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Empirically-based production environment soil health goals

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Abstract

Soil health metrics in agricultural systems require edaphic context, notably climate, soil type (soil texture and classification), as well as cropping system. Soil samples (n=1,334) from New York State (USA) with both texture and cropping system information were analyzed for eight physical and biological soil health indicators (soil organic matter, permanganate-oxidizable carbon, respiration, protein, available water capacity, wet aggregate stability, and penetration resistance from 0-15 and 15-45 cm), and population distribution functions were determined. Production environment soil health (PESH) goals were derived for four soil texture groups and six cropping systems by proposing the 75th and 90th percentile for each factorial class. Finer-textured soils and Pasture and Mixed Vegetable systems generally have higher values for soil health goals followed by Dairy Crop and Orchard systems, then Annual Grain, and Processing Vegetable systems. A comparison between Long Island and the rest of New York State demonstrated that soil organic matter PESH goals for Long Island were on average 0.8 % lower than those from the rest of the state. This indicates that regional PESH goals within a state or region may be warranted if edaphic context is considerably different.

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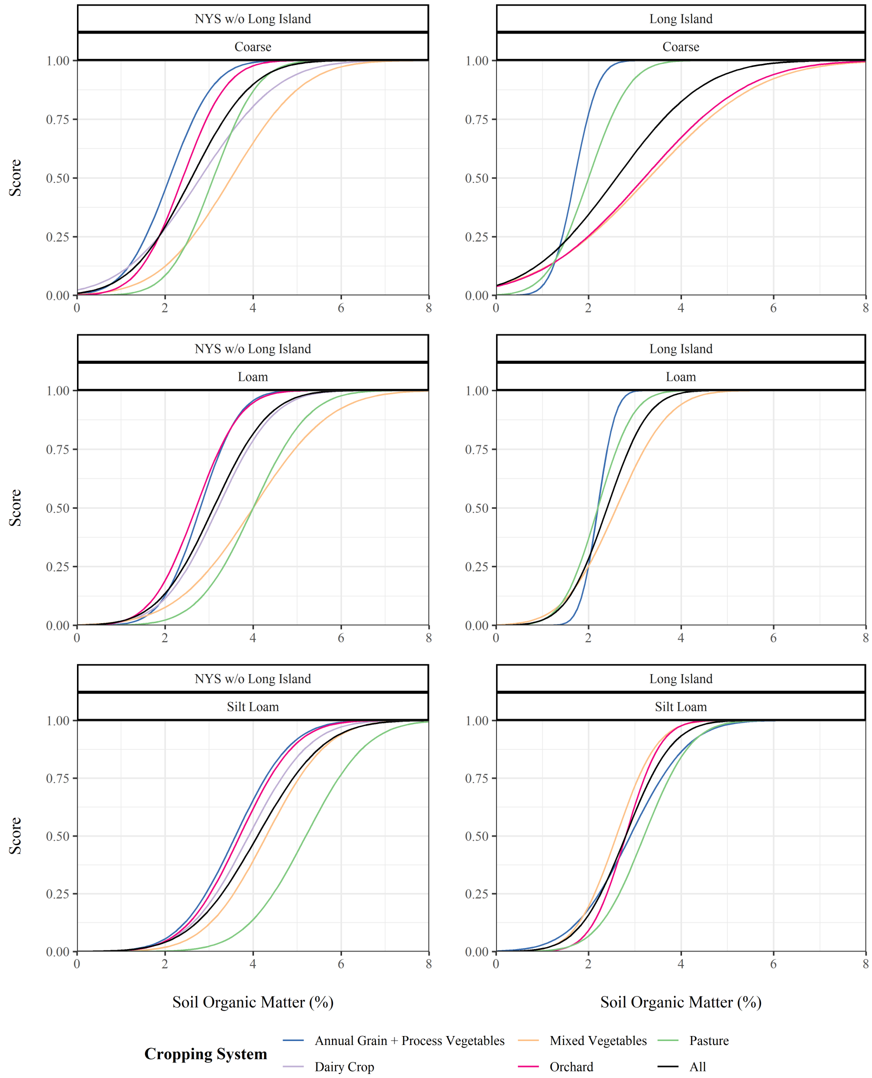

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Empirically-based production environment soil health goals

Core ideas:

- 1,334 soil health analyses from New York State were grouped by production environment (texture + cropping system)
- Production Environment soil health (PESH) goals were established for 4 textures and 6 cropping systems
- Pasture, Mixed Vegetable, and Dairy Crop systems have highest PESH goals
- 75^{th} and 90^{th} percentiles are both useful targets for selecting PESH goals
- Long Island had lower PESH goals than the rest of NYS presumably due to differences in climate and soil texture

Abbreviations:

AWC, available water capacity; WAS, wet aggregate stability; SOM, soil organic matter; SOC, soil organic carbon; SIC, soil inorganic carbon; Protein, soil protein, Resp, soil respiration from 4-day incubation; POXC, permanganate-oxidizable carbon; PR15, penetration resistance from 0-15 cm; PR45, penetration resistance from 15-45 cm; SH, soil health; CASH, Comprehensive Assessment of Soil Health; SHAPE, Soil Health Assessment Protocol and Evaluation; PESH, Production Environment Soil Health; CND, cumulative normal distribution; NYS, New York State; LI, Long Island.

Abstract

Soil health metrics in agricultural systems require edaphic context, notably climate, soil type (soil texture and classification), as well as cropping system. Soil samples (n=1,334) from New York State (USA) with both texture and cropping system information were analyzed for eight physical and biological soil health indicators (soil organic matter, permanganate-oxidizable carbon, respiration, protein, available water capacity, wet aggregate stability, and penetration resistance from 0-15 and 15-45 cm), and population distribution functions were determined. Production environment soil health (PESH) goals were derived for four soil texture groups and six cropping systems by proposing the 75^{th} and 90^{th} percentile for each factorial class. Finer-textured soils and Pasture and Mixed Vegetable systems generally have higher values for soil health goals followed by Dairy Crop and Orchard systems, then Annual Grain, and Processing Vegetable systems. A comparison between Long Island and the rest of New York State demonstrated that soil organic matter PESH goals for Long Island were on average 0.8 % lower than those from the rest of the state. This indicates

that regional PESH goals within a state or region may be warranted if edaphic context is considerably different.

1. INTRODUCTION

1. Interpreting Soil Health Data

Soil health concepts, practices, and testing are being rapidly adopted around the world. This growing interest reflects a heightened appreciation of the role that soils play in providing essential ecosystem services and concerns about the increasingly important influence of human activities, including agriculture, on soil health (SH). This includes the recent interest in ramping up agricultural practices that build soil organic carbon (SOC) as a climate mitigation strategy. A recent estimate for the United States (US) suggests that it is possible to sequester 68 Tg C yr^{-1} (250 Tg CO_2e) in croplands and grasslands with substantial investments in this area (Chambers, et al., 2016), equivalent to approximately 36% of total US agricultural emissions or 3.7% of total US emissions in 2018 (EPA, 2020).

Although quality standards have been developed to protect water and air, very few analogous metrics exist to promote the protection of soil quality or health. Defining quantitative soil health goals can support efforts to improve soil quality and meet humanity's climate mitigation and water quality goals, as well as help benchmark soil health in farmer fields. SH goals can also play an important role in assisting farmers with adapting to the impacts of climate change. However, useful comparisons require context with respect to regional soil types, climate, and cropping system in order to calibrate management.

Conventional soil nutrient contents are generally interpreted through a research base that establishes the optimum and suboptimum soil test values for different crops, and the fertility guidelines aim to reach optimum levels of each nutrient for a given crop (Magdoff and van Es, 2021). The concept of soil health is more holistic and refers to the overall well-being of the soil environment, with the interpretation frameworks for new biological and physical indicators rapidly evolving. Most frameworks for interpreting biological and physical SH indicators use soil texture groupings due to the documented differences in soil organic matter (SOM), SOC, and other SH indicators across texture groups (Amsili, et al., 2021, Fine, et al., 2017, Nunes, et al., 2021). Finer-textured soils tend to have higher inherent levels of SOC than coarser-textured ones, due to the greater capacity of fine silt and clay to stabilize SOC through chemical adsorption and physical protection (Schmidt, et al., 2011, von Lützow, et al., 2006). Additionally, in New York State (NYS), we found that texture group was a more useful predictor of SOM than taxonomic suborder and drainage class (Figure S1).

Emerging large SH datasets are allowing for interpretation of SH indicators across regions, soil textural classes, soil taxonomy, climate, and management effects (Fine, et al., 2017, Nunes, et al., 2020). A Bayesian interpretation approach for SOC was recently developed using texture, suborder classes, and mean annual temperature and precipitation (SHAPE; n=14,680) (Nunes, et al., 2021), which provides a valuable baseline for setting regional SH goals based on inherent soil health properties. However, SHAPE does not currently account for different production environments or cropping systems.

Several studies have compared SOC and other SH indicators between annual cropland and adjacent undisturbed systems (Beniston, et al., 2014, DeGryze, et al., 2004, Kaye, et al., 2005, Martens, et al., 2004, Mishra, et al., 2010, VandenBygaart, et al., 2003) that function as local SH benchmarks. Maharjan et al. (2020) introduced the Soil Health Gap concept as the "difference between soil health (SOC in this case) in an undisturbed native virgin soil and current soil health in a cropland in a given agroecosystem". This is a benchmarking approach that can be shared easily with agricultural professionals, farmers, and policymakers, and others, but it raises questions about the actual benchmark conditions, regional applicability, and whether comparison to virgin systems offers realistic and achievable goals for farmers. Alternatively, the Soil Health Target concept aims to identify soil health targets based on sites that have implemented soil health management systems over a long period of time (>10 years) (Looker, 2021). This approach relies on expert judgement about what constitutes the SH management system and the duration that SH management system has been in place.

Alternatively, scoring functions can be employed to establish population-based soil health goals for production environments (i.e., a group of samples within the same soil texture and cropping system so farmers can be compared to their peers). Such functions transform measured indicator values into SH scores (Andrews, et al., 2004, Karlen, et al., 2019), generally using cumulative normal distribution (CND) functions. The Comprehensive Assessment of Soil Health framework (Moebius-Clune, et al., ; 2017) (CASH) uses scoring functions based an empirical data where individual sample results are evaluated relative to a larger population of samples. These scoring functions in effect apply fuzzy logic (McBratney and Odeh, 1997) to SH test results rather than the discrete optimum-suboptimum approach or gap approaches. This also facilitates the establishment of population-based benchmarks for SH indicators, i.e., goals that are relevant to the production environment (soils, climate, cropping system). An empirical approach for defining production environment soil health (PESH) goals for New York State (NYS) was developed by estimating the 75^{th} percentile value within soil texture and cropping system groupings (Amsili, et al., 2020). More recently, Drexler et al. (2022) developed SOC standards for Germany by defining both lower and upper benchmarks (12.5^{th} and 87.5^{th} percentiles, respectively) for 33 strata that were defined by a combination of land use, soil texture, C/N ratio, and mean annual precipitation factor levels.

Global interest in improving soil health to reverse soil degradation, sustainably intensify agriculture, and mitigate and adapt to climate change requires guidance on SH and SOC goals for farmers, policymakers, and other stakeholders.

The State of New York passed soil health legislation in 2022 that required the establishment of voluntary standards for SH indicators (New York State Senate, 2022). Considering this global and local context, the objectives of this research were to (i) establish population-based PESH goals for NYS by soil texture and cropping system (production environments), (ii) compare resulting values, and (iii) evaluate different regional PESH goals within NYS. Our approach to defining PESH goals for NYS can serve as a template for other regions of the world.

2. MATERIALS AND METHODS

2.1. Dataset

A dataset on SH indicators was compiled from 1,334 soil samples (0-15 cm depth) from across NYS that were collected and analyzed between 2014-2021. The soil samples were derived from routine submissions to the Cornell Soil Health Laboratory and the majority of samples were collected by trusted researchers and agricultural professionals (n=1,054). This dataset was compiled from a larger database by removing urban, manufactured, landscaped, and muck soils to make interpretations more useful for agricultural soils. Soils with SOM values greater than the 98^{th} percentile of SOM content (7.4, 7.6, 7.6, and 8.1 % for coarse, loam, and silt loam, and fine textures, respectively) were filtered out to ensure all heavily amended soils were removed, which tended to include high tunnels and very small Mixed Vegetable Farms less than one acre in size. Finally, repeated submissions from the same fields or research experiments were also removed from the database. The majority of samples (n=1,234) came from commercial farm fields and the remaining samples (n=100) came from ten research experiments with a total of 41 different treatments with variations in tillage, organic matter inputs, or both. Samples were analyzed for soil texture and a suite of SH indicators according to the CASH protocol (Moebius-Clune, et al., ; 2017). These included four biological and four physical indicators: soil organic matter (SOM) by loss on ignition (NY-Method: 500°C for 2 hr with correction factor); permanganate oxidizable carbon (POXC) using $KMnO_4$ and colorimetric readings at 550 nm; soil protein (Protein) using citrate extraction, autoclaving, and bicinchoninic acid protein assay; soil respiration (Resp) quantified as emitted CO_2 after soil wetting and 4-day incubation; wet aggregate stability (WAS) based on soil aggregate breakdown under simulated rainfall; available water capacity (AWC) as the gravimetric soil water content difference between $-10\,\mathrm{kPa}$ and $-1500\,\mathrm{kPa}$ water potential in pressure chambers; and surface (0-15 cm; PR15) and subsurface hardness (15-45 cm; PR45) using a soil penetrometer (Schindelbeck, et al., 2016). A portion (32%) of the dataset had SOC measurements on them (n=428). For the remaining samples, SOC was predicted from SOM by applying the following regression equations by 0.69(SOM)-0.03, 0.70(SOM)-0.31, 0.70(SOM)-0.31, and 0.65(SOM)-0.26 for coarse, loam, silt loam, and fine textures respectively, based on best fit linear regression models between SOM (NY method) and SOC (Figure S2, n=5,063). Total C in this dataset was measured with a Primacs SNC-100 Combustion Analyzer (Skalar, Buford, GA). Samples with a pH above 6.5 were run through a modified calcimeter procedure to determine soil inorganic carbon (SIC) (Fonnesbeck, et al., 2013) and to calculate SOC (SOC=Total C-SIC). The combination of measured and predicted SOC values are presented here as *predicted SOC*. Analytical protocols are summarized in Amsili et al. (2021) with further details in Schindelbeck et al. (2016).

Soil samples also included crop code information denoting the current and past crops (3-years) in the rotation (Dairy One, 2020). These were grouped into six cropping system types, Annual Grain, Processing Vegetable, Dairy Crop, Mixed Vegetable, Orchard, and Pasture (Table 1). The Dairy Crop category denotes dairy cropping systems that include forage crops such as corn silage or alfalfa in rotation as feed for dairy cows. The majority of samples in the Pasture category were indeed pastures, but hayland samples were also included. The geographic distribution in part represents regional specializations within the state, with higher prevalence of vegetable crops and pastures in the southeastern part, dairy crops in the northern, central, and western parts, and annual grains and processing vegetables in the central and western part (Figure 1) (Amsili, et al., 2021). These six cropping system categories were chosen based on the available dataset and don't reflect all possible cropping systems or approaches to agriculture.

Table 1. Six cropping system groups were formed by combining related crops (n=1,334). Each crop is followed by the associated number of soil samples in parentheses. The original crop codes used to derive the crop type and the scientific names are present in the footnote below the table.

Cropping System	**Crops**[1,2]
Annual Grain	corn grain (174), soybean (100), wheat (40), dry beans (16), wheat straw (8)
Processing Veg	sweet corn (20), snap beans (15), pumpkins (13), tomato (11), cabbage transplanted (1
Dairy Crop	corn silage (174), alfalfa (25), alfalfa grass (24), clover grass (12)
Mixed Veg	mixed vegetable (262)
Orchard	apple (172), peach (13)
Pasture	pasture rotational grazing (73), grasses (38), pasture with native grasses (25), pasture

[1] COG=corn grain (*Zea mays)*, SOY=soybean (*Glycine max)*, WHT=wheat (*Triticum aestivum)*, BND=dry beans (*Phaseolus vulgaris*), WHS=wheat straw, SWC=sweet corn (*Zea mays* convar. *saccharata* var. *rugosa),* BNS=snap beans (*Phaseolus vulgaris*), PUM=pumpkin (*Cucurbita pepo*), TOM=tomato (*Solanum lycopersicum*), CBP=cabbage transplanted (*Brassica oleracea*), SQW=winter squash (*Cucurbita spp.*), COS=corn silage, ALE/ALT=alfalfa (*Medicago sativa*), AGE/AGT=alfalfa grass, CGT=clover grass, MIX=mixed vegetable, APP=apple (*Malus domestica*), PCH=peach (*Prunus persica),* PIT/PIE=pasture rotational grazing, PNT=pasture with native grasses, GRE/GRT=grasses, PLT=pasture with legumes.

[2] 84 samples were from crop codes with less than 5 samples.

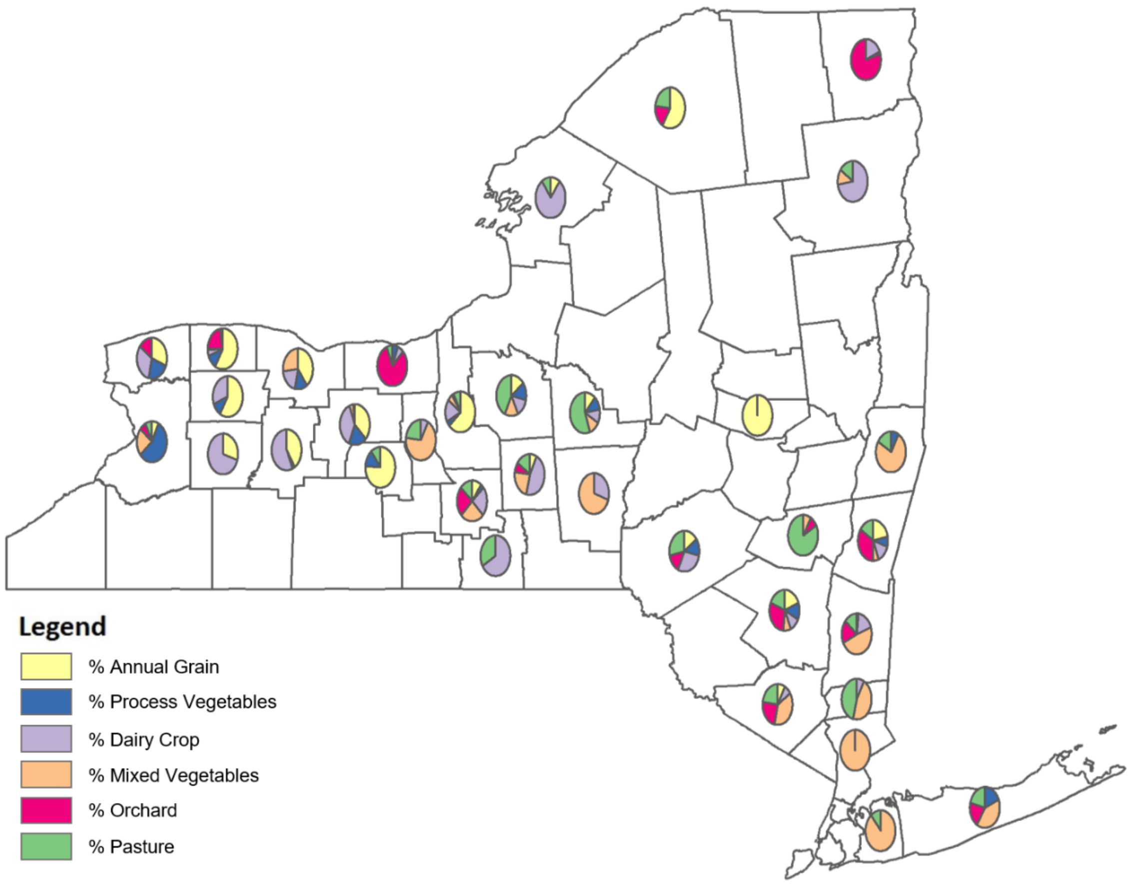

Figure 1. Geographic distribution of the six cropping systems included in the analysis.

2.2. Production Environment Soil Health Goal Approach

The soil samples submitted to the Cornell Soil Health Laboratory further include a range of management conditions and use of SH building or degrading practices (e.g., tillage intensity, cover cropping, organic amendments, etc.). The first step was to parameterize the CND scoring functions for each of the SH indicators of interest. Mean and standard deviations were estimated for 24 subgroup populations of all possible combinations of four soil texture groups and six cropping system types (Table 1). The four soil texture groups consisted of coarse-textured (loamy sand and sandy loam), loam (loam and sandy clay loam), silt loam, and fine-textured (clay loam, silty clay loam, and clay). Medium-textured classes were separated as they represent the majority of agricultural lands in NYS and consistent differences in SH indicators were observed between loam and silt loam texture classes. Two texture classes had limited sample sizes: sandy clay loam and clay with each only having 7 and 3 observations, respectively. These 24 subgroup populations represent different production environments, thereby integrating soil texture and cropping system variables.

PESH goals were calculated as the 75^{th} and 90^{th} percentile of the distribution for each biological and physical SH indicator in each of 24 sub groupings (Figure 2). Therefore, these PESH goals are achievable because 25% and 10% of the soil samples within each class have attained them. Furthermore, PESH goals at both the 75^{th} and 90^{th} percentiles were compared between the Long Island region of NY (LI; n=264; the majority of samples came from Suffolk County; n=255), and the rest of NYS (n=1,070), across coarse, loam, and silt loam soil textures. Fine-textured samples were excluded from this comparison because no fine-textured samples were collected from LI. This comparison was carried out due to the large apparent differences in soil type and climate across these regions, which could make assessing the effects of management on SH difficult if site inherent properties are too different. This comparison within NYS provides an important case study in the value of defining production environment soil health goals for states and regions that have large differences in climate and soil types. Summary statistics (mean, standard deviation, and quantiles) were calculated by texture, cropping system, and region. Statistical analyses and figures were run using the R statistical software (R Core Team, 2021).

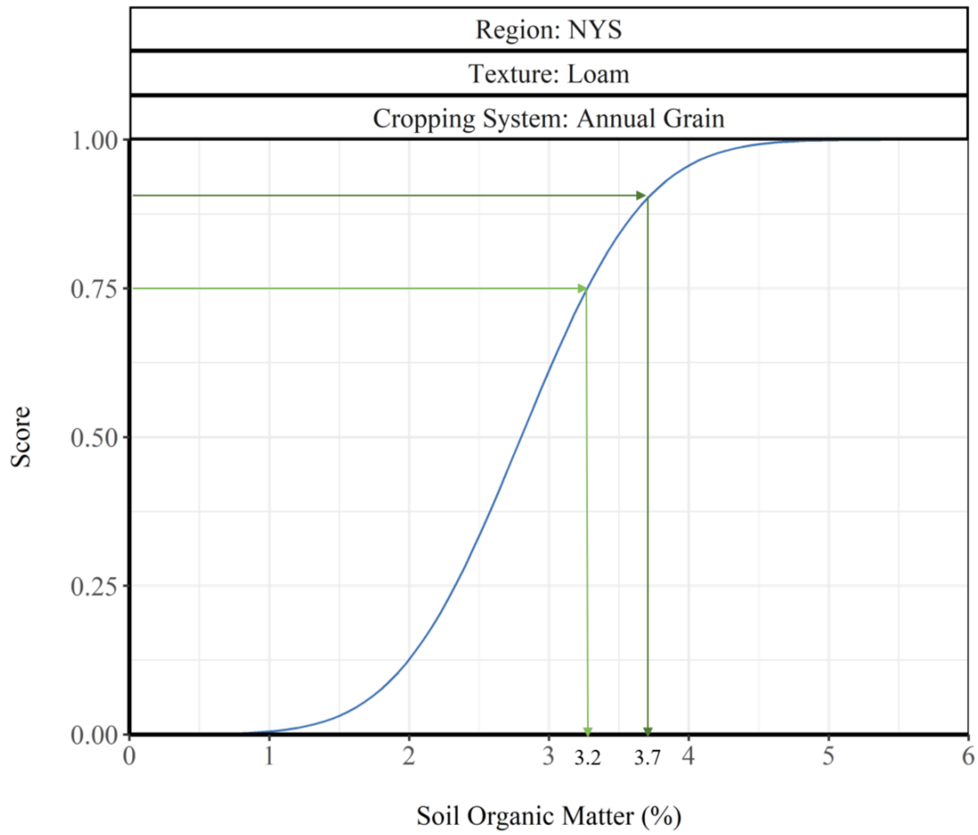

Figure 2. An illustration of the approach to calculate soil health goals at the 75^{th} and 90^{th} percentile of biological and physical SH indicators. This example is for SOM in Annual Grain systems on loam textured soils in New York State.

3. RESULTS AND DISCUSSION

3.1. Production Environment Soil Health Scoring Functions

This NYS SH dataset provided the foundation to define empirical scoring functions for SOM, predicted SOC, POXC, protein, WAS, and AWC for 24 production environments (all possible combinations of four soil texture and six cropping system groups) in NYS (Table 2). PESH scoring functions, as presented here are parameterized to integrate information about cropping system (human management impacts), which represents the next level of SH interpretation as it goes beyond solely inherent site characteristics (soil texture, soil taxonomy, region, and climate). Most likely, PESH scoring functions are only applicable at regional scales due to the vast numbers of strata that would be required to accommodate both site inherent properties and regionally unique cropping systems across the continental US. Therefore, regional scoring systems have the advantage that they can include cropping system information, which helps to constrain what management practices are realistic or possible to be implemented by farmers in a specific cropping system. This is particularly important for regions like the Northeast US, which hosts high diversity in the types of annual and perennial cropping systems that are present across the landscape.

Due to inconsistent effects of cropping systems on penetration resistance, we used established penetration resistance scoring functions for PR15 and PR45. Mean and standard deviation values were 1130 kPa and 650 kPa for PR15 and 2070 kPa and 760 kPa for PR45, respectively (Moebius-Clune, et al., ; 2017). Additionally, since our dataset is limited for fine-textured soils, PESH scoring functions for this texture grouping were poorly constrained and were also interpolated based on silt loam scoring functions. For fine-textured cropping system categories with less than 10 samples, we made three assumptions to interpolate those scoring functions: 1) for biological indicators, PESH scoring function means should be slightly higher than those from silt loam soils and available data for annual grain and dairy crop systems set how much higher; 2) for aggregate stability, PESH scoring functions would be the same as those for silt loam soils; and 3) for available water capacity, PESH scoring functions would be the same as when fine-textured samples were pooled. Similar to SHAPE scoring functions (Nunes, et al., 2021), PESH scoring functions for NYS will be refined over time as sample sizes for certain production environments become larger. PESH scoring functions from 24 production environments provides the foundation to calculate PESH goals.

Table 2. Mean values (standard deviation; SD) for biological and physical soil health indicators across four soil texture groups. These mean and SD values are the parameters required for the CND scoring functions specific to cropping system and soil texture (production environment).

Cropping System	**SOM**	**Pred. SOC**	**POXC**	**Protein**	**Resp**	**WAS**	**AWC**
	%	%	mg C/kg	mg/g	mg CO_2/g	%	g H_2O/g soil
Coarse-Textured							
Annual Grain	(0.6)	(0.4)	(143)	(1.6)	(0.16)	(17.0)	(0.03)
Processing Veg	(0.7)	(0.5)	(150)	(1.9)	(0.19)	(14.9)	(0.04)
Dairy Crop	(1.4)	(1.0)	(270)	(2.7)	(0.28)	(22.5)	(0.07)
Mixed Veg	(1.7)	(1.2)	(298)	(5.1)	(0.37)	(19.0)	(0.06)

Cropping System	n	SOM	Pred. SOC	POXC	Protein	Resp	WAS	AWC
Orchard		(1.0)	(0.8)	(255)	(3.1)	(0.22)	(19.2)	(0.05)
Pasture		(0.9)	(0.7)	(195)	(3.1)	(0.26)	(22.8)	(0.05)
All		(1.3)	(0.9)	(257)	(3.9)	(0.28)	(20.5)	(0.05)
Loam								
Annual Grain		(0.7)	(0.5)	(158)	(1.7)	(0.15)	(15.5)	(0.03)
Processing Veg		(0.7)	(0.5)	(126)	(1.4)	(0.17)	(16.1)	(0.04)
Dairy Crop		(1.0)	(0.7)	(154)	(2.1)	(0.19)	(20.6)	(0.03)
Mixed Veg		(1.4)	(1.0)	(226)	(4.0)	(0.26)	(18.4)	(0.03)
Orchard		(0.8)	(0.6)	(168)	(2.1)	(0.19)	(19.5)	(0.04)
Pasture		(1.2)	(0.9)	(209)	(2.7)	(0.35)	(23.1)	(0.03)
All		(1.0)	(0.7)	(181)	(2.6)	(0.22)	(19.9)	(0.03)
Silt Loam								
Annual Grain		(1.0)	(0.7)	(202)	(3.1)	(0.24)	(21.8)	(0.05)
Processing Veg		(1.1)	(0.8)	(190)	(2.7)	(0.24)	(23.2)	(0.05)
Dairy Crop		(1.1)	(0.8)	(168)	(2.4)	(0.19)	(23.2)	(0.05)
Mixed Veg		(1.3)	(0.9)	(194)	(3.1)	(0.23)	(24.0)	(0.04)
Orchard		(1.0)	(0.7)	(159)	(3.0)	(0.28)	(20.5)	(0.05)
Pasture		(1.4)	(0.9)	(169)	(2.7)	(0.41)	(22.9)	(0.04)
All		(1.3)	(0.9)	(183)	(3.0)	(0.32)	(25.6)	(0.05)
Fine-Textured								
Annual Grain		(0.8)	(0.5)	(150)	(1.0)	(0.20)	(21.8)	(0.04)
Processing Veg	*	(0.8)	(0.8)	(150)	(1.0)	(0.20)	(23.2)	(0.04)
Dairy Crop		(0.8)	(0.4)	(120)	(2.3)	(0.14)	(23.2)	(0.04)
Mixed Veg	*	(1.2)	(0.8)	(120)	(2.3)	(0.14)	(24.0)	(0.04)
Orchard	*	(1.0)	(0.6)	(120)	(2.3)	(0.14)	(20.5)	(0.04)
Pasture	*	(1.5)	(0.9)	(185)	(2.5)	(0.30)	(22.9)	(0.04)
All		(0.9)	(0.6)	(150)	(1.9)	(0.27)	(21.5)	(0.04)

3.2 Production Environment Soil Health Goals

This research focuses on developing a framework for empirically defining PESH goals by soil texture, cropping system, and geography thereby providing realistic targets for farmers within the context of their farming environment. We developed PESH goals based on the 75th and 90th percentile of the peer distribution to support broader policy discussions around the most appropriate metrics for voluntary SH standards. Although our geographic focus is on NYS, this framework can be applied to any production environment where SH data are sufficient to develop a peer population-based analysis (i.e., a large enough sample dataset is generated to allow for comparison of individual sample results against their peers, results of all samples from the same production environment). PESH goals in NYS (Table 3) were highest in finer textured soils for SOM, POXC, and Resp in order of fine-textured = silt loam > loam > coarse-textured. Finer textured soils have a greater ability to retain and stabilize SOM against decomposition than coarse-textured soils (von Lützow, et al., 2006). Protein goals did not follow this trend, likely due to the effects of lower protein extraction efficiency in soils with higher clay content (Amsili, et al., 2021, Giagnoni, et al., 2013). WAS goals were also not strongly affected by soil texture group. AWC goals were highest for silt loam soils, conforming to established knowledge (Brady and Weil, 2008, Libohova, et al., 2018) (Table 4). SH goals for surface (0-15 cm; PR15) and subsurface hardness (15-45 cm; PR45) across soil texture and cropping system were not definable due to inconsistent effects (Amsili, et al., 2021) and the 25th and 10^{th} percentile values of the established generalized scoring functions were used (1720 and 690 kPa for PR15 and 1550 and 1100 kPa for PR45, respectively). (Note: PR measurements follow a less-is-better scoring function, hence the 25^{th} and 10^{th} percentile values; Moebius-Clune et al., 2016; Table 4).

Cropping systems were equally influential in shaping aspirational SH goals when compared to soil texture. Pastures, Mixed Vegetable, and Dairy Crop systems allow for the highest biological and physical SH goals, followed by Orchard systems. Pasture systems naturally maintain greater biological and physical health due to continuous perennial carbon inputs and an absence of cultivation, whereas Mixed Vegetable and Dairy Crop systems improve SH largely through cover cropping, perennial forages, and organic matter inputs. Orchard systems had intermediate aspirational goals presumably because some have quite poor soil health due to chemical fallow groundcover management that does not return OM inputs to the soil (Merwin, et al., 1994), while others maintain higher soil health by utilizing woodchip mulch to provide weed control and build SH. Annual Grain and Processing Vegetable systems were associated with lower biological and physical SH goals as the harvest and removal of most of the aboveground biomass and use of tillage generates off-farm carbon and nutrient flows without adequate replacement. Interestingly, for silt loam textures, SH goals for Dairy Crop and Mixed Vegetable systems appeared to converge with those for Annual Grain and Processing Vegetables.

By having PESH goals farmers may be more encouraged to implement management practices that build soil health because a more achievable target can be reached. For example, if a farmer currently has SOM levels of 2.0% but within the same soil texture class and cropping system has the ability to reach 4.0%, they can, with the help of an agriculture service provider, determine what change in practices are needed to build SOM and improve overall soil health. Reaching that 4.0% goal becomes more achievable to a farmer than if their results are being compared to a farmer working in a different soil type, cropping system, and environment.

One potential limitation of the empirical framework for defining PESH goals as the 75th or 90th percentile is that soils at the 75th or 90th percentile may still represent low soil health. Therefore, it is important that the population for each production environment includes farm fields that have had long-term implementation of best practices relevant to that cropping system. While this is not a limitation for this dataset, where many of NYS's most innovative regenerative farmers and long-term research experiments are well represented, this is would be a valid criticism for PESH goals that were developed from unrepresentative datasets that do not include fields with the full range soil health management practices.

Table 3. Production environment soil health goals (Q75 and Q90 basis) by cropping system and soil texture for biological SH indicators for NYS.

Cropping System	**Q75 SOM**	**Q90 SOM**	**Q75 Pred. SOC**	**Q90 Pred. SOC**	**Q75 POXC**	**Q90 POXC**	**Q75 Protein**	**Q90 Protein**	**Q75 Resp**	**Q90 Resp**
	%	%	%	%	mg C/ kg	mg C/ kg	mg/g	mg/g	mg CO_2/g	mg CO_2/g
Coarse-Textured										
Annual Grain										
Processing Veg										
Dairy Crop										
Mixed Veg										
Orchard										
Pasture										
All										
Loam										
Annual Grain										

Cropping System	Q75 SOM	Q90 SOM	Q75 Pred. SOC	Q90 Pred. SOC	Q75 POXC	Q90 POXC	Q75 Protein	Q90 Protein	Q75 Resp	Q90 Resp
Processing Veg										
Dairy Crop										
Mixed Veg										
Orchard										
Pasture										
All										
Silt Loam										
Annual Grain										
Processing Veg										
Dairy Crop										
Mixed Veg										
Orchard										
Pasture										
All										
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Mixed* Veg										
Orchard*										
Pasture										
All										

*Groups with fewer than 10 in the fine-textured categories were interpolated based off of silt loam values.

Table 4. Production environment soil health goals (Q75 and Q90 basis) by cropping system and soil texture for physical SH indicators for NYS. Soil health goals for PR15 and PR45 are presented in the section 3.2.

Cropping System	n	Q75 WAS	Q90 WAS	Q75 AWC	Q90 AWC
		%	%	g H_2O/ g soil	g H_2O/ g soil
Coarse-Textured					
Annual Grain					
Processing Veg					
Dairy Crop					
Mixed Veg					
Orchard					
Pasture					
All					
Loam					
Annual Grain					
Processing Veg					
Dairy Crop					
Mixed Veg					
Orchard					
Pasture					
All					
Silt Loam					
Annual Grain					
Processing Veg					
Dairy Crop					
Mixed Veg					
Orchard					
Pasture					
All					
Fine-Textured					

Cropping System	n	Q75 WAS	Q90 WAS	Q75 AWC	Q90 AWC
Annual Grain					
Processing Veg	*				
Dairy Crop					
Mixed Veg	*				
Orchard	*				
Pasture					
All					

*Cropping system goals in the fine-textured categories were assumed to be the same as the silt loam category for aggregate stability and the same as All fine-textured samples for AWC.

3.3. Comparing PESH Goals (Q75 vs Q90)

While targeting the 75$^{\text{th}}$ percentile is a sound approach for identifying achievable SH goals, choosing a higher quantile (e.g., 90$^{\text{th}}$ percentile) may be beneficial and of interest for certain subgroup populations to provide a more aspirational SH goal. The Q90 goal was 17.7%, 19.8%, 24.4%, 27.8%, 35.7%, and 9.0% higher than the Q75 goal for SOM, POXC, Protein, Resp, WAS, and AWC, respectively (Table 3; Table 4). A concern is that certain subgroup populations with narrow distributions might not contain those systems with aspirational soil health practices and outcomes at the 75$^{\text{th}}$ percentile. In those cases, choosing the 90$^{\text{th}}$ percentile as the PESH goal may remedy that situation. For SOM, the percent and absolute difference between the 90$^{\text{th}}$ and 75$^{\text{th}}$ percentile was 14.5% and 0.5% for Annual Grain and Processing Vegetable systems, but was 23.1% and 1.0% for Dairy Crop and Mixed Vegetables systems. This indicates that choosing the 90$^{\text{th}}$ percentile instead of the 75$^{\text{th}}$ percentile might be more appropriate for Annual Grain and Processing Vegetable systems, especially on coarse and loam textures where the differences between other systems were more pronounced. Ultimately, providing both Q75 and Q90 PESH goals gives agricultural professionals, farmers, and policymakers options about which goal seems to be the most appropriate for their specific situation.

3.4. Regional Goals within New York State

Although the development of PESH goals for NYS provides a first step forward to defining appropriate standards for NYS glaciated soils and cropping systems, further regionalization of PESH goals may be necessary. The soils of LI were formed from sorted sand and gravel glacial outwash parent materials that are characteristic of the southern edge of the Pleistocene glaciers (Warner, et al., 1975). Generally, soils on LI are coarser textured (higher sand and lower clay content) than the rest of NYS (Aller, et al., 2022). The mean annual temperature on LI is approximately 3.3 °C warmer than all other agricultural areas in the rest of NYS. These soil and climatic differences are a likely explanation for the overall lower biological SH values for LI compared to the rest of NYS (Table 5). The comparison of Q75 and Q90 SH goals demonstrated large differences across soil texture and cropping systems. PESH goals for SOM (Q75) for LI subgroup populations had on average 0.8 % lower SOM compared to their corresponding subgroup populations from the rest of NYS (Table 5; Figure 3). These differences between LI and the rest of NYS also appeared larger in loam and silt loam texture groups than for coarse-textured soils (Table 5).

While the effects of temperature on microbial decomposition of SOM are difficult to unravel, topsoil SOC concentrations appear to decrease as mean annual temperature increases within certain ranges (Guo, et al., 2006). Specifically, loam and silt loam groups on LI had 5% less clay than those textures from the rest of NYS. These differences in clay content increased at the upper end of the distribution of clay content in loam and silt loam soils. Therefore, the coarser-textured soils of LI may have a lower inherent capacity to stabilize SOM against decomposition due to less protective capacity of the soil than the same soil texture classes from the rest of the state (von Lützow, et al., 2006). Finally, LI has a long history of intensive processing vegetable production including lima beans, cauliflower, and potatoes (Bond, 1954, Faber, 1975, Lazarus and White, 1984), which might be a third factor contributing to low topsoil SOM values. Continuous processing vegetable production involves intensive soil disturbance and few organic matter inputs to the soil, which can lead to lower SOM concentrations over time (Angers, et al., 1999).

Table 5. Mean values (standard deviation; SD) and Production Environment Soil Health goals (Q75 and Q90 basis) by cropping system and soil texture for soil organic matter in NYS with Long Island removed vs. Long Island.

	NYS w/o Long Island	**Long Island**						
Cropping System	**n**	**Mean (SD) SOM**	**Q75 SOM**	**Q90 SOM**	**n**	**Mean (SD) SOM**	**Q75 SOM**	**Q90 SOM**
		%	%	%		%	%	%
Coarse								
Annual Grain		(0.6)			-	-	-	-

	NYS w/o Long Island	**Long Island**				
Processing Veg		(1.0)		(0.4)		
Dairy Crop		(1.4)	-	-	-	-
Mixed Veg		(1.3)		(1.9)		
Orchard		(0.8)	*	(1.8)		
Pasture		(0.8)		(0.7)		
All		(1.1)		(1.5)		
Loam						
Annual Grain		(0.7)	-		-	-
Processing Veg		(0.7)		(0.3)		
Dairy Crop		(1.0)	-		-	-
Mixed Veg		(1.4)		(0.9)		
Orchard		(0.8)		(0.7)		
Pasture		(1.0)	*	(0.6)		
All		(1.0)		(0.7)		
Silt Loam						
Annual Grain		(1.0)	-	-	-	-
Processing Veg		(1.1)		(1.0)		
Dairy Crop		(1.1)	-	-	-	-
Mixed Veg		(1.1)		(0.7)		
Orchard		(1.0)		(0.6)		
Pasture		(1.1)		(0.8)		
All		(1.2)		(0.8)		

*Groups with fewer than 10 observations should be interpreted with caution.

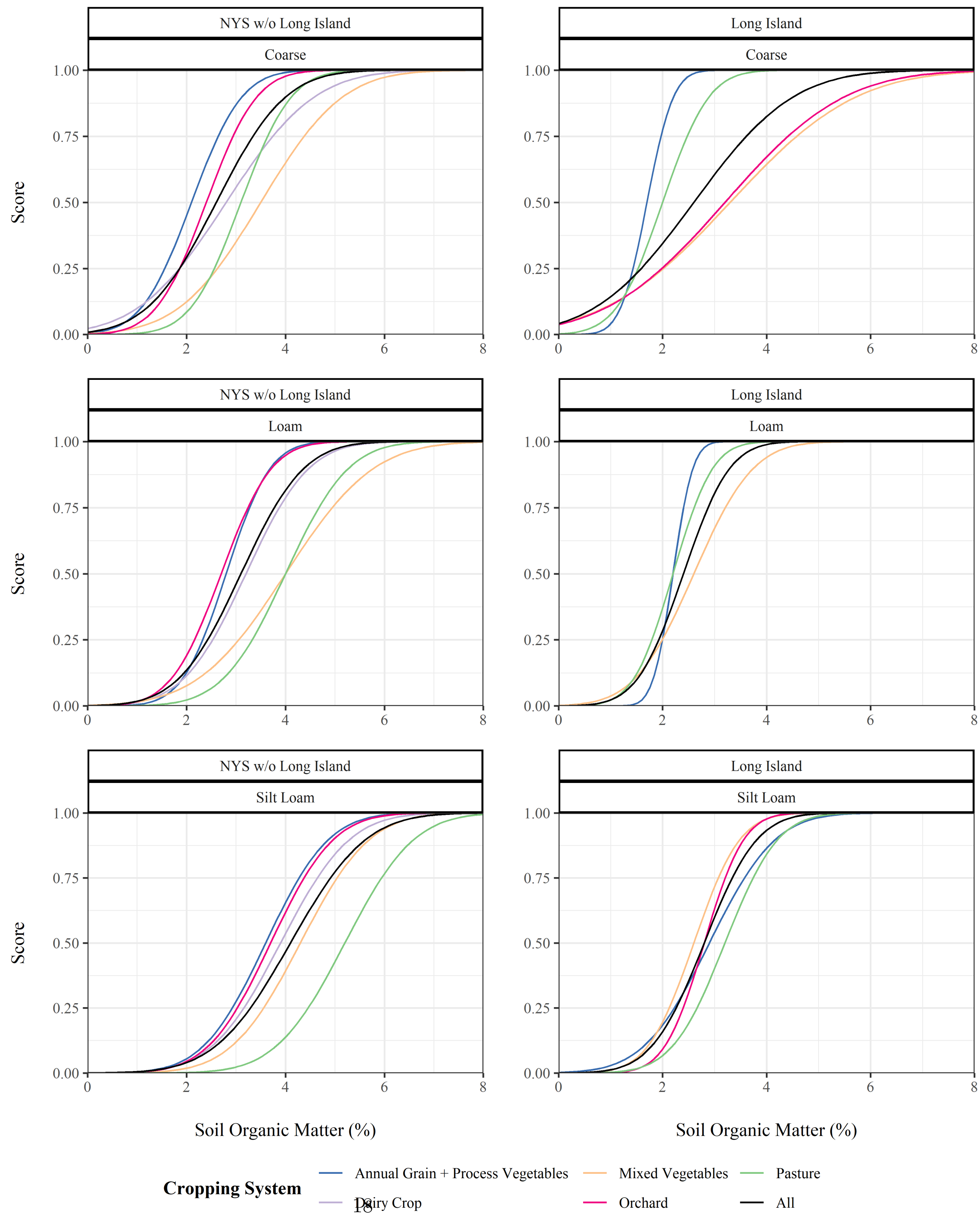
NYS w/o Long Island
Coarse
Long Island
Coarse
NYS w/o Long Island
Loam
Long Island
Loam
NYS w/o Long Island
Silt Loam
Long Island
Silt Loam
Score
0.00
0.25
0.50
0.75
1.00
0
2
4
6
8
Soil Organic Matter (%)
Cropping System
Annual Grain + Process Vegetables
Mixed Vegetables
Pasture
Dairy Crop
Orchard
All

Figure 3. Scoring functions for soil organic matter representing two regions in NY and three soil texture classes. Scoring functions were presented for Annual Grain + Process Vegetables, Dairy Crop, Mixed Vegetables, Orchard, Pasture, and All data within each texture group. Annual Grain and Process Vegetable data was grouped since CND functions were quite similar for those systems. There were no Annual Grain or Dairy Crop systems on Long Island.

4. CONCLUSIONS

Increased interest in soil health and building SOC requires benchmarks for assessing progress within the context of region, soil type, cropping system, and climate. PESH goals which group soil texture and cropping system can provide more realistic soil health goals to help growers calibrate their management. For instance, realistic PESH goals for Pasture, Mixed Vegetable, and Dairy Crop systems are different than those for Annual Grain and Processing Vegetable systems across soil texture groups, mostly as a result of fundamentally different agronomic management practices that are implemented in these systems (i.e., tillage and amount of organic carbon inputs). The development of separate PESH goals for areas within a state may be justified if significant differences in soil type and climate exist, which was the case for Long Island, NY.

Supplemental Material

Supplemental figure S1 presents a variable importance diagnostic plot which supports the selection of soil texture group over drainage class and taxonomic suborder as the key inherent property for NYS production environments. Figure S2 shows linear regression equations between SOM-NYS and SOC for coarse, loam, silt loam, and fine soil textures that was derived from a large (n=5,063) continental soil health database.

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