Legacy of Intensive Agricultural History in the Health of (Sub)Tropical Landscapes

Susan Crow (crows@hawaii.edu)
University of Hawaii Manoa https://orcid.org/0000-0001-8735-1580
Hannah Hubanks
University of Hawaii Manoa
Jonathan Deenik
University of Hawaii Manoa
Tai Maaz
University of Hawaii Manoa
Christine Tallamy Glazer
University of Hawaii Manoa
Elaine Vizka
University of Hawaii Manoa
Johanie Rivera-Zayas
University of Hawaii Manoa

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Title: Legacy of intensive agricultural history in the health of (sub)tropical landscapes

Authors: Susan E. Crow*[1], Hannah Hubanks[1], Jonathan L. Deenik[2], Tai McClellan Maaz[2], Christine Tallamy Glazer[1], Elaine Vizka[1], Johanie Rivera-Zayas[1]

Affiliations:[1]Department of Natural Resources and Environmental Management, University of Hawai‘i Mānoa, Honolulu, Hawai‘i, USA, 96822
[2]Department of Tropical Plant and Soil Science, University of Hawai‘i Mānoa, Honolulu, Hawai‘i, USA, 96822

***Corresponding author:** Susan E. Crow, 1910 East West Road, Sherman Lab 101, Honolulu, Hawai‘i, USA, 96822; office phone 808-956-8149; **Email:** crows@hawaii.edu; orchid.org/000-0001-8735-1580

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Abstract
Soil health conceptualized as a measurable ecosystem property provides a powerful tool for monitoring progress in restoration projects or implementation of best management practices to promote sustainable agroecosystems. We surveyed soils collected from a range of land uses (i.e., protected native and non-native forest, managed pasture, unmanaged previously intensive agricultural lands, organic cropland, and conventional cropland) across a range of soil orders (Oxisol, Mollisol, Andisol, Inceptisol, and Vertisol) on three Hawaiian Islands. Forty-six metrics associated with soil health and encompassing biological, chemical, and physical properties were measured. In this multivariate survey, the most distinct group was the unmanaged, previously intensive agriculture lands, which was significantly different from all other land uses regardless of mineralogy. Importantly, the soil health of well-managed pastures in Hawaiʻi was not different from protected forests, suggesting that well-managed grazing lands may be as healthy and resilient as protected forests. A suite of 11 readily measured parameters emerged out of a first-principle approach to determining a holistic indication of soil health across a range of soils and systems in Hawaiʻi encompassing much of the diversity in the tropics and subtropics. Every land use may improve its soil health status within a reasonable range of expectations for a soil's land use history, current land use, and mineralogy. Key drivers of the measures for soil health, including intensive land use history, current land use practices, and mineralogy, must be interwoven into the soil health index, which should set minimum and maximum benchmarks and weight parameters according to equitable standards.

Significance Statement
The heterogeneity of natural and working lands may be harnessed to help broadly define soil health for an expansive role in describing diverse, multi-functional and sustainable landscapes beyond the current focus on agriculture. Hawaiʻi is geographically tropical and climatically subtropical; it encompasses 83% of global soil diversity and recent patterns of deforestation and extractive, intensive agriculture mirror histories worldwide. Intensive and extensive monocropping cultivation leaves a legacy of poor soil health that challenges efforts to aggrade it with improved practices or restoration. Now, with large-scale agriculture abandoned and ambitious state-level carbon and energy mandates, Hawaiʻi is emerging as a model system for land-based action that simultaneously meets food, energy, and water needs while rebuilding healthy relationships between humans and managed or unmanaged landscapes.

Introduction
The degradation of tropical and subtropical soils is widespread, and degraded lands increasingly are targeted for land-based climate action and other efforts to restore ecosystem function and resilience [1]. Globally, the soil carbon (C) debt driven by the expansion and intensification of agriculture is substantial [2] and recent studies of biodiversity [3] and reforestation to potentially sequester C [4] highlight the challenges of regaining what is lost following deforestation. Conceptually, climate smart soils [5], the 4 per mille initiative [6,7], and other efforts aimed at building soil C as a natural climate solution (e.g., [8]) focus on C and climate change mitigation; but more broadly encompass soil health, which is a holistic concept with multiple co-benefits to the environment, economy, and society [9,10].

Soil organic matter is the critical link between C sequestration and soil health. Soil organic matter is approximately 58% C and central to soil functions that are supported by biological, chemical, and physical properties and affect the balance and flow of water, nutrients, and energy through the soil ecosystem [11]. Measures of soil health, which include key biological, chemical, and physical properties, are connected to ecosystem services through their functional roles (such as erosion control, C storage, nutrient transformation, water filtration, and essential food, indigenous crop, forest, etc. production). Through this lens, the well-being of humans improves as a result of enhanced soil health and function, thus directly supporting a number of sustainability goals [12] such as UN Sustainable Development goals 2 (Zero Hunger) and 3 (Good Health and Well-Being) [13]. Thus, soil organic matter and healthy soils increasingly are linked to healthy societies [14].

To this point, the technical discussion surrounding soil health centers primarily on agronomic systems to target improving crop yields and economic return and biological properties of the soil microbiome using innovative technology not readily accessible [10,15,16]. No study has yet embraced the heterogeneity of natural and working lands and multiple land use needs to broadly define soil health for a more expansive role in diverse, multi-functional landscapes. Complex, competing demands on natural and working landscapes for food, fiber, fuel, and urbanization will continue to drive sustainable development plans. Land use and management options that reconcile productivity with maintenance and enhancement of biodiversity, soil health, and associated ecosystem services in human-dominated landscapes are critical [17].

The unique diversity of tropical/subtropical soils and ecosystems (including natural and working lands, or agroecosystems) in the small geographic space of Hawaiʻi is an opportunity to explore complex relationships between land use, land use history, soil type, and soil health. In Hawaiʻi, the reconciliation of potentially competing issues of development, food production, and biodiversity, together with the added pressure of climate change [18], is urgent. In the last few decades, large-scale plantation agriculture declined drastically, leaving large areas of abandoned agricultural lands across the islands. Current state law mandates improvements in soil health, C sequestration, and yields across agricultural sectors and forested land while in pursuit of achieving at least state-level C neutrality by 2045. But, like other regions across the tropics and subtropics, there are not yet science-based programs in place to support this outcome due, in part, to insufficient science specific to Hawaiʻi's soils and systems. Knowledge addressing this gap in Hawaiʻi, serving as a model system, can be transferred to other tropical and subtropical regions.

In this context, we asked: as a dynamic ecosystem property not limited to agricultural systems, what were the predominant drivers of healthy soils and how is soil health most effectively assessed across tropical and subtropical regions and volcanic islands? We hypothesized that, within the land uses and soils studied, volcanic ash-derived soil would exhibit fundamentally different soil health characteristics than the others and that current land uses would affect soil health parameters secondarily to inherent soil differences.

Results

What comprises soil health?

Soil was collected from a range of land uses (identified *a priori* as protected native and non-native forest, managed pasture, unmanaged previously intensive agricultural lands (UPIAL), organic cropland, and conventional cropland) **(Fig. 1)** across a range of soil orders and clay mineralogy (Oxisol, Mollisol, Andisol, Inceptisol, and Vertisol) on three islands. When possible, pairs or triplets of sites were obtained on the same, or related, soil series but different land use. Forty-six parameters across biological, chemical, and physical soil properties were measured and analyzed with a multivariate approach to 1) test for the predominant drivers of soil health on a heterogenous landscape and 2) deduce a key set of indicators that represent soil health as an ecosystem property. Four significant principle components analysis (PCA) axes cumulatively explained 71.7 % of the variance within the soil health dataset. The two dominant axes explained 43.0 and 12.3 % of variance, followed by the next two that explained a further 9.0 and 7.4 %. Many of the parameters across biological, chemical and physical soil properties, strongly correlated (i.e., r > 0.5) to the positive or negative side of axis 1 (**Table S1**).

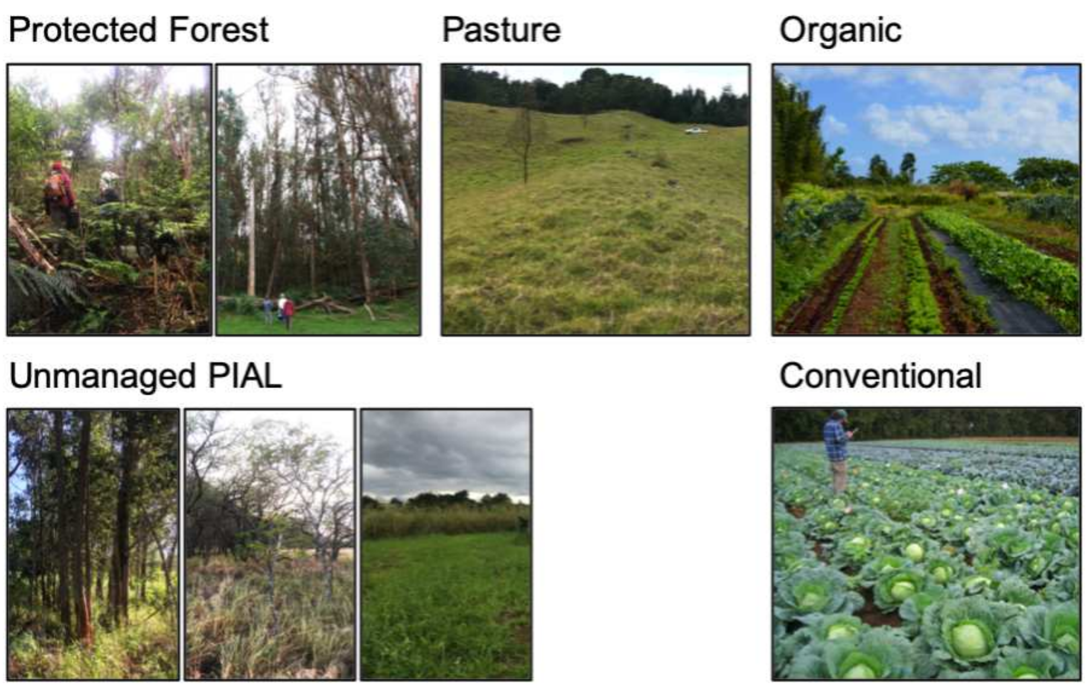

Figure 1. Images from field sites in each category of current land use. Protected forest included both native (left) and non-native (right) stands. Unmanaged, previous intensive agriculture lands (PIAL) included forest stands (left), shrub lands (center), and grasslands (right). Pasture sites were managed grazing lands; croplands included organic and conventional managements.

Land use, specifically the legacy of intensive cultivation, predominated over soil type to influence soil health. Visualization of axis 1 and 2 of the PCA showed that regardless of current land use and soil type, sites with a history of long-term intensive cultivation clustered independently from other land uses within forest and pasture classifications (**Fig. 2**). Sites without a plantation agricultural history (i.e., 80+ years of sugarcane or pineapple) separated out from those sites with intensive land use history along axis one. The top five strongest (i.e., r > 0.95) parameters driving the sites with no intensive agricultural history toward the negative side of axis 1 were high gram negative bacteria, total phospholipid fatty acids (PLFA), organic carbon (OC) concentration, total N concentration, and actinomycetes. The negative side of axis 1 was also driven by high values of many additional biological parameters not listed as well (**Table S1**). In contrast, those sites with a plantation history had low concentration of those parameters negatively related to axis one, and high bulk density (BD), dissolved OC (DOC) to dissolved organic N (DON) ratio, actinomycetes to bacteria ratio, clay concentration, and crystalline Fe oxides. Axis 2 did not provide a clear separation among the past or current land use classifications.

To a certain degree, some current land uses correspond to areas with an intensive agricultural past and others to areas without due to land availability and suitability. For example, the sampling sites classified as conventional cropland and UPIAL (by its own definition) reside exclusively within the cluster defined by an intensive agricultural history. Likewise, all the sampled protected forests occurred in areas without the agricultural past. However, organic croplands and pastures resided within both types of areas with and without the intensive agricultural past. Visualization of axes two and three showed no separation among land use history or current status (**Fig. S1**).

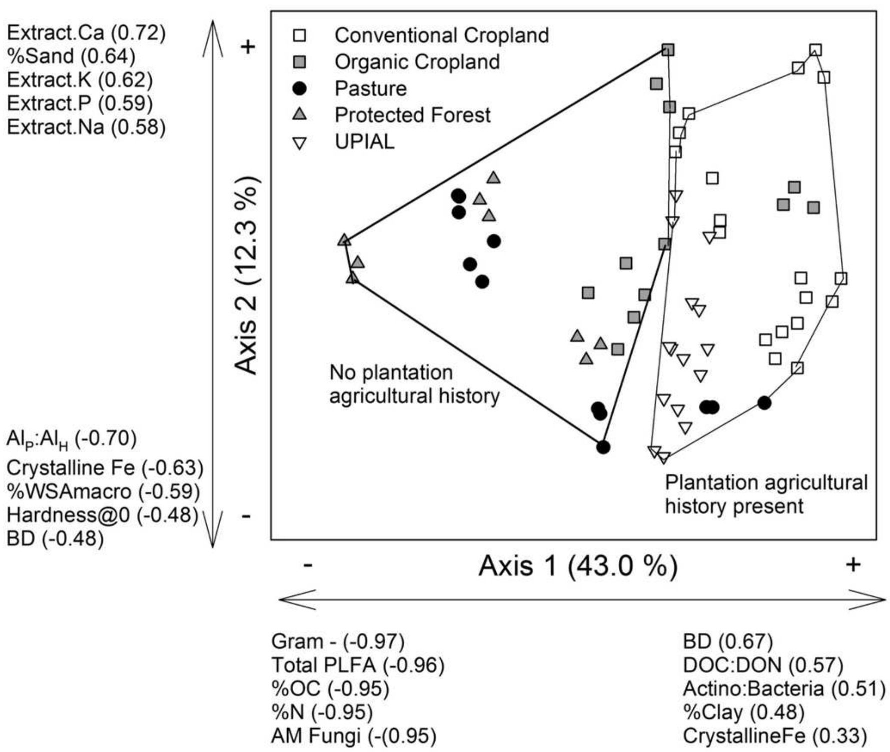

Figure 2. Principal components analysis of all potential soil health indicators with the top five most negatively and positively correlated variables to axis 1 and axis 2. Correlation values for each parameter to the axis follow it in parentheses. Groups are delineated based on whether an intensive plantation agricultural history is present or absent at that site. The current land use of each site is also indicated: conventional cropland (white square), organic cropland (grey square), pasture (black circle), protected forest (grey triangle), or unmanaged previously intensive agriculture (UPIAL, upside down white triangle). The amount of variability explained by each axis is in parentheses.

Soil type, as defined by soil order and more broadly by mineralogical class (i.e., high activity clays, low activity clays, poorly and non-crystalline minerals, and histic) was not strongly associated with axis 1 (**Fig. 3**). Both high and low activity clays aligned with the positive side of axis 1 associated with high BD, DOC:DON, clay and crystalline minerals. However, high activity clays included Vertisols and Mollisols, and associated with the positive side of axis two, driven by high extractable Ca^{2+}, K^{+}, P, and Na^{2+}, and sand concentration. Low activity clays included Ultisols and Oxisols, and associated more with the negative side of axis 2, driven by high ratio of pyrophosphate to hydroxylamine extractable Al, crystalline Fe oxides, concentration of mega size class water stable aggregates, soil hardness at the surface layers, and BD. Histic soils fell on the negative side of Axis 1 which correlated highly with total OC, total N, Actino:Bacteria, and AM Fungi. Visualization of axis 2 and 3 helped further separate out the histic and poorly and non-crystalline mineral (PNCM) groups (**Fig. S1**). Particularly with respect to the Andisols and andic Inceptisols having high concentration of poorly and non-crystalline minerals (Al_H+0.5Fe_H), PNCM separation from other soils was driven by silt and sand concentration, fungi to bacteria ratio, and concentration of "mega" size class water stable aggregates.

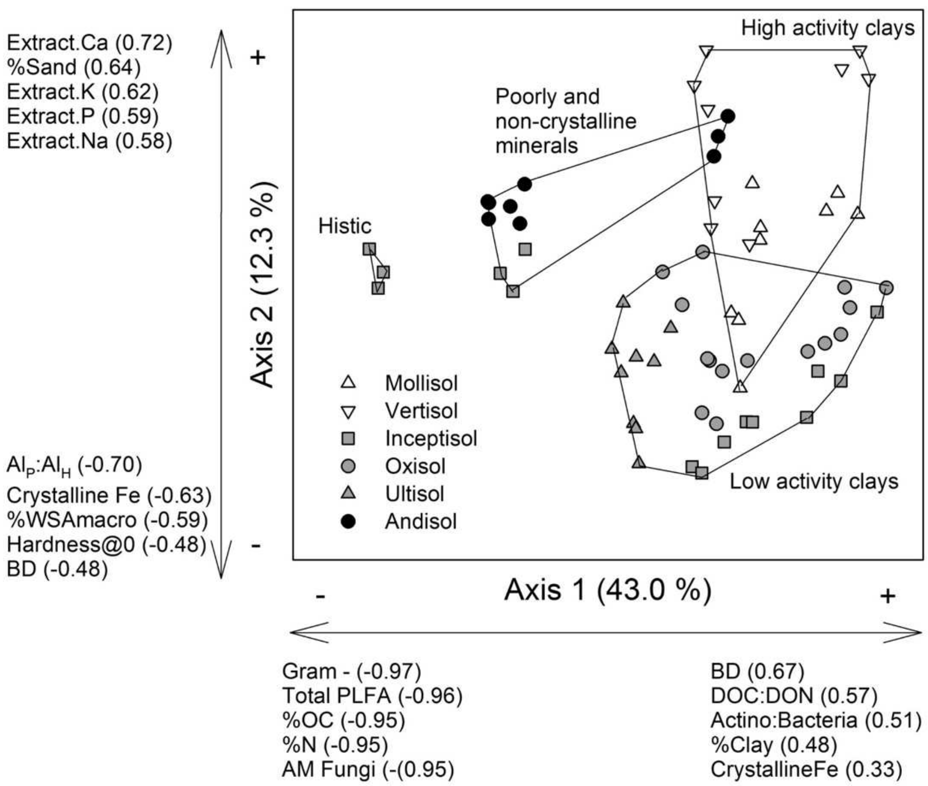

Figure 3. Principal components analysis of all potential soil health indicators with the top five most negatively and positively correlated variables to axis 1 and axis 2. Correlation values for each parameter to the axis follow it in parentheses. Groups are delineated based on broad mineralogical categorization at that site. The soil order of each site is indicated as Mollisol (white triangle), Vertisol (upside down white triangle), Inceptisol (grey square), Oxisol (grey circle), Ultisol (grey triangle), and Andisol (black circle). The amount of variability explained by each axis is in parentheses.

Predominant drivers of the measures for soil health

Multiple multi-response permutation procedure (MRPP), a nonparametric multivariate test of differences between groups [19], models were run among the categorical classifications and selected combinations for hypothesis testing to determine the drivers of soil health parameters (**Table S2**).

The combination of agricultural history and disturbance level was the second most significant contrast (adjusted p = 0.008, *A* value = 0.2636). The significant pairwise comparisons indicate that those sites classified as PIAL-medium are different than those PIAL-high and none-high; none-low is different than PIAL-medium and none-high. These results indicate first that sites with a plantation history and medium disturbance classification were more like one another than to those with a high disturbance level (i.e., currently in intensive cultivation), regardless of whether there was plantation past land use or not. Second, undisturbed sites with no plantation history were more like one another than to those with a plantation history and medium current disturbance classification or those with no plantation history but currently under intensive practices. The combination of agricultural history and current land use was also among the significant contrasts tested and yielded similar results to the interaction with plantation history and disturbance level. In the pairwise comparisons, those sites classified as PIAL and currently unmanaged (UPIAL) are different from PIAL and currently in conventional cropland, and from sites with no plantation history and currently in organic cropland, pasture, or protected forest. The simpler current land use model had the third highest *A* value (0.2583) and 10 pairwise contrasts that separated from one another along the dominant PCA axis.

The most distinct group was the UPIAL land use class, which was significantly different from all other land uses (**Fig. 4**). Pasture sample units spanned axis 1 yet were significantly different than UPIAL and organic croplands in multivariate space indicating a latent interaction with mineralogy unable to be explored further within the constraints of our dataset. Pastures were not different from protected forests and the two groups showed a lot of overlap in the 2-dimensional visualization of axis 1 and 2, also signaling a potential influence of similar mineralogy. In the case of conventional agriculture, the sample units were so dispersed within the group, that no differences emerged between it and the other current land uses, except for UPIAL. However, organic croplands were similar enough to one another to be significantly different than UPIAL, pastures, and protected forests.

The combination of cropland and mineral classifications also was among the significant contrasts tested (**Table S2**) and provided additional insight into the nature of the interaction of minerals with land use by sub-setting the dataset to reduce the complexity of the five current land use classes to simply cropland (organic and conventional) and not cropland (UPIAL, pasture and protected forest). The non-cropland PNCM sites were different from non-cropland HAC and LAC. For both HAC and LAC, those sites in croplands were different from those not in cropland. Within the constraints of the dataset, which has greater coverage of HAC and LAC across the cropland/not cropland designations, being in cropland affected soil health for both HAC and LAC. Additionally, HAC in cropland was different from LAC not in cropland, and vice versa.

Key soil health indicators for tropical/subtropical soils

Eleven dynamic soil parameters emerged from a multi-step dimension reduction process as indicators of ecosystem health across diverse land uses, histories, and soil types. First, at its foundation PCA is a dimension reduction approach, and 26 parameters correlated strongly (≥ 0.5 or ≤ -0.5) with axis one. A correlation matrix of the untransformed values showed covariance among many of those 26 parameters (**Fig. S2**). From this covarying block, consideration of the practicality of the parameter's inclusion in a rapid, accessible soil health index (i.e., cost and difficulty) and coverage of biological, chemical, and physical parameters further reduced the list to CO_2 burst, HWEC, PMN, total OC %, and WHC. Among the parameters not included in the block: ß-glucosidase, ß-glucosaminidase, and water stable mega aggregates (mega WSA), the

DOC to DON ratio, actinomycetes to bacteria ratio, and BD remained. Because actinomycetes to bacteria ratio is not feasible in a rapid soil health test, it was removed from the final list.

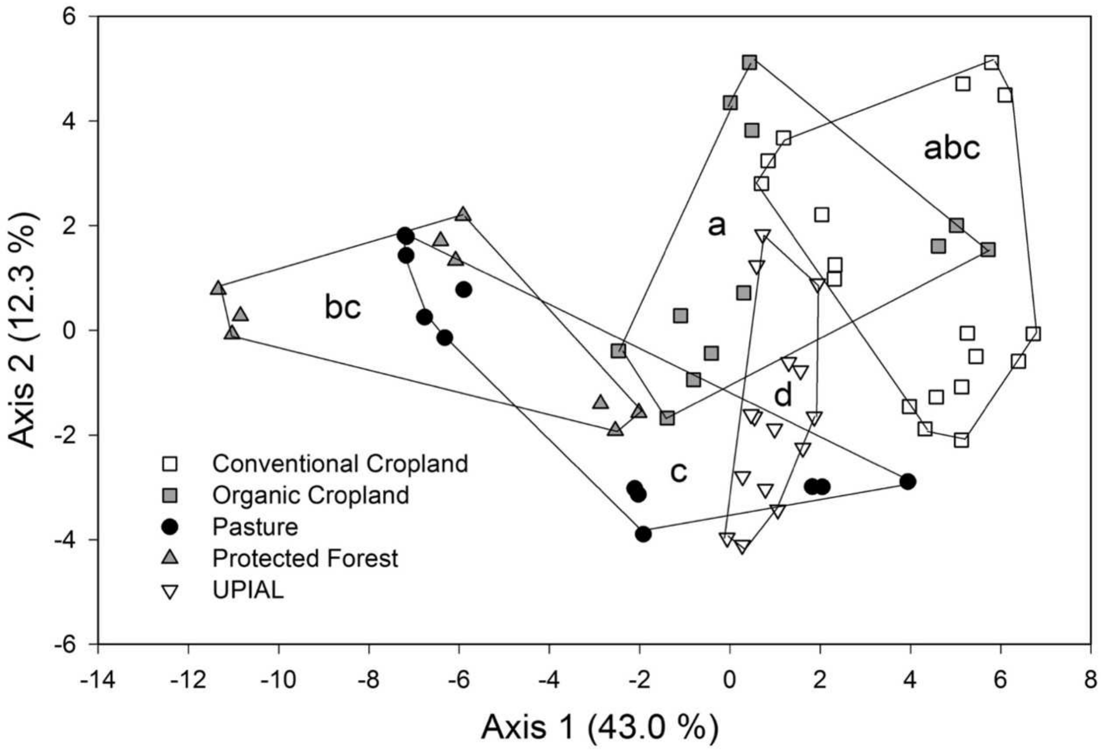

Figure 4. Axes 1 and 2 of the principal components analysis for all potential soil health indicators including the multi-response permutation procedures results comparing the multivariate within and between group testing among the current land uses. Conventional cropland (white square), organic cropland (grey square), pasture (black circle), protected forest (grey triangle), or unmanaged previously intensive agriculture (UPIAL, upside down white triangle). The amount of variability explained by each axis is in parentheses. Groups with different letters have statistically greater similarity within the group than to others in multivariate space.

With the criteria of strong relationship to PCA axis 1, non-covariance, practicality, and inclusion of biological, chemical, and physical parameters, 11 parameters emerged as potential indicators of a soil health gradient across the soils and ecosystems in Hawai‘i (**Table 1**). Summary values show the range, mean, and median of each parameter across the dataset (**Table 2**). For contextualization, all parameters except pH and BD are greater in soils without an intensive plantation history than in those with. For several of these parameters (total OC %, CO_2 burst, ß-glucosidase, ß-glucosaminidase, PMN, and HWEC), protected forests are greater than conventional croplands, while the DOC to DON ratio was lower. Similar differences were also present for pasture compared to conventional cropping except for a few (PMN and HWEC). Among those parameters with significant contrasts, total OC %, CO_2 burst, PMN, and HWEC are the same for UPIAL versus conventional cropland, but ß-glucosidase and ß-glucosaminidase are greater while the DOC to DON ratio was lower for UPIAL than conventional cropland. There were fewer differences between organic and conventional cropping, but organic cropping had greater total OC%, and ß-glucosaminidase than conventional.

Table 1. After assessing the sensitivity, interpretation value, and feasibility (i.e., resources required for field collection and laboratory assays), the recommended indicators to use in a routine soil health test for Hawai‘i and potentially other tropical-subtropical and volcanic regions, were reduced to 11 parameters.

Proposed Hawai‘i Soil Health Indicators	
Parameter	Function and interpretation
Total organic carbon (%)	As the backbone of soil organic matter, a proxy measurement of the amount of soil organic matter; higher value typically relates to benefits of multiple biological, chemical, and physical aspects of soil function
<u>Biological Properties</u>	
24 hr CO_2 burst ($\mu g\ g^{-1}$)	Soil respiration in response to readily available substrate; higher value indicates high microbial activity and high quality organic matter pools
ß-glucosidase (mg p-nitrophenol kg^{-1} soil h^{-1})	Proximate microbial metabolism of amino-containing substrate; higher value indicates nutrient, predominantly N, mineralization
ß-glucosaminidase (mg p-nitrophenol kg^{-1} soil h^{-1})	Potential N supply; higher value indicates bioavailable N forms to support soil productivity
Mineralizable nitrogen ($\mu g\ g^{-1}$)	Potential N supply; higher value indicates bioavailable N forms to support soil productivity
<u>Chemical Properties</u>	
pH	Biological and nutrient availability; 6.0—7.0 is ideal, this is the pH range where plant essential elements are most available, and toxicities are negligible
DOC:DON ratio	Integrated indicator of the balance of organic carbon and organic nitrogen pools; lower is better; higher value indicates disturbance - high DOC indicates available microbial substrate but also potential runoff, priming, and loss if too high, DON is readily broken down by soil microbes into inorganic forms, but low values are associated with N-deposition or poor nutrient management in disturbed systems
Hot water extractable carbon ($\mu g\ g^{-1}$)	Readily available metabolic substrate; higher value indicates soluble organic matter and lysed microbial cells that support microbial activity
<u>Physical Properties</u>	
Water holding capacity (%)	Plant-water relations; higher values indicate improved water storage
Water stable mega-aggregates (%)	Water infiltration, porosity, aeration; higher values improve retention/transport water, promote root growth, provide habitat for microbes, reduce bulk density, and resist erosion
Bulk density (g cm^{-3})	Infiltration, porosity, and rooting environment; lower values indicate soils that are light, aerated, porous, promote root growth, and more workable

Table 2. Data summary for the proposed key indicators of health for subtropical/tropical and volcanic soils. Significant differences are indicated by * for the past land use (PIAL versus None) comparison and letters for the current land use comparisons (Tukey-adjusted comparison, p-value <0.05).

	Min	Max	Mean	Median	None n=27	PIAL n=39	Protected Forests n= 9	Pasture n=12	Unmgd PIAL n=15	Organic Cropland n=12	Conv Cropland n=18
%OC	0.83	32.5	5.73	2.33	11.0 ± 3.34*	2.10 ± 0.39*	18.5 ± 7.84^{a}	8.58 ± 3.55^{a}	2.20 ± 0.15^{ab}	3.09 ± 0.91^{a}	2.12 ± 1.25^{b}
CO_2 Burst	13.3	527.1	102.6	51.4	195.2 ± 50.79*	37.2 ± 5.22*	274.5 ± 126.7^{a}	177.8 ± 69.5^{a}	52.1 ± 8.87^{ab}	69.5 ± 19.0^{ab}	30.5 ± 8.67^{b}
β-Gluc	20.7	230.5	92.1	83.8	119.5 ± 18.24*	72.3 ± 12.4*	117.3 ± 32.2^{a}	131.1 ± 37.6^{a}	113.6 ± 18.9^{a}	78.2 ± 9.86^{ab}	44.9 ± 14.6^{b}
β-Glucmin	7.71	134.1	47.6	39.0	77.5 ± 12.8*	27.7 ± 4.72*	81.3 ± 26.4^{a}	90.9 ± 19.9^{a}	44.52 ± 5.31^{a}	33.6 ± 7.15^{a}	13.9 ± 2.13^{b}
PMN	0.00	304.8	41.1	20.3	83.7 ± 28.7*	11.6 ± 2.88*	152.8 ± 76.2^{a}	54.3 ± 15.1^{ab}	21.7 ± 3.48^{bc}	23.2 ± 8.67^{bc}	4.70 ± 2.79^{c}
pH	3.71	7.86	6.44	6.7	6.43 ± 0.39	6.42 ± 0.26	6.04 ± 1.17	6.51 ± 0.32	6.21 ± 0.39	7.13 ± 0.27	6.32 ± 0.57
DOC:DON	2.03	808.9	169.1	38.0	94.1 ± 89.4*	203.0 ± 51.6*	2.68 ± 0.45^{b}	17.0 ± 13.9^{b}	169.5 ± 110.8^{b}	313.7 ± 191.9^{ab}	257.0 ± 73.3^{a}
HWEC	48.4	13,400	1096.5	331.6	2378.1 ± 1390.7*	197.3 ± 29.8*	5245.0 ± 4085.6^{a}	1001.1 ± 444.0^{ab}	297.2 ± 27.1^{ab}	466.3 ± 143.0^{ab}	172.0 ± 59.1^{b}
WHC	56.7	208.5	85.2	69.2	108.5 ± 16.7*	69.7 ± 2.14*	136.7 ± 40.3	97.9 ± 23.8	67.4 ± 2.49	76.0 ± 5.37	72.0 ± 5.6
%WSAmega	0.00	96.9	96.9	47.1	67.4 ± 11.0*	29.5 ± 8.54*	73.2 ± 15.0	79.9 ± 12.7	46.4 ± 14.9	29.6 ± 15.7	24.4 ± 18.2
BD	0.22	1.19	0.84	0.91	0.69 ± 0.10	0.94 ± 0.05	0.54 ± 0.20	0.80 ± 0.20	1.01 ± 0.04	0.86 ± 0.03	0.85 ± 0.11

PIAL = previously intensive agricultural lands; None = no plantation history; %OC = Total organic carbon; β-Gluc = ß-glucosidase; β-Glucmin = ß-glucosaminidase; PMN = Potentially mineralizable nitrogen; DOC:DON = DOC to DON ratio ; HWEC = Hot water extractable carbon; WHC = water holding capacity; %WSAmega = Water stable mega-aggregates; BD = bulk density; Unmgd = Unmanaged; Conv = Conventional

For the subset of soils with adequate representation across mineralogy (HAC and LAC) and current land use (UPIAL, organic cropland, and conventional cropland) the interactive effects of these parameters on several soil health indicators, total OC %, CO_2 burst, ß-glucosidase and ß-glucosaminidase, PMN, HWEC, and mega-WSA, were significant (**Fig. 5**). For LAC soils, many parameters were consistently lower for conventional than organic croplands, including OC %, CO_2 burst, ß-glucosidase, ß-glucosaminidase, PMN, and mega-WSA. In general, UPIAL tended to have lower values than organic management, but greater than conventional cropland, which was especially apparent for total OC %. In contrast to LAC soils, very few significant effects of land use on HAC soils were detected, and only PMN and HWEC was less in conventional than in organic croplands while mega-WSA were greater. Of those parameters without significant interactions, mineralogy was significant for the DOC to DON ratio and WHC, and in both cases HAC was greater than LAC (**Fig. 6**). Current land use was significant for the DOC to DON ratio (conventional > UPIAL), WHC (organic > UPIAL and conventional croplands), and BD (UPIAL > organic croplands) (**Fig. 7**). Mineralogy and land use had no detectable effect on soil pH.

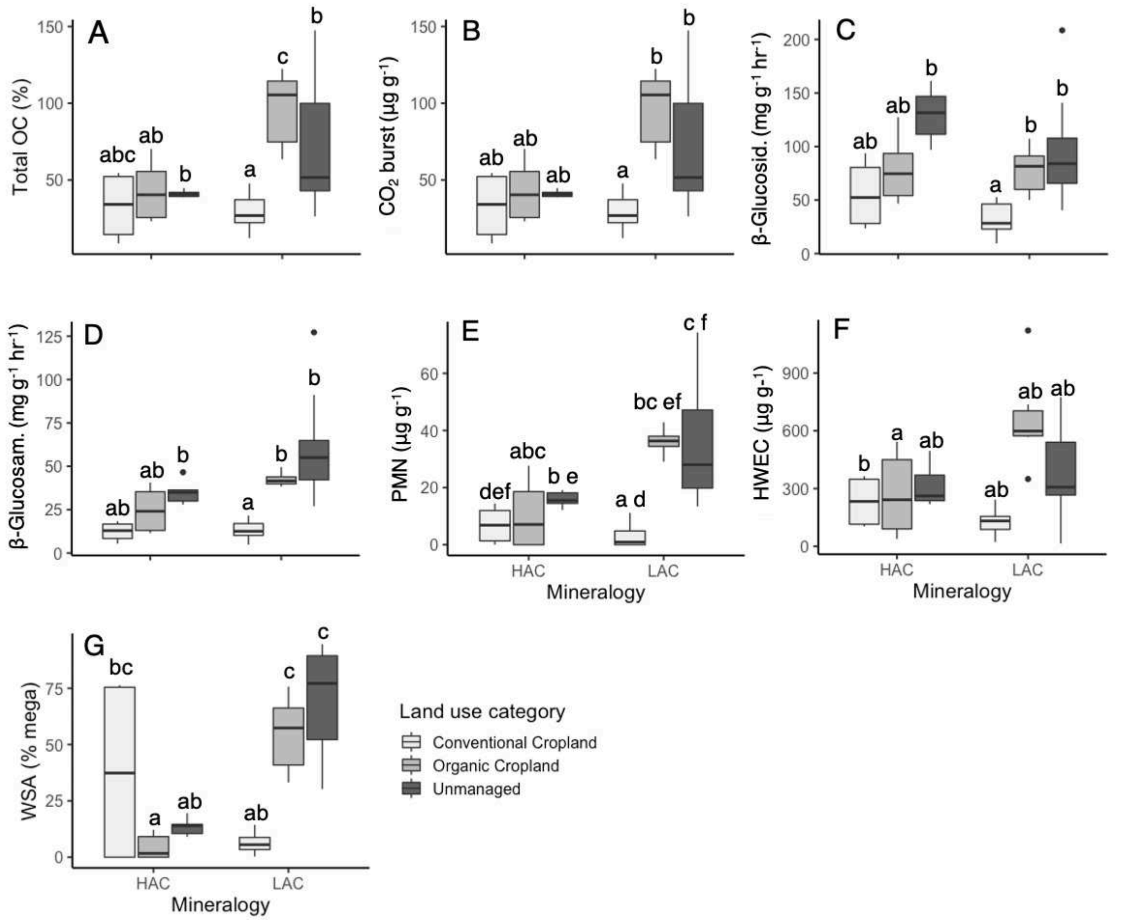

Figure 5. Boxplots for the proposed key indicators of health for a subset of high (HAC) and low activity clay (LAC) soils under land use classes for conventional cropland, organic cropland, and unmanaged previously intensive agriculture. Means sharing a letter are not significantly different (Tukey-adjusted comparison of least square means at p-value < 0.05.) n=51

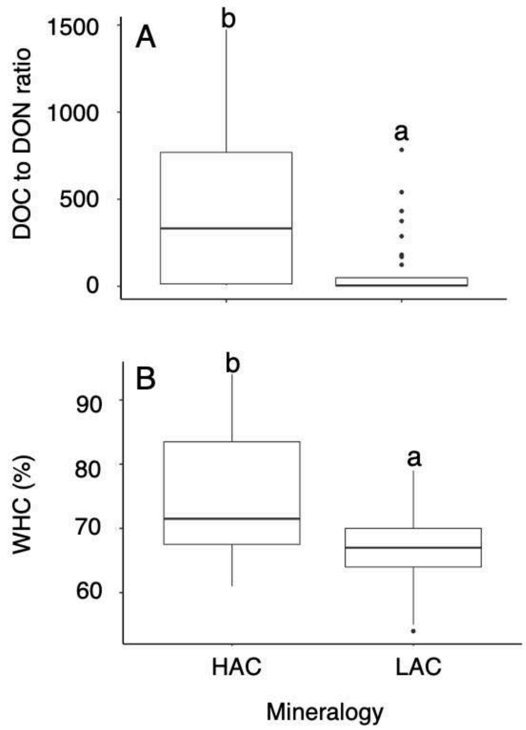

Figure 6. Boxplots for the proposed key indicators of health for a subset of high (HAC) and low activity clay (LAC) soils averaged across land use classes. Means sharing a letter are not significantly different (Tukey-adjusted comparison of least square means at p-value < 0.05.) n=51

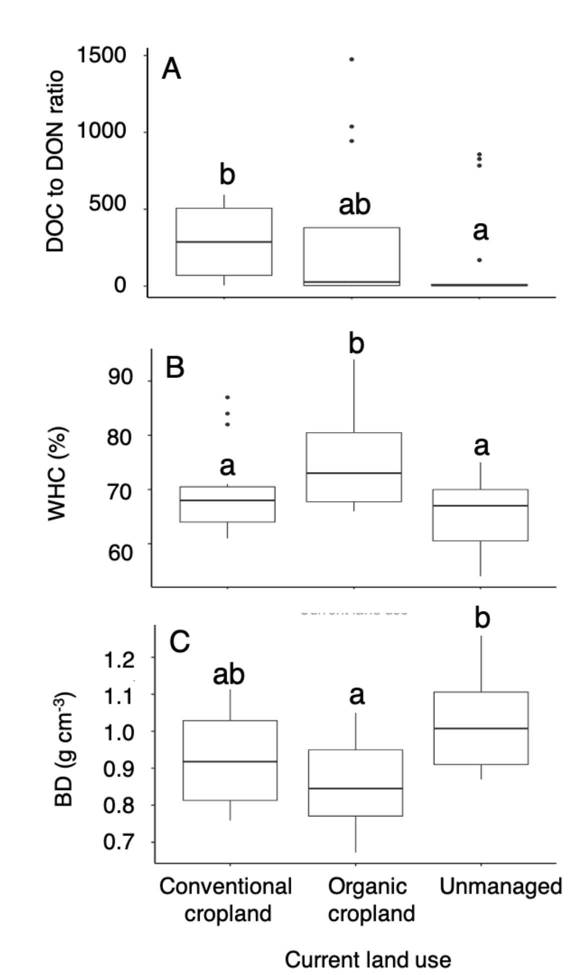

Figure 7. Boxplots for the proposed key indicators of health for a subset of soils across land use classes for conventional cropland, organic cropland, and unmanaged previously intensive agriculture averaged across high (HAC) and low activity clay (LAC) soils . Means sharing a letter are not significantly different (Tukey-adjusted comparison of least square means at p-value < 0.05.) n=51

Discussion

Soil health is an ecosystem property

Soil health conceptualized as a measurable ecosystem property provides a powerful tool for monitoring progress in restoration projects or implementation of best management practices to promote sustainable agroecosystems. A new paradigm of soil organic matter dynamics, which is central to soil health, is driving the development of new compartmental models tied to measurable soil parameters [20]. Soil organisms, particularly microbial communities that are proximately responsible for the flow of nutrients, C, and energy in the soil ecosystem, rely on accessible organic matter for metabolic substrate. Many of the emergent process-based ecosystem models are microbial models (e.g., [21,22]) and hold promise to improve both decision support tools and earth system projections.

In policy and programs intended to incentivize maintaining and aggrading soil health across multifunctional landscapes and diverse stakeholders, expectations must be gauged accordingly. Long-term, intensive monocrop agriculture, which in Hawaiʻi was predominantly pineapple and sugarcane plantations established post-Western contact, leaves a detrimental legacy on soil health. The adverse effects on soil biological properties and microbial communities persists following both abandonment and land use/management change to practices consistent with soil health management principles (e.g., perennial grasses or crops, organic matter inputs, and no or reduced tillage). Especially because the legacy of intensive cultivation history may carry-over into the success of land-based initiatives now and into the future, it is important to understand the resultant differences in baseline conditions as well as the limitations to improvements in soil health when building decision support tools and programs.

Soil health metrics interwoven with process-based ecosystem models that underpin decision support tools used by policy makers may also assist in accessing aid and improved economic outcomes that are critical to success in overcoming adoption barriers. Ecosystem functions such as greenhouse gas emission, C storage, nutrient transformation, biomass production, and regulation of hazards and extreme events link directly to key services contributing to human well-being [12,23]. Conventional soil organic matter models (e.g., RothC, DNDC, EPIC, and CENTURY) embedded within established decision support tools that assist land managers and policy makers alike contain some of these ecosystem functions. However, their ability to simulate (sub)tropical or volcanic soils which have very different properties from the temperate or continental soils for which they were developed currently limits their usefulness. Alternatively, microbial models such as (MEMS v1.0) developed from the Microbial Efficiency-Matrix Stabilization framework incorporates measurable parameters that constrain C pools sizes and modulate fluxes [22]. Measurable pools and rate modifiers in MEMS v1.0 include microbial biomass and turnover, dissolved organic matter, sorption/desorption dynamics, and exoenzyme activity. The overlap between these parameters and the measures of soil health suggest that compartmental models designed to simulate soil organic SOM matter dynamics and nutrient and GHG fluxes may benefit from the integration of soil health into their initialization and projections for (sub)tropical soils.

In the process of aggrading soil health, landscapes regain resilience through improved soil functions. For Hawaiʻi and other (sub)tropical and volcanic regions, land-based management relating to conservation, biocultural restoration, climate action for mitigation/adaptation, and increased local food production strive for their specific goals. But, also contribute more broadly to sustainability when viewed through the lens of improved soil health and the associated expansive network of co-benefits and regulation services. Understanding, representing, and projecting outcomes associated with soil health is critical to incorporating their full value into complex watershed-based management and interdisciplinary social-ecological forecasting that link directly to building resilient, climate ready landscapes and communities.

Land use history, current land use practices, and mineralogy are predominant drivers of ecosystem soil health

Key drivers of the measures for soil health, including land use history, current land use practices, and mineralogy, must be understood and integrated into the development of a soil health index. Any index should set minimum and maximum benchmarks and weigh parameters according to equitable standards. Therefore, the state of each driver (e.g., timeline of intensive use history, time since implementation of current land use and management, and predominant mineralogy) must be ascertained and recorded in databases designed for syntheses of soil health into the future.

The legacy of a plantation history is a strong driver of soil health, but greater complexity associated with current land use, management, and soil type also is present and important to understand while developing a robust soil health index for the (sub) tropics. For example, the level of disturbance in current management practices and, outside of croplands, mineralogy both also affected soil health. Results suggest that soil health may differ inherently for high versus low activity clays and whether a system is cultivated intensively for food production (cropland) under conventional versus organic management affects soil health regardless of mineralogy.

Importantly, the soil health of pastures was not different from protected forests, suggesting that well-managed grazing lands may be as healthy and resilient as protected forests. However, the most distinct group was the unmanaged, previously intensive agriculture lands (UPIAL land use class), which was significantly different from all other land uses. Unmanaged abandoned agricultural lands are more similar to each other than to sites that remain in intensive cultivation. But, they are also more similar to each other than to sites without plantation history and currently are in organic croplands, pasture, or protected forest. Upon further inspection, the univariate analysis suggests that, while the relationship between organic versus conventional cropland was largely consistent across soil type for most soil health parameters, abandoned cropland was more variable. For UPIAL, in some cases, soil health indicators fell in between organic and conventional croplands, while sometimes aligning more closely to conventional or organic for other indicators. This finding further highlights the imprint that intensive agriculture may have on the health of a soil and demonstrates the constraints to rebuilding soil health upon the cessation of soil disturbance without proactive management strategies.

Proposed "Hawaiʻi Soil Health Indicators" for (sub)tropical and volcanic soils and systems

A suite of readily measured parameters emerged out of a first-principle approach to determining a holistic indication of soil health across a range of soils and systems in Hawaiʻi encompassing much of the diversity in the tropics and subtropics. These parameters integrate biological, chemical, and physical properties with key functions associated with soil C and nutrient cycling, water relations, and generally, the provisions of a soil environment conducive to a diverse soil organismal community. These parameters are consistent with current measures of soil health, but developed with a more organic and equitable process, without carry over of ingrained bias. In the development of a soil health index, parameters may be weighted differentially for systems. Further, cropping systems should be paired with additional fertility testing and nutrient management for optimal environmental and yield outcome. Every land use may improve its soil health status within a reasonable range of expectations when considering land use history, current land use, and mineralogy.

The measurement of soil health as a dynamic ecosystem property is only possible by properly identifying the right suite of parameters specific to a region and metering that measurement to appropriate benchmarks for a system defined by past land use, current land use, and mineralogy. Moving forward, providing a soil health index of (sub)tropical and volcanic soils will help to assist currently underserved producers and land managers improve the health and productivity of their lands and simultaneously reap co-benefits of a healthier environment and society. Within this framework, fair and equitable programs can be established to improve economic outcomes as well as C neutrality goals.

Conclusion

Land use, particularly where a legacy of intensive cultivation existed, predominated soil health metrics, which supports continued policies and programs that help incentivize producers and land managers to implement best practices. Because of the close association of soil health and C cycling, climate change mitigation is a powerful co-benefit of improving soil health in degraded systems. As Amundson and Biardeau [24] put forward, "soil carbon sequestration is an elusive climate mitigation tool." However, soil health is a more inclusive measure of the holistic value of improving the state of a natural resource key to achieving multiple sustainability goals worldwide.

Competing demands for food, fiber, fuel, and urbanization will continue. In Hawai‘i, especially, competing land uses associated with development, food production, and biodiversity under climate change is a pressing issue. Improved land use projections are critical for reducing uncertainties in indicators for ecosystem services in a changing environment [25]. Land use and management options that reconcile production with maintenance and enhancement of biodiversity, soil health and associated ecosystem services in human dominated landscapes now and into the future are critical. We conclude that soil health is a measurable ecosystem property and that land use history, current land use practices, and mineralogy are all predominant drivers of soil health in landscapes. Our proposed "Hawai‘i Soil Health Indicators" may be further validated for (sub)tropical and volcanic soils and systems and are critical to developing regionally appropriate incentives programs and policy.

Materials and Methods

<u>Site selection and general approach</u> Twenty-two sites were selected across three islands (Oahu, Maui, Molokai) within the main Hawaiian archipelago to cover a diversity of soil management, fertility, and taxonomy to maximize the variance in parameters associated with soil health. Preliminary assessments helped categorize sites into 1) current land management/use, 2) land use history, 3) disturbance level, 4) soil order, and 5) predominant mineralogy. Current land management/uses included protected forests (managed to preserve long-term non-native or native forest, greater than 100 years no disturbance from feral ungulates), unmanaged previously intensive agricultural lands (UPIAL, previously monocrop plantation with no current management system, grasses, shrubs, or forest as dominate cover, and less than 100 years no disturbance), pasture (managed with pasture grasses for rearing livestock), organic croplands (no use of chemical pesticides), and conventional croplands (use of chemical pesticides). Land use history indicated simply whether an intensive plantation history (for Hawai‘i, this is typically sugarcane or pineapple) was present or absent. Disturbance level was defined categorically as low, medium, and high (**Table 3**). Soil order was according to final GPS coordinates of sample

location and NRCS NCSS taxonomic classification (Web Soil Survey). Predominant mineralogy was assigned using taxonomic classification and a diagnostic key (**Table S3**).

Table 3. Assessment of level of disturbance for each study site is categorized based on the time frames described since the most recent soil disturbance, based on available history of land use. Disturbance was considered to be land that has undergone man-made change to soil's surface layer by physical disruption of the soil structure and ecosystem, such as tillage or compaction.

Level of Disturbance	Description
Low	At least 50 years no disturbance
Medium	Disturbed in the last 50 years
High	Disturbed in the last 10 years

The final compilation included an integration of sites across soil types, land use history, and natural versus agricultural landscapes that is representative of Hawai'i (**Table 4**). However, as is reflective of reality, some soil types are more represented in some land uses and some current land uses are more likely to be represented in one past land use history or another. Therefore, we purposefully designed this study as a multivariate approach to identifying parameters indicative of soil function, specifically healthy soil function, for the ecosystems of Hawai'i (and other similar tropical/subtropical, and volcanic regions). Then, we narrowed down to key parameters that can be linked to drivers to facilitate the next steps of developing an index of soil health and refining the parameters for specific systems with the goal of assisting landowners, managers, and farmers to improve the health and resilience of their lands.

Table 4. Summary of sample numbers for each mineralogy class and current land use.

Mineralogy	Protected Forest	Pasture	Unmanaged PIAL	Organic Cropland	Conventional Cropland
HAC	0	0	6	6	6
LAC	3	6	9	6	9
PNCM	3	6	0	0	3
Histic	1	0	0	0	0

HAC = High activity clays; LAC = Low activity clays; PNCM = Poorly and non-crystalline minerals

Soil collection Three replicate samples were collected from each of the 22 sites. Each sample was comprised of five soil cores taken from the 0-15 cm depth of mineral soil using established sampling methods form the Cornell Soil Health Manual [26,27]. Briefly, the organic horizon was removed prior to soil coring 0-15 cm of mineral soil at five locations within a 1m^2 quadrant. The soil from five cores was homogenized into one sample in a bucket in the field. Three quadrants that each produced one soil sample for a site were located at least five m apart within the site. Thus, 66 soil samples were packaged in a cooler with ice and transported to the lab for analysis. Samples were transported to processing and storage facilities at UH Mānoa and subsets were frozen at -20 °C and air-dried (<10 % moisture). Additionally, a subset for phospholipid fatty acid testing (see below) was kept chilled, not frozen, and shipped immediately under refrigeration to the analysis facility.

Soil health parameters Forty-six parameters classified as biological, chemical, or physical and tied to soil function or health were measured for each of the 66 samples **(Table 5)**.

Table 5. Methods and functional interpretation of forty-six parameters classified as biological, chemical, or physical and tied to soil function or health were measured for each of the 66 samples.

Protocol	Methods reference(s)	Associated parameter	Function	Key functional reference(s)
Biological				
PLFA	(31)	Total PLFA	A key component of microbial cell membranes and analysis of PLFA provides a snapshot of microbial community structure; estimate of total microbial biomass	(32–34)
		Actinomycetes	Sometimes known as actinobacteria, are active in organic matter decomposition, similar filamentous growth form to fungal hyphae, bridge gaps between water films and withstand water stress	(35)
		Gram + bacteria	Dispersed in soil profile, decompose partially decayed organic matter, resistant to water stress	(34, 36, 37)
		Gram – bacteria	Plant rhizosphere member, improve plant growth by increasing solubility of nutrients, include Rhizobium which are N-fixing species	(34, 36, 37)
		Eukaryotes	Includes fungi, algae, nematodes, earthworms, insects, arthropods, and protozoa soil community members; consume organic matter, bacteria, plants, and each other	(38)
		Arbuscular mycorrhizae	Colonize roots in symbiotic relationship, grow as long, thin hyphae that extend the reach of roots into the rhizosphere, increase access to nutrients (e.g., N, P, S, Zn, and Cu) and water during drought	(34, 36, 37)
		Anaerobic bacteria	Low oxygen environments of wet or deep soils, sediments, or interior of aggregates	(34, 36, 37)
		Fungi	Particularly important lignin degraders, wide variety of forms, saprophytic fungi breakdown organic matter and release nutrients, prefer more acidic environments than bacteria	(38)
		Actino:bacteria ratio	Indicates actinomycetes taking up the role of fungi when fungal abundance is low, e.g., application of fungicide	(39, 40)
		Fungi:bacteria ratio	Significant role of fungi in litter decomposition and potentially higher C storage potential	(32, 40)
Enzyme activity	(41)	ß-glucosidase	Recycling C compounds into energy for microbes, a reliable predictor of organic matter decomposition	(42, 43)
	(44)	ß-glucosaminidase	Soil enzymes to decompose organic matter and release nutrients into plant available forms of N	(42–44)
	(45)	Acid phosphatase	Recycling of phosphorus, both important cycles related to nutrient uptake by plants	(42–44)
Potentially mineralizable N	(46)	Potentially mineralizable N	Estimate of the capacity of the soil microbes to recycle nitrogen into plant available forms	(26)
CO_2 burst	(47)	CO_2 burst	Rapid soil quality indicator of microbial activity, highly related to soil fertility	(48, 49)

Chemical				
Elemental analysis	(26)	OC concentration (%)	Associated with organic matter content, which correlates with various critical soil functions.	(26)
		N concentration (%)	Total available N resource pool	(26)
		OC to N ratio	Indicates microbial substrate quality, plant nutrient availability.	(26)
Water-extractable C	(50)	Hot water extractable carbon (HWEC)	Associated with biological activity as the hot water lyses microbe cells and releases biomass components	(49)
		% of total OC that was HWEC	Extractable carbon pool is associated with aggregate formation as well as a reserve of nutrients and energy for plants and microbes	(49)
		Total water extractable C pool (Cold water extractable organic carbon + HWEC)	Soluble and hot water lysed organic carbon	(49)
Mineralizable C pool	(51)	C pool respired in 4 months	Labile C pool readily accessible by soil microbes during laboratory incubation	(51, 52)
pH		pH	Influences essential nutrient availability, plant toxicity, and microbial community	(32, 53)
Extractable nutrients	(54)	Extractable Ca^{2+}	Soil fertility	(54)
	(54)	Extractable K^{+}	Soil fertility	(54)
	(54)	Extractable Na^{2+}	Soil fertility and salinity	(54)
	(54)	Extractable P	Soil fertility	(54)
Dissolved C and N	(47, 49, 55)	Dissolved organic C	Cold water extractable organic carbon (WEOC) provides energy source for soil microbes as an active soil C pool	(26, 49, 56)
		Total dissolved N	Cold water extractable organic and inorganic forms of N are available for microbial and plant uptake	(26, 49)
		Ammonium	Microbe and plant-available nutrient	(26, 49)
		Nitrate	Microbe and plant-available nutrient	(26, 49)
		Dissolved inorganic N	Total microbe and plant-available nutrients	(26, 49)
		Dissolved organic N	Organic forms of soluble microbe and plant-available nutrients under certain environmental conditions and plant communities. Highly related to WEOC pool and contains potentially mineralizable N.	(26, 49, 56)
		Ratio of DOC to DON	Balance of C and N forms in solution, imbalance of inorganic N forms and/or DOC indicates disturbance, N deposition, or inefficient nutrient cycle	(56)
Extractable Fe and Al	(57)	Crystalline Fe-oxides	The amount of “free” secondary crystalline Fe oxides	(58)
		Poorly and non-crystalline minerals	Sorption of C to mineral surfaces, water retention	(59)
		Ratio of Al_P to Al_H	Controls aluminum in surface horizons of mineral soils and O-horizons of organic matter-rich soils	(60–62)

Physical				
Bulk density	(63)	Bulk density	Degree of soil compaction and potential root growth restriction and pore space.	(26)
Hardness	(63)	Hardness measured at surface	Relates to the compactness of a soil as well as the cementing features of its mineral structure.	(26)
		Hardness measured at 15 cm	Presence and penetrability of plow layer.	(26)
Water holding capacity	(64)	Water holding capacity	Vital for sustained plant growth and supporting microbial life	(26, 49)
Aggregate stability	(65)	% WSA in the mega size class	Increased water infiltration, water storage, water and gas exchange, and resistance to erosion	(66)
		% WSA in the macro size class	Store and protect organic carbon from being lost from the soil as a physical protection mechanism from microbes as well as restricting the diffusion of oxygen and enzymes	(67, 68)
Soil texture	(69)	% Sand	Water infiltration, available pore space, poor water retention	(69)
		% Silt	Water infiltration, available pore space, plant available water, soil fertility.	(69)
		% Clay	Water infiltration, plant available water, soil fertility.	(69)

Principal components analysis The soil health of each sample location was summarized using principal components analysis (PCA in *PC-ORD* v.7.0) The response matrix included 46 parameters in 66 soil samples. Uneven distribution of data (i.e., a slight horseshoe shape with clear outliers) in the 2D output suggested the need to transform data, which was confirmed by assessing distribution tables of each variable for non-normality [19]. Transformations of log, cube root, and square root were tested on each highly skewed variable since all were either positively or negatively skewed with single peaks. Transformed variables were rerun for skewness and the transformation with the lowest skewness value was selected as the best possible transformation. A new PCA using variables transformed for normality showed an improved graphical display regarding spatial distribution of plots and outlier assessment.

Values from the 46 measured parameters served as the main dataset for PCA ordination, and overlays of supplemental environmental data operated as the second matrix including current land management, historical disturbance, soil order, and soil series. Potential variables were individually removed and re-added to determine their influence on the PCA and assess any significant impact on results, while using the second matrix overlays to identify issues with the distributions of data balance or flag potential errors in data manipulation. To avoid potential bias, variables problematic to overall balance were removed. Supplemental environmental data operated as the second matrix including current land management/use, land use history, disturbance level, soil order, predominant mineralogy, and combinations relevant to hypothesis testing.

The normally distributed soil health matrix was analyzed using a standardized PCA with a correlation cross-products matrix, which produces correlation coefficients among the variables and further standardizes non-comparable response variables. This method provides a broken stick eigenvalue; the broken stick eigenvalue was less than the actual eigenvalue for the first four axes, therefore these are all presented and interpreted to some degree [19]. Rnd-Lambda randomization results agreed with the broken stick method, the last useful axis is four with $p = 0.001$ and cumulative variance explained at 71.7 %.

Multi-response permutation procedure (MRPP) is a nonparametric multivariate test of differences between groups [19]. The A statistic describes effect size with respect to how similar within-group samples are compared to outside the group samples. When $A = 1$, sample units within each group are identical, when $A = 0$, groups are no more different than expected by chance. We tested all possible models based on the site attributes - agricultural history, current land use, soil order, mineralogical class, disturbance level, and cropland versus non-cropland. The MRPP was run with Euclidean distance measure on the transformed data. Any contrast with less than two sites (6 sample points) was excluded. In the final model, an adjusted p value was calculated by dividing the model p value by the number of pairwise contrasts, the adjusted p value was used to determine whether a pairwise contrast was significant or not.

Dimension reduction The list of 46 potential indicators of soil health was reduced to a short list of key indicators that meet multiple criteria for capturing the breadth of soil health as an ecosystem property, reducing multicollinearity with other variables, and practicality for inclusion in a routine soil test. First, potential parameters were removed if $r < 0.50$ or > -0.50 with axis 1 in the PCA, which left 26 selected for further assessment. A hierarchical ordering correlogram of the untransformed values for remaining 26 selected parameters was performed in R. Highly correlated parameters were reduced further on the basis of practicality (i.e., combination of cost and difficulty). The final list was cross checked to maintain balanced coverage across biological, chemical, and physical properties. Within the constraints of the original sample design, the key parameters of soil health were compared across a subset of mineral and land use classes to assess their utility as indicators of soil health.

Univariate analyses were conducted to first determine the effect of past land use (PIAL versus none) and then assess the effect of current land use (protected forest, pasture, UPIAL, organic cropland, versus conventional cropland) on each of the 11 soil health indicators. A mixed model ANOVA approach was used to assess the main effect of past or present land use with soil mineralogical classes as the random effect (lmer function in the lme4 package [28]). General linear hypothesis testing (glht function in multcomp package [29]) was performed to compare group means (Tukey-adjusted). For a subset of the data (including UPIAL, organic cropland, and conventional cropland in LAC and HAC soils), mixed factorial ANOVA was performed to examine the interactive effect of soil mineralogical class and current land use on each soil health indicator with farm/location as the random effect (lmer function in the lme4 package). Group differences were assessed by Tukey multiple comparisons of least square means (lsmeans function in emmeans package). For all post-hoc multiple comparisons with the Tukey test, letter groupings were assigned with the cld function (multcomp package [30]).

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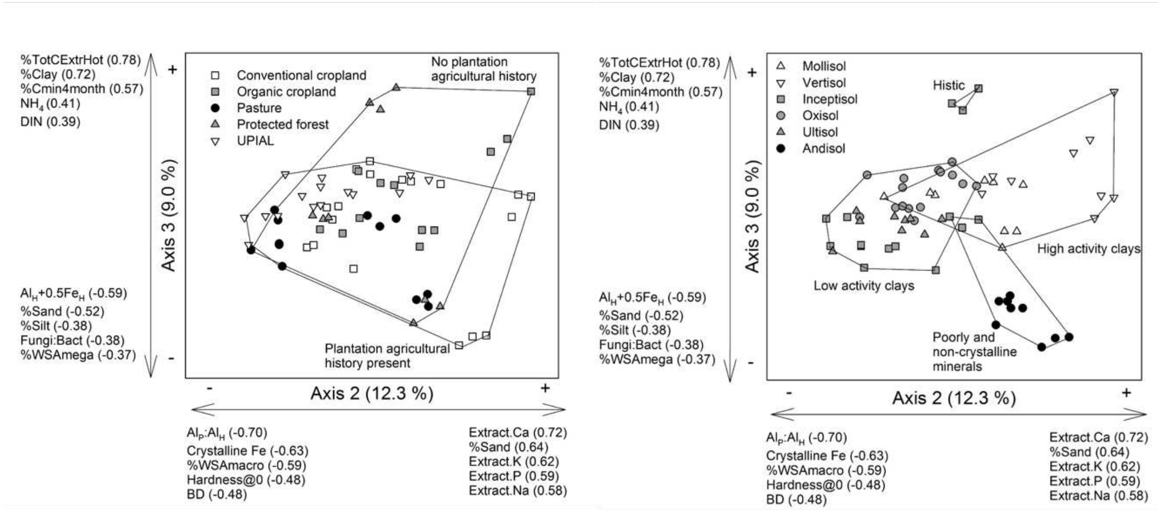

Figure S1. Principal components analysis of all potential soil health indicators with the top five most negatively and positively correlated variables to each axis. Correlation values for each parameter to the axis follow it in parentheses. Left - Groups are delineated based on whether an intensive plantation agricultural history is present or absent at that site. The current land use of each site is also indicated: conventional cropland (white square), organic cropland (grey square), pasture (black circle), protected forest (grey triangle), or unmanaged previously intensive agriculture (UPIAL, upside down white triangle). Right - Groups are delineated based on broad mineralogical categorization at that site. The soil order of each site is indicated as Mollisol (white triangle), Vertisol (upside down white triangle), Inceptisol (grey square), Oxisol (grey circle), Ultisol (grey triangle), and Andisol (black circle). The amount of variability explained by each axis is in parentheses.

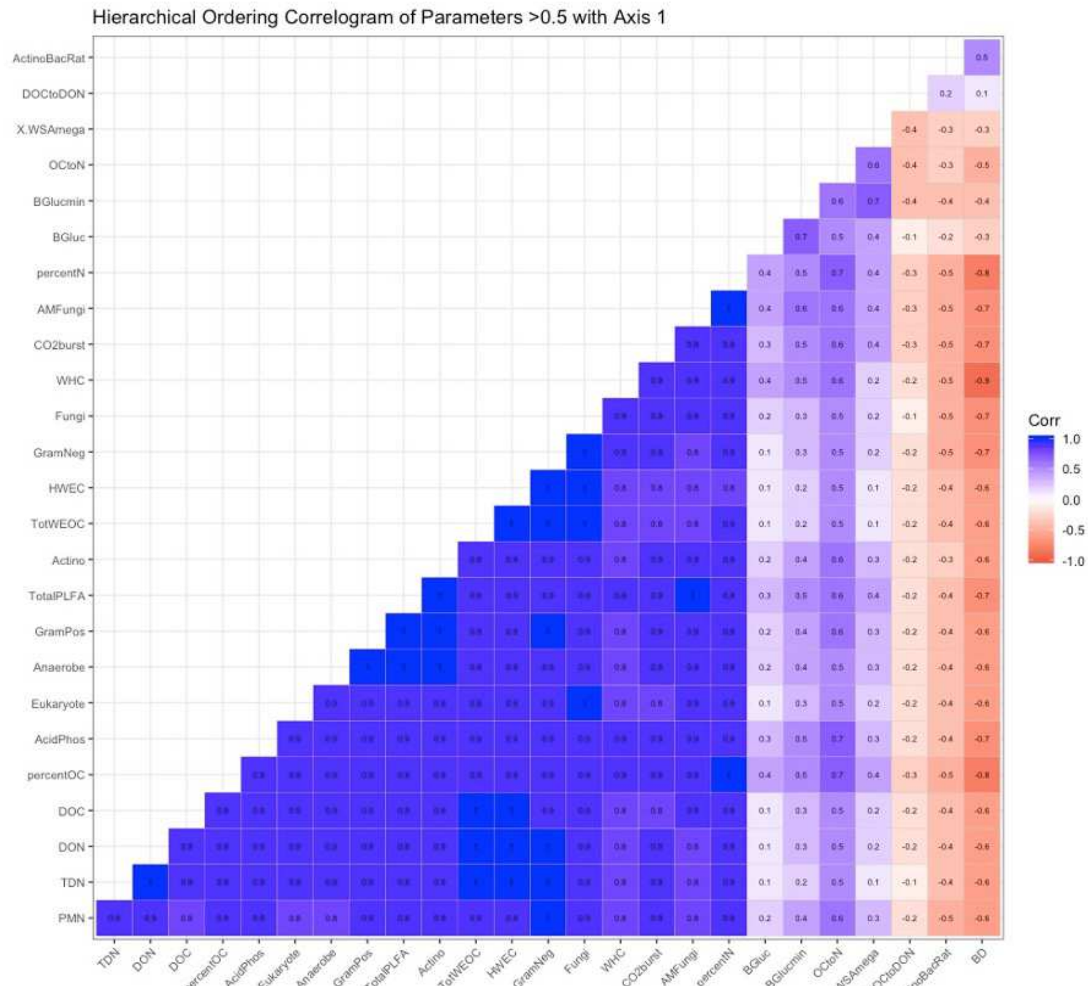

Figure S2. A correlation matrix between the 26 untransformed parameters with > 0.50 correlation to axis 1 of the principal components analysis that could be eliminated from a soil health index due to multicollinearity. Values range from -1 to 1 and are also indicated by color. In this figure, values are hierarchically clustered to clearly show those that can be considered for reduction. A large block of highly positively correlated parameters with r ≥ 0.8 includes 1) biological - Total PLFA (TotalPLFA), actinomycetes (Actino), gram + bacteria (GramPos), gram - bacteria (GramNeg), eukaryotes, arbuscular mycorrhizae (AMfungi), anaerobic bacteria (anaerobe), fungi, acid phosphatase, potentially mineralizable N (PMN), CO_2 burst (CO2burst), 2) chemical – total OC %, total N %, hot water extractable C (HWEC), total water extractable C pool (TotWEOC), dissolved organic C (DOC), total dissolved N (TDN), dissolved organic N (DON), and 3) physical - water holding capacity (WHC). Soil OC to N ratio (OCtoN) also was positively correlated (r ≥ 0.5) to the parameters in this block.

Table S1. Correlation values of indicators to all four significant principal components analysis axes. The five parameters most positively and negatively correlated to each axis are in ***bold italics***. Parameters with correlation values to axes ±0.75-1.0 are dark grey, ±0.50-0.75 are medium grey, and ±0.25-0.50 are light grey. The biological factors and total organic C (OC) and TN concentrations were strongly negatively correlated with the axis 1. One exception was the actinomycetes to bacteria ratio, which was one of the strongest correlates with the positive side of axis 1. Other strong positive correlates to the first axis included the ratio of dissolved organic carbon (DOC) to dissolved organic nitrogen (DON) and bulk density (BD). Biological parameters did not contribute to the spread across axis 2, whereas chemical and physical parameters correlated strongly with both sides (positive and negative). The strongest correlates with axis 3 were fewer than for the first two axes, but largely derived from the chemical and physical categories. Interestingly, biological parameters emerged again as strong negative correlates with axis 4, and chemical and physical parameters were associated with both sides of that axis.

	Response (abbreviated)	Full Response Variable Name	Axis 1 (43.0 %)	Axis 2 (12.3 %)	Axis 3 (9.0 %)	Axis 4 (7.4 %)
B	Total PLFA	Total PLFA	***-0.9611***	-0.0056	0.1262	-0.1651
	Actino	Actinomycetes	-0.908	0.0299	0.1767	-0.2706
	Gram+	Gram + bacteria	-0.9492	-0.0527	0.174	-0.1579
	Gram-	Gram - bacteria	***-0.9707***	0.0040	0.1316	-0.0520
	Eukaryote	Eukaryotes	-0.8176	-0.1146	-0.0352	-0.1549
	AM Fungi	Arbuscular mycorrhizal fungi	***-0.9492***	0.0428	0.0107	-0.1549
	Anaerobe	Anaerobic bacteria	-0.7087	0.1248	0.0966	***-0.4195***
	Fungi	Fungi	-0.9094	-0.0076	0.0995	0.1364
	Actino:Bact	Actinomycetes to bacteria ratio	***0.5116***	0.1913	0.061	***-0.5679***
	Fungi:Bact	Fungi to bacteria ratio	-0.4173	0.0256	***-0.3756***	0.2604
	β-Gluc	β-glucosidase	-0.5852	0.0055	-0.0975	***-0.5143***
	β-Glucmin	β-glucosaminidase	-0.8102	-0.2495	-0.1007	-0.3571
	AcidPhos	Acid phosphatase	-0.8671	-0.1148	-0.0128	-0.0296
	PMN	Potentially mineralizable N	-0.8944	-0.1944	0.1554	-0.0483
	CO_2 burst	CO_2 burst	-0.9277	-0.0536	0.1401	-0.0422
C	%OC	OC concentration (%)	***-0.9529***	0.0876	-0.2058	0.0844
	%N	N concentration (%)	***-0.9522***	0.1432	-0.1757	0.1013
	OC:N	OC to N ratio	-0.7622	-0.1112	-0.2812	0.0077
	HWEC	Hot water extractable carbon	-0.9196	0.0779	0.2539	-0.0423
	%TotCExtrHot	% of total OC that was HWEC	-0.4575	-0.0135	***0.7813***	-0.1075
	TotWEOC	Total water extractable C pool	-0.9321	0.0791	0.2392	-0.0443
	%Cmin4mon	C pool respired in 4 months	-0.0225	-0.3394	***0.5742***	-0.2223
	pH	pH	0.3022	0.2938	-0.2281	***-0.7024***
	Extract.Ca	Extractable Ca^{2+}	-0.0853	***0.7181***	-0.1962	***-0.4073***
	Extract.K	Extractable K^{+}	0.0014	***0.6168***	0.2059	-0.3681
	Extract.Na	Extractable Na^{2+}	0.3222	***0.5818***	0.282	-0.1768
	Extract.P	Extractable P	0.2578	***0.5947***	0.2913	0.0933
	DOC	Dissolved organic C	-0.8177	0.0882	0.1608	-0.0374
	TDN	Total dissolved N	-0.8202	0.2732	0.2589	0.0508
	NH_4	Ammonium	0.1177	0.4561	***0.4144***	-0.0299
	NO_3	Nitrate	-0.4452	0.1096	0.2782	***0.5894***
	DIN	Dissolved inorganic N	0.0298	0.4531	***0.3907***	***0.3026***
	DON	Dissolved organic N	-0.7385	0.0281	0.3527	***0.3867***
	DOC:DON	Ratio of DOC to DON	***0.5715***	0.3174	0.1873	0.1719
	CrystalFe	Crystalline Fe-oxides	***0.3346***	***-0.6349***	0.1083	-0.2700
	$Al_H+0.5Fe_H$	Poorly and non-crystalline minerals	-0.4269	0.4558	***-0.5928***	0.0952
	$Al_P:Al_H$	Ratio of Al_P to Al_H	-0.1610	***-0.7001***	0.2242	0.2471
P	BD	Bulk density	***0.6703***	***-0.4751***	0.1398	-0.3749
	Hardness@0	Hardness measured at surface	-0.1323	***-0.5626***	0.0964	***0.2647***
	Hardness@15	Hardness measured at 15 cm	0.1545	-0.3770	0.1843	-0.3087
	WHC	Water holding capacity	-0.7694	0.4398	0.0272	***0.3018***
	%WSAmega	% WSA in the mega size class	-0.6471	-0.3222	***-0.3692***	-0.2533
	%WSAmacro	% WSA in the macro size class	-0.3920	***-0.5985***	-0.3143	-0.2202
	%Sand	% sand	-0.2938	***0.6362***	***-0.5157***	-0.0281
	%Silt	% silt	-0.3697	-0.3906	***-0.3809***	0.1959
	%Clay	% clay	***0.4800***	-0.1171	***0.7205***	-0.1778

B = Biological; C = Chemical; P = Physical

Table S2. Results of a multi-response permutation procedure to test significance of multidimensional spatial differences between the proposed varying management groups. Higher A value indicates stronger model, adjusted p-value is 0.05 divided by the number of pairwise contrasts and was used to determine the significance of pairwise comparisons in the final model. Groups with fewer than one site (i.e., three within-site sample units) were excluded from the model. These classifications include agricultural history (previously intensive agricultural lands “PIAL” or “none”), current land use (conventional cropland, organic cropland, pasture, protected forest, or unmanaged previously intensive agriculture), soil order (Mollisol, Vertisol, Inceptisol, Oxisol, Ultisol, and Andisol) mineralogical class (high activity clays “HAC”, low activity clays “LAC”, poorly and non-crystalline minerals “PNCM”, and histic “HIS”), disturbance (“low” at least 50 yr no tillage, “medium” tilled in the last 10-50 yr, and “high” tilled in the last 10 yr), and cropland (“not cropland” or “cropland”). The categorical combination of current land use and minerals was the most significant model tested ($A = 0.2926$, $p < 0.0001$). However, due to the high numbers of pairwise contrasts and excluded groups, this model was not accepted as valid.

Classification or combination	A	p-value	# contrasts	Adj. p-value	Excluded groups
Current land use x Minerals	0.2926	< 0.0001	28	0.0018	ConvPNCM, ProForPMCN, ProForHIS, ProFor LAC
Agricultural history x Disturbance	0.2636	< 0.0001	6	0.0083	
Current land use	0.2583	< 0.0001	10	0.0050	
Disturbance	0.2559	< 0.0001	3	0.0167	
Agricultural history x Current land use	0.2544	< 0.0001	10	0.0050	PIALOrg and PIALPas
Cropland x Minerals	0.2203	< 0.0001	10	0.0050	NotCropHIS, CropPNCM
Agricultural history x Minerals	0.1396	0.001651	6	0.0083	NoneHIS, NoneHAC, PIALPNCM
Agricultural history	0.0944	0.000300	1	0.0500	
Cropland	0.0890	0.000453	1	0.0500	
Order	0.0879	n.s.	15	0.0033	
Minerals	0.0416	n.s.	3	0.01667	HIS

ConvPNCM = Conventional cropland; poorly and non-crystalline minerals; ProFor = Protected forest; HIS = Histic; LAC = low activity clays; PIAL = Previously intensive agricultural lands (i.e. plantation agricultural history present); Org = organic croplands; Pas = Pasture; NotCrop = A non-cropland land use designation; Crop = Cropland land use designation; None = No plantation history; HAC = high activity clays.

Table S3. Broad mineralogical classification into high activity clay (HAC), low activity clay (LAC), poorly and non-crystalline minerals (PNM), and histic (HIS) was made using a key system with criteria derived from standard NRCS taxonomy.

	Key	Criteria		
Q1	High poorly and non-crystalline mineral concentration?	$Al_H + 0.5Fe_H$concentration over 2 %	If yes, then	PNCM*
			If no, then	Q2
Q2	High concentration of total oxides?	CrystalAl+CrystalFe over 50 g /kg soil	If yes, then	LAC*
			If no, then	Q3
Q3	High extractable bases?	Ca + Na + K cmol c over 10	If yes, then	HAC*
			If no, then	Q4
Q4	At least one classification?		If yes, then	proceed to final decision
			If no, then	proceed to HISTIC
HISTIC	Does the site belong as Histic?	high OC and low BD	If yes, then	HIS
			If no, then	Additional information needed
Final decision				
Q5	If LAC + HAC, is it currently cropland?		If yes, then	LAC, but double check taxonomy and management
			If no, then	proceed to Q6
Q6	If LAC + HAC, does it have a recent agricultural history?		If yes, then	LAC, but double check taxonomy and management
			If no, then	proceed to Q7
Q7	If LAC + HAC, is it an undisturbed, or protected system?		If yes, then	HAC, but double check taxonomy and management
			If no, then	Additional information needed

* all samples proceed

Classification notes for tropical soils

- Inceptisols, in particular, need additional information to determine which class they belong to.
- Other than Inceptisols, classes usually align with taxonomy.