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Cropping system and soil texture shape soil health outcomes and scoring functions

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A R T I C L E I N F O

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A B S T R A C T

Inherent soil properties often define the soil's basic functions, but human management can have superimposing impacts on the quality of soil. It is therefore challenging to interpret Soil Health (SH) measurements in the context of a region's soils and cropping systems. We examined the effects of soil texture, a dominant inherent soil property, and cropping system on SH indicators for New York, USA soils. A dataset of 1,750 soil samples was analyzed for SH indicators including Soil Organic Matter (SOM), Permanganate-Oxidizable Carbon (POXC), Soil Respiration (Resp), soil protein (Protein), Available Water Capacity (AWC), Wet Aggregate Stability (WAS), surface and subsurface penetration resistance, and seven soil chemical properties. Measured physical and biological indicators were affected by both soil texture and cropping system. AWC measured on disturbed samples was mostly affected by texture (37.4% variance explained), while Resp, Protein, and WAS were mostly impacted by cropping system (11.7%, 14.7%, and 22.1% variance explained, respectively). POXC was equally affected by texture and cropping system. Pasture and Mixed Vegetable systems tended to have the highest biological and physical soil health, followed by Dairy Crop systems. Annual Grain and Processing Vegetable cropping systems tended to have the lowest soil health. The effects of cropping systems are presumably linked to differences in the carbon and nutrient balances and the amount of soil disturbance through tillage. New scoring functions based on soil texture classes and cropping systems were developed for New York State to facilitate interpretation of SH test results in the context of the production-specific environments.

Abbreviations

AWC	available water capacity
WAS	wet aggregate stability
SOM	soil organic matter
LOI	loss on ignition
Protein	soil protein
Resp	soil respiration during a 4-day incubation
POXC	permanganate-oxidizable carbon
PR15	penetration resistance from 0–15 cm
PR 45	penetration resistance from 15–45 cm
SH	soil health
CASH	Comprehensive Assessment of Soil Health
SMAF	Soil Management Assessment Framework
CND	cumulative normal distribution
NYS	New York State

1. Introduction

Around the world, farmers, agriculture professionals, and researchers are embracing the concept of soil health which has been defined as "the capacity of the soil to function as a vital living ecosystem that sustains plants, animals, and humans" (USDA-NRCS, 2020). This interest is rooted in the growing recognition that soil biology, soil physics, and soil chemistry need to be considered in an integral manner to sustainably manage soil resources (Bünemann et al., 2018).

Soils are affected by a combination of inherent and anthropogenic factors. Inherent properties such as soil texture and mineralogy exert strong controls on the amount of storable carbon and nutrients, native pH, aggregation, water holding capacity, and more (Libohova et al., 2018; von Lützow et al., 2006). But the characteristics of naturally occurring soils have been increasingly superimposed by human management. Tillage, cropping practices, as well as carbon and nutrient flows through erosion, organic amendments, and residue harvesting choices have altered the "natural" carbon and nutrient balances and the

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physical and biological health of the soil (Bünemann et al., 2018; Nunes et al., 2018; Wills et al., 2017). Therefore, soil health can be assessed based on inherent and dynamic soil properties (Karlen et al., 1997), associated with soil genoforms and phenoforms, respectively (Rossiter & Bouma, 2018). A soil genoform provides a reference state that encompasses inherent soil capability under specific long-term circumstances as a product of the complex interplay among climate, parent material, biology, topography, and time. Whereas, phenoforms are defined within the context of their parent genoforms, and reflect significant divergences in their dynamic soil properties due to the influence of human land use, which has dramatically intensified in recent decades.

While it is well understood that nutrient availability and soil pH can constrain crop productivity, biological and physical limitations can be harder to measure. In this context, scientists have recently deepened their understanding of the role of soil biology and physics in many ecosystem processes (Lehman et al., 2015; Magdoff & van Es, 2009). Soil health testing has emerged as a way to assess biological and physical processes in the soil in conjunction with traditional nutrient testing, and can be a useful part of land managers' strategies to address production constraints. Indicators generally need to be agronomically meaningful, low-cost, and sensitive to management (Idowu et al., 2008). Soil health frameworks were developed to provide routine interpretation of biological and physical tests that were previously used exclusively by researchers and were not available to the public. Even SOM, which is routinely included in standard nutrient analysis tests has never been formally interpreted in standard nutrient analysis reports. Early soil health frameworks were the Soil Management Assessment Framework (SMAF; Karlen et al., 2019) and the Comprehensive Assessment of Soil Health (CASH; Idowu et al., 2008; Schindelbeck et al., 2008). The latter quantifies soil health indicators, identifies specific soil health constraints (e.g., compaction, low labile C and N), and suggests management approaches, and thereby focuses more on the needs of farmers, consultants and applied researchers.

Both frameworks use cumulative normal distribution functions (CND) to standardize soil data and derive interpretive scores (between 0 and 100). The CASH scoring approach is basically a fuzzy peer population-based interpretation where CND parameters can be derived from similar production environments (McBratney and Odeh, 1997). To facilitate appropriate interpretations of SH test results, CASH uses separate scoring functions for different soil texture groupings to account for their strong influence on some measured values, i.e., a genoform effect. The CASH approach has focused on texture-based scoring functions because it is arguably the single most influential inherent soil property shaping soil biological and physical properties. The focus on soil texture as the chief inherent soil property is particularly well justified in the Northeast, USA, where an exploratory random forest analysis revealed that texture group was a more important predictor of SOM content than taxonomic suborder and drainage class (Amsili, unpublished results). More recently, large U.S. soil health databases allowed for the development of robust continental-scale SH interpretation functions based on multiple site-based inherent properties (soil texture, taxonomic suborder, and climate variables; Nunes et al., 2021)

Soil indicators are mainly divided into three scoring curves, "More is better", "Less is better" and "Optimum", and the trace elements uses a special assignment method, with the critical value as the standard. Bilgili, et al. (2017) found that non-linear scoring functions for CASH were more sensitive to management impacts than linear scoring.

CASH has been applied to document soil health impacts from soil management in New York (Idowu et al., 2009; Nunes et al., 2018), residue removal in corn (Moebius-Clune et al., 2008) and tillage and organic management practices in North Carolina (van Es & Karlen, 2019). These studies generally show that the indicators associated with labile forms of carbon and nitrogen (POXC, Protein, Resp) and aggregation (WAS) were most sensitive to management effects and good indicators of biological and physical soil health. Also, van Es and Karlen (2019) determined that tillage-induced corn and soybean yield differences were more strongly related to labile carbon and nitrogen indicators than total organic matter.

Regional adaptations of the CASH approach were done by Bhadha et al. (2018) in Florida, Sintim et al. (2019) in Washington State, Pieper et al. (2015) in Rhode Island, and Van Eerd et al. (2014) in Ontario, Canada. CASH has also been applied to document soil health and (in some cases) crop yield impacts of land degradation in Kenya (Moebius-Clune et al., 2011), cropping systems in Pakistan (Iqbal et al., 2014), cropping and landscape factors in India (Frost et al., 2019), coffee systems in Colombia (Rekik et al., 2018), and oil seed trees in China (Liu et al., 2017).

1.1. *Carbon and Nutrient Cycles and Flows*

Traditional farming styles with integrated crops and animals generally have tight cycling of carbon and nutrients on the farm (Magdoff & van Es, 2021). But the recent trend toward farm specialization, mostly driven by economic forces, has resulted in a break in carbon and nutrient cycles by separating animals from the land that grows their feed (Magdoff et al., 1997). This was accompanied by crop breeding efforts to increase biomass and nutrient harvest indexes for specialized grain production, particularly corn and soybeans (Sinclair, 1998). Although varying by crop type, annual grain production systems now remove approximately 50% of C, 65% of N, and 80% of P as grain that is subsequently sold off the farm (Ciampitti et al., 2013; Pedersen & Lauer, 2004). Specialized corn and soybean operations generally supply nutrients through synthetic fertilizer inputs instead of relying on crop rotation (legume sods, cover crops) and animal manures. Conversely, specialized large-scale animal facilities, like dairy farms, generally cycle carbon and nutrients through manure, and can even accumulate them through additional feed purchases from off-farm sources (Rasmussen et al., 2006). Many organic horticultural operations have also been shown to concentrate carbon and nutrients due to imports of compost and manure (Morris, 2004).

In all, farm specialization has resulted in a wide range of patterns of carbon and nutrient flows that potentially impact soil health (Magdoff and van Es, 2021). Indeed, Fine et al. (2017) documented regional soil health differences and hypothesized that they were associated with different cropping systems and associated carbon flows. Notably the row crop-based annual grain production that is dominant in the Midwest region showed significantly lower soil health outcomes than the more diversified agriculture in the Northeast and Mid-Atlantic regions. Nunes et al. (2020) similarly documented US continental scale effects of cropping systems, soil types, and climate on soil organic matter. This suggests that soil health is shaped by a complex interplay of agronomic management with regional soil types and climate, and that more context-specific interpretation frameworks (scoring functions, management recommendations, etc.) are needed.

The objectives of this study were to (i) determine the relative impacts of an inherent soil property - soil texture - and anthropogenic effects - cropping systems - on the SH indicators (ii) quantify how SH indicators are affected by these factors in New York State (NYS), and (iii) develop regional scoring parameters that account for field-specific production environments.

2. Materials and Methods

2.1. *Dataset*

A SH dataset was compiled from 1,750 soil samples from New York State that were analyzed by the Cornell Soil Health Laboratory for a suite of soil health indicators and soil texture (Moebius-Clune et al., 2017). The soil specimens were not derived from a deliberate sampling scheme but from the lab submissions during the period 2014 to 2021 that included relevant information on location and cropping. Nevertheless, the geographical distribution represented the major agricultural regions of the state (Fig. 1). Urban, manufactured, and landscaped soils were removed from the database to make interpretations more useful for agricultural soils. Repeated submissions from the same fields or research experiments were also removed from the database. Soil health results were summarized by four textural groups. The Coarse category was comprised of sand, loamy sand, and sandy loam texture classes (n = 407), the Loam group was comprised of loam and sandy clay loam textures (n = 714; only 11 for the latter), the Silt Loam group was comprised of just the silt loam texture class (n = 583), and the Fine group was composed of clay loam, silty clay loam, sandy clay, silty clay and clay texture classes (n = 46). These groupings reflect the fact that agricultural lands in NYS are primarily associated with medium-textured (loam and silt loam) soils (Fig. 2). Samples with SOM contents above 7.4%, 7.6%, 7.6%, 8.1% for Coarse, Loam, Silt Loam, and Fine groups, respectively were excluded to further ensure that all heavily amended soils were removed. These criteria represent the 98th percentile of organic matter from these four texture groups in NYS.

Approximately one half of the soil samples (n = 857) included crop code information that denotes the current and past crops in the rotation (Dairy One, 2020). These were grouped into five cropping system types: Annual Grain, Dairy Crop, Pasture, Processing Vegetable, and Mixed Vegetable (Table 1; Fig. S1). The Processing Vegetable and Mixed Vegetable distinction was made to capture differences between single-crop vegetable production and diversified vegetable production (often organic). The geographic distribution represents the regional specialization within the state, with higher prevalence of vegetable crops and pastures in the southeastern part, dairy crops in the northern, central and western part, and annual grains, and processing vegetables in the central and western part. One important consideration of this dataset was that number and proportion of samples from each cropping system were not perfectly balanced for the four soil texture groups. There were 178, 392, 255, and 32 samples in coarse, loam, silt loam, and fine texture groups, respectively (Table 2). For example, coarse-textured soils had a relatively larger quantity of Pasture, Processing Vegetables, and Mixed Vegetables compared to other systems. Whereas, Annual Grain and Dairy Crop systems were most likely to be located on loam textures (Table 2, Table S1). Therefore, the database structure must be considered when interpreting the influence of cropping system irrespective of soil texture group.

2.2. *Sampling Procedures and Soil Health Analysis*

Soil samples were assumed to have been collected following guidelines which specify the compositing of more than five soil slices (0-to-15 cm depth) collected using a spade from different locations in a field or plot. More than half of the soil samples (n = 1,072) included surface hardness (0–15 cm; PR15) and subsurface hardness (15–45 cm; PR45) measurements which were collected in the field at the time of sampling. According to CASH guidelines, PR measurements are made under field-moist conditions using a field penetrometer, twice at five or more locations in a field or plot (Cornell University Soil Health laboratory, 2020). All soil samples were analyzed according to the standard CASH package at the Cornell University Soil Health Laboratory (Ithaca, NY), which includes four biological indicators, four physical indicators, seven chemical indicators, and soil texture. Soil texture was measured according to a rapid and quantitative texture method that uses 3% sodium hexa-metaphosphate to disperse soil samples (Kettler et al., 2001; Schindelbeck et al., 2016). Then samples are run through sieving and sedimentation steps to determine the percentage of sand, silt, and clay. Analytical protocols for each indicator are summarized below, while detailed information is available from Schindelbeck et al. (2016).

Biological soil health indicators

SOM was analyzed by mass loss on ignition (LOI) in a muffle furnace at 500°C for two hours. The % LOI was converted to % SOM using an Eq. 1 from Storer (1984), which is the standard method for calculating % SOM in New York State.

$$\%\,\mathrm{SOM} = (\%\,\mathrm{LOI} \times 0.7) - 0.23 \tag{1}$$

POXC was measured as permanganate oxidizable carbon, measured in duplicate, by reacting a 2.5 g soil sample with 20 mL 0.02 M potassium permanganate ($KMnO_4$) solution (pH 7.2). Extracts were shaken

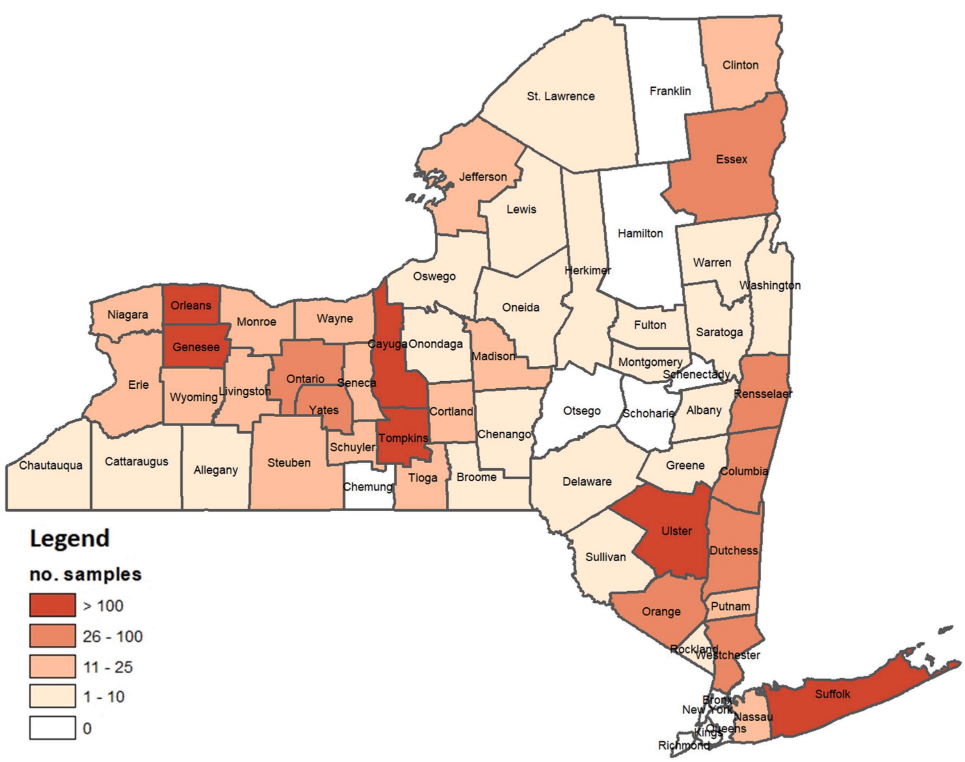

Fig. 1. Distribution of soil health samples by county across New York State (n = 1,750). Most counties without samples are forested.

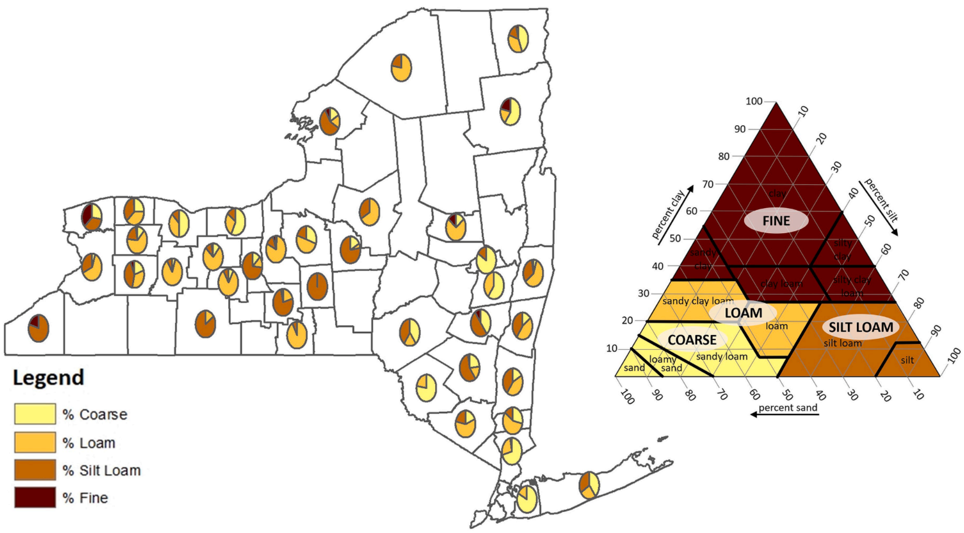

Fig. 2. Distribution of soil samples for CASH analysis based on texture grouping by county across New York State (n = 1,750). Counties with fewer than five samples were excluded from this map.

Table 1
Five cropping system groups were formed by combining related crop codes (n = 857). Each code is followed by the associated number of soil samples in parentheses.

Cropping System	Crop Codes†
Annual Grain	COG (166), SOY (90), WHT (18), BND (14), WHS (8)
Processing Veg	SWC (18), SQW (17), BNS (13), CBP (10), POT (8), PUM (8), TOM (8), …[‡]
Mixed Veg	MIX (189)
Dairy Crop	COS (106), ALE (13), AGT (11), AGE (9), ALT (7)
Pasture	PIT (34), GRT (22), PIE (21), PNT (20), GRE (12), PLE (6), PLT (5)

† COG=corn grain, SOY=soybean, WHT=wheat, BND=dry beans (*Phaseolus vulgaris*), WHS=wheat with legume, SWC=sweet corn (*Zea mays* convar. *saccharata* var. *rugosa),* SQW=winter squash (*Cucurbita spp.*), BNS=snap beans (*Phaseolus vulgaris*), CBP=cabbage transplanted (*Brassica oleracea*), POT=potato (*Solanum tuberosum*), TOM=tomato (Solanum lycopersicum), MIX=mixed vegetable, COS=corn silage, ALE/ALT=alfalfa, AGE/AGT=alfalfa grass, PIT/PIE=pasture rotational grazing, GRT/GRE=grasses, PNT=pasture with native grasses, PLT/PLE=pasture with legumes.

[‡] 25 samples were from crop codes with 5 or fewer samples.

Table 2
The number of samples from different cropping system groups and the proportion of samples within each cropping system that come from the four texture groups.

Cropping System	n	% Coarse	% Loam	% Silt Loam	% Fine
Annual Grain	299	12	60	26	2
Processing Veg	107	29	41	29	1
Mixed Veg	191	30	35	36	0
Dairy Crop	146	16	46	25	3
Pasture	114	27	32	37	4
All	857	21	46	30	4

for 2 min at 120 rpm and then allowed to settle for exactly 8 min. An aliquot of solution was diluted 100-fold before absorbance readings were taken at 550 nm using a handheld spectrophotometer (Hach, Loveland, CO) and converted to mg POXC per kg soil using the equation of Weil et al. (2003). In addition, the ratio of POXC over SOM was used to assess soil organic matter *quality* (Eq. 2).

$$\%\,\mathrm{POXC}\Big/\mathrm{SOM} = \left(\frac{\mathrm{POXC}}{\mathrm{SOM}}\right) \times (100) \tag{2}$$

Protein was measured by extracting a 3.0 g soil sample with a 0.02 M sodium citrate at pH 7. The extract was then quantified by bicinchoninic acid assay against a bovine serum albumin standard curve for soil protein concentration after a sequence of centrifugation and autoclaving steps (Hurisso et al., 2018; Wright & Upadhyaya, 1998). Similar to POXC, the ratio of Protein over SOM was used as another index of soil organic matter *quality* (Eq. 3).

$$\%\,\mathrm{Protein}\Big/\mathrm{SOM} = \left(\frac{\mathrm{Protein}}{\mathrm{SOM}}\right) \times (100) \tag{3}$$

Resp was measured after a four-day incubation using an alkali trap to measure CO_2 production. Soil samples weighing 20 g were placed in a perforated aluminum weighing boat and put inside a glass jar sitting atop two staggered Whatman qualitative filter papers. A pre-assembled alkali trap placed onto the weigh boat and the beaker was filled with 9 mL of 0.5 M KOH. Distilled water (7.5 mL) was pipetted alongside the jar to facilitate rewetting of the sample via capillary rise. The amount of CO_2 respired and absorbed by the KOH trap over the course of incubation was determined by measuring the change in electrical conductivity of the solution with an OrionTM DuraProbeTM 4-Electrode Conductivity Cell (ThermoFisher Scientific, Inc., Waltham, MA). The necessary background correction for atmospheric CO_2 was quantified using blank incubations without soil (Nunes et al., 2018; Schindelbeck, et al., 2016).

Physical soil health indicators

In addition to measurement of PR15 and PR45 in the field, WAS is measured based on the ability of soil aggregates to resist failure when wetted and struck by deionized water drops. Soil samples were prepped by shaking soil for 10 s on a mechanical shaker with stacked sieves of 2 and 0.25 mm to collect aggregates between 0.25-to-2 mm. A single layer of aggregates was spread on a 0.25 mm mesh sieve, which was placed 0.5 m below the rainfall simulator fitted with Teflon capillaries generating 0.6 mm water drops (Ogden et al., 1997) to apply 2.5 J of energy over a 5 min period. WAS was determined as the fraction of soil remaining on the sieve, correcting for solid particles > 0.25 mm. AWC was determined from disturbed soil specimens that were equilibrated after initial saturation to pressures of -10 kPa and -1500 kPa on porous ceramic pressure plates in pressure chambers (Soil Moisture Equipment Corp., Goleta, CA). (Reynolds and Topp, 2008; Schindelbeck, et al., 2016).

Chemical soil health indicators

Soil pH was measured in a 1:2 soil:water slurry. Nutrients were extracted with a Modified Morgan solution (ammonium acetate plus acetic acid, pH 4.8) and then analyzed using inductively coupled plasma optical emission spectrometry (SPECTRO Analytical Instruments Inc., Mahwah, NJ; Wolf and Beegle, 1995; Schindelbeck, et al., 2016). All nutrient contents are reported in units of mg kg^{-1} soil (ppm).

2.3. Statistical Analyses

ANOVA models with soil texture or cropping system as fixed effects were used to assess differences in the biological, physical, and chemical soil parameters. Multiple comparisons were made using a Tukey adjustment at $\alpha = 0.05$ with the R package Agricolae (De Mendiburu, 2017). Variance component analysis was used to evaluate how well soil texture and cropping system factor levels could explain variance in different indicators. Pearson correlation coefficients were used to assess relationships among indicators. All statistical analyses were run using the R statistical software (R Core Team, 2019).

3. Results and Discussion

3.1. Indicator sensitivity to inherent vs. dynamic factors

Effects of soil texture (an inherent and invariable soil property) and cropping system (an anthropogenic effect) on various soil health parameters are inadequately known. A variance component analysis of this SH dataset quantified their relative influence (Table 3; Table S2). Soil texture explained a larger quantity of variance in SOM than cropping system, but cropping system remained an important predictor as well (21.8% and 8.2%, respectively). Whereas both texture and cropping system explained a similar amount of variance in POXC (7.9% and 9.2%, respectively; Table 3). POXC showed higher unexplained random variance than SOM (81.6% and 66.3%, respectively). This implies that SOM and POXC can reveal human management consequences, but inherent textural effects need to be accounted for.

Cropping system explained higher fractions of variation in Protein, Resp, and WAS (11.7%, 14.7%, and 22.1%, respectively) than texture (Table 3; Table S2). This shows that human management significantly impacts the labile carbon and nitrogen pools and structural stability, and that the effects of texture were less than those of cropping system. Soil texture effects on WAS, Protein, and Resp were 4.2%, 5.3%, and 7.2%, respectively (Table 3; Table S2).

Conversely, soil texture effects were dominant on AWC (37.4% variance explained), while cropping system effects were small (4.2%; Table 3). This corroborates earlier results (Nunes et al., 2018; van Es & Karlen, 2019) that showed AWC measured on disturbed samples is less sensitive to management than biological and physical CASH indicators. If AWC, measured gravimetrically on disturbed samples according to standard methods in this study, mostly represents textural effects, it is less useful as an indicator for soil change, yet changes in management practices and cropping patterns are generally known to affect crop drought sensitivity. Alternatively, AWC from undisturbed cores has been shown to be more sensitive to management practices, although this method is less amenable with routine soil analysis (Bean, 2020; Norris, et al., 2020). It is postulated that the standard AWC measurement may be inadequate because (i) Disturbed samples equilibrated to fixed soil water pressures do not well represent *in-situ* field conditions, and (ii) Crop benefits from management changes may be more related to improved porosity and rooting volume than changes in gravimetric water retention capacity as measured from a disturbed soil (Tormena et al., 2017).

The two indices of soil organic matter quality that we explored, POXC/SOM and Protein/SOM, were also explained to a greater extent by soil texture (7.8% and 37.5%, respectively) than cropping system (3.1% and 4.2%, respectively; Table 3). This is notable considering a significant amount of the variance in individual indicators, SOM, POXC, Protein, and Resp, was explained by cropping system levels. This was especially true for the Protein/SOM ratio, which was explained by texture to a similar extent as AWC. Therefore, these SOM quality indices may be less useful for assessing management compared to the individual biological indicators (SOM, POXC, Protein, Resp). If these ratios are used to characterize SOM quality, they have a strong texture dependence.

The variance component analysis indicates that the soil hardness indicators (PR15 and PR45) are not explained by either texture or cropping system and more than 95% of the variation is random (Table S2). This implies that this measurement is very specific to individual fields and production environments, and possibly field conditions at the time of measurement. Soil texture x cropping system interaction terms were generally low (<4.0%) for all soil health indicators, suggesting that the main effects are generally meaningful as described above (Table 3; Table S2). The only exception was Resp, which had an interaction term of 11.6%, resulting from more pronounced effects of cropping system in loam and silt loam soils than coarse textured soils. The results of this variance components analysis may be regionally specific to New York State and the Northeast USA, but the larger trends in the relative influence of soil texture or cropping system is likely true across regions in the U.S. and globally.

A large amount of variance, greater than 57% remained unexplained by either texture group and cropping system factor levels and their interactions. Although factor levels are useful to analyze the data, considerable variation exists within them that may help to explain more variance. For soil texture, more quantitative soil texture information, i.e., percent sand, silt, and clay, explains additional variation in indicators compared to discrete texture group levels (Table S3). Similarly, there is a large amount of variation that exists within each cropping system category due to differences in management practices. For example, one Annual Grain operation may use intensive tillage and no cover crops while another might be planting no-till with cover cropping.

3.2. Soil texture effects

Soil texture effects on biological indicators

Although biological soil health properties are variably impacted by soil (Table 3), mean separations in all cases showed some significant effects of the soil texture groupings (Table 4). Fine-textured soils had higher SOM, Resp, and POXC than Coarse-textured soils by 64%, 40%, and 34%, respectively. The average SOM value of the dataset is 3.1%, but it ranged from 2.5% for the coarse texture class to 4.1% for the fine texture group, reflecting the general higher carbon retention through

Table 3
Variance explained from variance component analysis with Texture (T), Cropping System (CR), and their interaction for individual biological and physical SH indicators.

Components	DF	SOM	POXC	POXC/SOM	Protein	Protein/SOM	Resp	AWC	WAS
					% Total Variance Explained				
Texture	3	21.8	7.9	7.8	5.3	37.5	7.2	37.4	4.2
Cropping System	4	8.2	9.2	3.1	11.7	4.2	14.7	4.3	22.1
T x CR	11	3.7	1.4	0.3	4.0	0.0	11.6	1.2	2.1
Error	838†	66.3	81.6	88.8	78.9	58.3	66.5	57.2	71.6

† Protein and Protein/SOM had three fewer samples than the other variables presented here, therefore DF should be 835 for Protein and Protein/SOM.

Table 4
Mean values (SD) of biological soil health indicators and indices across four soil texture groups. Mean values followed by different letters are significantly different at the 0.05 error level.

Texture	n	SOM	POXC	POXC/SOM	Protein	Protein/SOM	Resp
		%	mg kg^{-1}	%	mg g^{-1}	%	mg CO_2 g^{-1} 4 $days^{-1}$
Coarse	407	2.5c (1.4)	498d (251)	2.1a (0.7)	7.2a (4.3)	29.4a (8.3)	0.48c (0.27)
Loam	714	3.0b (1.1)	548c (201)	1.9b (0.5)	6.5b (3.2)	21.4b (5.8)	0.59b (0.25)
Silt loam	583	3.7a (1.3)	578b (201)	1.6c (0.4)	7.7a (3.1)	21.4b (4.6)	0.69a (0.33)
Fine	46	4.1a (1.3)	666a (183)	1.7bc (0.3)	6.4b (2.9)	15.8c (4.6)	0.67ab (0.29)
All	1750	3.1 (1.3)	549 (216)	1.9 (0.6)	7.1 (3.5)	23.1 (7.1)	0.60 (0.29)

Table 5
Mean values (SD) of physical soil health indicators across four soil texture groups. Mean values followed by different letters are significantly different at the 0.05 error level.

Texture	n	WAS %	AWC g H_2O g^{-1} soil	n	PR15 kPa	PR45 kPa
Coarse	407	38.7a (21.2)	0.17c (0.05)	234	1229 (507)	2042b (588)
Loam	714	32.5b (20.9)	0.21b (0.04)	453	1205 (612)	2053b (593)
Silt loam	583	39.9a (25.4)	0.26a (0.05)	351	1280 (537)	2226a (740)
Fine	46	33.6ab (22.7)	0.22b (0.04)	34	1055 (647)	1951b (696)
All	1750	36.4 (22.9)	0.22 (0.06)	1072	1230 (568)	2104 (652)

Soil texture effects on physical indicators

clay mineral-organic bonds (von Lützow et al., 2006). Although POXC and Resp measure labile carbon and microbial activity, they followed a similar pattern as SOM with decreasing mean values with increasing coarseness of the texture group. Therefore, POXC and Resp may be effective indicators for measuring management impacts in field trials conducted on the same soil type (Nunes et al., 2018; van Es & Karlen, 2019; Weil et al., 2003), but textural effects still need to be considered when comparing measurements across broader soil regions.

Protein does not follow the pattern of increasing concentrations in finer texture groups, and only Loam and Fine texture groups were significantly lower than Coarse and Silt Loam (Table 4). This likely reflects a lower extraction efficiency in soils with a higher clay content despite possibly overall higher concentrations, as suggested by Giagnoni et al. (2013).

Two indicators of organic matter *quality*, Protein/SOM and POXC/SOM, were 86% and 24% higher in coarse-textured than fine-textured soils, respectively (Table 4), indicating a higher proportion of extractable, available, and “fresh” organic matter relative to more “stable” mineral-protected organic matter in coarse-textured soils compared to fine-textured soils. These indicators thereby followed a negative correlation with clay content ($r = -0.49$ and $r = -0.21$, respectively; Table S3). This is likely partly associated with the above-mentioned differential extraction efficiency effect due to the quantity and type of clay minerals in a soil (Giagnoni et al., 2013). Also, coarse textured soils retain less stable organic carbon (Six et al., 2002) and therefore, with equivalent labile C cycling within a cropping system, tend to contain a higher relative fraction of labile C and mineralizable N compared to fine-textured soils (Hassink, 1994; Scott Bechtold & Naiman, 2006), and similarly higher C and N mineralization per unit of microbial biomass (Franzluebbers et al., 1996).

Although soil texture has a dominant effect on AWC (Table 5; Table S4), the relationship does not follow the same coarse-to-fine trend as in SOM. Following accepted knowledge in soil physics (Brady & Weil, 2008; Libohova et al., 2018), the highest mean AWC is associated with silt loam soils, followed by fine, loam and coarse texture classes. Specifically, soils with intermediate textures, like silt loams and to a somewhat lesser extent loams, generally store the most plant available water (Pearson correlation between silt content and AWC: $r = 0.72$; Table S3). When considering individual texture classes, silt loam soils had 273%, 139%, 47%, and 28%, higher AWC than sand, loamy sand, sandy loam, and loam soil textures (Table S4). Fine-textured soils in our database had similar AWC to silt loam soils despite the different texture grouping because they were only marginally different in clay content (mean of 31.7 %, modestly above the 27% upper limit for the silt loam texture class).

Contrary to previous findings that higher concentrations of clay content are associated with greater aggregate stability (Skidmore and Layton, 1992), there was little interpretable effect of soil texture on WAS. In fact, coarse-textured soils had marginally higher WAS than loam and fine-textured soils (Table 5), similar to Fine et al. (2017). This may be an artifact of the analysis methodology, which differs from the more widely used Kemper and Rosenau (1986) method that uses wet sieving apparatus (Eijkelkamp), in that sand particles offer a small degree of protection to aggregates from the impact of rainfall droplets in the methodology. Also, a smaller portion of a coarse-textured soil sample can pass through the 0.25 mm sieve than soil samples with less sand content and a smaller proportion of the weight is available to test for aggregate stability. Additionally, the generally high silt contents, low clay contents, and absence of expansive clays in NYS agricultural soils make it difficult to observe an effect of clay content on aggregate stability (Bradford et al., 1987; Lado et al., 2004; Skidmore and Layton, 1992). At this time, it is difficult to know if these results across texture groups are an artifact of the method used or if they would remain true with the more common wet sieving method (Kemper and Rosenau 1986).

Minimal soil texture effect was observed for PR15 and PR45, although silt loams had slightly higher subsurface hardness values than coarse, loam and fine-textured soils (Table 5). Fine-textured soils are more cohesive and tend to have a higher penetration resistance than coarse-textured soils (Daddow & Warrington, 1983), but they also tend to maintain higher field moisture levels when penetrometer measurements are made. Therefore, standard penetrometer readings during field-moist conditions may inadequately reflect possible high hardness levels when finer-textured soils become dry during the peak growing season.

Soil texture effects on chemical indicators

Soil texture affects the availability of some macronutrients and micronutrients in the soil. Extractable P, K, Mg, and Zn levels all varied across texture groups (Table 6), while soil pH, extractable Fe and Mn did not consistently differ among them. The mean extractable P and Zn in coarse-textured soils was 4.4 and 2.5 times higher than in fine-textured soils, respectively (Table 6). This has been confirmed in past studies looking at the effect of soil texture on extractable nutrient fractions (Fine et al., 2017; Kamprath & Watson, 1980; Wuenscher et al., 2015; Zheng et al., 2003). Lower extractable P in finer textured soils is related to the ability of soils with a higher clay content or exchangeable Al and Fe to fix more phosphorus (Cox, 1994; Zheng et al., 2003). These soils have a larger buffering capacity, meaning that per unit of applied P, extractable P rises more slowly. Wyoming is the only state in the US that uses soil texture data to modify the soil’s ability to fix phosphorus (Sharpley et al., 2003). Vermont uses extractable Al to modify a soils ability to fix phosphorus (Magdoff et al., 1999; University of Vermont Extension, 2018).

In contrast, extractable K and especially Mg levels were higher in fine-textured soils compared to coarse-textured soils (Table 6). The

Table 6
Mean values (SD) of soil chemical properties across four soil texture groups. Different letters after mean values are significantly different at the 0.05 error level.

Texture	n	pH 1:2 H_2O	P ppm	K ppm	Mg ppm	Fe ppm	Mn ppm	Zn ppm
Coarse	407	6.4b (0.7)	24.3a (51.8)	98b (91)	128d (101)	5.7a (9.8)	7.6b (7.4)	1.6a (2.0)
Loam	714	6.7a (0.7)	16.3b (24.7)	116ab (77)	191b (105)	3.5b (5.7)	10.5b (7.7)	1.1b (2.0)
Silt loam	583	6.2b (0.6)	14.1b (15.5)	122a (78)	173c (87)	6.2a (11.3)	12.2a (9.9)	1.3b (1.6)
Fine	46	6.8a (0.7)	5.7b (4.1)	121ab (57)	346a (158)	3.4b (3.8)	10.8ab (6.8)	0.6b (0.4)
All	1750	6.4 (0.7)	17.2 (31.2)	114 (81)	175 (107)	4.9 (9.0)	10.4 (8.6)	1.3 (1.9)

former has higher cation exchange capacities (Ersahin et al., 2006) that retain extractable base cations and have lower potential for K leaching losses (Bertsch & Thomas, 1985). Furthermore, the weathering of clay minerals and release of fixed potassium in the relatively young glaciated soils of New York State provides a steady supply of K and Mg.

3.3. Cropping system effects

Cropping system effects on soil health

The cropping system categories highlighted in this analysis integrate some key differences of various practices, which have a significant effect on soil health indicators at all soil texture levels. Pasture systems are expected to maintain high overall soil health because these fields are seldom disturbed by tillage and receive year-round root and shoot inputs (directly or through a grazing animal). Mixed Vegetable systems typically involve certified organic operations with diverse rotations, cover cropping, and significant quantities of organic nutrient amendments such as compost (Morris, 2004). Dairy Crop systems can maintain soil health due to cycling of carbon and nutrients through manure inputs and rotations that include perennial legume or grass sod crops. Conversely, Annual Grain and Processing Vegetable systems are intensively managed, and typically don't apply enough organic amendments to replace the organic matter that is annually removed (Bender et al., 2015). Our analysis focuses on the average effect of cropping systems and does not further address unknown additional management variations like intensive vs. reduced tillage, erosion, cover cropping, or unknown organic amendments, which are expressed as variable soil health outcomes within each cropping system.

Cropping system effects on biological soil health indicators

Cropping system is a strong determinant of the *quantity* and *quality* of SOM, which were assessed using four biological soil health indicators. Pasture had the highest SOM followed by Mixed Vegetable, Dairy Crop, and Annual Grain and Processing Vegetable (Table 7). This finding was most evident on silt loam and loam texture groups (Table 7). Pasture soils are able to maintain higher levels of SOM likely due to year-round root and shoot biomass inputs, an absence of tillage, and potential manure droppings. The percentage of SOM in pasture soils likely represents a good upper limit for what may be stored for each texture group (Dexter et al., 2008). Small-scale diversified Mixed Vegetable farms

Table 7
Mean values (SD) of soil biological properties by cropping system and soil texture. Mean values followed by different letters are significantly different at the 0.05 error level.

Cropping System	n	SOM %	POXC mg kg^{-1}	POXC/SOM %	Protein mg g^{-1}	Protein/SOM %	Resp mg CO_2 g^{-1} 4 $days^{-1}$
				Coarse-Textured			
Annual Grain	35	2.2b (0.6)	425b (153)	2.0 (0.7)	5.7b (1.8)	25.8b (4.7)	0.47 (0.16)
Processing Veg	31	2.0b (0.9)	385b (190)	1.9 (0.7)	5.1b (2.5)	26.1b (5.0)	0.38 (0.28)
Mixed Veg	57	2.9a (1.4)	583a (271)	2.2 (0.8)	8.9a (4.9)	30.3a (7.4)	0.50 (0.24)
Dairy Crop	24	2.7ab (1.4)	534ab (291)	2.0 (0.6)	6.4b (2.9)	25.9b (8.7)	0.53 (0.31)
Pasture	31	2.5ab (1.0)	467ab (170)	1.9 (0.5)	6.8ab (3.1)	27.5ab (6.3)	0.48 (0.22)
All	178	2.5 (1.2)	491 (236)	2.0 (0.7)	6.9 (3.8)	27.6 (6.8)	0.47 (0.24)
				Loam			
Annual Grain	179	2.8b (0.7)	530b (160)	2.0a (0.5)	5.4c (1.9)	20.0b (4.8)	0.53c (0.16)
Processing Veg	44	2.7b (0.9)	418c (123)	1.6b (0.5)	5.4c (2.3)	20.1b (4.3)	0.45c (0.18)
Mixed Veg	66	3.6a (1.4)	641a (238)	1.8ab (0.4)	8.4a (4.2)	22.8a (5.2)	0.55c (0.21)
Dairy Crop	67	3.3a (1.0)	623a (187)	1.9a (0.5)	6.4bc (2.2)	19.6b (3.9)	0.67b (0.20)
Pasture	36	3.7a (1.2)	610ab (225)	1.7b (0.3)	7.7ab (3.0)	20.7ab (4.0)	0.81a (0.36)
All	392	3.1 (1.1)	559 (195)	1.9 (0.5)	6.3 (2.8)	20.5 (4.3)	0.57 (0.22)
				Silt Loam			
Annual Grain	78	3.7b (1.1)	617a (206)	1.7 (0.5)	7.7bc (3.1)	20.9ab (4.5)	0.65b (0.24)
Processing Veg	31	3.2b (1.1)	496b (180)	1.6 (0.5)	6.4c (2.4)	20.6ab (4.0)	0.51b (0.24)
Mixed Veg	68	3.7b (1.2)	624a (204)	1.7 (0.4)	8.1b (3.0)	21.9a (4.3)	0.57b (0.22)
Dairy Crop	36	3.8b (1.0)	629a (179)	1.7 (0.4)	7.5bc (2.1)	19.6b (2.5)	0.67b (0.16)
Pasture	42	4.9a (1.3)	694a (174)	1.5 (0.4)	9.7a (2.7)	20.4ab (3.7)	1.07a (0.42)
All	255	3.8 (1.2)	618 (199)	1.7 (0.5)	8.0 (2.9)	20.9 (4.1)	0.68 (0.32)
				Fine-Textured†			
Annual Grain	7	4.1 (0.9)	615 (160)	1.5 (0.2)	6.2 (1)	15.3 (1.7)	0.57b (0.14)
Process Vegetables	1	-	-	-	-	-	-
Dairy	19	4.2 (0.7)	732 (121)	1.8 (0.3)	6.2 (2.1)	14.6 (3.6)	0.57b (0.13)
Pasture	5	4.8 (1.5)	737 (185)	1.7 (0.7)	7.9 (2.5)	17.4 (6.6)	1.22a (0.16)
All	32	4.3 (0.9)	707 (142)	1.7 (0.4)	6.5 (2)	15.4 (4.0)	0.67 (0.27)
				All Textures			
Annual Grain	299	3.0c (1.0)	542b (181)	1.9a (0.6)	6.1b (2.4)	20.8bc (4.7)	0.55c (0.19)
Processing Veg	107	2.7c (1.1)	434c (168)	1.7bc (0.6)	5.7b (2.4)	22.0b (5.1)	0.45d (0.23)
Mixed Veg	191	3.5b (1.4)	617a (237)	1.9a (0.6)	8.5a (4.1)	24.8a (6.7)	0.54c (0.22)
Dairy Crop	146	3.4b (1.1)	624a (205)	1.9ab (0.5)	6.6b (2.3)	20.0c (5.5)	0.63b (0.21)
Pasture	114	3.9a (1.5)	608a (211)	1.7c (0.4)	8.2a (3.1)	22.3b (5.7)	0.84a (0.42)
All	857	3.2 (1.2)	568 (210)	1.8 (0.5)	6.9 (3.1)	21.9 (5.8)	0.59 (0.27)

† Cropping systems within the fine-textured group had very small sample sizes.

were also able to build high SOM levels, presumably through repeated additions of organic amendments such as compost or manure, diverse rotations, and intensive cover cropping. Specifically, Mixed Vegetable systems had higher SOM than Annual Grain and Process Vegetables on coarse and loam textured soils. Intensive tillage and limited additions of organic amendments keep Annual Grain and Processing Vegetable systems with lower SOM (Table 7).

Labile organic matter indicators similarly reflected carbon and nutrient dynamics. POXC tended to be highest in Mixed Vegetable, Dairy Crop, and Pasture systems compared to Annual Grain and Process Vegetables. Interestingly, despite Process Vegetable and Annual Grain systems having similar SOM levels in coarse and loam textured soils, Processing Vegetable had low POXC, which may reflect less crop residues and potentially more tillage passes. Protein was consistently higher in Pasture and Mixed Vegetable farms across soil textures indicating that organic nitrogen reserves were higher in these soils. It is noteworthy that trends in POXC and Protein were not always the same across cropping systems, following other studies on the effects of tillage intensity and organic matter input on biological soil health indicators (Bongiorno et al., 2019; Nunes et al., 2018).

Unlike POXC and Protein, Resp was consistently much higher in Pasture systems than other systems on loam and silt loam soils. While greater availability of organic substrates is likely an important explanation, Pasture soils had proportionally higher Resp rates than would be predicted from differences in SOM. For example, Pasture systems had 57% and 111% higher Resp rates than Mixed Vegetable systems on loam and silt loam soils respectively, but only 5% and 35% higher SOM (Table 7). Two explanations are possible. First, sampling and processing of undisturbed pasture soils in the lab (where they are sieved and crushed, i.e., altered from their undisturbed field status) allows microbes to access labile organic matter that was previously protected. Second, the sealed chamber alkali trap method may lead to higher respiration rates in soils with a larger fungal/bacterial ratio, which was likely higher in untilled Pasture soils compared to Annual Grain and Processing Vegetable systems (Bailey et al., 2002; Finney et al., 2017).

The organic matter *quality* indices, POXC/SOM and Protein/SOM were not able to detect differences in SOM quality across different cropping systems within soil texture groups (Table 7). The only instance of a trend was a slightly higher Protein/SOM in Mixed Vegetable soils compared to Annual Grain, Processing Vegetable, and Dairy Crop soils. One difficulty in interpreting POXC/SOM results is that it is negatively correlated with SOM, meaning that soils with higher SOM tend to have a lower POXC/SOM ($r = 0.26$; Table S3). It is believed that this is partly a texture effect as discussed above: fine-textured soils generally contain more SOM, but a larger fraction is stable, mineral-bound, and less biologically active.

As we noted in the Methods section, there are potential confounding influences of soil texture when we look at the effect of cropping system across the all textures category (Table 7). For example, the Annual Grain system likely has lower biological indicator means over all texture classes because a larger proportion of Annual Grain samples came from loam textured soils.

Cropping system effects on physical soil health indicators

The different cropping systems exerted a stronger control on WAS than the other three physical soil health indicators: AWC, PR15 and PR45. Pasture soils had a higher mean WAS than soils from other cropping systems across all texture groups. Specifically, WAS averaged 2.6, 2.3, 2.0, and 1.6 times higher than Processing Vegetable, Annual Grain, Dairy Crop, and Mixed Vegetable cropping systems, respectively (Table 8). High SOM in undisturbed pasture systems combined with intact root systems and their associated arbuscular mycorrhizal fungi (AMF) help build and maintain stable soil aggregates (Beare et al., 1997; Six et al., 2006). Meanwhile, conventional tillage has been shown to decrease aggregate stability compared to no-till and perennial systems (Beare et al., 1997; Nunes et al., 2018). Despite the use of intensive tillage in Mixed Vegetable systems to manage weeds and nutrients, these systems were able to maintain 59%, 46%, and 22% higher WAS than Processing Vegetable, Annual Grain, and Dairy Crop systems (Table 8). This is presumably due to the common use of composts and other

Table 8
Mean (SD) physical soil health indicator values by cropping system and soil texture. Mean values followed by different letters are significantly different at the 0.05 error level. Note that PR15 and PR45 measurements had smaller samples sizes than WAS and AWC.

System	n	WAS %	AWC g H_2O g^{-1} soil	n	PR15 kPa	PR45 kPa
			Coarse-Textured			
Annual Grain	35	37.4b (17.0)	0.16 (0.04)	32	1117 (637)	1423 (640)
Processing Veg	31	26.0b (18.5)	0.17 (0.05)	27	1119 (536)	1399 (623)
Mixed Veg	57	37.5b (19.5)	0.18 (0.05)	30	1270 (291)	1177 (341)
Dairy Crop	24	40.8ab (23.1)	0.16 (0.07)	16	1470 (580)	1280 (621)
Pasture	31	50.6a (24.8)	0.18 (0.05)	24	1390 (488)	1153 (553)
All	178	38.2 (21.5)	0.17 (0.05)	129	1247 (525)	1293 (564)
			Loam			
Annual Grain	179	28.7cd (16.6)	0.20b (0.03)	150	1195b (605)	1339 (624)
Processing Veg	44	20.9d (16.6)	0.19b (0.04)	36	1103b (601)	1380 (723)
Mixed Veg	66	35.2bc (18.4)	0.22a (0.03)	30	1155b (569)	1165 (420)
Dairy Crop	67	38.3b (19.0)	0.20b (0.04)	50	1266ab (586)	1387 (536)
Pasture	36	56.5a (24.4)	0.22a (0.03)	20	1705a (935)	1430 (478)
All	392	33.1 (20.2)	0.20 (0.04)	286	1228 (636)	1341 (596)
			Silt Loam			
Annual Grain	78	38.7b (22.0)	0.23c (0.05)	65	1163ab (636)	1128 (663)
Processing Veg	31	33.0b (23.8)	0.23bc (0.05)	24	1132ab (522)	1336 (642)
Mixed Veg	68	40.3b (22.8)	0.26a (0.05)	34	993b (411)	1204 (343)
Dairy Crop	36	39.0b (20.3)	0.26ab (0.05)	23	1310ab (448)	1225 (483)
Pasture	42	72.0a (20.0)	0.28a (0.05)	26	1445a (672)	1264 (531)
All	255	44 (25.1)	0.25 (0.05)	172	1187 (577)	1205 (565)
			Fine-Textured			
Annual Grain	7	26.6b (10.1)	0.23 (0.02)	6	1282 (590)	1263 (481)
Process Veg	1	21.4b	0.22	1	772	627
Dairy	19	30.3b (16.4)	0.22 (0.05)	15	886 (782)	865 (534)
Pasture	5	69.8a (22.3)	0.22 (0.05)	4	1316 (606)	1003 (642)
All	32	35.4 (21.7)	0.22 (0.04)	26	1039 (706)	969 (536)
			All Textures			
Annual Grain	299	32.3c (18.6)	0.20c (0.04)	253	1179b (614)	1294 (639)
Processing Veg	107	25.9d (19.9)	0.20c (0.05)	88	1112b (552)	1365 (665)
Mixed Veg	191	37.7d (20.4)	0.22ab (0.05)	94	1133b (448)	1183 (365)
Dairy Crop	146	37.9d (19.8)	0.21bc (0.06)	104	1253ab (605)	1259 (559)
Pasture	114	61.2a (24.4)	0.23a (0.06)	74	1490a (701)	1259 (533)
All	857	37.5 (22.5)	0.21 (0.05)	613	1212 (601)	1277 (583)

organic amendments in Mixed Vegetable systems that help build and maintain SOM and Protein. Both SOM and Protein have positive relations to WAS (Pearson correlation: $r = 0.61$ and $r = 0.56$, respectively; Table S3).

Cropping systems that maintain higher SOM levels can positively affect AWC (Libohova et al., 2018). This study and other research show that SOM was more strongly related to AWC in coarse-textured soils ($r = 0.48$) compared to loam and silt loam soils ($r = 0.14$ and $r = 0.12$, respectively; Table S5-S7; Libohova *et al.*, 2018). Additionally, we found that coarse-textured Pasture soils had 40%, 31%, and 62% higher AWC than coarse-textured Annual Grain, Processing Vegetable, and Dairy Crop soils. Whereas silt loam textured Pasture soils only had 27%, 17%, and 8% higher AWC than Annual Grain, Processing Vegetable, and Dairy Crop soils. These greater increases in AWC in coarse-textured soils than loam, silt loam, and fine-textured soils is meaningful in that the former soils tend to be more prone to drought.

While the effects of cropping system on soil compaction were inconsistent across soil textures, two logical insights were derived from the results. In coarse-textured soils, Dairy Crop fields averaged 60% higher PR15 than Annual Grain fields (Table 8), which is likely due to heavy manure equipment passes that often occur under marginally wet soil moisture conditions. Second, when all samples were considered, Processing Vegetable farms experienced 24% greater subsurface compaction issues compared to Mixed Vegetable farms (Table 8). This may be explained by the benefits of higher SOM for reducing soil compaction (Hamza and Anderson, 2005) and possibly the use of heavier field equipment in larger-scale processing vegetable operations.

Cropping system effects on chemical soil health indicators

Unlike biological and physical properties, routine testing and recommendations for different crops are well established for soil chemical properties. Soil chemical constraints are also much easier to rectify with lime or inorganic fertilizer application. Therefore, soil chemical properties tended to be in line with recommendations for highly managed systems such as Annual Grain systems (Table S8). Pasture systems, which are less intensively managed and have lower nutrient requirements, tended to have a lower pH than Annual Grain and Dairy Crop systems. This is likely a geographical issue related to the higher prevalence of pastures on soils with inherently lower pH in the southern region of NYS (Cline, 1953).

Cropping systems affected the quantity of extractable P and Zn across soil textures. Phosphorus, an essential macronutrient, can pose an environmental threat to water bodies if it has built up in soils and is subject to runoff or erosion, which in NYS is especially of concern with dairy farms (Rasmussen et al., 2006). Still, when all samples were considered, phosphorus was highest in Mixed Vegetable systems, followed by Processing Vegetable, Dairy Crop, Annual Grain, and Pasture systems (Table S8). This suggests that high-value crops tend to receive more P, which is probably related to the lower input cost relative to the crop value. Moreover, the repeated application of organic amendments (compost, manure) on organic Mixed Vegetable farms to maintain soil fertility often results in excessive P buildup (especially on coarse-textured soils in our data set), as also determined by Morris (2004). But these operations also tend to have small fields with buffers and may pose only a modest risk for water quality. Interestingly, zinc was also consistently higher in Mixed Vegetable systems compared to other cropping systems, which is likely also due to repeated use of organic amendments.

3.4. Scoring functions

This research provides the data necessary to define scoring functions for NYS soil texture groups and cropping systems. The CASH framework uses scoring functions based on the cumulative normal distribution functions that use mean and standard deviation values for various biological and physical indicators at different texture group levels. To date, the CASH has scored biological and physical soil health indicators based on coarse, medium (loam and silt loam are combined in the current framework), and fine texture groups for certain indicators (Moebius-Clune et al., 2017). These scoring functions were updated in 2017 based on the analysis of a large dataset ($n = 5{,}767$) containing Midwest, Northeast, and Mid-Atlantic soils (Fine et al., 2017; Moebius-Clune et al., 2017) and insights from long-term research sites in NYS. Our analysis in NYS indicates that separate scoring functions by texture groups are warranted for WAS, AWC, SOM, POXC, Resp, and Protein. This is a slight deviation from Fine et al. (2017) that found that Resp did not differ between soil texture groups. This study thus provides updated parameters for New York State-specific soil health scoring functions to assess management effects within the context of the state's soil texture groupings. Furthermore, this study shows that cropping system information is relevant in scoring soil health test results if the objective is to evaluate soil health relative to other fields under the same management system. The mean and standard deviation values in Tables 7 and 8 for each combination of the four soil texture groups and five cropping system groups can be used to parameterize 20 sets of unique cumulative normal distribution scoring functions for NYS farms that are specific to soil texture and cropping system. Since our dataset is limited for fine-textured soils, such scoring functions are not yet available for this texture grouping.

4. Conclusions

Increased knowledge of the effects of soil texture, the most defining inherent soil property, and cropping system on soil health indicators is important to understanding how agricultural management affects soil functioning. Our study found important differences in soil health properties across four soil texture groups and five cropping systems. Several important findings were uncovered, including a reaffirmation of the strong texture dependence of SOM, POXC, Resp, and AWC. Furthermore, we demonstrated that cropping systems - presumably through differences in their carbon and nutrient balances that are shaped by crop rotation and perenniality, tillage practices, and applied organic amendments - greatly influence the health of New York State soils. Specifically, Pasture and Mixed Vegetable systems have the highest soil health, followed by Dairy Crop, and then Annual Grain and Processing Vegetable cropping systems. We also demonstrated that the Resp, Protein, and WAS soil health indicators were strongly influenced by cropping system type, while AWC is mostly defined by soil texture. A specific output of this study is new scoring functions by soil texture and cropping system for NYS soils, which enables interpretation of soil health data within the context of specific crop production environments.

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Declaration of interests

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Supplementary materials

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