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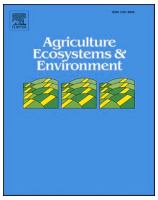

Applicability of soil health assessment for wheat-maize cropping systems in smallholders' farmlands

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ABSTRACT

Soil health assessment is fundamental to guiding sustainable soil management practices, ensuring healthy soil, crop productivity, and provision of other ecosystem services. Interpretation of soil health in intensive agriculture in the North China Plain (NCP) is still lacking due to an over emphasis on soil chemical management and large variations among smallholders' farmlands. The objectives of this study were to (i) compare soil health assessment approaches in response to fertilization regimes, (ii) quantify relationships between soil health and agronomic outcomes, (iii) develop a minimum data set to simplify soil health assessment, and (iv) validate soil health assessment frameworks in smallholders' fields on the NCP. We collected soil samples from eight wheat-maize rotation long-term experiments which were divided into three fertilization regimes: (1) NPK, application of chemical fertilizers only; (2) M, application of organic materials only; and (3) MNPK, combined application of organic materials with chemical fertilizer application. Three soil health indexing (SHI) approaches, Comprehensive Assessment of Soil Health (SHI-CASH), linear (SHI-L) and sigmoidal (SHI-Sig) were evaluated. SHIs in the M and MNPK treatments were significantly higher than those in the NPK treatment across assessment approaches and were positively correlated with maize yield. A minimum data set including subsurface hardness, wet aggregate stability, available K, available Fe, soil organic carbon and soil protein was established using best subset regression. The soil health indices of smallholders' farmlands using CASH and MDS were 0.58 (0.42–0.73) and 0.63 (0.40–0.87), respectively. More than 60% smallholders' fields was at middle or low level. The relationship between SHI-CASH and SHI-MDS (Sig) was better than those for the CASH and linear methods. Our results demonstrate that an MDS based on best subset regression is applicable for evaluating soil health in wheat-maize rotation systems in the NCP. Soil health assessment in smallholders' farmland indicates that soil health constraints are related to soil and biomass management, which provides insights on pathways towards addressing soil health gaps.

1. Introduction

Soil health has been defined as "the capacity of soil to function as a vital living system, within 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 et al., 1996). A healthy soil provides numerous ecosystem services in addition to maintaining crop productivity. Interpretation of soil health status is challenging as soils vary greatly as a result of inherent factors such as climate, parent material, biology, topography, time, and anthropogenic management (Karlen et al., 2003). Accordingly, soils vary greatly across different soil types, climates, and regions (Fine et al., 2017), as well as cropping systems (Amsili et al., 2021; Li et al., 2022). Hence, developing context-specific soil health indicators is valuable.

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Several approaches have been used to semi-quantitatively or quantitatively assess soil health, each having its strengths and weaknesses. The semi-quantitative methods included the visual soil evaluation (Emmet-Booth et al., 2016) and soil indicator assessment (Lilburne et al., 2004). Notable quantitative approaches include the soil quality index method (Doran et al., 1996), soil quality card design and field test kit (Ditzler and Tugel, 2002), soil management assessment framework (Andrews et al., 2004), and the Comprehensive Assessment of Soil Health (CASH) (Moebius-Clune et al., 2016). Among these approaches, CASH aims to identify specific biological, physical, and chemical soil constraints in order to guide management (Moebius-Clune et al., 2016). The framework has been widely adapted to assess soil health in different regions under various management practices and in different cropping systems, such as mapping soil health of agriculturally important areas in Israel (Svoray et al., 2015), tillage and crop rotation in Canada (Congreves et al., 2015), long-term agronomic management trials in different physiographic regions (mountain, piedmont and coastal plain) in North Carolina, USA (van Es and Karlen, 2019), coffee farms in Colombia (Rekik et al., 2018), landscape positions (upland, midland and lowland) in India (Frost et al., 2019), and diverse soil textures and cropping system (Amsili et al., 2021) in the USA. The CASH framework currently uses texture-based scoring functions to interpret measured indicator values, but it will be adapted using the Soil Health Assessment Protocol and Evaluation (SHAPE) interpretation framework that accounts for texture, suborder classes, and mean annual temperature and precipitation in the continental US (Nunes et al., 2021). Furthermore, the CASH framework is currently developing scoring functions and soil health goals for production environments (region × texture × cropping system) in New York State, USA (Amsili et al., 2022). Few soil health studies have been carried out in cereal cropping systems in the North China Plain (NCP), where serious soil constrains, such as decline of soil organic matter, soil compaction, sealing and salinization, have been widely reported (Kopittke et al., 2019). Given that global food demand is increasing rapidly (Godfray et al., 2010; Tilman et al., 2011), identifying the constraining factors and developing sustainable management in areas with intensive food production are important for maintaining food security.

The selection of indicators is the first step for soil health assessment. The indicators should be relevant to soil functioning, sensitive to management, and inexpensive to measure (Lehmann et al., 2020). As such, more indicators increase the expected collinearity (Bünemann et al., 2018), and the measurement of diverse indicators may become cost prohibitive, especially at the regional or national scale. A minimum data set (MDS) of soil health generally involves identifying between 6 and 8 attributes based on expert opinions and multivariate analysis e.g. principal component analysis, redundancy analysis, discriminant analysis, and best subsets regression (Bünemann et al., 2018; Maurya et al., 2020). For example, the MDS for wheat and maize cropping systems in Mexico included time-to-ponding, aggregate stability, permanent wilting point, topsoil penetration resistance, and soil nutrients (Govaerts et al., 2006). Five indicators (organic matter, alkali-hydrolysable nitrogen, the ratio of microbial biomass nitrogen to total nitrogen and available zinc) were selected from 26 soil attributes in a smallholder-dominated agricultural system in the NCP (Li et al., 2019). In another study soil organic carbon, available zinc, fungal species richness, carbon pool activity, total chromium content and acid phosphatase activity were chosen from 37 soil attributes to evaluate soil health in the NCP (Li et al., 2022). A common feature of all these studies is that the MDSs include SOC, which is widely regarded as a keystone soil health indicator (Nunes et al., 2021). Here we aimed to establish the MDS based on the indicators of CASH for the wheat-maize rotation systems.

After the establishment of the MDS, each soil health indicator needs to be interpreted using a scoring approach (Andrews et al., 2004). The linear, non-linear (e.g. sigmoidal) and threshold value scoring function methods are widely used to interpret soil health indicators (Andrews et al., 2004; Askari and Holden, 2015; Jia et al., 2022; Li et al., 2019; Li et al., 2022; Raiesi, 2017). The linear and sigmoidal scoring function methods were used for vegetable production systems (Andrews et al., 2002), agricultural management systems (Askari and Holden, 2015) and cropping systems (Li et al., 2022). The threshold value scoring function methods were used to assess soil health in wheat-maize cropping system (Li et al., 2019) and orange production systems (Cheng et al., 2016). However, threshold values for many biological and physical indicators are difficult to be defined or depend on edaphic factors, which may cause problems for using threshold value scoring methods. The linear and non-linear scoring function methods overcome the disadvantages. The CASH belongs to the non-linear method, and have widely been be used to evaluate soil heath (Amsili et al., 2021; Fine et al., 2017; Rekik et al., 2018). Here we compared the three methods to calculate soil health across different fertilization regimes in NCP.

This study was conducted in the winter wheat-summer maize rotation system in the NCP. The winter wheat-summer maize is the predominant cropping system in the NCP and that contributes to approximately 50% and 33% of national wheat and maize productions, respectively (Wang et al., 2012), which plays a critical role in ensuring food security in China. Excessive application of chemical fertilizers (662 N, 110 P and 103 K kg ha^{-1} $year^{-1}$) in this system has been documented (Ju et al., 2007). Poor agricultural management practices have led to excessive loss of topsoil through erosion, poor physical soil structure, soil acidification, excessive salt and nitrate accumulation (Ju et al., 2007; Guo et al., 2010). The average soil organic matter content at 0–20 cm is 15.2 (9.9–19.2) g kg^{-1} in the NCP (Han et al., 2017). Updated approaches (e.g. soil testing, substitution of chemical fertilizer with organic fertilizer, etc.) are now being recommended to improve nutrient use efficiency and soil health (Jiao et al., 2018). But the recommended approaches have low adoption rates by the smallholders (Bai et al., 2018), which may partially explain the low soil health outcomes (Li et al., 2019). Some studies have investigated soil conditions in the NCP (Li et al., 2019; Li et al., 2022), but few have applied comprehensive soil health tests based on biological, physical, and chemical indicators. The objectives of this research were to 1) assess the effects of fertilization regimes on the biological, physical, and chemical health of the soil; 2) quantify relationships between soil health and agronomic outcomes, 3) develop a minimum data set from the 14 indicators used in the CASH assessment; and 4) to validate this new MDS on nearby smallholders' fields.

2. Materials and methods

2.1. Location of the study area

The study site is located in Quzhou County (36.9°N, 115.0°E, 40 m a.s.l.), Hebei Province, NCP. The region was characterized as a warm temperate semi-humid continental monsoon climate, with a mean annual precipitation of 604 mm. More than 60% of the mean annual precipitation occurs between July and September. The mean annual temperature is 13.1 ℃, and the annual frost-free period averages 201 days. Winter wheat (*Triticum aestivum* L.) is planted in early October and harvested in June, followed by the summer maize (*Zea mays* L.).

2.2. Experimental design, soil sampling and measurement

This study included eight long-term experiments, that were established between 1993 and 2014. All were conducted as randomized blocks design with three or four replicates. The treatments, experimental design and fertilizer application rates of all the long-term experiments are detailed in Table S1. The long-term experiments were divided into three groups: (1) NPK, application of chemical fertilizers only; (2) M, organic materials only (e.g. cattle manure, compost or bio-compost, peat vermiculite etc.); and (3) MNPK, organic materials combined with chemical fertilizer. Across all experiments, the number of individual

NPK, M, and MNPK treatment plots were 97, 44, and 34, respectively.

In order to validate the usefulness of the MDS, soil samples were collected from 45 smallholders' fields in the nearby village of Wangzhuang. The average size of smallholders' farmland was 0.13 ha. Average chemical fertilizers application rates were 180 kg N ha^{-1} (108–320 kg ha^{-1}), 58 kg P_2O_5 ha^{-1} (30–135 kg ha^{-1}) and 47 kg K_2O ha^{-1} (30–113 kg ha^{-1}) for maize.

Soil samples of long-term experiments and smallholders' fields were collected from 0 to 20 cm soil depth at the time of maize harvest in October 2020. After removing crop residues on the soil surface, three core samples were collected per plot using an auger (5 cm diameter) and then thoroughly mixed to yield one composite sample. Soil samples were divided into two. One part was air-dried at room temperature and then passed through 2 mm sieve for soil properties analysis. The remaining soil was used to measure soil respiration. At harvest, maize ears were sampled from 6 to 18 m^2 areas in each treatment and grain was dried to determine the maize yield.

Measured physical soil health indicators included wet aggregate stability (AgStab), surface hardness (SurfHard) and subsurface harness (SubHard). Wet aggregate stability was determined using an aggregate analyzer (DM185, Information Technology Inc., Dimart, Shanghai, China) based on wet-sieving where the percentage of stable aggregates sized between 0.25 mm and 2 mm represented aggregate stability (Moebius et al., 2007). Surface (0–10 cm soil depth) and subsurface hardness (10–20 cm soil depth) were measured in the field using a penetrometer (Moebius-Clune et al., 2016).

For chemical indicators, soil pH was determined in a 1:2.5 ratio of soil in water. Available P (Olsen-P; extracted with 0.5 mol L^{-1} $NaHCO_3$) and K (extracted with 1 mol L^{-1} NH_4OAc) were assayed by the phosphomolybdate method and flame photometry, respectively. Exchangeable Mg was extracted with 1 mol L^{-1} NH_4OAc and measured by ICP-MS analyzer (7700x series, Agilent Technologies, Santa, Monica CA, USA). Available Fe, Mn and Zn were extracted with a DTPA solution and analyzed using an Inductively Coupled Plasma-Optical Emission Spectrometer (OPTIMA 3300 DV, Perkins Elmer, USA).

For biological indicators, soil organic content (SOC) and permanganate oxidizable carbon (POXC) were determined using $K_2Cr_2O_7$ oxidation-reduction titration method and $KMnO_4$ oxidation (Weil et al., 2003), respectively. Soil proteins were extracted using sodium citrate and measured by spectrophotometric plate reader (Wright, Upadhyaya, 1996). Soil respiration was determined using a gas chromatograph (7890 A; Agilent Technologies, Santa Clara, CA, USA) after the soil was incubated at a constant temperature (25 ℃) for 24 h.

2.3. Soil health scoring and calculating

The CASH protocol (Moebius-Clune et al., 2016), as well as linear and non-linear equations (Askari and Holden, 2015; Raiesi, 2017) were used to calculate unitless scores. For the CASH approach, the mean and standard deviation of each variable in our data set were used to calculate the scoring equation as a cumulative normal distribution (Fine et al., 2017):

$$p = f(x,\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{+\infty} e\frac{-(x-\mu)^2}{2\sigma^2}dx \quad (1)$$

where p is the probability (range 0–1), x the measured value (-∞ to +∞,), and μ and σ the mean and standard deviation of each indicator in the dataset, respectively. Three types of scoring functions were used: "more is better" (AgStab, AP, AK, Mg, Fe, Mn, Zn, SOC, POXC, soil protein and respiration); "less is better" (SurfHard and SubHard), and "optimum range" (soil pH). Regarding the "more is better" scoring functions, when soil nutrient concentrations (e.g. AP, AK, Mg, Fe, Mn, Zn) reached or surpassed the upper thresholds, the scores were set to 1. The upper threshold of AP, AK, Mg, Fe, Mn, and Zn were 25, 120, 60, 15, 20, and 4.7 mg kg^{-1}, respectively (Liu et al., 2017; National Agricultural Technical Extension and Service Center, 2015).

For the linear and non-linear scoring function methods, each soil health indicator was normalized into scores ranging from 0–1 (Andrews et al., 2004; Askari and Holden, 2015; Raiesi, 2017). For linear scoring, the indicators belonging to the "more is better" and "less is better" scoring functions were calculated using the algorithms of Eqs. (2) and (3), respectively. For the indicators having "optimum range", Eq. (2) was applied to calculate scores when values were below the optimum range, and Eq. (3) was applied to calculate scores when the values were above the optimum range.

$$S_L = x/x_{max} \quad (2)$$

$$S_L = x_{min}/x \quad (3)$$

where S_L is the linear score of the soil indicators, x is the measured values of soil health indicator, x_{max} and x_{min} are the maximum and minimum values (Askari and Holden, 2015; Raiesi, 2017).

Another scoring approach, a sigmoidal function was applied:

$$S_{Sig} = \frac{a}{1+(x/x_\mu)^b} \quad (4)$$

where S_{Sig} is the non-linear score of the soil indicator between 0 and 1; a is the maximum score reached by the function, which is equal to 1 in this study; x_μ is the mean value of each soil indicator for the whole dataset; and b is the slope which is set to − 2.5 for the scoring function of "more is better" and 2.5 for the scoring function of "less is better" (Askari and Holden, 2015; Raiesi, 2017).

After transformation, the indicator scores were integrated into a composite soil health index (SHI) using equal weighted addition:

$$SHI = \sum_{i=1}^{n} S_i \Big/ n \quad (5)$$

Where S_i is the indicator scores of CASH, linear, or sigmoidal, and n is the number of soil indicators integrated in the SHI.

2.4. Best subsets regression and statistical analyses

Best subsets regression (BSR) was used to evaluate whether overall soil health index could be predicted with a smaller set of indicators and to determine which indicator(s) are highly predictive. This was to tailor a number of soil health indicators from 14 soil attributes (Fine et al., 2017; Rekik et al., 2018). Three important metrics of adjusted R^2, AIC (Akaike's information criteria) and BIC (Bayesian information criteria) were used to decide the best fitness of the models (Lindsey and Sheather, 2010). The higher the adjusted R^2, the better the model. In contrast, the lower the AIC and BIC metrics, the better the model. Best subsets regression was performed in R (version 4.0.5). The predictor variables were used to establish the minimum data set (MDS), which in turn was used to calculate the composite soil health index (Eq. 5).

Other statistical analyses were conducted using the IBM SPSS 25.0 for Windows. The normality and homogeneity of variances were checked using the Kolmogorov-Smirnov test, and variables were log-transformed, square root transformed or inversion-transformed when necessary. One-way analysis of variance (ANOVA) was performed to test the effects of different fertilization management on the 14 soil health indicators, overall SHIs, and maize yield. The Duncan's multiple range test was conducted for further significant difference at the $P < 0.05$ level. The F value and coefficient of variance (CV) were used to test the measurement reliability of three soil health assessment methods. Pearson correlation matrix among soil attributes and SHIs, and correlation between SHIs and maize yield were carried out in R (version 4.0.5). Regression analysis was used to describe the relationships between SHI-CASH and SHI-MDS.

Table 1
Descriptive statistics of measured soil properties in the long-term experiments.

	Soil attributes	Minimum	Maximum	Mean	StDev	CV (%)
Physical indicators	SurfHard (kPa)	82	1457	394	289	73.2
	SubHard (kPa)	181	2598	913	586	64.2
	AgStab (%)	4.20	48.8	19.2	9.76	50.8
Chemical indicators	pH	7.2	8.6	8.0	0.3	3.70
	AP (mg kg^{-1})	1.22	153	16.7	19.1	115
	AK (mg kg^{-1})	90.9	722	242	129	53.1
	Mg (mg kg^{-1})	293	671	458	83.5	18.2
	Fe (mg kg^{-1})	6.21	35.0	12.4	4.28	34.6
	Mn (mg kg^{-1})	7.21	18.5	12.1	2.19	18.1
	Zn (mg kg^{-1})	0.38	15.1	2.34	2.93	126
Biological indicators	SOC (g kg^{-1})	6.18	22.0	11.2	3.35	30.0
	POXC (mg kg^{-1})	246	739	403	100	24.8
	Protein (mg g^{-1})	1.06	5.46	2.47	0.90	36.4
	Resp. (mg CO_2-C kg^{-1} d^{-1})	7.89	30.2	16.1	4.25	26.4

Note: SurfHard, surface hardness; SubHard, subsurface hardness; AgStab, soil wet aggregate stability; AP, available P; AK, available K; SOC, soil organic carbon; POXC, permanganate oxidizable carbon; Resp, soil respiration; StDev, standard deviation; CV, coefficient of variation.

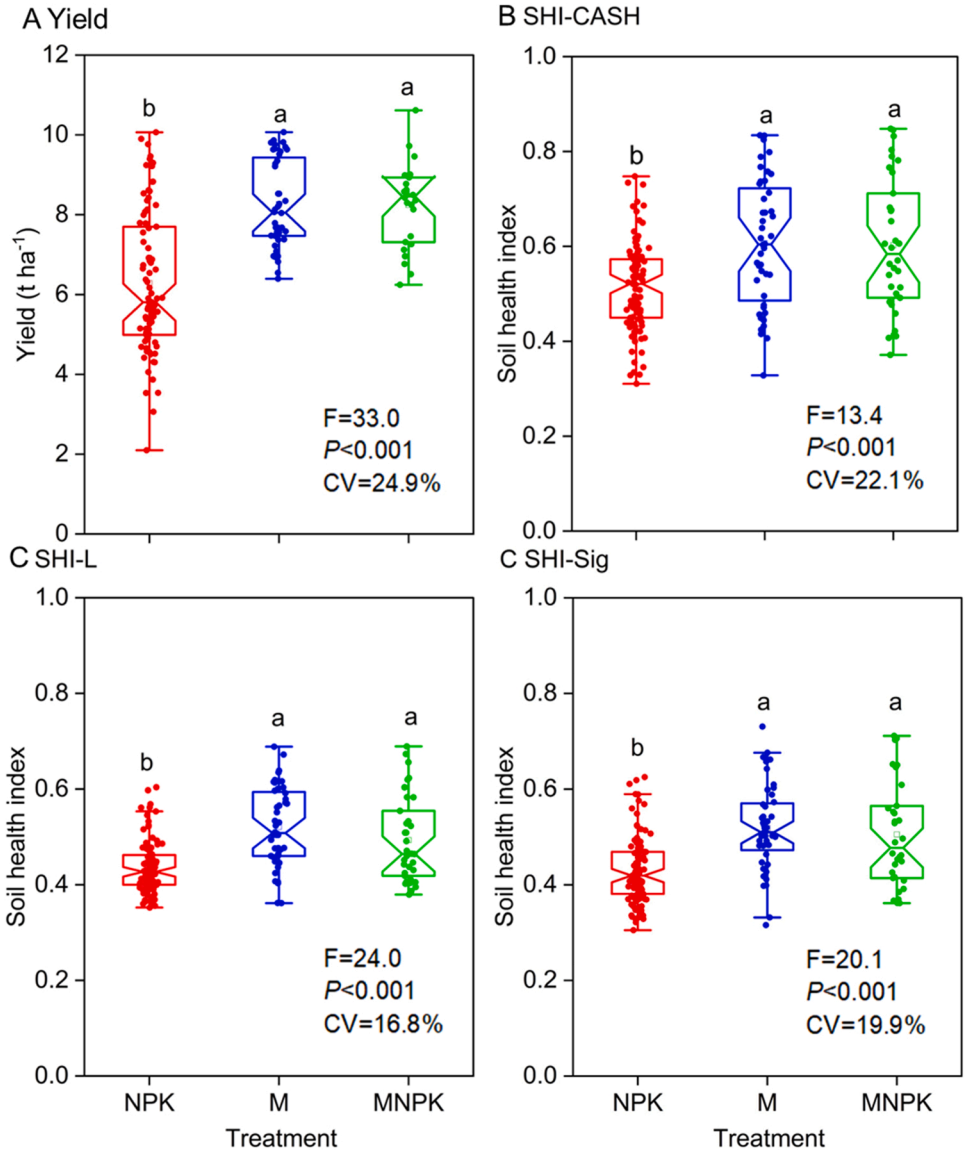

Fig. 1. Effect of different fertilization treatments on maize yields (A) and soil health indices (B, C and D) in the long-term experiments. Treatments: NPK, application of chemical fertilizers only; M, organic materials only; MNPK, organic materials combined with chemical fertilizer. The box boundaries indicate the upper and lower quartiles. The lower and upper quartiles are the 25th and 75th percentiles. The median (notch) is the middle. The whiskers indicate 1.5 times the interquartile range. Different lowercase letters indicate significant difference among different fertilization treatments at $P < 0.05$. The SHI-CASH, SHI-L and SHI-Sig indicate Comprehensive Assessment of Soil Health, linear and sigmoidal scoring function methods, respectively.

Table 2
Effect of different fertilization management practices on the physicochemical properties in the long-term experiments.

	Soil attributes	NPK	M	MNPK
Physical indicators	SurfHard (kPa)	289 ± 26.0c	594 ± 44.8a	437 ± 37.1b
	SubHard (kPa)	736 ± 51.7c	1235 ± 98.3a	1002 ± 88.3b
	AgStab (%)	17.3 ± 0.96b	20.3 ± 1.37ab	23.4 ± 1.73a
Chemical indicators	pH	8.1 ± 0.03a	7.9 ± 0.05b	7.9 ± 0.04b
	AP (mg kg^{-1})	11.5 ± 1.69b	28.5 ± 3.64a	16.2 ± 1.70b
	AK (mg kg^{-1})	218 ± 9.68b	268 ± 22.6ab	278 ± 28.5a
	Mg (mg kg^{-1})	426 ± 5.95b	541 ± 11.6a	442 ± 13.9b
	Fe (mg kg^{-1})	11.1 ± 0.31b	15.4 ± 0.91a	12.1 ± 0.39b
	Mn (mg kg^{-1})	12.4 ± 0.16a	11.2 ± 0.39b	12.2 ± 0.49a
	Zn (mg kg^{-1})	1.14 ± 0.17c	5.12 ± 0.62a	2.13 ± 0.14b
Biological indicators	SOC (g kg^{-1})	9.44 ± 0.19b	13.4 ± 0.50a	13.2 ± 0.64a
	POXC (g kg^{-1})	359 ± 7.36b	444 ± 15.2a	477 ± 17.8a
	Protein (mg g^{-1})	2.03 ± 0.07b	3.10 ± 0.14a	2.93 ± 0.11a
	Resp (mg CO_2-C kg^{-1} d^{-1})	16.3 ± 0.36a	15.8 ± 0.61a	15.7 ± 1.04a

Note: SurfHard, surface hardness; SubHard, subsurface hardness; AgStab, soil wet aggregate stability; AP, available P; AK, available K; SOC, soil organic carbon; POXC, permanganate oxidizable carbon; Resp, soil respiration. Treatments: NPK, application of chemical fertilizers only; M, organic materials only; MNPK, organic materials combined with chemical fertilizer.

Table 3
Results of best subsets regression using 14 soil health indicators across three scoring methods.

Methods	Number of predictors	Variables	R^2	R^2 (adj.)	AIC	BIC
SHI-CASH	1	SOC	0.68	0.67	-430	-932
	2	SOC, Resp	0.79	0.79	-505	-1007
	3	Fe, Mn, SOC	0.84	0.83	-546	-1049
	4	K, Fe, Mn, Protein	0.87	0.86	-579	-1083
	5	K, Fe, Mn, AgStab, Protein	0.89	0.88	-607	-1111
	6	K, Fe, Mn, AgStab, Protein, Resp	0.90	0.90	-632	-1137
SHI-L	1	SOC	0.74	0.74	-623	-1124
	2	AK, SOC	0.81	0.81	-677	-1178
	3	AK, Fe, SOC	0.87	0.87	-748	-1249
	4	AK, Fe, SOC, Resp	0.89	0.88	-764	-1266
	5	AK, Fe, Zn, SOC, Resp	0.90	0.90	-782	-1284
	6	AK, Fe, Zn, SubHard, AgStab, SOC	0.92	0.91	-812	-1314
SHI-Sig	1	SOC	0.65	0.65	-515	-1016
	2	AK, Fe	0.79	0.79	-602	-1103
	3	AK, Fe, SOC	0.84	0.84	-650	-1151
	4	AK, Fe, SubHard, SOC	0.87	0.86	-677	-1179
	5	AK, Fe, SubHard, AgStab, SOC	0.89	0.89	-711	-1211
	6	AK, Fe, SubHard, AgStab, SOC, Protein	0.90	0.90	-730	-1230

Note: SOC, soil organic carbon; POXC, permanganate oxidizable carbon; SubHard, subsurface hardness; AgStab, soil wet aggregate stability; AK, available K; Resp, soil respiration; AIC, Akaike's information criteria; BIC, Bayesian information criteria. The SHI-CASH, SHI-L and SHI-Sig indicate Comprehensive Assessment of Soil Health, linear and sigmoidal scoring function methods, respectively.

3. Results

3.1. Soil attributes and crop yields in response to different fertilization treatments

Descriptive statistics for the 175 soil samples are presented in Table 1. The range of SurfHard and SubHard were 82–1457 kPa and 181–2598 kPa, respectively. The values of AgStab ranged from 4.20% to 48.8% with an average value of 19.2%. For the chemical indicators, the range of soil pH, AP, AK and exchangeable Mg were 7.2–8.6, 1.22–153 mg kg^{-1}, 90.9–722 mg kg^{-1} and 293–671 mg kg^{-1}, respectively. Micronutrient concentrations of Fe, Mn, and Zn were 6.21–35.0 mg kg^{-1}, 7.21–18.5 mg kg^{-1} and 0.38–15.1 mg kg^{-1}, respectively. SOC, POXC, soil protein and respiration fell within the range of 6.18–22.0 g kg^{-1}, 246–739 mg kg^{-1}, 1.06–5.46 mg g^{-1} and 7.89–30.2 mg CO_2-C kg^{-1} d^{-1}, respectively.

The average maize yields in the NPK, M and MNPK treatment were 6.3 (rang 2.1–10.1), 8.3 (6.4–10.1) and 8.2 (6.2–10.6) t ha^{-1} respectively (Fig. 1A). Yields in the M and MNPK treatments were significantly higher than in the NPK treatment. No significant difference was observed between the M and MNPK treatments (Fig. 1A).

Soil pH values were significantly higher in the NPK treatment than in the M and MNPK treatments, and the latter two treatments were not significantly different (Table 2). The M treatment showed significantly

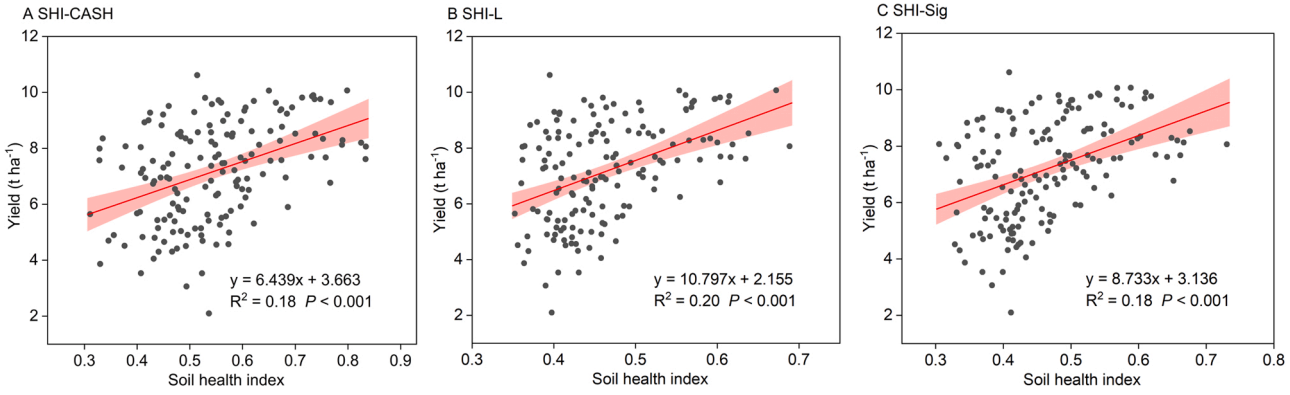

Fig. 2. Regression analysis between soil health indices and maize yields in the long-term experiments. The solid line represents the fitted ordinary least squares (OLS) linear regressions. The shaded area represents the 95% confidence. The SHI-CASH, SHI-L and SHI-Sig indicate Comprehensive Assessment of Soil Health, linear and sigmoidal scoring function methods, respectively.

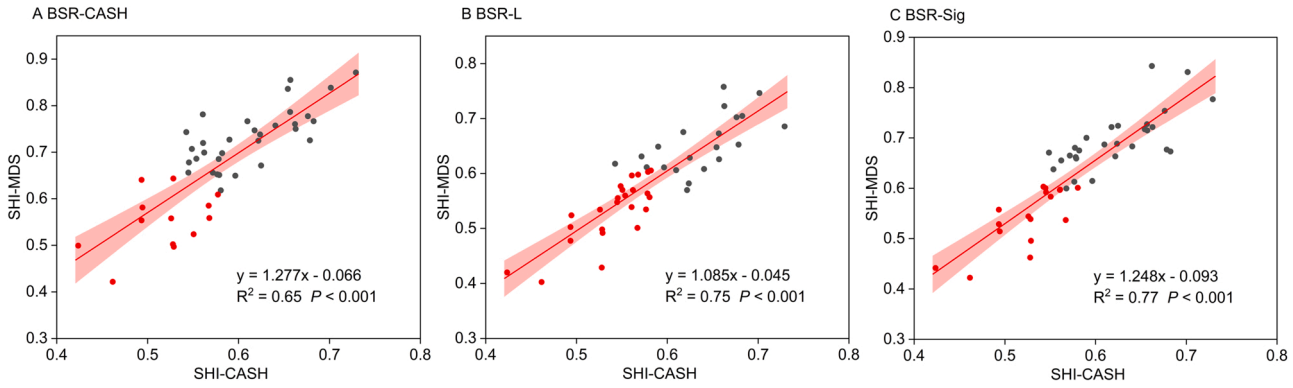

Fig. 3. Regression analysis between SHI-CASH and SHI-MDS in smallholders' fields. Solid line represents the fitted ordinary least squares (OLS) linear regressions. The shaded area represents the 95% confidence. The red dots indicate the SHI value below 0.60. The SHI-CASH, SHI-L and SHI-Sig indicate Comprehensive Assessment of Soil Health, linear and sigmoidal scoring function methods, respectively.

higher soil SurfHard, SubHard and Zn concentration than the NPK and MNPK treatments. AgStab and AK in the MNPK treatment were significantly higher than those in the NPK treatment (Table 2). AP, Mg and Fe concentrations in the M treatment were significantly higher than those in the NPK and MNPK treatments, while Mn concentration exhibited a reverse trend. SOC, POXC, and protein were significantly higher in in M and MNPK compared to NPK treatments. No significant difference in soil respiration was observed among NPK, M and MNPK treatments (Table 2).

3.2. SHI and relationship with maize yield

All composite soil health indices (SHI) were significantly affected by fertilization treatments. SHI values were significantly lower in the NPK treatment than in the M and MNPK treatments, while the latter two did not differ significantly (Fig. 1B, C and D). With respective to each experiment established in different years, SHI in the M or MNPK treatments was significantly higher than those in the NPK treatment (expect the experiment established in 1993) (Table S2). The SHI ratio of MNPK to NPK treatment increased from 1.1 (established in 2010) to 1.3 (established in 2000), indicating that there are potential accumulative effects of manure application on soil health.

The CV of SHI-CASH (CV = 22.1%) and SHI-Sig (CV = 19.9%) were higher than those of SHI-L (CV = 16.8%; Fig. 1B, C and D). All composite SHIs were significantly positively correlated with maize yield ($P < 0.001$) (Fig. 2). The linear-regression analysis indicated that all soil attributes (except Fe, Mn and Resp) were significantly correlated with maize yield. The highest R^2 was for protein (0.42), followed by SOC (0.38; Table S3).

3.3. Establishment and validation of MDS

The BSR analysis indicated that a combination of six indicators in all composite SHIs predicted more than 90% of the variability (Table 3). These included AgStab, AK, Fe, Mn, Protein and Resp using the CASH approach. The combination of SubHard, AgStab, AK, Fe, Zn and SOC using the linear approach, and the combination of SubHard, AgStab, AK, Fe, SOC and protein using the sigmoidal approach.

Soil survey from the smallholders was used to validate the applicability of the selected MDS (Table S4). The SubHard, AgStab, AK, Fe, SOC and Protein based on the sigmoidal approach were measured in smallholders' farmlands. The average values were 998 kPa, 20.0%, 207 mg kg^{-1}, 17.0 mg kg^{-1}, 10.5 g kg^{-1} and 2.93 mg g^{-1}, respectively (Table S4). The average composite soil health indices using the CASH and MDS were CASH and MDS were 0.58 (0.42–0.73) and 0.63 (0.40–0.87), respectively. More than 60% smallholders' fields (28 out of 45) were below 0.60 (Fig. 3). Significantly positive relationships were observed between SHI-CASH and SHI-MDS (Fig. 3). The R^2 values between SHI-CASH and SHI-MDS were 0.77 based on the BSR using the sigmoidal approach, which were slightly higher than the CASH (R^2 = 0.65) or the linear (R^2 = 0.75) approach. SubHard, AgStab, AK, Fe, SOC and Protein were selected as the MDS.

4. Discussion

4.1. Soil health in response to fertilization

In this study, we assessed soil health using the linear (L), sigmoidal (Sig) and CASH methods on long-term fertilization experiments conducted in the NCP (Askari and Holden, 2015; Fine et al., 2017; Raiesi, 2017). Among the three, the CASH approach appeared to be moderately sensitive to different fertilization managements, as shown by the higher CV values relative to those based on the SHI-L (Fig. 1B, C and D). Previously the CASH method has been applied to assess soil health in coffee farms, commercial potato crop rotations, cropping and landscape positions, and tillage management (Frost et al., 2019; Rekik et al., 2018; Van Eerd et al., 2014; Whittaker et al., 2023).

In alignment with previous studies (He et al., 2022; Liu et al., 2022), our results highlight the importance of organic fertilizers in improving soil health (Fig. 1B, C and D; Table S2), and exclusive application of NPK for fertility enhancement is not sufficient to improve soil health and thereby attain high yield (Figs. 1 and 2). Across these experiments, manure treatments mainly improved biological and chemical indicators, and to a lesser extent physical indicators (Table 2). The values of AP, AK, Mg, Fe and Zn concentrations in the M and MNPK treatments were increased by on average 94%, 25%, 15%, 24% and 218% compared to those in the NPK treatment (Table 2). A study carried out in Sichuan Basin, Southwest China also demonstrated that manure combined with chemical fertilizer significantly increased topsoil available phosphorus (43%) and potassium (40%) concentrations in a maize-wheat rotation system compared to NPK treatment (Luo et al., 2021). Manure application but not NPK treatment had positive effects on micro-nutrient concentrations (Table 2).

For soil biological attributes, SOC, POXC and protein in the M and MNPK treatments were on average 41%, 28% and 49% higher, respectively, compared to those in the NPK treatment (Table 2), consistent with another long-term experiment on the NCP where soil carbon content and active carbon were increased by average 26% and 31%, compared to NPK treatment, respectively (Liang et al., 2012; Sun et al., 2021). The higher SOC, POXC, and protein concentration may be associated with greater microbial biomass, enhanced nutrient availability, and improved soil aggregation (Jia et al., 2022). This may explain the positive yield effects in the M and MNPK treatments (Fig. 1 A), which the regression analysis further confirmed as maize yields were

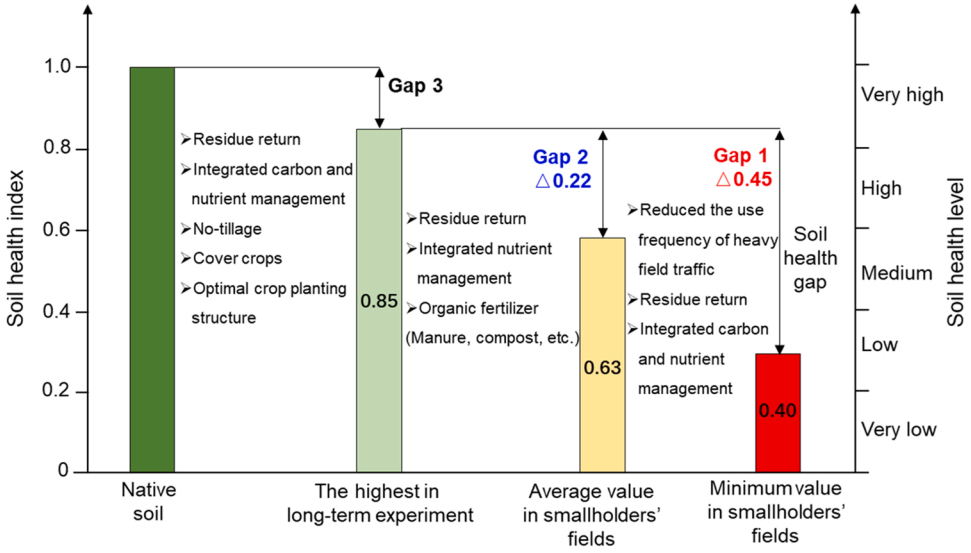

Fig. 4. Conceptional model to show effective management practices to close the soil health gap. The red, orange, light green and dark green columns indicate the minimum value of soil health index in smallholders' fields, the average value in smallholders' fields, the highest in the long-term experiment and the value in the undisturbed native soils. The values within the column indicated soil health index in different scenarios. The delta values are the soil health gaps between different management practices.

significantly correlated with SOC, POXC and protein (Table S3).

Notably there is a temporal accumulative effect on SHI with increasing years of organic fertilizer application. The SHI ratio of MNPK and NPK treatments increased from 1.1 (established in 2010) to 1.3 (established in 2000), primarily due to higher values for SOC, nutrient concentrations and water-stable aggregation (Table 2). The meta-analysis also showed that SOC, AP, AK and water-stable aggregation significantly increased with the experimental duration (Luo et al., 2018; Du et al., 2020). Hence, proper application of organic fertilizers should be a long-term investment to improve soil health.

4.2. Selection of MDS

Assessing multiple soil health indicators requires a balance between cost and relevancy to soil health, sensitivity, practicality, and being informative for management (Bünemann et al., 2018; Lehmann et al., 2020; Rinot et al., 2019). Reducing the suite of indicators to the most informative set can increase cost efficiency, but can also limit general applicability when it is based on a limited range of production environments (cropping systems, climate soil types). Based on the BSR using CASH, the linear or sigmoidal methods, three (AK, Fe, and AgStab) out of six soil health indicators were all selected (Table 3), indicating that these indicators are important for soil health in the cropping system. However, the discrepancy in other three indicators also implies that the selection of indicator is method dependent. It is therefore recommended to explore different approaches to choose the better ones. In the present study, the regression between SHI-CASH and SHI-MDS based on sigmoidal approach had a higher coefficient compared to CASH or sigmoidal methods (Fig. 3). In fact, six soil indicators of SubHard, AgStab, AK, Fe, SOC and Protein were selected for the MDS, contribute more than 90% of the total variability (Table 3). The selected indicators represent soil physical, chemical and biological attributes and had middle or high variation (Table 1), indicating that they are sensitive to soil and crop management. Another study of wheat and maize cropping systems in Mexico determined physicochemical indicators in an MDS to include time-to-ponding, aggregate stability, permanent wilting point, topsoil penetration resistance, soil C, N, K and Zn concentrations (Govaerts et al., 2006). Biochemical indicators including SOC, AP, microbial biomass and diversity were used to evaluate soil health in the NCP (Jia et al., 2022; Li et al., 2022). Other studies identified AP and pH or AK/Mn, SOC, POXC, Resp or Protein in coffee and rice-based systems (Frost et al., 2019; Rekik et al., 2018). A common feature in previous (Frost et al., 2019; Rekik et al., 2018) and our study is that the biological indicators (i.e., SOC, POXC, Resp or protein) are generally selected for the MDS. This implies that optimum MDSs may be specific to a special context, but also always include soil biological indicators which highlights their importance in soil health assessment. In this study the physical indicator of SubHard and AgStab are also included. This may be related to the large variations, e.g. 64.2% for SubHard and 50.8% for AgStab, respectively (Table 1).

4.3. Applicability of soil health assessment in smallholders' fields

Smallholders are the main force for grain production in the NCP, and are characterized by large variations in yield and management (Lu and Fan, 2013; Wang et al., 2023). Maize yield and nitrogen input are generally within the range of 8.2–11.4 t ha^{-1} and 181–300 kg ha^{-1}, respectively (Ren et al., 2021). A survey showed that organic nutrient application averages 2.25 t ha^{-1} (CV=122%), and the agrochemical inputs were 120 USD ha^{-1} (CV=50%) in the wheat-maize rotation system (Li et al., 2021). In our study, soil health using the SHI-MDS and SHI-CASH approach were significantly positively correlated for smallholders' fields, indicating that the MDS may be a suitable method for soil health assessment (Fig. 3).

The average composite SHI in smallholders' fields was 0.63 (0.40–0.87) based on the MDS, which falls within the high rang according to the criterion of the CASH framework (Moebius-Clune et al., 2016). However, average 40% of SHI-MDS scores were at middle or low level. Previous studies in smallholder' fields also had the similar results, and the reported average composite SHI was 0.47 (0.12–0.96) (Li et al., 2019). The gap between minimum (0.40) and average SHI (0.63) in smallholders' fields is mainly due to low scores of the SubHard and AgStab, which may be caused by soil compaction due to heavy field traffic. In order to close the soil health gap between minimum and average values, residue return, reduced the use frequency of heavy field traffic and integrated carbon and nutrient management are recommended to close the soil health gap in smallholders' farms (Fig. 4). The soil health gap between smallholders' fields and the long-term experiment field (M and MNPK treatments) are mainly attributable to agronomic (land preparation, fertilizer application rate and frequency, planting density, variety, etc.), infrastructural, and socioeconomic factors (Zhang et al., 2016). Nutrient and carbon management was one of the important agronomic practices to affect soil health level. Compared to the M and MNPK treatments in the experiments, SOC and POXC in smallholders' fields were generally lower, but the chemical and physical attributes were higher or similar (Table 2 and S3). The continuous utilization of chemical fertilizers appears responsible for the decline of SOC, low soil microbial activities and increase in soil hardness (Pahalvi

et al., 2021). Also, smallholders generally apply less organic inputs. According to our survey more than 90% famers did not apply any organic materials except returning residues of maize stover and wheat straw, despite of the importance for improving soil health (He et al., 2022; Jia et al., 2022; Liu et al., 2022). Therefore, closing the soil health gap between smallholders' farms and the highest SHI value in the long-term experiment, straw residue return, and integrated carbon and nutrient management are suggested (Fig. 4). Third, the adoption of nutrient management technology is also an important factor affecting soil health (Zhang et al., 2016). Although there exists a little SHI gap between the highest values in the long-term experiments vs the native soils (Fig. 4), 41% fields in the M and MNPK treatments are at middle level. Some effective management practices (residue return, integrated carbon and nutrient management, cover crops, no-tillage etc.), and diversified crop planting are proposed to address the soil health gap and improve soil productivity (Fig. 4).

5. Conclusions

The CASH scoring method was more sensitive than the linear and sigmoidal approaches under different nutrient management regimes involving organic and synthetic fertilizers. Soil health under the treatments involving manure application, M and MNPK, were significantly higher than that the NPK treatment. Soil health indices also had a significantly positive correlation with maize yield. Six soil attributes including subsurface hardness, wet aggregate stability, available K, available Fe, soil organic carbon and soil protein were selected as a minimum set of indicators for soil health evaluation for wheat-maize rotation systems in the NCP. On the smallholders' farms, composite soil health indices based on SHI-CASH and SHI-MDS had significant positive relationships. Our results indicate that MDS is applicable to evaluate soil health in the agricultural production. Soil health assessment in smallholders' farms also provided insights on pathways towards addressing soil health gaps, including improved biomass cycling and reduced soil disturbance.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

Data will be made available on request.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.agee.2023.108558.

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