Spatial and Temporal Variability of Soil Health Scores and their Relationship to Crop Yield

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A paper from the Proceedings of the

17th International Conference on Precision Agriculture and 11th Brazilian Congress on Precision and Digital Agriculture

13-15 July 2026

Porto Alegre, Brazil

Abstract.

Soil health is the continued capacity of the soil to function as a vital living ecosystem that sustains plants, animals, and humans. To assess and evaluate soil health, the Comprehensive Assessment of Soil Health (CASH) was established. In CASH, different soil health indicators are used to assign a score. These indicators are soil properties that can vary spatially and temporally. In this study, soil health scores were determined across a landscape to evaluate their spatial and temporal variability and then used to evaluate the relationship between the scores and crop yield. The study evaluated physical, chemical, and biological soil properties, which were scored based on the CASH scoring system. Soil samples were collected throughout five seasons from twenty-four different blocks for various indicators. Based on the results, it showed that soil health scores varied through space and time. The effect of the block was significant on soil health scores ($p = 0.001$). This significant effect of space can be due to varying soil properties in the field, such as soil texture. Throughout the seasons, the scores were relatively different within blocks. The analysis also showed that block and season interactions were significant ($p < .001$) suggesting that differences among blocks were not consistent across all sampling seasons but instead emerged under specific seasonal conditions. Linear regression models were used to examine the relationship between soil health score and yield. Although the relationship between soil health score and wheat yield during the summer season was statistically significant ($p = 0.05$), the model explained only a small portion of the yield variability ($R^2 = 0.16$), indicating that factors other than soil health influenced yield outcomes. Multiple linear regression analysis revealed that extractable potassium and organic matter had the strongest positive standardized effect on yield, whereas soil respiration and extractable phosphorus were negatively associated with yield. This result indicates that nutrient availability and carbon content are critical contributors to crop productivity, however the scoring for these parameters may not translate the actual condition of the soil and its ability to provide nutrient to the crop.

Keywords.

Soil Health, Indicators, Scoring, Soil Properties, Productivity, Spatiotemporal

Rationale

Soil, a dynamic and living system, is the foundation of life on Earth. It serves as a medium for plant growth, regulates water supply, acts as nature's recycling system, and provides habitat for diverse flora and fauna. Soil influences the atmosphere's composition and physical condition through carbon (C) sequestration and is crucial as an engineering medium (Weil & Brady, 2016). This ability of the soil to function and provide ecosystem services is what we refer to as soil health (Van Es & Karlen, 2019). Healthy soil should be able to support food and fiber production at a quality and quantity that is enough for human needs, while it continues to deliver its ecosystem services, which are important to maintain the quality of human life and biodiversity conservation (Kibblewhite et al., 2008). The US Department of Agriculture – Natural Resources Conservation Service (USDA-NRCS) defines soil health as "the continued capacity of soil to function as a vital living ecosystem that sustains plants, animals, and humans" (NRCS, 2024). The concept of soil health is often used interchangeably with soil quality and is a dynamic and evolving field of study. The terminology, operationalization, and understanding of soil health are continuously developing (Lehmann et al., 2020) and different measurements and assessments of physical, chemical, and biological soil properties are being developed to evaluate soil health.

One of the ways to assess the health of the soil is the Comprehensive Assessment of Soil Health (CASH). It was designed to be a practical, standardized, diagnostic tool to make assessments scientific and useful for on-farm decision-making (Karlen et al., 2019; Moebius-Clune, 2016). Within CASH, indicators are screened based on three criteria: (1) their ability to indicate change in soil function, (2) ease of sampling and measurement, and their accessibility and interpretability to general users, and (3) their applicability to field conditions and sensitivity to climate and management variations (Guo, 2021). Thus, the different indicators that are used in CASH include physical, chemical, and biological properties that capture the multifaceted nature of the soil ecosystems and the services that soil can provide (Lehmann et al., 2020). After the analysis of the different indicators, their influence on soil health is interpreted using a scoring system which follows "more is better" for most physical and biological indicators and except for penetration resistance, which follows "less is better". For scoring chemical properties, the optimal function was used, which assigns the highest soil health score when the measured value falls within a defined optimum range, acknowledging that both insufficient and excessive levels can impair soil function. The average of these sub-scores is then calculated for the overall soil health score (Fine et al., 2017; Moebius-Clune, 2016). The advancement of CASH shows that a soil health assessment should be scientifically comprehensive, accessible and useful in its output (Idowu et al., 2008).

Considering that soil health scores are based on soil properties that vary spatially in the field including texture, bulk density, porosity, and water holding capacity (Yang et al., 2020), there stands to reason that differences in soil health scores may also vary within the field. In addition to spatial factors, temporal factors including the type of cultivated crop, inter-annual changes driven by crop growth stages and the changing demand for plant nutrients, dynamic soil properties, and seasonal environmental changes (Hoosbeek, 1998; Wolna-Maruwka et al., 2023) may also affect soil health scores. These factors affect soil health scores since they reflect the nutrient status of the soil and the activity, population, and communities of microorganisms, which affect the soil's capacity to perform ecological functions (Yang et al., 2020).

The variability of different soil properties that could affect soil health scores may also affect crop yield, since they reflect the availability and retention of nutrients and water and root penetration, which are vital for crop growth (Yang et al., 2020). For instance, areas with finer soil texture retain more water, which supports more stable crop yields (Fowler et al., 2024). Temporal factors such as seasonal changes in temperature and precipitation affect cycling and the availability of nutrients. High amounts of rainfall can cause the leaching of nutrients, and drought conditions can restrict water and nutrient uptake, which can negatively impact crop yield (Chen et al., 2011).

Understanding the significance of soil health and its assessment is important in quantifying the capacity of the soil for retaining and cycling of nutrients to support plant growth, C sequestration, facilitating water movement, suppressing pest, disease and weeds, waste management, and supporting the production of food, feed, fiber, and fuel (Moebius-Clune, 2016). However, there are still gaps in understanding the effect of temporal and spatial variability on soil health and how this variability within a field is related to crop yield. Exploring these complex interactions is essential to identify knowledge gaps and create more effective soil and crop management strategies that enhance agricultural productivity and sustainability.

Materials and Methods

Study Location and Experimental Design:

A field study was conducted to investigate the spatial and temporal variation in soil health scores using the CASH method and how it is related to crop yield. The study was conducted over one year with seasonal sampling periods – Summer 2024, Fall 2024, Winter 2025, Spring 2025 and Summer 2025 – and was located at the Oklahoma State University Lake Carl Blackwell Agronomy Research Station in Stillwater, Oklahoma, USA. The study was established in the fall of 2023 with crop rotation as the main plot factor. The crops used in this study were wheat and sorghum and was set up so that each phase of the rotation (wheat or sorghum) would be present in each year. A total of 24 blocks were established in the field, with each block measuring 21.34 by 36.58 meters (70 x 120 feet), for a total experimental area, including the alleys between main plots, of 3.44 hectares or 8.5 acres. The experimental design of the study was a repeated-measures split-plot design, with the block as the whole plot factor and the season for collecting the sample as a sub-plot factor. Two sampling plots per block were considered as replication in this study.

Soil Sampling and Analysis:

Soil samples were collected five times during the study period and analyzed for various chemical, physical, and biological properties. At each sampling event, composite soil samples of 10 to 15, 1.9-cm cores were collected at a depth of 15.24 cm from the same two plots of the 24-block study, for a total of 48 samples. The soil samples were oven-dried at 65°C for two to three days and ground to pass a 2-mm sieve using a rotary flail grinding machine prior to analyses.

Physical, chemical, and biological soil properties were measured to determine a soil health score. The soil properties used in this study are included in the soil health indicators listed in CASH (Table 1), except active carbon, autoclaved citrate extractable (ACE) protein and minor elements.

Table 1. Soil health indicators included in the Cornell Soil Health Test and Comprehensive Assessment of Soil Health and associated processes (Idowu et al., 2008; Moebius-Clune, 2016).

Soil Indicator	Soil Functional Process
Physical	
Soil texture	All
Aggregate stability	Aeration, infiltration, shallow rooting, and crusting.
Available water capacity	Plant-available water retention
Soil strength (penetration resistance)	Rooting
Biological	
Organic matter content	Energy/C storage, water, and nutrient retention
Active carbon content	Organic material to support biological functions
Soil Respiration	Metabolic activity of the soil microbial community
Autoclaved Citrate Extractable Protein Assay	Represents the large pool of organically bound nitrogen in the soil organic matter.
Chemical	
pH	Toxicity, nutrient availability
Extractable phosphorous	Phosphorus availability, environmental loss potential
Extractable potassium	Potassium availability
Minor element contents	Micronutrient availability, elemental imbalances, and toxicity.

Soil physical properties determined were soil texture, available water capacity (AWC), penetration resistance, and wet aggregate stability (WAS). Particle size analysis was done using the hydrometer method in a soil suspension of 40 g oven-dried soil in a 1-L mixture of 100 ml Na-hexametaphosphate ($NA_6(PO3)_6$) solution and deionized water. To determine the AWC of the soil samples, the water content at field capacity and permanent wilting point were determined in the laboratory and their difference was calculated. To establish the permanent wilting point, soil samples were placed on ceramic plates with known porosity and were moistened to saturation. The ceramic plates were then placed into a high-pressure chamber with -1500 kPa pressure to extract moisture at the permanent wilting point. Then the field capacity of the soil was determined by placing an undisturbed soil core sample in a kaolin box with saturated kaolin clay layer connected to a reservoir to impose a constant matric potential at -10kPa. Water was drawn from the core samples until they maintain a constant weight. The soil water content at each pressure (-1500 kPa and -10kPa) was determined, and the available water capacity was then calculated as the soil water loss between the field capacity and the permanent wilting point (Moebius-Clune, 2016). Penetration resistance at 0 to 15-cm and 15 to 45-cm depths was measured in the field using a tractor-drawn Veris Tech P4000 developed by Veris Technologies, Inc. (Kansas, USA). Wet aggregate stability was determined using Yoder (1936) wet-sieving method, modified by Kemper & Rosenau (1986) using the wet-sieving apparatus developed by Eijkelkamp Agrisearch Equipment (the Netherlands). connected to a reservoir to impose a constant matric potential at -10kPa. Water was drawn from the core samples until they maintain a constant weight. The soil water content at each pressure (-1500 kPa and -10kPa) was determined, and the available water capacity was then calculated as the soil water loss between the field capacity and the permanent wilting point (Moebius-Clune, 2016). Penetration resistance at 0 to 15-cm and 15 to 45-cm depths was measured in the field using a tractor-drawn Veris Tech P4000 developed by Veris Technologies, Inc. (Kansas, USA). Wet aggregate stability was determined using Yoder (1936) wet-sieving method, modified by Kemper & Rosenau (1986) using the wet-sieving apparatus developed by Eijkelkamp Agrisearch Equipment (the Netherlands).

Chemical properties determined were soil pH, electrical conductivity (EC), and extractable P and K. Soil pH was measured by suspending one part of the soil in two parts of water (1:1) and determined using a pH electrode probe (Sikora & Moore, 2014). Electrical conductivity (EC) was measured in the field using a tractor-drawn Veris Technologies Soil EC Surveyor 3D developed by Veris Technologies, Inc. (Kansas, USA). Extractable P and K were extracted using Mehlich 3 solution (Mehlich, 1984) and were quantified using an ICP spectrometer. After quantification, Mehlich-3 extractable P and K (ppm) were converted to their Modified Morgan-equivalent values (ppm) to align into the scoring system of CASH. The equation used was adopted from Ketterings et al., 2002.

$$Morgan\ Soil\ Test\ P\ (ppm) = -55.53 + (1.366\ \times Mehlich\ 3\ P) - (0.001284\ \times Mehlich\ Ca) + (21.78\ \times pH) + (0.00005626\ \times Mehlich\ 3\ \ P\ \times Mehlich\ 3\ Ca) - (0.5244\ \times Mehlich\ 3\ P\ \times pH) - (2.028\ \times pH) + (0.0490\ \times Mehlich\ 3\ P\ \times\ pH^2) \quad (1)$$

$$Morgan\ Soil\ Test\ K\ (ppm) = (1.1\ \times Mehlich\ 3\ K) - 24 \quad (2)$$

$$Modified\ Morgan\ Soil\ Test\ P\ (ppm) = \frac{Morgan\ P}{0.90} \quad (3)$$

For K, the Morgan and Modified Morgan tests give nearly identical results, so no further conversions were needed.

Biological properties determined were soil organic matter and soil respiration. Total C was determined by using the LECO Truspec CN dry combustion analyzer LECO CN628 (LECO Inc., St. Joseph, MI, USA) and soil organic matter was calculated using the value of total C multiplied by 1.74 (Minasny et al., 2020). Soil respiration was measured by the CO_2 burst method adopted from McGowen et al., 2018.

Climatic Data:

Average daily precipitation (mm day^{-1}) and air temperature (℃) were obtained from the Oklahoma Mesonet Lake Carl Blackwell Station, which was located 0.32 km away from the study area. From the daily measurements, cumulative precipitation, average seasonal precipitation, number of rain days (daily precipitation (P) ≥ 1 mm), maximum 1-day precipitation, longest dry spell (consecutive days with P < 1 mm), and the number of wet spells (≥3 consecutive rain days) were summarized for each season (Table 2).

Table 2. Seasonal precipitation and temperature summary across five study seasons

Season	Days	ΣP (mm)	Average P (mm)	Rain days (≥1 mm)	Max 1-day P (mm)	Longest dry spell (d)	Wet-spell count	Mean T (°C)	Tmin min (°C)	Tmax max (°C)
Summer 2024	92	197	2.14	15	61	16	0	26.8	19.7	31.6
Fall 2024	91	294	3.23	11	79.5	36	1	17.4	1.28	29.8
Winter 2025	90	57.4	0.64	11	19.3	22	0	2.7	-14	14.5
Spring 2025	92	364	3.96	24	47.2	24	3	16.1	5.21	25.7
Summer 2025	112	507	4.53	25	69.6	29	2	25.5	17.4	31.3

Metrics include: seasonal total precipitation (ΣP), mean seasonal precipitation (mm) number of rain days (P ≥1 mm), maximum 1-day precipitation (Max 1-day P), longest dry spell (consecutive days with P < 1mm), wet-spell count (runs of ≥ 3 rain day), and temperature statistics (mean, seasonal minimum and maximum of daily mean air temperature).

Temperature summaries included mean daily temperature and seasonal extremes. The same precipitation and temperature metrics were also computed over fixed antecedent windows (0 to 7, 8 to 14, and 15 to 30 days) for each sampling date to contextualize wet/dry and cool/warm conditions (Table 3).

Table 3. Antecedent precipitation and temperature preceding each soil sampling event

Season	Sample date	Window	ΣP (mm)	Rain days	Mean T (°C)
Summer 2024	July 17, 2024	0–7 d	0.25	0	28.20
Summer 2024	July 17, 2024	8–14 d	18.80	2	25.20
Summer 2024	July 17, 2024	15–30 d	3.05	1	30.80
Fall 2024	Nov. 25, 2024	0–7 d	24.90	1	9.85
Fall 2024	Nov. 25, 2024	8–14 d	10.70	2	13
Fall 2024	Nov. 25, 2024	15–30 d	231	6	15.20
Winter 2025	Feb. 6, 2025	0–7 d	1.78	1	7
Winter 2025	Feb. 6, 2025	8–14 d	2.54	1	1.50
Winter 2025	Feb. 6, 2025	15–30 d	7.37	2	−1.75
Spring 2025	March 31, 2025	0–7 d	7.87	1	16.60
Spring 2025	March 31, 2025	8–14 d	0	0	13.70
Spring 2025	March 31, 2025	15–30 d	33.50	1	11.20
Summer 2025	June 24, 2025	0–7 d	33	2	27.20
Summer 2025	June 24, 2025	8–14 d	91.70	2	23.60
Summer 2025	June 24, 2025	15–30 d	176	6	23.30

For each sample, totals and means are reported for fixed windows of 0 to 7, 8 to 14, and 15 to 30 days before the sampling date. Metrics include cumulative precipitation (ΣP), number of rain days (P ≥1 mm), and mean daily air temperature (Mean T).

Soil Health Scoring:

The scoring of the soil health indicators followed the CASH scoring system, by Fine et al. (2017). The unweighted mean of the individual scores of the indicators was determined to be the overall soil health score. Scores of each soil health indicator were illustrated using a five-color scale with a corresponding score range: red for very low (0 to 20), orange for low (20 to 40), yellow for medium (40 to 60), light green for high (60 to 80), and dark green for very high (80 to 100). Higher scores indicate better soil health conditions in most indicators.

The "more is better" function, where scores are higher with increasing measured values, was followed in most physical and biological indicators except for penetration resistance, where a "less is better" curve was used, and lower measured values were assigned a higher score. The scoring functions of physical and biological indicators, except penetration resistance, were dependent on the textural group of the soil (Fig. 1).

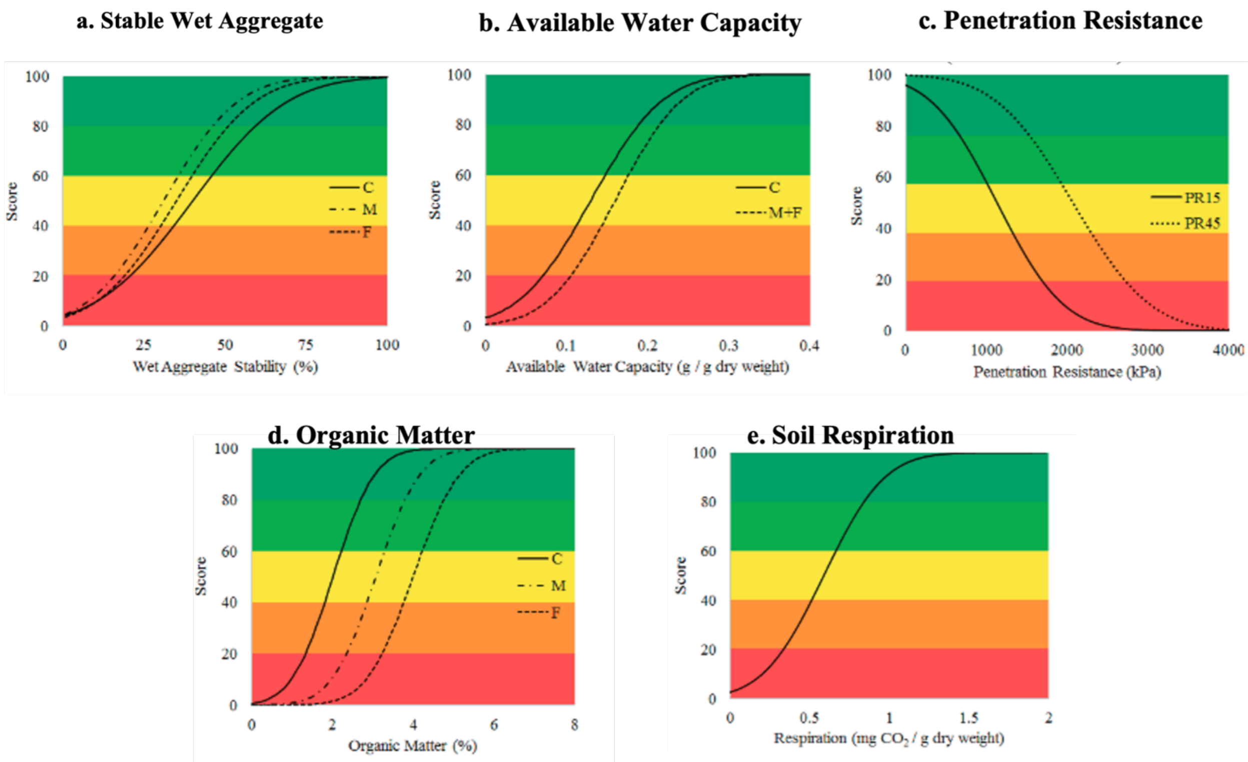

Figure 1. Soil health scoring functions from CASH, as modified by Fine et al., 2027, for physical (a-c) and biological (d-e) indicators. Functions based on soil texture (C – coarse, M – medium, F – fine) are overlaid on the expanded CASH five-color scheme (Fine et al., 2027)

An optimal function was used to score soil pH. Values ranging from 6.3 to 7.2 were considered optimum and received a score of 100, while pH ≤ 5.4 or pH ≥ 7.7 received a score of 0. pH values between optimum and extreme values, was calculated using linear interpolation. Extractable-P was also scored using an optimal function. Concentrations ranging from 3.5 to 21.5 ppm were scored as 100, while concentrations considered deficient (≤ 0.45 ppm) or excessive (≥ 100) were scored as 0. The "more is better" function was used to score extractable-K, where values greater than 74 ppm were scored as 100 (Fig. 2). This optimum scoring function was based on the optimal conditions where soil can carry out its ecological functions.

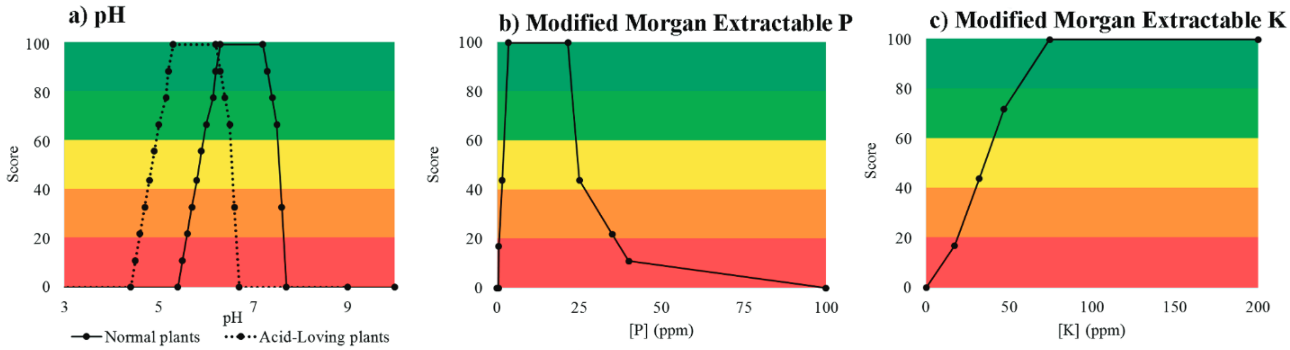

Figure 2. Soil health scoring functions from CASH for chemical (a-c) indicators. (Fine et al., 2027)

Data Analysis:

The computed soil health scores from each block and season were analyzed using R software. A linear mixed-effects model reflecting the split-plot-in-time design, where season, crop, and their interaction were treated as fixed effects, and random intercepts were included for block, block x season, and plot nested within block to account for hierarchical experimental structure and repeated measure. Model fitting was performed using the *lmerTest* package in R, with Satterthwaite-adjusted degrees of freedom for fixed-effects test.

For blocks within each season, a one-way ANOVA was conducted; if significant, Tukey's HSD identified differing blocks and significance letters were displayed only for those seasons and blocks.

To complement the mixed-model results, ordinary kriging interpolation was also performed in ArcGIS Pro (Geostatistical Analyst extension). A continuous prediction surface for soil health score within the field per season was generated for each season from 48 sampling points. A spherical variogram model was fitted, and the kriging neighborhood was restricted to the 5 nearest observation points.

Wheat (*Triticum aestivum*) and grain sorghum (*Sorghum bicolor*) yields from 2025 were analyzed to evaluate their relationships with soil health scores. Simple linear regression was used to assess this relationship, while multiple linear regression models were used to determine the individual contribution of each soil health indicator to crop yield. All statistical tests were evaluated at an alpha level of 0.10, corresponding to a 90% confidence level.

Results and Discussion

Spatial and Temporal Variability of Soil Health Scores:

The fixed effect of the linear mixed-effect model analysis revealed that season and crop and their interaction did not have a significant effect on soil health scores (season $p = 0.22$, crop $p = 0.70$

and season x crop $p = 0.27$) (Table 4), and the random effect of the model showed that block, and block by season had significant effect on soil health score with p values of 0.001 and 0.02, respectively (Table 5). These results support our hypothesis that soil health scores vary among blocks and change across seasons, reflecting spatial and temporal heterogeneity within the field.

Table 4. Linear mixed-effect model ANOVA for fixed effects summary

Source of Variance	df	SS	MS	F value	P value
Seasons	4	25.68	6.42	1.48	0.22
Crop	1	0.67	0.67	0.15	0.70
Season x Crop	4	23.38	5.84	1.34	0.27

Degree of freedom: Satterthwaite; effects tested with Type III ANOVA. α = 0.10

Table 5. Linear mixed-effect model ANOVA for random effect summary

Random Term	Variance	SD	Total Variation (%)	LRT χ^2	df	p
Block	7.47	2.09	36.50	10.80	1	0.001*
Block x Season	2.58	1.41	9.76	5.20	1	0.02*
Block x Plot	6.65	2.58	32.48			
Residual	4.35	2.09	21.27			

**Significant values at α = 0.10*

The significant effect of block explains a significant portion of the total variance in soil health score (p = 0.001), indicating substantial variability among blocks. Variability among blocks can be attributed to the soil texture changes in different parts of the field. Particle size analysis of the collected samples indicated a generally medium to coarse texture with most of the field as sandy loam and loam texture. Variability in soil texture can lead to differences in values and scores of different soil health indicators. Indicators that are scored based on the soil texture include aggregate stability (AS), available water capacity (AWC) and organic matter (OM).

Aggregate stability can be affected by different soil factors and processes, including soil texture, decomposition and addition of organic matter, tillage, and environmental conditions such as precipitation and temperature (Chenu et al., 2000; Carrizo et al., 2015; Castiglioni et al., 2018; Li et al., 2022). In this study, block 20 which had medium textured soil and a relatively high organic matter statistically exhibited the highest AS (Table 6). The significantly high AS observed in this block may be attributed to the interaction between organic matter and the fine mineral fraction. Organic matter (OM) can bind with silt and clay minerals that strengthens aggregates, which helps enhanced the stability of aggregates (Carrizo et al., 2015; Chenu et al., 2000). These results suggest that soil with good amounts of silt and clay provides an optimal balance of mineral surface area and pore connectivity for OM to bind particles effectively and stabilize soil structure.

Table 6. Block estimated means within season of the different soil health indicators.

Block	Texture	pH	OM (%)	Penetration Resistance 15 cm (kPa)	Penetration Resistance 45 cm (kPa)	AWC ($g\ g^{-1}$)	WAS (%)	Resp (mg CO_2 g^{-1} dry weight)	P (ppm)	K (ppm)
1	Coarse	5.51^{b}	1.03	8357.20	3834.44	0.10	16.30^{ab}	0.13^{ab}	31.61^{b}	100.67^{ab}
2	Coarse	5.77^{b}	0.99	3338.11	3840.79	0.12	15.04^{b}	0.14^{ab}	32.77^{b}	92.96^{ab}
3	Medium	5.93^{b}	1.38	3992.61	4450.29	0.16	23.56^{ab}	0.14^{ab}	41.42^{b}	107.15^{ab}
4	Coarse	5.51^{b}	1.29	5313.31	4964.94	0.11	26.05^{ab}	0.12^{ab}	30.83^{b}	123.32^{ab}
5	Coarse	5.34^{b}	1.05	7267.99	5014.82	0.14	23.38^{ab}	0.11^{b}	24.09^{b}	100.92^{ab}
6	Medium	5.83^{b}	1.48	2268.01	5414.81	0.16	26.26^{ab}	0.15^{ab}	39.08^{b}	125.64^{ab}
7	Coarse	5.55^{b}	1.18	8418.77	5634.84	0.16	27.30^{ab}	0.13^{ab}	31.56^{b}	128.02^{ab}
8	Coarse	5.50^{b}	0.87	6236.54	5949.52	0.15	24.47^{ab}	0.13^{ab}	30.62^{b}	77.89^{b}
9	Coarse	5.71^{b}	1.08	6459.96	7383.58	0.14	19.61^{ab}	0.14^{ab}	37.32^{b}	109.01^{ab}
10	Coarse	5.66^{b}	1.09	6937.68	8340.31	0.15	18.56^{ab}	0.14^{ab}	28.34^{b}	82.72^{ab}
11	Coarse	5.79^{b}	1.09	3319.98	8351.58	0.14	20.26^{ab}	0.14^{ab}	31.29^{b}	94.49^{ab}
12	Coarse	5.38^{b}	1.23	4077.23	8523.21	0.16	20.35^{ab}	0.13^{ab}	24.49^{b}	146.75^{ab}
13	Coarse	5.43^{b}	0.94	3716.89	9738.34	0.14	22.73^{ab}	0.11^{b}	25.05^{b}	91.40^{ab}
14	Coarse	5.64^{b}	1.15	3133.92	10396.98	0.14	20.91^{ab}	0.12^{b}	26.55^{b}	94.48^{ab}
15	Coarse	5.63^{b}	1.50	3214.06	10437.73	0.13	23.08^{ab}	0.17^{a}	37.88^{b}	136.78^{ab}
16	Medium	5.53^{b}	1.19	6275.42	11031.39	0.12	16.61^{ab}	0.15^{ab}	34.97^{b}	101.92^{ab}
17	Coarse	5.17^{b}	0.98	4837.77	11291.08	0.13	21.15^{ab}	0.12^{b}	31.01^{b}	100.85^{ab}
18	Coarse	5.28^{b}	1.22	2075.83	11730.23	0.16	17.29^{ab}	0.13^{ab}	26.35^{b}	109.58^{ab}
19	Coarse	6.03^{ab}	0.87	4563.26	11889.73	0.14	14.80^{b}	0.11^{b}	42.76^{b}	95.78^{ab}
20	Medium	5.28^{b}	1.55	3810.26	11951.70	0.16	32.43^{a}	0.13^{ab}	27.73^{b}	152.29^{ab}
21	Medium	5.54^{b}	1.45	3662.96	12588.84	0.15	22.20^{ab}	0.13^{ab}	37.44^{b}	157.40^{a}
22	Medium	6.85^{a}	1.29	4130.74	12625.07	0.14	20.86^{ab}	0.15^{ab}	78.51^{a}	116.87^{ab}
23	Medium	5.43^{b}	1.05	3468.60	13053.11	0.16	11.79^{b}	0.11^{b}	29.61^{b}	114.02^{ab}
24	Medium	5.30^{b}	1.20	4305.45	13262.76	0.14	$23.61a^{b}$	0.12^{ab}	36.58^{b}	105.07^{ab}

Indicators included: pH, organic matter (OM), penetration resistance at 15 cm and 45 cm, available water content (AWC), microbial respiration (Resp), extractable phosphorous (P) and extractable potassium (K).

Within each block, means followed by different superscript letters differ significantly at α = 0.10 (Tukey's HSD). Means sharing the same letter are not significantly different.

Aside from the effects of texture and OM on AS, the dry and warm conditions of the field with the moderate water-holding capacity of these medium textured soils slows OM mineralization (Li et al., 2022), therefore promoting C retention and the persistence of organic binding agents. The retained OM contributes to AS by enhancing cohesion among soil particles. Moreover, soil disturbance in a no-till system is minimal and organic residues remain on the surface protecting aggregates from disruption and maintaining favorable pore continuity (Castiglioni et al., 2018). Castiglioni et al. (2018) also observed that under no-till, soil aggregates remained stable across seasons due to the preservation of organic matter and biological binding agents. Taken together, these findings suggest that although warm temperatures typically accelerate organic matter decomposition, the dry conditions likely constrained microbial activity, allowing medium-textures soils under no-till management to maintain high aggregate stability due to slower decomposition and minimal mechanical disturbance.

Available water capacity (AWC) serves as a practical indicator of how different soils vary in their capacity to retain water that can be accessible for plant uptake (Ochsner, 2019). AWC was treated as time-invariant, but since the field was composed of varying soil textures, the AWC may differ from block to block. In this study, AWC values ranges from 0.10 to 0.16 g g^{-1} dry weight (Table 6), these recorded values highly consistent with the average range of total available water with similar soil textured soil from central and southwest Oklahoma that ranges from 0.12 to 0.13 g g^{-1} dry weight (Datta et al., 2017). Although the measured AWC values in this study are similar with the published estimates for medium to coarse textured soil, the CASH scoring system evaluates AWC relative to the expected water-holding potential of a textural class of the soil rather than absolute values. Because coarse-texture soils inherently have lower water retention capacity, even a relatively high AWC may still fall within the intrinsic limitations of the soil's texture, not inadequate water availability.

Despite textures in the field ranging from medium to coarse, AWC varied only modestly across the site. This is consistent with the expectation that within the medium to coarse spectrum, shifts in pore-size distribution are relatively small compared with transitions into finer-textured soils and in addition similar bulk density and soil structure between blocks may have also reduced textured driven contrast in water availability (Smith & Kucera, 2018). Another factor that could have affected the AWC values is the organic matter, while initial studies showed a strong correlation, the effects of organic matter on increasing AWC are generally modest unless C levels vary substantially (Minasny et al., 2020).

Organic matter did not vary significantly although soil texture differed among blocks with values ranging from 0.87-1.45% (Table 6). OM accumulation is controlled primarily by carbon inputs from roots and resides, and management practices, rather than texture alone (Lal, 2018; Six et al., 2002). All blocks in this field received a phase-balanced wheat-sorghum rotation with similar residue return and management history, meaning that the quantity and quality of organic carbon inputs were essentially uniform, leaving no mechanism for OM to diverge spatially. While texture influences the capacity of a soil to stabilize organic carbon through mineral surface are and formation of organo-mineral association (Six et al., 2002; Stewart et al., 2008), the texture present in the study site (medium to coarse) did not differ enough in clay content to create strong differences in OM protection potential. Additionally, increase in OM requires sustained surplus of organic inputs over decomposition (Lal, 2018), which were not different among blocks. Therefore, uniform management and carbon inputs likely outweighed the moderate texture variation, resulting in similar OM across blocks.

Since the CASH scoring framework evaluates OM relative to what is typically achievable for a given textural class rather than an absolute OM values, soils with medium to coarse texture inherently score lower even when OM and its moderate CASH score are consistent with the intrinsic constraints imposed by soil texture.

Soil fertility indicators such as pH, extractable and extractable K varied spatially among blocks, which was expected in this field-scale study due to inherent soil heterogeneity. Even if the field is managed in the same way (cropping system and tillage), soil-forming factors such as parent material, historical erosion and deposition patterns, microtopography and past agronomic activities can create localized differences in nutrient retention and chemical properties (Weil & Brady, 2016). Slight elevation differences can influence runoff and leaching, resulting in uneven redistribution of bases and plant-available nutrients. Variations in texture also contribute to spatial differences because medium textured soil with higher proportions of fine particles have higher surface area and cation exchange sites, allowing greater adsorption and retention of nutrient compared to coarse textures soil. In this study, blocks with coarse texture exhibited lower nutrient retention, while blocks with medium texture retained more nutrients.

With medium texture, near-neutral pH (6.85), and high extractable P (78.91 ppm) and K (116.87 ppm) block 22 stood out statistically. Medium textured soils have a balance of pore sizes and more mineral surface area than coarse soils, allowing better sorption of P and K and reducing leaching losses (Weil & Brady, 2016). Near neutral pH falls within the optimum range for nutrient availability, especially phosphorous, since phosphate is more susceptible to fixation by aluminum and iron under acidic conditions or calcium under alkaline conditions. In addition, the medium texture (loam to sandy loam) provides sufficient surface area and cation exchange sites to retain base cations such as K and decrease leaching losses, unlike coarse-textured soils that have minimal exchange capacity (Havlin et al., 2016; Weil & Brady, 2016).

Spatial variability in texture and subtle field-scale processes, such as microtopography, water redistribution, and past soil movement, help explain why pH, P, and K differed among blocks. These processes can create nutrient accumulation zones. Block 22 appears to be one of those zones, where medium texture and near-neutral pH favored nutrient retention, resulting in significantly elevated extractable P and K.

Descriptive summaries and spatial visualizations were also examined to understand how soil health scores varied across blocks. Examination of indicator means by block (Table 6) shows that blocks differed not only in their overall soil health scores but also in the underlying factors driving those scores. Blocks that consistently ranked among the highest, such as Blocks 3, 11, 18, and 23, tended to have comparatively higher organic matter, greater available water capacity, and lower penetration resistance at 15 cm. These characteristics promote favorable structure, aeration, and root growth, which were reflected in higher soil health values. In contrast, blocks that repeatedly scored lower (e.g., Blocks 1, 8, and 16) exhibited combinations of lower organic matter and higher penetration resistance, indicating compacted or less biologically active soil. Differences in extractable K (e.g., higher values in Blocks 13 and 20) also revealed localized fertility advantages tied to parent material or historical management. These spatial contrasts in individual indicators help explain why certain blocks persistently performed better across seasons; localized soil properties gave them inherent productivity advantages. Spatial patterns observed in the interpolated maps (Fig. 3) align with these findings: recurring high-score zones overlap blocks with more favorable physical and biological conditions, while low-score areas coincide with blocks exhibiting greater compaction and reduced organic matter.

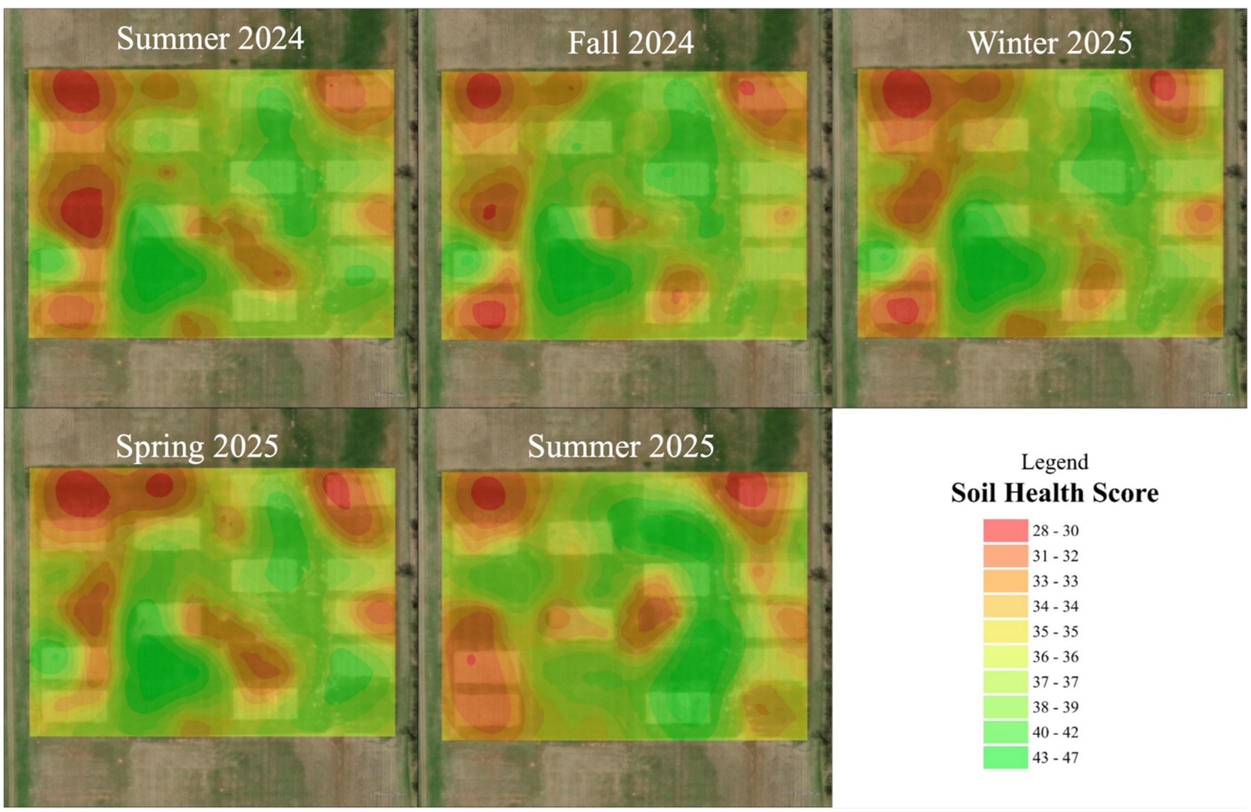

Figure 3. Kriging map for soil health score within different seasons showing visual difference of scores between blocks. Blocks numbered in a serpentine pattern, with numbers increasing left-to-right on the first row and then right-to-left on the next row (1–4, 8–5, 12–9, 16–13, 20–17, 24–21).

The significant random effect of block and season interaction suggests that differences among blocks were not consistent across all sampling periods but instead emerged under specific seasonal conditions. While some blocks have higher soil health scores in particular seasons, the overall relative scoring of blocks shifted as environmental conditions changed. This pattern implied that spatial variability in soil health may be partly driven by seasonally dependent factors such as soil moisture, temperature, and residue decomposition dynamics.

During Summer 2024, the mean precipitation was 2.14 mm, which was less than other seasons except for Winter 2025. Summer 2024 also experienced relatively higher temperature (Mean = 26.8 °C, Min. = 19.7 °C, Max = 31.6 °C) compared with the other seasons (Table 2). The antecedent precipitation and temperature data also support this result. Table 3 shows that the mean precipitation 0 to 7 days before the Summer 2024 sampling was 0.254 mm and the mean temperature was 28.2 °C which is relatively dryer and warmer compared with the other seasons. This dry and warm condition may affect different soil health indicators, especially indicators that are sensitive to moisture and temperature like microbial respiration.

Soil respiration reflects the metabolic activity of soil microorganisms. This indicator is measured by quantifying the released carbon dioxide (CO_2), from a re-wetted, air-dried sample. The higher the amount of CO_2 that is released, the more active the microbial population is (Moebius-Clune, 2016). During Summer 2024, the average soil microbial respiration was 0.09 mg CO_2 g^{-1} which was relatively low than the rest of the sampling seasons (Table 7). This result suggests that the relatively low moisture can constrain microbial activity despite warm temperatures. Zhang et al. (2018) showed that under water-limited conditions, soil moisture can decouple respiration from temperature because microorganisms cannot respond to heat if the soil is too dry. In another study conducted in the Southern Great Plains region of the USA, soil respiration increased linearly with mean annual precipitation, suggesting that when soil is moist in a warm environment, soil respiration increases (Zhou et al., 2009). These studies agree with our conclusion that soil microbial respiration is greatly affected by moisture even under warm conditions. The combination of low precipitation and warm temperature, also contributed to the seasonal stability of soil aggregates. Stable aggregates are soil particles that remain intact and retain their structure when exposed to high-impact wetting events, such as heavy rainfall or rapid irrigation after a dry period (Moebius-Clune, 2016). Aggregate stability during Summer 2024 was higher (28.63%) compared with the other seasons (Table 7). This result is similar to those reported in a study done under no-tillage, where soil aggregates were more stable during periods of higher temperature (Castiglioni et al., 2018). Another study conducted in a no-till system reported that the lowest soil aggregate stability was observed during the fall and winter seasons (Chan et al., 1994). This conclusion also supports our results, as percent stable aggregate in Fall 2024 and Winter 2025 were lower at 16.41% and 17.80%, respectively, compared with other seasons (Table 7). Relatively higher AS during Summer 2024 could also be related to the low soil microbial respiration (Table 7). Low microbial respiration could suggest that soil organic matter, which binds the soil aggregate was not being broken down by the microorganisms, leaving a well-cemented soil aggregate.

Table 7. Seasonal means of the different soil health indicators.

Season	pH	OM (%)	Penetration Resistance		AWC ($g\ g^{-1}$)	WAS (%)	Resp (mg CO_2 g^{-1} dry weight)	P (ppm)	K (ppm)
			15 cm (kPa)	45 cm (kPa)					
Summer 2024	5.50	1.26	3524.57	7569.40	0.14	28.63	0.09	37.10	104.32
Fall 2024	5.70	1.06				16.41	0.14	41.83	106.52
Winter 2025	5.71	1.16				17.80	0.14	42.13	112.85
Spring 2025	5.56	1.22				22.34	0.14	38.17	117.29
Summer 2025	5.57	1.17	9481.43	13826.60		20.78	0.13	11.16	114.44

Indicators included: pH, organic matter (OM), penetration resistance at 15 cm and 45 cm, available water content (AWC), microbial respiration (Resp), extractable phosphorous (P) and extractable potassium (K).

Another soil indicator that is affected by environmental factors such as rainfall and temperature is the penetration resistance (PR), which is an indicator of compaction in the soil surface (15-cm depth) and subsurface (45-cm depth). Measurement of PR should be taken when the soil is friable, so in this study, PR was only measured during the Fall 2024 and Summer 2025 samplings when antecedent precipitation was relatively higher (Table 3). In this study, PR at 15 cm ranged from 1863.39 to 8631.22 kPa and from 3726.24 to 13154.56 kPa at 45 cm (Table 6). Values above ~2,000 kPa are known to restrict root penetration, suggesting that portions of the field experienced moderate to severe compaction, particularly at the 45-cm depth. Higher PR values are typically associated with lower soil health scores because compaction reduces pore space, impairs water movement, and limits root exploration for nutrients.

These shifts in individual indicators explain the seasonal fluctuation in soil health scores. Since soil health score is calculated as the composite of multiple physical, chemical, and biological metrics, interactions of block and seasonal changes in indicators such as soil respiration, aggregate stability and penetration resistance generally fluctuates the soil health score. Thus, the block and seasonal variation observed in the score reflects the cumulative response of these underlying indicators to changing environmental conditions, particularly moisture availability, temperature, and residue decomposition dynamics.

Relationship Between Soil Health Scores and Crop Yield

Simple linear regression was used to examine the relationship between soil health scores and crop yield (Fig. 4). The crop yields used for comparison were from the 2025 grain sorghum and wheat crops. The analyses revealed no significant relationship between soil health scores and crop yield, for any season except for Summer 2024 ($p < 0.05$).

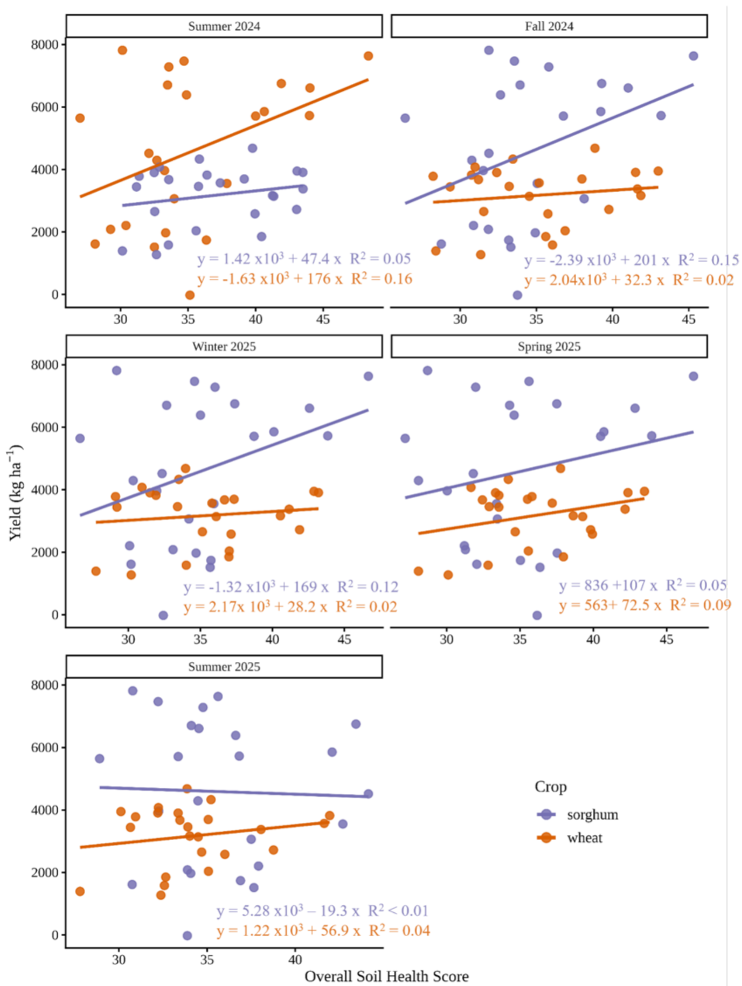

Figure 5. Scatterplots of yield versus overall soil health score by seasons, with separate linear fits for wheat (orange) and sorghum (purple). Each label shows the crop-specific regression equation and R^2 within season.

Despite the statistical significance of the relationship, the fact that soil health score can only explain 16% of the variation in wheat yield suggests that there are several other factors affecting wheat grain yield more than the soil health score. This result agrees with Crookston et al. (2022) who reported that crop yield and soil health score do not always move together. In some locations in their study, higher soil health scores were related to higher yields, but in many others, there were no clear relationships, or the relationships had low R^2 values indicating that there could be other factors affecting yield besides the score such as the environmental conditions and management strategies. They also pointed out that patterns were stronger when the collected data covered multiple years at the same site. Considering only one year of data often misses the relationship since weather and management changes from year to year strongly affect yields.

Multiple linear regression was used on the Summer 2024 data, which was the only seasonal soil health score significantly correlated with 2005 wheat yield, to assess the relative contribution of soil health indicators to the overall soil health score. Extractable K and OM showed the highest positive standardized effect (K βstd = 0.18, OM βstd = 0.15) and soil respiration and extractable P had a negative standardized effect (Soil respiration βstd = -0.62, P = βstd = -0.1.27) (Table 8).

Table 8. Multiple linear regression on soil health indicators for summer 2024 and 2025 wheat yield.

Season	Indicator	Standardized Coefficient	R2	Adj. R2	p value
Summer 2024	Soil pH	0.028	0.306146	0.061256	0.951
	Organic Matter	0.153			0.600
	Extractable P	-0.127			0.800
	Extractable K	0.180			0.528
	Soil Respiration	-0.621			0.074*
	Stable Wet Aggregates	0.091			0.743

*Significant values at α = 0.10

Similar to the findings of Crookston et al. (2022), the results in this study showed that only 30.6% of the within-season variation of yield could be explained by the indicators used to compute a soil health score. The direction of the standardized coefficient suggests that productivity tends to increase with higher OM and extractable K and decrease with higher respiration. However, given the modest effect sizes, these relationships should be interpreted as trends rather than strong causal conclusions. A possible explanation for this negative relationship could be the elevated respiration in the dry and warm seasonal condition (Table 7), or it could be a result of a temporal mismatch between microbial activity and crop demand. Similar inconsistencies were also noted by Crookston et al. (2022), where it was found that respiration and yield relationships varied widely among sites and soil textures. Moreover, elevated respiration may represent a period of microbial stress or inefficient carbon use by decomposer-dominated microbial communities, leading to reduced nutrient synchronization with crop demand. Therefore, soil respiration should be interpreted with caution, since high CO_2 flux can signify both biological activity and potential soil carbon depletion depending on management and environmental content.

Summary, Conclusion and Recommendations

Summary:

This study aimed to determine if there is spatial and temporal variability in soil health scores assessed using the comprehensive assessment of soil health (CASH) and to analyze the relationship of soil health score and crop yield. The study was carried out in a repeated-measures split-plot design, with the block as the whole plot factor and the season of sample collection as a sub-plot factor. Two sampling plots per block were considered as replication in this study. Soil samples were taken during the summer and fall of 2024 and winter, spring and summer of 2025. The blocks were considered for spatial variability, and the seasons were considered for temporal variability. Different soil health indicators were analyzed including several soil physical, chemical and biological properties. The results of these various analyses were then scored and the overall score was computed using the unweighted average of the sub scores, following the CASH scoring as modified by Fine et al., 2017.

The results revealed that soil health score significantly varied among blocks and the interaction between blocks and season was also found to be significant, implying that certain blocks responded differently to seasonal variations.

This spatial variability of soil health was driven by indicators that were influenced by the interplay of soil texture and organic matter such as aggregate stability, available water capacity, soil pH and extractable P and K. The temporal effect of block and season on soil health scores was driven by indicators that can be affected by seasonal change of precipitation and temperature, such as aggregate stability, soil respiration and penetration resistance.

When the relationship between soil health score and crop yield were assessed using linear regression, a weak relationship was observed as indicated by the low R^2 values. Only the relationship between soil health scores in the summer of 2024 and wheat yield of 2025 was found to have a significant relationship. These results may suggest that soil health score cannot predict yield since there can be other factors that could be more influential to crop yield. When multiple linear regression was performed to determine which soil health indicators were most closely related to grain yield, it showed that extractable K and organic matter had positive effects, while soil respiration exhibited a strong negative effect.

Conclusion:

The overall findings in this study highlight that soil health scores vary within fields and across seasons, emphasizing the importance of considering temporal and spatial variability when assigning a soil health score to a field. Additionally, the weak association between soil health score and crop yield suggests that yield performance is governed less by soil health status than by other environmental or management-related factors.

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