41	0.12	0	0.33	-0.03	0.18	-0.29	0.08
	EC	0.16	-0.04	0.22	0.23	0.26	-0.44	0	0.1	0.13	0.09	0.02	0.6	-0.18	0.12	0.07	0.02	-0.37	0.49	0.32	0.06
Biological	Active C	0.23	0.27	0.04	0.06	-0.14	-0.05	0	0.15	-	-	-	-	-	-	-	-	-	-	-	-
	CO_2	0.14	0.18	-0.05	0.38	-0.27	0.09	-0.19	0.09	-	-	-	-	-	-	-	-	-	-	-	-
	N_2O	0.21	0.17	-0.11	-0.11	0.23	0.34	0.12	0.13	-	-	-	-	-	-	-	-	-	-	-	-
	PMN	0.11	0.15	0.08	0.37	-0.24	-0.07	-0.24	0.08	-	-	-	-	-	-	-	-	-	-	-	-
	Protein	0.17	0.3	-0.11	-0.17	-0.07	-0.04	0.02	0.1	-	-	-	-	-	-	-	-	-	-	-	-
Physical	Sand	-0.25	0.23	0.17	-0.06	0.04	0.12	-0.27	0	-0.31	0.11	0.03	-0.04	-0.26	0	-0.34	-0.03	-0.03	-0.09	0.17	0
	Silt	0.07	0.11	-0.17	0.2	-0.17	-0.2	0.76	0.06	-0.03	-0.16	0.26	0.21	0.67	0.05	-0.05	-0.06	0.27	0.54	-0.29	0.03
	Clay	0.22	-0.31	-0.08	-0.05	0.05	-0.02	-0.14	0	0.32	-0.02	-0.18	-0.08	-0.13	0.11	0.34	0.06	-0.12	-0.19	0	0.13
	WAS	0.26	-0.14	0.02	0.08	-0.2	0.27	0.01	0.07	0.3	0.02	-0.05	-0.05	0.03	0.14	0.29	0.01	-0.09	-0.25	0.13	0.1
	FC	0.27	-0.14	-0.1	-0.03	-0.11	-0.19	-0.04	0.03	0.29	-0.02	0.08	-0.14	0.22	0.15	0.31	0.05	0.07	0.2	-0.15	0.16
Eigenvalue		7.88	5.36	3.00	1.87	1.70	1.18	1.00		8.14	4.15	2.39	1.35	1.14		7.37	4.49	2.22	1.67	1.24	
% variation		30.32	20.6	11.54	7.20	6.54	4.55	3.84		38.76	19.77	11.36	6.42	5.45		35.12	21.39	10.57	7.95	5.93	
Cumulative % variation		30.32	50.92	62.47	69.66	76.2	80.75	84.59		38.76	58.53	69.89	76.31	81.76		35.12	56.51	67.08	75.03	80.96	
p_k		0.36	0.24	0.14	0.09	0.08	0.05	0.05		0.47	0.24	0.14	0.08	0.07		0.43	0.26	0.13	0.1	0.07	

- not measured

The Saskatchewan soil health score

The SSHS averaged 56.97% in the 0-15 cm depth and was lower compared to the 15-30 and 30-60 cm depths, which had average scores of 63.88 and 64.33%, respectively (Fig. 6A). 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 SSHS for the 0-60 cm ranged from 41.24 to 77.05%—the highest score belonging to the native prairie soil. The overall SSHS for the 0-60 cm depth did not differ across soil zones, and median of overall SSHS was 60.17, 65.68, 62.92, 61.02% in Gray, Black, Dark Brown, and Brown soil zone, respectively.

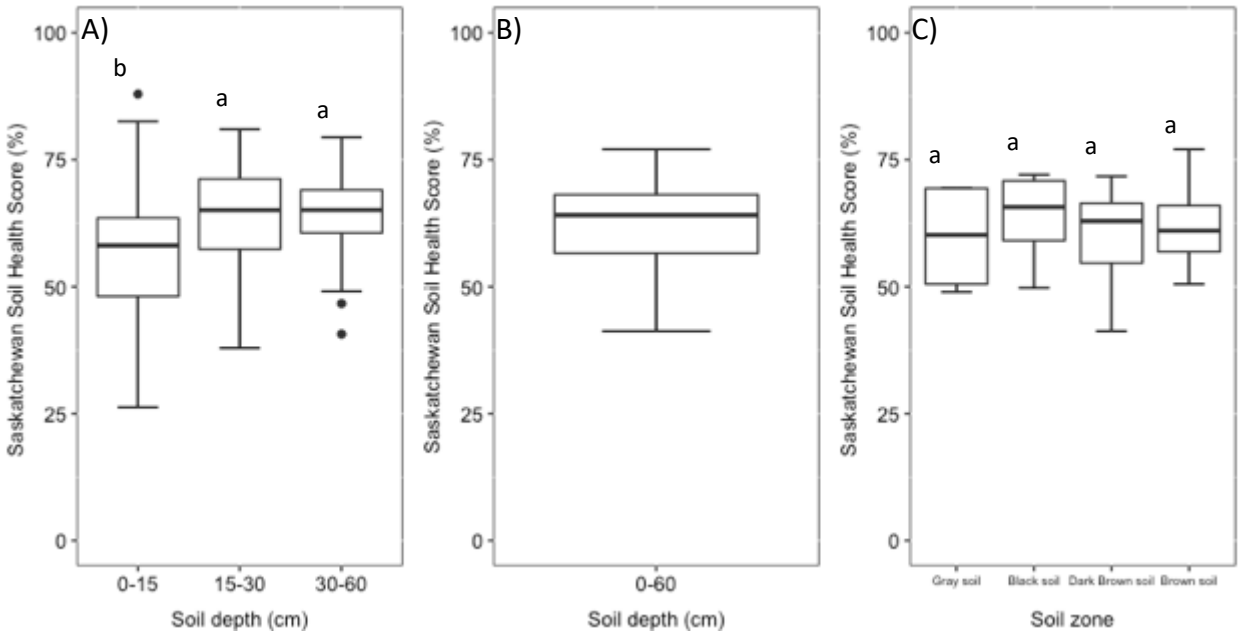


Figure 6. The Saskatchewan soil health score A) by soil depth increment, B) for the full 0-60 cm, and C) by soil zone (0-60 cm depth). Boxplots with the same letters are not significantly different (*P* > 0.05) according to Tukey's multiple means comparison.

Linking the Saskatchewan Soil Health Score to crop yields

For the most part, cereal crop yields were not well correlated to the SSHS; 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 values of < 0.1 or $p < 0.15$, the SSHS was positively correlated to 5- or 10-yr average yields (Table 3).

Table 3. The correlation between the Saskatchewan Soil Health Score (SSHS) and average cereal crop yields obtained from rural municipalities from 2009 to 2019. Significant correlations are indicated at $p < 0.05$ (*), $p < 0.1$ (†) and $p < 0.15$ (‡). Cereal crop yield and precipitation data are included for each year.

	Correlation between cereal crop yield and soil health (Pearson's coefficient)			Crop yields, Mg ha^{-1} (min, median, max)	Average precipitation, mm (annual, Apr-June)
Year	SSHS (0-15 cm)	SSHS (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-yr (2014-2018)	0.47†	0.44‡		2.4, 2.7, 3.4	385.2, 126.5
10-yr (2009-2018)	0.41‡	0.41‡		2.2, 2.8, 3.1	409.5, 149.3

8. Discussion

Carbon and nitrogen are key regulators of soil health

Of all the attributes measured, soil protein, active C, total N and C, and SOC explained the greatest amount of variance in the dataset; resulted in greater individual weights for computing the overall score (Table 2). Unsurprisingly, these C- and N-based attributes were also highly correlated to each other (R^2 of 0.68 to 0.97). 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 2014, 2016). By having C- and N-based attributes highly weighted in the SSHS 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, changes in soil organic matter or total C may only be detected in the long-term (5-10-yrs or more) (Simonsson et al. 2014). The conundrum is that 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 carbon indictors are included to work as the early detector 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 (total C and N, SOC), the SSHS framework might offer a more useful metric to detect early changes, rather than relying on soil organic matter measures alone.

Consideration of soil depths beyond 0-15 cm

The SSHS 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 SSHS considers each depth increment independently (i.e., weighting factors are different for each depth increment, as shown in Table 2). If a score for subsurface soil is computed using the same weighting factors as the 0-15 cm depth, the result would 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. The surface soil is arguably the most weathered and impacted by agricultural management after the conversion from native grassland to arable cropland; thus, seems logical that the surface soil health score is more variable and numerically lower than the subsurface soils (Fig. 6A). 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). Future work should consider incorporating biological indices for the subsurface soil, along with the physical and chemical indicators.

How the Saskatchewan Soil Health Test compares to others?

For meaningful interpretation of soil health and functioning, regional soil health tests are recommended (Frost et al., 2019). 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, each assigned an equal contribution. Other methods integrate several attributes via a weighted average approach. Principal component analyses are often used to inform the relative contribution different attributes should contribute to an overall score (Andrews and Carroll 2001; Bi et al. 2013; Purakayastha et al. 2019; Karaca et al. 2021). 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).

No scoring approach is without limitations. It is acknowledged that the SSHS 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. Nonetheless, the SSHS presented herein provides a regional adaptation for a soil health score for one of Canada's most important agricultural regions. Tracking the soil health score over time, together with crop metrics, will provide the information needed to inform and adjust management plans aimed at

improving soil health and functioning. Extension tools should be developed to transform farmers' routine soil test data into a soil health score, informed by our scoring approach.

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. However, 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 corresponded to greater corn yields in 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 the labile organic matter—C and N-based indices—is central for linking soil health and crop productivity. Likewise, our SSHS framework prioritizes soil C and N-based attributes and showed promise for linking soil health to crop yield (Table 3). Although this is in agreement with others (Lal 2016; Garcia et al. 2018), 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 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 during years with low precipitation only (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.

9. Conclusions and Recommendations

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 it has not been tailored to Saskatchewan soils—until now. Herein, we present a soil health testing protocol and scoring functions for arable cropping systems in Saskatchewan (the SSHS). Our testing protocol and scoring functions provide the foundation for developing extension tools that are capable of transforming farmers' routine soil test data into a soil health score. As an example, a grower-friendly online tool which outputs the SSHS from lab results would be valuable to producers and industry. Our results indicate C and N-indices primarily drive soil health

differences, and therefore indicate that management decisions aimed at improving C and N sequestration will also improve soil health scores. It is possible that healthier soils may help to safeguard crop yields during sub-optimally dry growing seasons, but further research is recommended to explore this linkage more closely.

10. Success stories/practical implications for producers or industry

This research project provides practical implications for producers and industry because it lays the foundation for a regional soil health test for arable cropping systems.

11. Patents/IP generated/commercial products

None generated from this project

12. List of technology transfer activities

Webinars:

Wu Q., Taye Z., Congreves K.A. (2021). Introducing a Soil Health Testing Protocol for Arable Cropping Systems in Saskatchewan. *WEBINAR WILL BE AVAILABLE ON CONGREVES' WEBSITE IN MAY/June 2021 (ideally after a round of peer-review). I originally wanted to host an in-person workshop for this, however, with the COVID-19 pandemic, this Virtual Webinar is the safest way to reach producers.*

Theses:

Wu Q. Developing a soil health testing protocol for arable cropping systems in Saskatchewan. MSc Thesis, Department of Plant Sciences. *Thesis draft submitted to Advisory Committee (Apr 7, 2021), and the Defense is expected to take place in May/June 2021.*

Publications:

Van Eerd, L.L., Congreves, K.A., Arcand, M.M., Lawley, Y., Halde, C. Soil health and management. (2021). Canadian Perspectives on Soil Science, Introductory Textbook. Canadian Society of Soil Science, *In Press.*

Wu, Q., Farrell, R.E., Congreves, K.A. (Under Review). Fine-tuning the methodology for measuring soil protein. *Submitted to Canadian Journal of Soil Science, Mar 16, 2021.*

Wu, Q. and Congreves, K.A. (In preparation). A soil health test for arable cropping systems in Saskatchewan Canada. *To be Submitted to Canadian Journal of Soil Science.*

Presentations:

Congreves, K.A. Developing a Soil Health Scoring System for Saskatchewan. (2020) Agronomy Research Update. Virtual Presentation to > 600 people. Dec 10, 2020. ***Invited talk.***

Congreves, K.A. Soil Health by Numbers. (2020) Saskatchewan Seed Potato Growers Association, Annual General Meeting. Virtual Presentation to 20 people. Dec 10, 2020. ***Invited talk.***

Congreves, K.A. "A story about soil", Nutana Rotary Club, Saskatoon, SK. Nov 24, 2020. ***Invited talk.***

Wu, A., Farrell, R.E., Knight, J.D., Congreves, K.A. (2020). Developing a soil health testing protocol for Saskatchewan cropping systems. Canadian Society for Horticulture Science Online Graduate Student Conference. Aug 27, 2020. ***Best Student Oral Presentation in Soils/Environment Section. *Wu is my MSc student.***

Congreves, K.A. (2019). Trials and tribulations of digging into soil health and greenhouse gas emissions. Department of Renewable Resources, Faculty of Agriculture, Life and Environmental Sciences, University of Alberta, Edmonton, AB. Mar 15, 2019.

Congreves, K.A., Norris, C.E., Farrell, R.E., and Arcand, M.M., (2018). Update on soil health and nutrient research in progress. 2018 Agronomy Update, Saskatoon, SK, Dec 11, 2018. (~150 participants). ***Invited and opening talk.***

Congreves, K.A., Norris, C.E., and Arcand, M.M., (2018). Regenerative agriculture on soil health and crop production. SSCA Field Day, Bangor, SK, Aug 9, 2018. (~50 participants). ***Invited talk****.*

Congreves, K.A. 'Researcher-Producer Cover Crop Video Conference' (Yorkton, Saskatoon, Swift Current Ministry of Agriculture Offices) (Mar 29, 2018).

Congreves, K.A. 'Introduction to Industry and Funders' at the "Meeting of Minds Workshop", Saskatchewan Ministry of Agriculture (Mar 21, 2018). ***Invited talk****.*

Congreves, K.A. (2018). Soil Organic Matters for Soil Health. Soils and Crops, Prairieland Park, Saskatoon, SK, March 7, 2018. (~200 participants). ***Invited and opening talk for the Agronomist workshop.***

Congreves, K.A. (2018). Soil health for vegetable crop production. SVGA Produce Conference, Saskatoon, SK. Jan 20, 2018. (~40 participants). ***Invited talk.***

Congreves, K.A. (2018). Soil Organic Matters for Soil Health. SSCA Conference, Saskatoon, SK. Jan 8, 2018. (~175+ participants). ***Invited talk.***

Articles in extension outlets:
Congreves, K.A. Soil Health Test Under Development. Article for Better Farming Magazine, July 16, 2020.

Congreves, K.A. Soil health on farm, in the lab, and back again. Prairie Steward Article for the Saskatchewan Soil Conservation Association Newsletter, Apr 17, 2020.

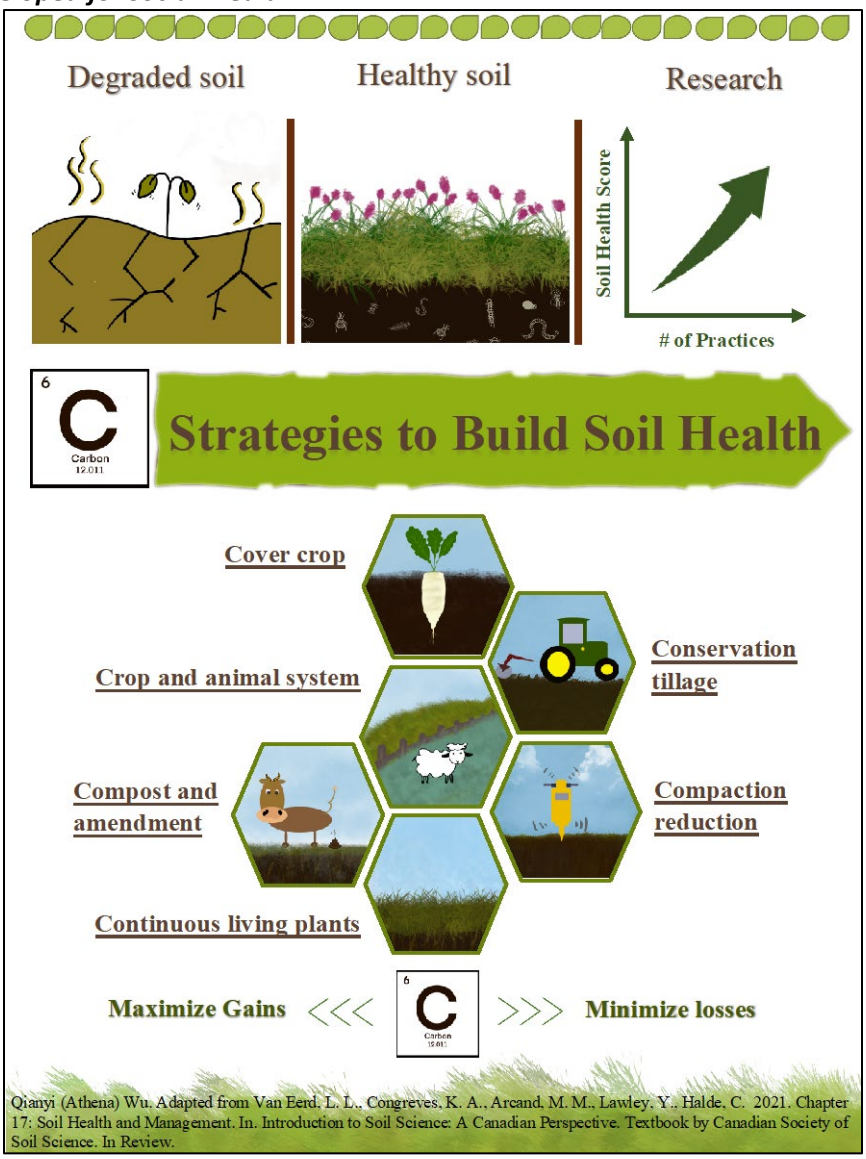
Media interviews:

Interview, Toronto Star, Journalist Diana Zlomislic. Interviewed June 17, 2019. Article '*How Saskatchewan farmers are preparing for climate change* 'Field of Dreams'
http://projects.thestar.com/climate-change-canada/saskatchewan

Interview, Agricultural Freelance Writer, Lara Barrera (North Dakota). Interviewed Sept 13, 2018. *Article 'Capturing carbon for healthier soil' published in Newground Magazine, a Midwestern USA/Prairie Canada Agriculture Magazine:* http://www.newgroundmagazine.com/capturing-carbon-for-healthier-soil/

AgWest Bio Outreach Video Series: Featured in a film highlighting agricultural scientists in Saskatoon. Interviewed Mar 16 and 26, 2018. #ScientistsArePeopleToo

Infographic developed for social media:



Infographic showing the recommended management practices aimed at improving soil health.

13. List of industry contributions or support received

Funding was supplied by ADF, WGRF, SWDC, and SaskCanola. In addition, other funding was secured via scholarship support (the Dollie Hantleman Scholarship) to support MSc student, Ms. Athena Wu.

14. Is there a need to conduct follow up research?

To build off this project, we are currently working on a "Phase-2" follow-up project, aimed at refining the soil scoring functions for each soil zone (Brown, Dark Brown, Black, and Gray soil zones). Phase-2 is presently funded by SWDC and SaskCanola. Further, we are exploring other soil biological attributes that will be included in a Phase-2 soil health test (microbial community structure, and carbon substrate use). Also, we will be applying the soil health test to fields under different management scenarios, i.e., conventional and regenerative agricultural practices to determine how management influences soil health scores. Our research points towards the possibility where healthier soil may provide crop benefits during suboptimal growing conditions, and follow-up research is recommended to explore this relationship for a finer-scale understanding.

15. Acknowledgments

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 their contributions to the field and lab activities, as well as the Prairie Environmental Agronomy Research Lab for the soil sample collection. Special thanks Drs. Rich Farrell, Diane Knight, and Melissa Arcand for valuable input throughout the project.

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16. Appendices — Supplemental Material

Data distributions

Chemical attributes

Soil EC and pH distributions were unimodal regardless of depth, with EC as highly right-skewed and pH as highly left-skewed (Fig. S1A). Soil EC averaged 0.33, 0.31, 0.39 ms cm^{-1} in the 0-15, 15-30, and 30-60 cm depth, respectively; soil pH averaged 7.24, 7.54, 7.93 in the same depth increments, respectively. Soil EC medians did not dramatically differ by soil zone, whereas pH medians were generally higher for the brown soil zone and lower for the gray zone (Fig. S1A).

Soil TC, SOC, and TN distributions were near normal with some extreme values (Fig. S1A). For all three attributes, the values decreased with increasing soil depth (Fig. S1A). Soil TC averaged 26.44, 19.28, 18.21g kg^{-1}, for the 0-15, 15-30, 30-60 cm depths, respectively; whereas for the same respective depth increments, SOC averaged 24.16, 15.52, 12.20 g kg^{-1} and TN averaged 2.32, 1.48, 1.00 g kg^{-1}. Some extremely high SOC values were observed, such as 71.28 g kg^{-1} from the gray soil. For TC, SOC, and TN the difference between medians among soil zones decreased with soil depth (Fig. S1A). The gray and black soil zones had higher medians in the top 0-15 cm depth, while the gray soil zone had the lowest medians in the 30-60 cm depth. The interquartile range of the gray soil zone was wider than other soil zones for the top 0-15 cm, but sharply reduced with depth (Fig. S1A).

The shape of NO_3^- and NH_4^+ distributions were unimodal and slightly right-skewed. For NO_3^-, the 0-15 and 15-30 cm depths resulted in flatter distributions than the deeper 30-60cm data (Fig. S1A). Soil NO_3^- generally decreased with depth, averaging 12.33, 9.31, 4.78 ug g^{-1} in 0-15, 15-30, and 30-60cm, respectively (Fig. S1A). Soil NH_4^+, on the other hand, showed little variation by soil depth, averaging 4.39, 3.61, 3.77 ug g^{-1} in the 0-15, 15-30, and 30-60 cm, respectively (Fig. S1A). Noticeably, the gray soil has the lowest NO_3^- values, while the dark brown soil zone had the widest variation. Soil NH_4^+ medians remained fairly consistent among soil zones (Fig. S1A).

Soil Na, P, and Mn were near normally distributed, with some outliers (Fig. S1B). Soil Na averaged 90.19, 87.97, 135.63 mg kg^{-1}, for the 0-15, 15-30, 30-60 cm depths, respectively; whereas for the same respective depth increments, P averaged 532.35, 434.16, 419.41mg kg^{-1} and Mn averaged 482.86, 431.86, 408.58 mg kg^{-1}. Some extremely high Na were observed, such as 850.21 mg kg^{-1} in the surface soil from black soil zone and 838.06 mg kg^{-1} in soil depth 30-60cm from brown soil zone. The highest Na and P values existed in surface soil, while the highest Mn was in the deeper 30-6 0cm.

Soil Ca, S, and Mg distributions were mostly unimodal and right-skewed regardless of depth. For these three nutrients, the 0-15 cm depth had narrower distributions than the deeper 15-30 and 30-60 cm depths (Fig. S1B). Soil Ca averaged 10218, 15878, 24799 mg kg^{-1} from the soil in 0-15, 15-30, 30-60 cm depth, respectively, whereas for the same respective depth increments, S averaged 574.08, 645.35, 900.73 mg kg^{-1} and Mg averaged 5398.80, 6607.83, 8510.87 mg kg^{-1}. The black soil had highest median of soil Ca, S and Mg regardless of depth.

Soil Zn, Fe, and K distributions were bimodal with two distinct peaks (Fig. S1B). Soil Zn and K generally decreased with depth, which averaged 67.40, 63.16, 59.74 mg kg^{-1} of Zn and 3423.23, 2972.79, 2584.71 mg kg^{-1} of K in 0-15, 15-30, 30-60cm depth. Conversely, soil Fe generally increased with depth, averaging 17161, 17736, 17770 mg kg^{-1} in the same respective depth increments. No obvious differences were observed between soil zones by depth.

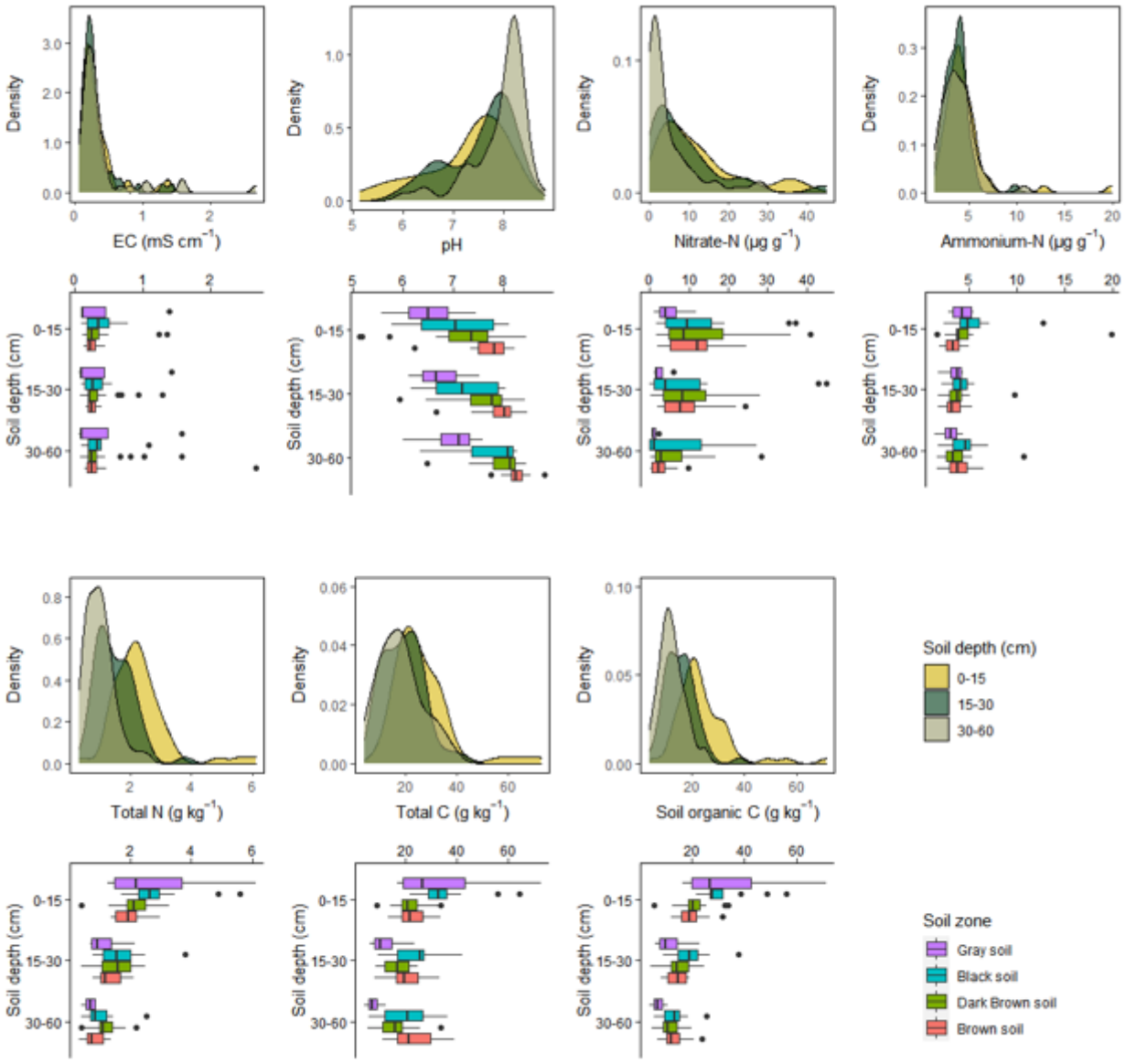

Figure S1A). The distribution for common soil chemical attributes, presented using density plots. The y-axis is the probability density (kernel estimation) per unit on the x-axis. Box-plots show the interquartile range (solid bar), median (the line inside bars), minimum and the maximum excluding outliers (the extreme line), and outliers (dots) for each soil zone.

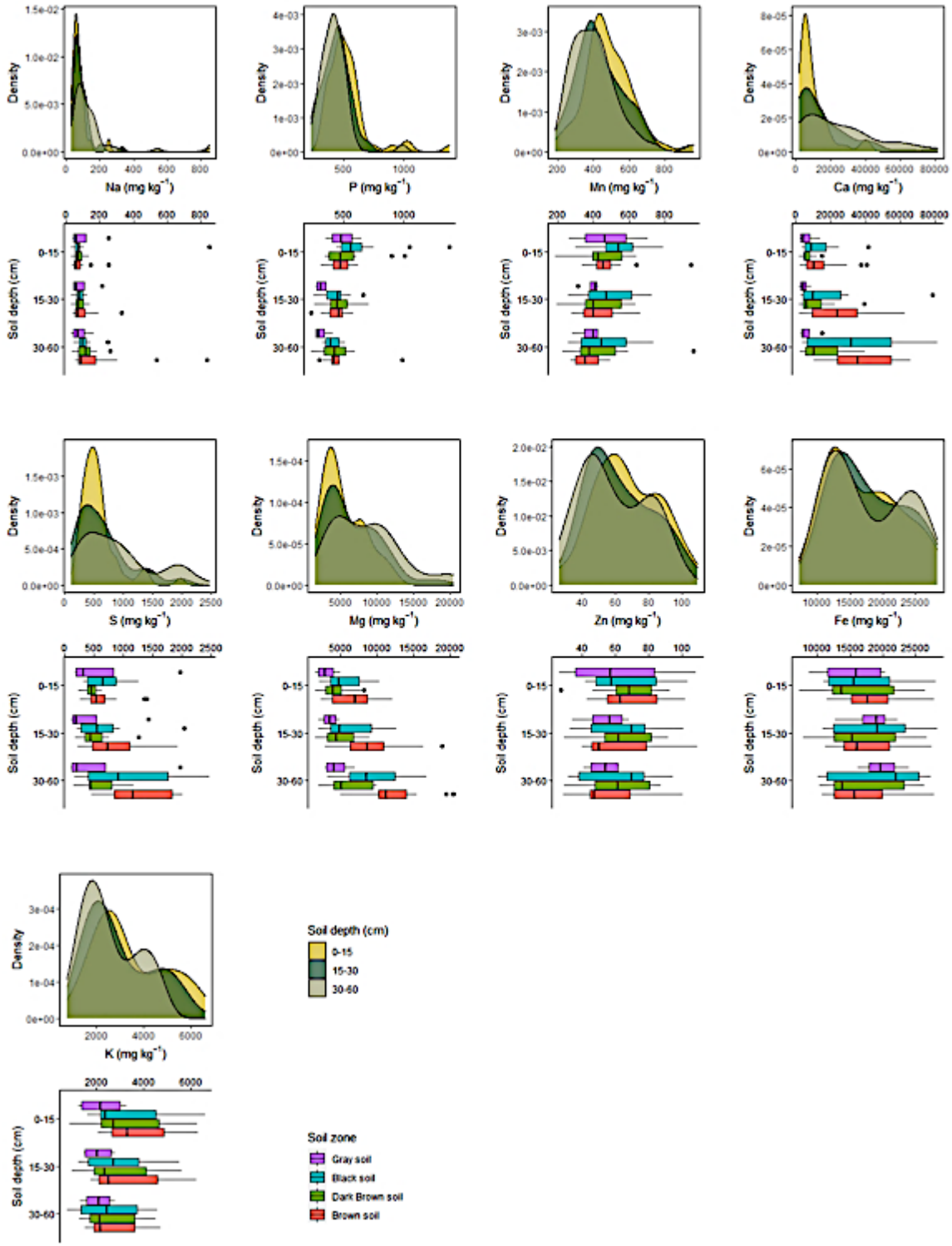

Figure S1B). The distribution of several soil nutrients as chemical attributes (other than those shown in Figure S1A), presented using density plots. The y-axis is the probability density (kernel estimation) per unit on the x-axis. Box-plots show the interquartile range (solid bar), median (the line inside bars), minimum and the maximum excluding outliers (the extreme line), and outliers (dots) for each soil zone.

Physical attributes

In our database, the percentage of sand in the soil ranged widely from 1.1% to 81% with a bi-modal distribution—a form that was shared by clay, only to a lesser degree due to the clustering around ~20% and 60% (Fig. S2). The silt percentage, on the other hand, showed a unimodal distribution centered around ~40% and was more right skewed with depth (Fig. S2). For sand and clay there was a fair amount of overlap in the interquartile range among the soil zones tested, but the soil zones tended to differentiate by silt (Fig. S2).

The WAS distribution was unimodal and slightly left-skewed for the 0-15 and 15-30 cm depths, but more uniform for the 30-60 cm depth (Fig. S2). The WAS generally decreased with soil depth, averaging 53%, 48%, 44% in 0-15, 15-30, 30-60cm, respectively. For WAS, the dark brown soil and black zone showed wider distributions than the brown or gray soil zones (Fig. S2). Soil FC showed a bi-modal distribution at ~40% to 60% with similarities among the soil zones, and little change in distribution with soil depth (Fig. S2). Soil FC was nearly consistent among depths, and averaged 46, 44, 43% in 0-15, 15-30, 30-60 cm.

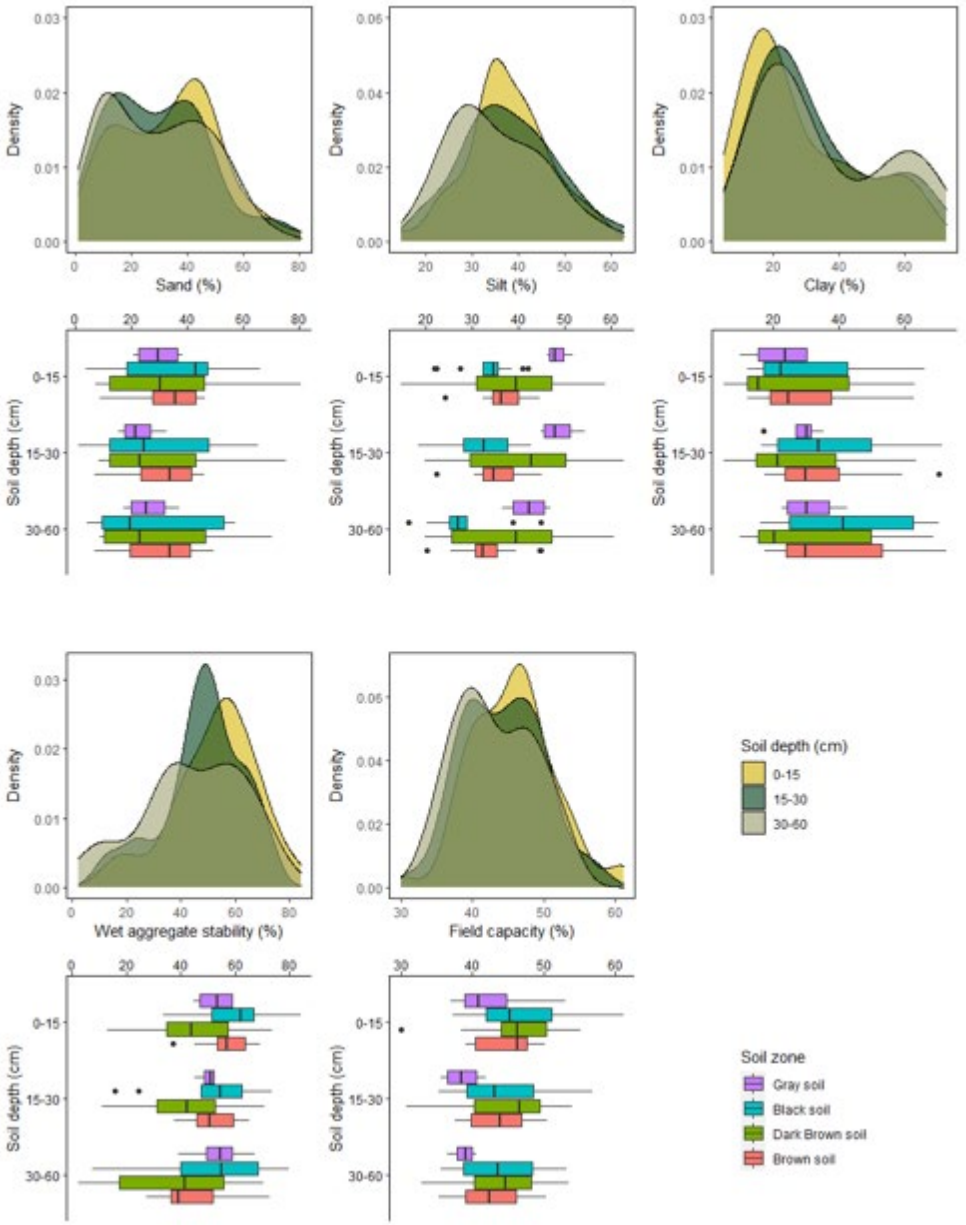

Figure S2. The distribution of soil physical attributes presented using density plots. The y-axis is the probability density (kernel estimation) per unit on the x-axis. Box-plots show the interquartile range (solid bar), median (the line inside bars), minimum and the maximum excluding outliers (the extreme line), and outliers (dots) for each soil zone.

Biological attributes

The data distribution for soil active C, CO_2 production, and protein were similar to each other, with unimodal distributions and similar patterns across soil zones (Fig. S3). Nitrous oxide production, on the other hand, showed a highly right-skewed unimodal distribution with few differences between soil zones (Fig. S3).

Soil protein levels in the 0-15 cm soil ranged from 1 to 17 mg g-1, with a unimodal distribution that is normal and a mean of 6.9 mg g-1 (Fig. S3). The gray soil zone produced a median protein level that was exceptionally higher than the other soil zones in 0-15 cm depth (Fig. S3).

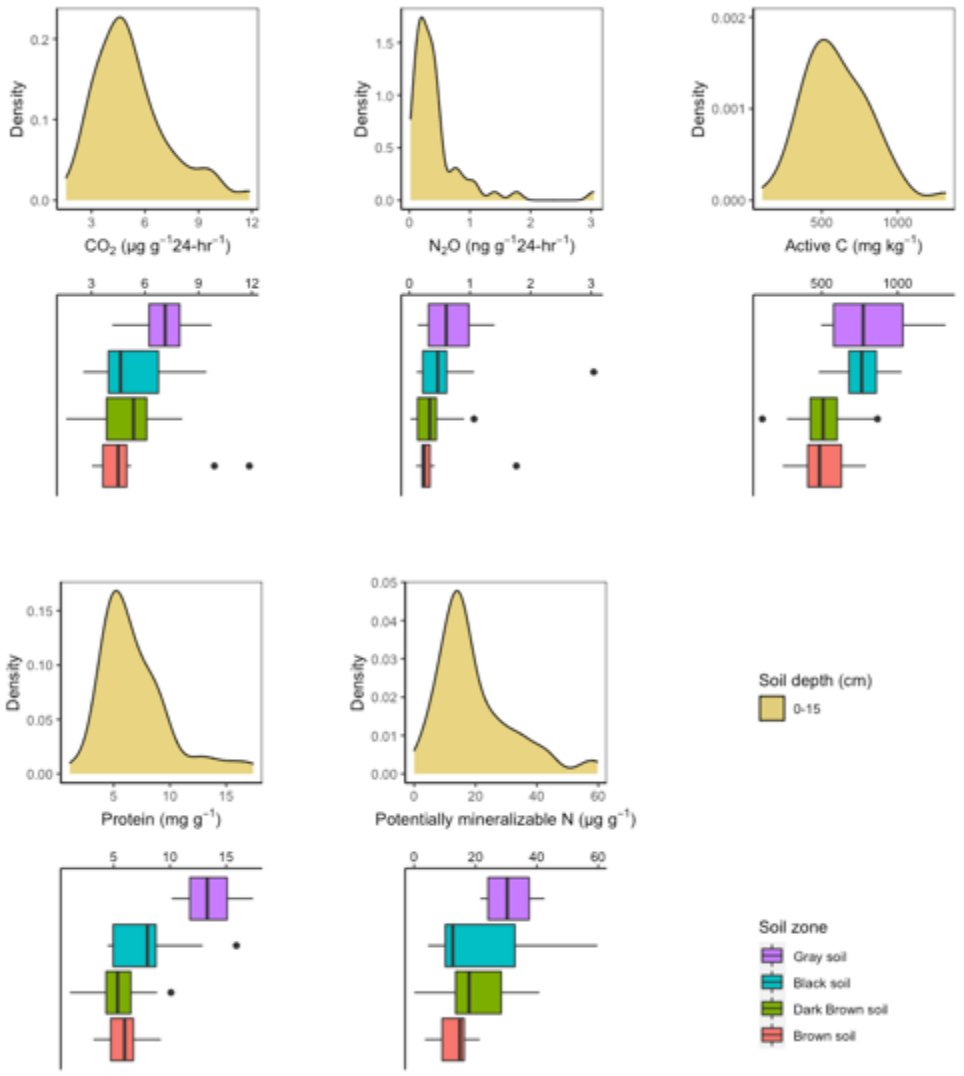

Figure S3. The distribution of soil biological indictors in the 0-15 cm depths, presented using density plots. The y-axis is the probability density (kernel estimation) per unit on the x-axis. Box-plots show the interquartile range (solid bar), median (the line inside bars), minimum and the maximum excluding outliers (the extreme line), and outliers (dots) for each soil zone.

Table S1. Shapiro-Wilk probability values indicating the distribution normality for each soil attribute. Where *P* values are < 0.05, a log or square root transformation was applied to improve normality.

Attributes	Dataset	Soil depth (cm)		
		0-15	15-30	30-60
Wet aggregate stability (%)	Original	0.38	0.30	0.16
Soil organic C (g kg^{-1})	Original	0.48	0.73	0.78
Total C (g kg^{-1})	Original	0.73	0.08	0.14
Total N (g kg^{-1})	Original	0.22	0.07	0.09
Protein (mg g^{-1})	Original	0.15	0.73	0.96
Active C (mg kg^{-1})	Original	0.93	-	-
CO_2 (µg g^{-1} $24hr^{-1}$)	Original	0.53	-	-
EC (mS cm^{-1})	Original	0.00	0.01	0.58
	Log transformation	0.16	0.43	
N_2O (ng g^{-1} $24hr^{-1}$)	Original	0.00	-	-
	Log transformation	0.20		
pH	Original	0.00	0.00	0.00
	Square root	0.05	0.04	0.08
Sand (%)	Original	0.06	0.04	0.00
	Square root		0.45	
Silt (%)	Original	0.82	0.69	0.22
Clay (%)	Original	0.00	0.00	0.00
	Log transformation	0.06	0.14	0.02
NO_3^{-1}-N (µg g^{-1})	Original	0.00	0.00	0.00
	Log transformation	0.22	0.04	0.73
NH_4^+-N (µg g^{-1})	Original	0.70	0.24	0.50
PMN (µg $g^{-1)}$	Original	0.01	-	-
	Log transformation	0.38	-	-
Field capacity (%)	Original	0.49	0.66	0.18
Na (mg kg^{-1})	Original	0.15	0.04	0.04
	Log transformation		0.58	0.56
P (mg kg^{-1})	Original	0.43	0.58	0.73
Mn (mg kg^{-1})	Original	0.90	0.27	0.14
Ca (mg kg^{-1})	Original	0.00	0.00	0.00
	Log transformation	0.67	0.08	0.05
S (mg kg^{-1})	Original	0.33	0.00	0.00
	Log transformation		0.84	0.07
Mg (mg kg^{-1})	Original	0.00	0.00	0.00
	Log transformation	0.29	0.28	0.26
Zn (mg kg^{-1})	Original	0.45	0.04	0.01
	Log transformation		0.33	0.03
Fe (mg kg^{-1})	Original	0.01	0.02	0.00
	Log transformation	0.07	0.11	0.00
K (mg kg^{-1})	Original	0.00	0.00	0.00
	Log transformation	0.11	0.14	0.05

- , data not available because only the surface-most depth increment was analyzed

Table S2. Model selection for predicting soil health scores from soil attribute measurements according to the "more is better" function. For all models, *x* is the observed soil score and *y* is the modelled soil health score. Models are selected based on R^2 and root mean square error (RMSE), indicated in bold.

Soil depth (cm)	Attributes		Model: Polynomial with intercept (order =2)	polynomial without intercept (order =2)	polynomial (order=1)	Power	Inverse power	Square root	Hoerl's	Logarithmic
0-15	Wet aggregate stability (%)	R^2	**0.96**	0.95	-	0.86	0.98	0.92	0.97	0.85
		RMSE	**5.59**	6.60	-	10.72	3.80	8.33	4.76	11.29
	Soil Organic C (g kg $^{-1}$)	R^2	**0.96**	0.94	0.96	0.89	-	0.93	0.95	0.85
		RMSE	**5.68**	7.45	5.69	9.95	-	7.64	6.27	11.36
	Total C (g kg $^{-1}$)	R^2	**0.97**	0.93	0.97	0.87	-	0.96	1.00	0.92
		RMSE	**5.34**	7.82	5.41	11.06	-	6.24	1.56	8.50
	Total N (g kg $^{-1}$)	R^2	**0.95**	0.94	-	0.88	-	0.89	-	0.77
		RMSE	**6.26**	7.42	-	10.24	-	9.55	-	14.21
	Protein (mg g^{-1})	R^2	**0.95**	0.91	0.95	0.85	-	0.92	0.95	0.81
		RMSE	**6.60**	8.99	6.82	11.19	-	8.34	6.83	12.67
	CO_2 (mg g^{-1} 24hr^{-1})	R^2	**0.97**	0.92	0.96	0.86	0.98	0.96	0.99	0.92
		RMSE	**5.04**	8.31	5.58	11.02	4.18	5.80	3.02	8.05
	Active C (mg kg $^{-1}$)	R^2	**0.97**	0.95	0.97	0.92	-	0.94	0.97	0.86
		RMSE	**5.05**	6.77	5.05	8.52	-	7.20	5.16	11.29
	Potential mineralizable N (ug g^{-1})	R^2	-	0.94	0.76	0.71	0.96	**0.94**	0.96	0.91
		RMSE	-	6.87	14.01	15.37	5.61	**7.15**	5.97	8.81
15-30	Wet aggregate stability (%)	R^2	**0.98**	0.96	0.97	0.87	0.97	0.94	1.00	0.90
		RMSE	**4.47**	5.47	5.09	10.32	4.87	6.97	0.97	9.36
	Soil Organic C (g kg $^{-1}$)	R^2	**0.97**	0.93	0.97	0.88	0.99	0.95	0.98	0.90
		RMSE	**5.49**	8.01	5.60	10.56	3.71	6.74	4.50	9.76
	Total C (g kg $^{-1}$)	R^2	**0.98**	0.91	0.94	0.83	0.98	0.96	0.99	0.95
		RMSE	**4.43**	9.08	6.99	12.34	4.01	5.58	2.71	6.77
	Total N (g kg $^{-1}$)	R^2	**0.98**	0.95	0.98	0.92	0.99	0.97	0.98	0.92
		RMSE	**4.65**	7.20	4.82	8.61	3.15	5.78	4.14	8.76
	Protein (mg g $^{-1}$)	R^2	**0.97**	0.94	0.97	0.88	0.98	0.95	0.99	0.91
		RMSE	**5.10**	7.34	5.13	10.16	3.80	6.33	2.32	9.13
30-60	Wet aggregate stability (%)	R^2	**0.98**	0.98	0.97	0.98	-	0.90	0.94	0.73
		RMSE	**4.24**	4.69	4.83	4.26	-	9.38	7.41	15.64
	Soil Organic C (g kg $^{-1}$)	R^2	**0.98**	0.94	0.97	0.90	0.99	0.96	0.99	0.91
		RMSE	**4.75**	7.12	4.83	9.43	3.30	5.98	3.09	8.87
	Total C (g kg $^{-1}$)	R^2	**0.98**	0.95	0.97	0.93	-	0.97	0.98	0.91
		RMSE	**4.19**	6.49	5.18	8.05	-	5.35	4.05	8.79
	Total N (g kg $^{-1}$)	R^2	0.98	0.91	0.95	0.85	0.98	**0.97**	0.99	0.95
		RMSE	4.23	8.61	6.88	11.37	3.79	**5.43**	2.70	6.78
	Protein (mg g $^{-1}$)	R^2	**0.96**	0.94	0.96	0.92	0.92	0.92	0.93	0.81
		RMSE	**5.56**	6.98	5.56	8.39	8.56	8.17	7.55	12.74
Average		R^2	**0.97**	0.94	*	0.89	*	0.94	*	0.88
		RMSE	**5.10**	7.31	*	9.78	*	6.94	*	10.23

-, the curve created by particular model doesn't follow the scoring type; *, the model is not applicable for all selected attributes.
The model with bolding values is the selected model for the attributes in table. Polynomial with intercept (order =2), $y=a+bx+cx^2$. Polynomial without intercept (order =2), $y=ax+bx^2$. Polynomial with intercept (order =1), $y=a+bx$. Power, $y=ax^b$. Inverse power, $y=a*e^{(b/x)}$. Square root, $y=a+b*\sqrt{x}$. Hoerl's, $y=a*x^b*e^{(C*x)}$. Logarithmic, $y=a+b*\ln(x)$.

Table S3. Model selection for predicting soil health scores for each soil attribute of "less is better" type in the 0-15, 15-30, and 30-60 cm depth, based on R^2 and root mean square error (RMSE). For all models, *x* is the observed soil health score and *y* is the modelled soil health score. Bolded R^2 and RMSE values indicate the selected model.

Soil depth (cm)	Attributes		Polynomial with intercept (order =2)	Polynomial without intercept (order =2)	Polynomial (order=1)	Power	Modal Inverse power	Square root	Hoerl's	Logarithmic
0-15	EC (mS cm $^{-1}$)	R^2	-	-	-	-	-	**0.97**	-	0.99
		RMSE	-	-	-	-	-	**5.30**	-	3.75
	N_2O (ng g^{-1} $24hr^{-1}$)	R^2	-	-	-	-	-	**0.95**	-	0.95
		RMSE	-	-	-	-	-	**6.48**	-	6.77
15-30	EC (mS cm $^{-1}$)	R^2	-	-	0.89	0.72	0.51	**0.95**	-	-
		RMSE	-	-	9.59	15.41	20.39	**6.24**	-	-
30-60	EC (mS cm $^{-1}$)	R^2	-	-	0.97	-	-	**0.96**	-	0.90
		RMSE	-	-	5.21	-	-	**5.98**	-	9.32
Average		R^2	*	*	0.93	*	*	**0.96**	*	0.95
		RMSE	*	*	7.51	*	*	**5.62**	*	6.38

-, the curve created by particular model doesn't follow the scoring type;

*, the model is not applicable for all selected attributes.

Polynomial (order=1), $y=a+bx$. Polynomial with intercept (order =2), $y=a+bx+cx^2$. Polynomial with intercept (order =2), $y=ax+bx^2$. Power, $y=ax^b$. Inverse power, $y=a*e^{(b/x)}$. Square root, $y=a+b*\sqrt{x}$. Hoerl's, $y=a*x^b*e^{(C*x)}$. Logarithmic, $y=a+b*In(x)$;

Table S4. The formulas and threshold limits that correspond to the models presented in Figures 7 to 9.

	0-15 cm depth			15-30 cm depth			30-60 cm depth		
Attribute	**Equation**	**Upper threshold**	**Lower threshold**	**Equation**	**Upper threshold**	**Lower threshold**	**Equation**	**Upper threshold**	**Lower threshold**
				More is better					
Wet aggregate stability (%)	y= =-30.752 +1.077*x+0.008*x^2	84.16	16.69	y=-36.408 +1.1296*x+0.011*x^2	73.53	21.58	y=-9.442 +1.071*x +0.006*x^2	79.94	2.12
Soil organic C (g kg^{-1})	y=-42.350+3.967*x+0.006*x^2	3.85	0.54	y=-46.456+6.950*x -0.035*x^2	27.06	4.11	y=-38.912 +8.107*x -0.042*x^2	20.74	3.69
Total C (g kg^{-1})	y=-62.579+5.014*x -0.016*x^2	4.19	0.89	y=-46.464+6.388*x-0.064*x^2	42.41	6.24	y=-25.786+4.864*x -0.036*x^2	39.04	4.04
Total N (g kg^{-1})	y=-34.953+30.982*x+3.820*x^2	0.34	0.04	y=-44.239+72.271*x -4.622*x^2	2.48	0.39	y=-84.735+138.353*$\sqrt{x}$	2.20	0.32
Protein (mg g^{-1})	y=-44.708 +16.897*x^1 -0.272*x^2	12.31	1.11	y=-47.697+27.304*x -0.363*x^2	6.33	1.16	y=-23.544 +32.625*x+0.110*x^2	4.14	0.36
Active C (mg kg^{-1})	y=-30.213+0.139*x	1026.02	108.67						
CO_2 (μg g^{-1} $24hr^{-1}$)	y=-56.012 +25.727*x -0.751*x^2	8.79	1.57						
Potential mineralizable N (μg g^{-1})	y=-54.072+25.581$\sqrt{x}$								
				Less is better					
EC (mS cm^{-1})	y=178.487-261.560*$\sqrt{x}$	0.53	0.10	y=172.103-256.986*$\sqrt{x}$	0.55	0.07	y=182.305-273.560*$\sqrt{x}$	0.47	0.06
N_2O (ng g^{-1} $24hr^{-1}$)	y=148.330-188.642*$\sqrt{x}$	0.74	0.04						
				Optimum is best					
pH	$y=\left(\frac{3-\left\lvert\frac{\sqrt{10^x}-5815.680)}{3855.037}\right\rvert}{3}\right)*100$	8.45	5.15	$y=\left(\frac{3-\left\lvert\frac{\sqrt{10^x}-7380.540)}{4133.261}\right\rvert}{3}\right)*100$	8.48	5.94	$y=\left(\frac{3-\left\lvert\frac{\sqrt{10^x}-11095.846)}{4452.383}\right\rvert}{3}\right)*100$	8.82	6.49
Sand (%)	$y=\left(\frac{3-\left\lvert\frac{x-33.507)}{17.774}\right\rvert}{3}\right)*100$	80.59	4.06	$y=\left(\frac{3-\left\lvert\frac{\sqrt{x}-5.180)}{1.670}\right\rvert}{3}\right)*100$	75.18	1.09	$y=\left(\frac{3-\left\lvert\frac{log_{10}((\lvert log_{10}x/100\rvert)+0.261)}{0.238}\right\rvert}{3}\right)*100$	70.30	4.37
Silt (%)	$y=\left(\frac{3-\left\lvert\frac{x-37.820)}{9.040}\right\rvert}{3}\right)*100$	58.86	14.45	$y=\left(\frac{3-\left\lvert\frac{x-37.918)}{10.122}\right\rvert}{3}\right)*100$	62.79	18.29	$y=\left(\frac{3-\left\lvert\frac{x-34.954)}{10.244}\right\rvert}{3}\right)*100$	60.72	16.27
Clay (%)	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-1.378)}{0.271}\right\rvert}{3}\right)*100$	66.25	4.96	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-1.445)}{0.250}\right\rvert}{3}\right)*100$	71.60	4.98	$y=\left(\frac{3-\left\lvert\frac{log_{10}((\lvert log_{10}x/100\rvert)-0.165)}{0.074}\right\rvert}{3}\right)*100$	72.76	10.03
NO_3^{-1}-N (μg g^{-1})	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-0.856)}{0.342}\right\rvert}{3}\right)*100$	25.11	1.19	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-0.660)}{0.461}\right\rvert}{3}\right)*100$	22.89	0.28	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-0.311)}{0.632}\right\rvert}{3}\right)*100$	28.36	0.04
NH_4^+-N (μg g^{-1})	$y=\left(\frac{3-\left\lvert\frac{x-3.943)}{1.233}\right\rvert}{3}\right)*100$	7.08	1.56	$y=\left(\frac{3-\left\lvert\frac{x-3.490)}{0.974}\right\rvert}{3}\right)*100$	5.54	1.71	$y=\left(\frac{3-\left\lvert\frac{x-3.632)}{1.328}\right\rvert}{3}\right)*100$	6.93	1.31
Field capacity (%)	$y=\left(\frac{3-\left\lvert\frac{x-45.603)}{5.880}\right\rvert}{3}\right)*100$	61.12	29.99	$y=\left(\frac{3-\left\lvert\frac{x-44.157)}{5.531}\right\rvert}{3}\right)*100$	56.84	30.85	$y=\left(\frac{3-\left\lvert\frac{x-43.173)}{5.459}\right\rvert}{3}\right)*100$	53.51	32.94
Na (mg kg^{-1})	$y=\left(\frac{3-\left\lvert\frac{x-66.472)}{22.268}\right\rvert}{3}\right)*100$	113.29	29.16	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-1.864)}{0.168}\right\rvert}{3}\right)*100$	152.52	28.82	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-1.979)}{0.204}\right\rvert}{3}\right)*100$	245.63	32.20
Ca (mg kg^{-1})	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-3.816)}{0.282}\right\rvert}{3}\right)*100$	24698.46	1615.49	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-3.991)}{0.432}\right\rvert}{3}\right)*100$	78616.06	1842.94	$y=\left(\frac{3-\left\lvert\frac{log_{10}x-4.216)}{0.425}\right\rvert}{3}\right)*100$	81258.63	2099.80

P (mg kg^{-1})	$y=(\frac{3-\lvert\frac{x-489.637}{94.889}\rvert}{3})*100$	747.99	315.01	$y=(\frac{3-\lvert\frac{x-434.159)}{105.232}\rvert}{3})*100$	706.88	232.08	$y=(\frac{3-\lvert\frac{x-408.124)}{82.978}\rvert}{3})*100$	592.75	230.86
S (mg kg^{-1})	$y=(\frac{3-\lvert\frac{x-490.313)}{174.303}\rvert}{3})*100$	892.06	178.02	$y=(\frac{3-\lvert\frac{log_{10}x-2.713)}{0.296}\rvert}{3})*100$	2043.56	100.63	$y=(\frac{3-\lvert\frac{log_{10}x-2.840)}{0.337}\rvert}{3})*100$	2471.25	105.64
Mg (mg kg^{-1})	$y=(\frac{3-\lvert\frac{log_{10}x-3.669)}{0.221}\rvert}{3})*100$	11970.17	1526.70	$y=(\frac{3-\lvert\frac{log_{10}x-3.751)}{0.248}\rvert}{3})*100$	18870.92	1535.62	$y=(\frac{3-\lvert\frac{log_{10}x-3.865)}{0.244}\rvert}{3})*100$	20371.58	1970.63
Zn (mg kg^{-1})	$y=(\frac{3-\lvert\frac{x-67.397)}{20.225}\rvert}{3})*100$	108.65	26.35	$y=(\frac{3-\lvert\frac{log_{10}x-1.779)}{0.137}\rvert}{3})*100$	109.31	29.26	$y=(\frac{3-\lvert\frac{log_{10}x-1.751)}{0.151}\rvert}{3})*100$	100.57	28.72
Fe (mg kg^{-1})	$y=(\frac{3-\lvert\frac{log_{10}x-4.211)}{0.146}\rvert}{3})*100$	28111.60	7152.07	$y=(\frac{3-\lvert\frac{log_{10}x-4.227)}{0.138}\rvert}{3})*100$	28392.45	7879.71	*	27860.79	10050.85
K (mg kg^{-1})	$y=(\frac{3-\lvert\frac{log_{10}x-3.490)}{0.202}\rvert}{3})*100$	6593.32	866.90	$y=(\frac{3-\lvert\frac{log_{10}x-3.426)}{0.204}\rvert}{3})*100$	6213.33	991.55	$y=(\frac{3-\lvert\frac{log_{10}x-3.370)}{0.194}\rvert}{3})*100$	4724.46	763.12
Mn (mg kg^{-1})	$y=(\frac{3-\lvert\frac{x-468.261)}{115.276}\rvert}{3})*100$	791.37	183.10	$y=(\frac{3-\lvert\frac{x-431.861)}{126.577}\rvert}{3})*100$	728.37	195.35	$y=(\frac{3-\lvert\frac{x-390.575)}{104.663}\rvert}{3})*100$	960.86	223.63