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Soil health improvement and climate change mitigation in soybean agroecosystems

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Abstract

Although soil health indicator (SHI) is extensively examined worldwide, Japan has yet to establish a soil health assessment framework calibrated to the unique properties of Andosols. In this study, we evaluated a long-term (19-year) organically managed soybean field and generated soil health scores using a cumulative normal distribution function to develop a site-specific benchmark. Treatments were tillage (no-tillage, moldboard plowing, and rotary tillage), cover crop (rye, hairy vetch, and fallow), and the addition of fertilizer or biochar in four replications. Intensive tillage reduced soil health, with SHS under moldboard plowing significantly lower than no-tillage during 2020–2022 ($p < 0.05$). No-tillage with cover crop and biochar enhanced SHS by sustaining soil organic carbon (SOC) at 3.8–4.8%. Overall SHS was positively correlated with SOC ($r = 0.7$; $p < 0.01$), while higher SHS was strongly associated with reductions in net global warming potential ($r_s = –0.95$; $p < 0.01$). SOC emerged as one of the most influential indicators, directly influenced soil ß-glucosidase activity (r = 0.84, $p < 0.001$), substrate-induced respiration (r = 0.7, $p < 0.001$), NO_3^- (r = 0.65, $p < 0.05$), and EC (r = 0.36, $p < 0.01$). Although NT-based systems may not achieve the highest yields due to interannual variability, they may offer substantial environmental benefits by contributing to long-term climate change mitigation.

Keywords: agroecosystems, farming management, soil health indicators, sustainable agriculture

1. Introduction

Soil health assessments are aimed at maintaining soil health and achieving sustainable land management. Soil health, also referred to as soil quality, has been broadly defined as the capacity of soil to function within natural or managed ecosystem boundaries to sustain plant and animal productivity, maintain or enhance water and air quality, and promote plant and animal health[1]. According to the U.S. Department of Agriculture[2], soil functions include cycling nutrients, providing physical stability and support, filtering and buffering potential pollutants, sustaining plant and animal life, and regulating water. According to Landmark, soil function encompasses the ability to support primary productivity (food, feed, fiber, and fuel) as well as ecosystem services, such as water purification and regulation, climate regulation and carbon sequestration, soil biodiversity and habitat provisioning, and nutrient cycling[3,4]. Healthy soils exhibit stability and resilience to physical, biological, and chemical stresses. They also reduce the risk of soil erosion, improve aeration and water infiltration, and minimize run-off[4]. Thus, to ensure sustainable land management, assessments must be conducted to anticipate potential deterioration in soil function. These assessments can yield three possible outcomes: the improvement, degradation, and maintenance of soil health[5].

Several tools exist to evaluate soil health status (SHS). The most widely used are the Soil Management Assessment Framework (SMAF) and Cornell's Comprehensive Assessment of Soil Health (CASH)[5,6,7].

Other methods include the Agroecosystem Performance Assessment Tool[8], Haney's Soil Health Test[9], regional indices (e.g., Alabama[10], Ontario[11]), the Soil Conditioning Index, and visual scorecards developed in the U.S.[5], U.K.[12], and Europe[12]. These frameworks vary in indicators and protocols. To reduce inconsistencies, the Soil Health Institute proposed a standardized suite of indicators—such as soil organic carbon, mineralizable carbon, aggregate stability, and water-holding capacity—applicable to U.S. soils[13]. However, further studies are needed to test their relevance for other soil types. Given Japan's diverse soils, especially Andosols covering 31% of its land, evaluating the applicability of these tools is essential[14].

Soil represents the largest terrestrial organic carbon reservoir and plays a crucial role in regulating the global carbon cycle[15,16]. Andosols are soils formed from volcanic ash and cover less than 1% of the world's terrestrial land. They are primarily found in the Ring of Fire, a volcanic region encompassing countries such as Colombia, Chile, Ecuador, Mexico, Indonesia, New Zealand, and notably, Japan[17]. They develop from fresh volcanic tephra, which serves as the parent material and undergoes erosion and deposition processes. Topographical studies have shown that the predominant soil types in Japan include Brown Forest soil (33%), Andosol (30%), and fluvic soil (14%)[18]. Andosols are the second most extensive agricultural soil in Japan categorized into allophanic and non-allophanic types. Allophanic Andosols, dominant in regions with extensive Holocene tephra deposits, account for nearly 70% of Japan's Andosols area, while non-allophanic types represent about 30% and occur in areas with limited tephra deposition. Both share features such as a thick black A-horizon, high phosphate fixation, strong water retention, and low bulk density. However, non-allophanic Andosols are distinguished by 2:1 clay minerals and high exchangeable aluminum, which often induces severe aluminum toxicity in crops [16,19, 20]. The SOC stock in Andosols can reach up to 127 Mg C ha^{-1}, which is significantly higher than that in other soil categories[21]. Hairiah et al. (2025)[4,22] also reported that the average SOC stock of Andosols underutilized land in West Sumatera, Indonesia was 115 Mg ha^{-1} or about 30% higher than that in Inceptisol 83 Mg ha^{-1}. An integrated multiscale assessment of Andosols degradation in southern Mexico City further highlighted their vulnerability, natural grassland soils (0–15 cm) contain 7.6–11.2% SOC (mean: 9.8%), whereas cropped Andosols show markedly lower levels, ranging from 3.3–6.6% SOC (mean: 4.7%) in the topsoil[23]. The mineral composition and climatic differences contribute to the variability of Andosols worldwide. Derived from volcanic materials, Andosols contain high levels of short-range-order minerals (e.g., amorphous oxides of silicon, aluminum, and iron, as well as Al-humus complexes), which influence SOC content in the topsoil[20,24]. Climate influences the weathering rate of volcanic materials and the release of elements that affect SOC distribution. Hence, SOC levels vary across different regions, including Japan. In Japan, Andosols are classified into three categories: high-humic, humic, and low-humic. These categories exhibit variations in SOC stock and C:N ratios among the carbon subgroups of Andosols[21]. Considering the critical role of Andosols in global ecosystems, periodic assessments of soil health are essential. Recognizing these challenges, the government of Hokkaido, Japan, launched its “Clean Agriculture” strategy, employing soil diagnosis to establish criteria for healthy soils and guide fertilizer recommendations. While the Hokkaido Fertilizer Recommendations share similarities with U.S. guidelines, they differ in emphasizing soil physical properties—an aspect less prioritized in North American and European framework[25]. This indicates that standard global soil health assessments may be less accurate for local agricultural management. Establishing ecosystem-specific soil health benchmarks is essential for guiding context-appropriate management practices and ensuring accurate interpretation of soil health outcomes[26]. Therefore, a soil health assessment framework specifically tailored to the unique properties of humic Andosols in Japan needs to be developed [18].

Most studies have indicated that soil composition and intended use vary, necessitating the establishment of region-specific SHIs. These indicators should be based on criteria such as effectiveness, readiness, measurement repeatability and sensitivity, and decision relevance[19]. Thus, this study aims to calibrate a context-specific set of soil health indicators (SHIs) derived from experimental data of soybean-producing agroecosystems established on Andosols under a temperate

Asian monsoon climate. Specifically, the research aims to evaluate the effects of different tillage systems, cover crop (CC) rotations, and biochar application within organic management practices. In light of the global emphasis on strengthening soil health to enhance crop productivity, rehabilitate degraded land, and mitigate climate change, the study further assesses overall soil health scores based on the proposed SHIs in relation to key soil functions, including SOC sequestration, crop yield, and climate change mitigation potential between conventional organic farming and regenerative organic farming (Fig. 1). Finally, the study aims to provide recommendations for SHIs that are contextually appropriate for evaluating upland Andosols.

2. Results

2.1 Descriptive statistic of SHI and new scoring function adjustment

Supplementary Table 1 details the physical, biological, and chemical SHIs, from which a new scoring function suited to upland Andosols was derived (Supplementary Figs. 1–2). Among the physical indicators, soil bulk density (BD) was incorporated into the new scoring function that ranged from 0.4 to 0.8 g cm^{-3}, with a “less is better” scoring approach. Soil hardness, expressed as penetration resistance (PR), ranged from 0.4 to 1.8 MPa at 0–30 cm and varied from 0.3 to 1.8 MPa at 30–75 cm, both following a “less is

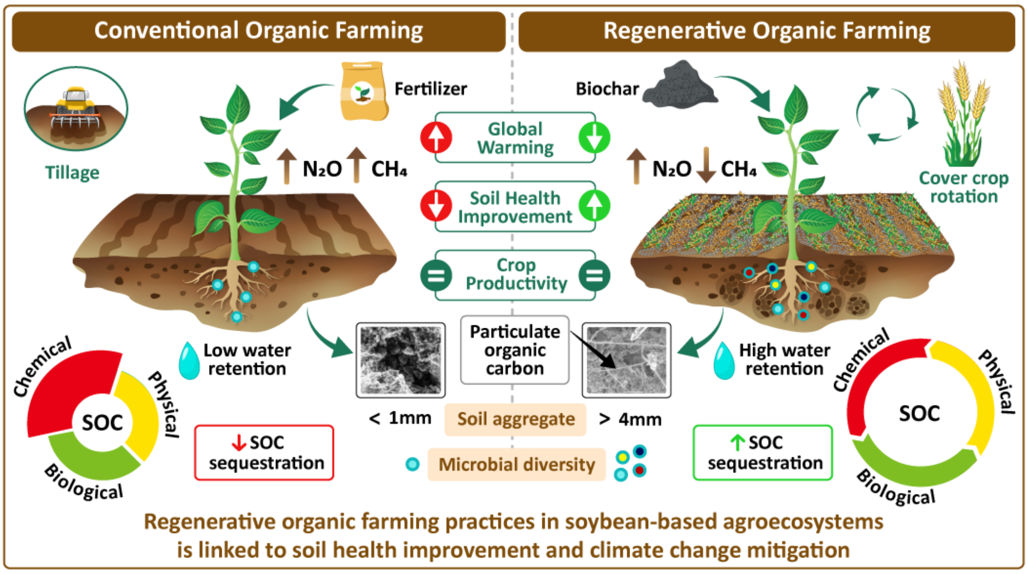


Fig. 1 Overview of the Agroecosystem management between conventional organic farming (left) and regenerative organic farming (right) approaches according to their function and their areas of application. Left: Conventional organic farming often provides intensive tillage, and apply the fertilizer, results no soil cover, decline of soil aggregate and lower water retention, although the soil chemical status was relatively high; Right: Regenerative organic farming, the elimination of tillage inversion and permanent soil cover, maintain the soil aggregate and keep the soil organic carbon, and enhance the microbial diversity resulting in improving the holistic soil health index of chemical, biological and physical aspect (drawn by Ratih Kemala Dewi and Masakazu Komatsuzaki).

better” scoring pattern. Conversely, indicators such as easily plant-available water (EPAW) and aggregate stability (ASI) followed a “more is better” scoring function. EPAW ranged from 0.03 to 0.18 $cm^3\ cm^{-3}$, while ASI ranged from 55.9% to 89.3%. Biological indicators—including SOC, active C, substrate-induced respiration (SIR), and soil β-glucosidase (BG)—also followed a “more is better” scoring function. Their values ranged as follows: 2.58–5.72% for SOC, 949.6–1587.3 mg kg^{-1} for active C, 2.2–166.5 μg h^{-1} g^{-1} for SIR, and 79.4–471.1 μg p-nitrophenol released g^{-1} h^{-1} for BG. Among the chemical indicators, soil acidity (pH) exhibited an “optimum range” scoring function, which could not be adjusted for this field[7]. Other chemical indicators, such as electrical conductivity (EC), nitrate nitrogen (NO_3^-), ammonium nitrogen (NH_4^+), available phosphate (av. P), exchangeable cations (exc. K^+, Ca^{2+}, and Mg^{2+}), and cation exchange capacity (CEC), followed a “more is better” scoring function. The observed values were as follows: 26–83 μS cm^{-1} for EC, 6.5–27.2 mg kg^{-1} for NO_3^-, 1.7–41.5 for NH_4^+, 2.7–36.9 mg kg^{-1} for av. P, 107.9–634.6 mg kg^{-1} for exc. K^+, 265.2–1734.8 mg kg^{-1} for exc. Ca^{2+}, 30.2–143.5 mg kg^{-1} for Mg^{2+}, and 6.4–68.9 $cmol^+$ kg^{-1} for CEC.

2.2 Soil health assessment

We evaluated soil health using an adjusted scoring function across various SHIs in 2017, 2020, 2021, and 2022 according to original experiment data (Supplementary Table 2–6). Fig. 2 presents the physical, biological, chemical, and overall soil health scores assessed in different years. The soil disturbance intensity had a significant effect on soil health scores (p < 0.05). The physical soil health score was significantly higher under moldboard plowing (MP) than under no-tillage (NT) or rotary tillage (RT) in 2017 (p < 0.05). However, this trend was reversed in 2020, with NT and RT exhibiting higher physical soil health scores than MP ($p < 0.05$). In 2021, no significant differences were observed in the physical soil health scores among tillage treatments ($p > 0.05$). By 2022, NT and RT again had significantly higher physical soil health scores than MP ($p < 0.05$). The biological soil health score was consistently higher under NT than under RT and MP in

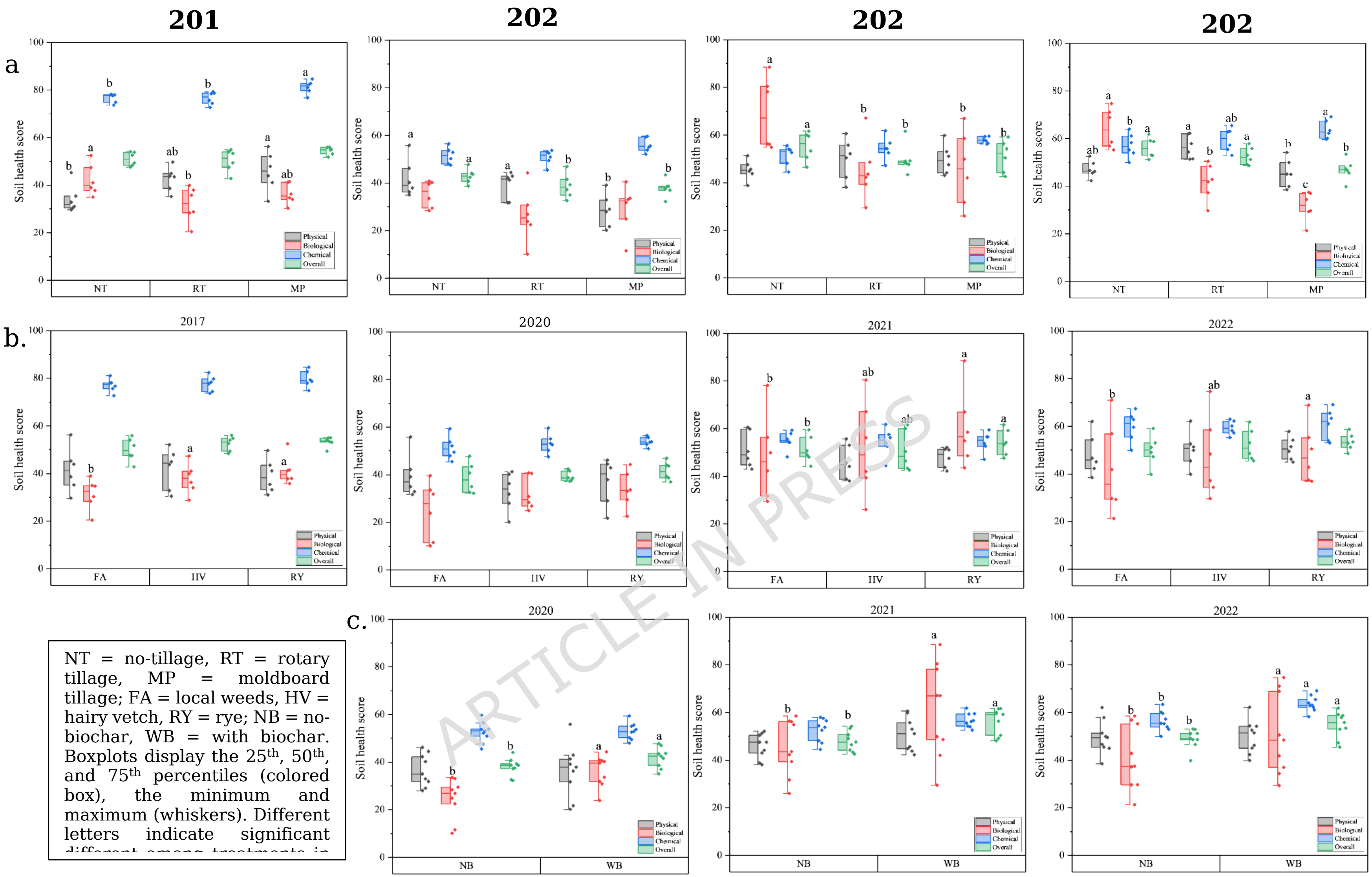


Fig. 2 Soil health score according to: a. soil disturbance intensity, b. cover crop input, c. biochar input in different years of assessment

all assessed years ($p < 0.05$), except in 2020, when no significant differences were observed ($p > 0.05$). The chemical soil health score was higher under MP than under NT or RT in 2017 ($p < 0.05$). In 2020 and 2021, no significant differences in chemical soil health scores were observed among tillage treatments ($p > 0.05$). However, in 2022, MP and RT exhibited significantly higher chemical soil health scores than NT ($p < 0.05$). For the overall soil health score, NT was significantly superior to RT and MP from 2020 to 2022 ($p < 0.05$).

The soil health score was also influenced by biomass input from CC practices. The impact of CC rotation on soil health was particularly notable in the biological soil health score, with rye (RY) and hairy vetch (HV) showing significantly higher scores than local weeds (FA) in 2017, 2021, and 2022 ($p < 0.05$). Additionally, the effects of RY and HV on the overall soil health score were significantly higher than those of FA, but only in 2021 ($p < 0.05$) (Fig. 2). The addition of biochar significantly increased both biological and overall soil health scores from 2020 to 2022 ($p < 0.05$) and significantly improved the chemical soil health score by 2022 ($p < 0.05$) (Fig. 2). The relative influence of management factors on soil health scores shifted across years. Fertilizer was most dominant in 2017, biochar in 2020, and tillage in 2021–2022. Across all years, however, tillage consistently emerged as the strongest driver of soil health, while cover crops contributed less directly to score variation.

The evaluation of the overall soil health score across different agro-systems indicated that the SHS of the 18 farming management systems in 2017 was similar to a “medium” classification. However, after 3 years, the SHS of some farming systems deteriorated from “medium” to “low” in fields managed with tillage, CC rotation, and biochar addition. This decline was observed in MP FA, MP HV, and MP RY without biochar application, MP HV and MP RY with biochar application, RT FA with or without biochar application, and RT HV and RT RY without biochar application. In NT field studies, a decline in SHS was noted in NT HV without biochar application. However, the SHS was restored from “low” to “medium the following year. Interestingly, the addition of biochar improved the SHS classification, elevating NT HV, NT RY, and RT HV from “medium” to “high.” By 2022, the SHS of MP FA without biochar addition declined from “medium” to “low.” Meanwhile, the SHS of NT RY and NT HV with biochar application declined from “high” to “medium.” Other farming management systems remained stable, maintaining a “*medium*” classification (Supplementary Table 7).

2.3 Pathway analysis of SHIs

The relationships between the individual SHIs and their respective soil health scores are shown in Fig. 3. This relationship was assessed using a structured equation model (SEM), which was deemed satisfactory based on the standard model fit criteria[27]. The path analysis results demonstrated that the hypothesized model linking physical soil health indicators (SHIs) to the composite physical soil health score exhibited an excellent overall fit. The chi-square statistic was non-significant ($\chi^2 = 3.991$, degrees of freedom (DF) = 6, $p = 0.678$), indicating no meaningful discrepancy between the observed and model-implied covariance structures. The relative chi-square (CMIN/DF = 0.665) was well below the conventional threshold of 3.0, further supporting model adequacy. Fit indices consistently confirmed the robustness of the model: the Goodness-of-Fit Index (GFI = 0.925) exceeded the recommended minimum of 0.90, the Comparative Fit Index (CFI = 1.000) indicated perfect comparative fit, and the Root Mean Square Error of Approximation (RMSEA = 0.000) suggested a close fit with no residual error [27]. Collectively, these indices suggest that the model adequately represents the observed relationships, although

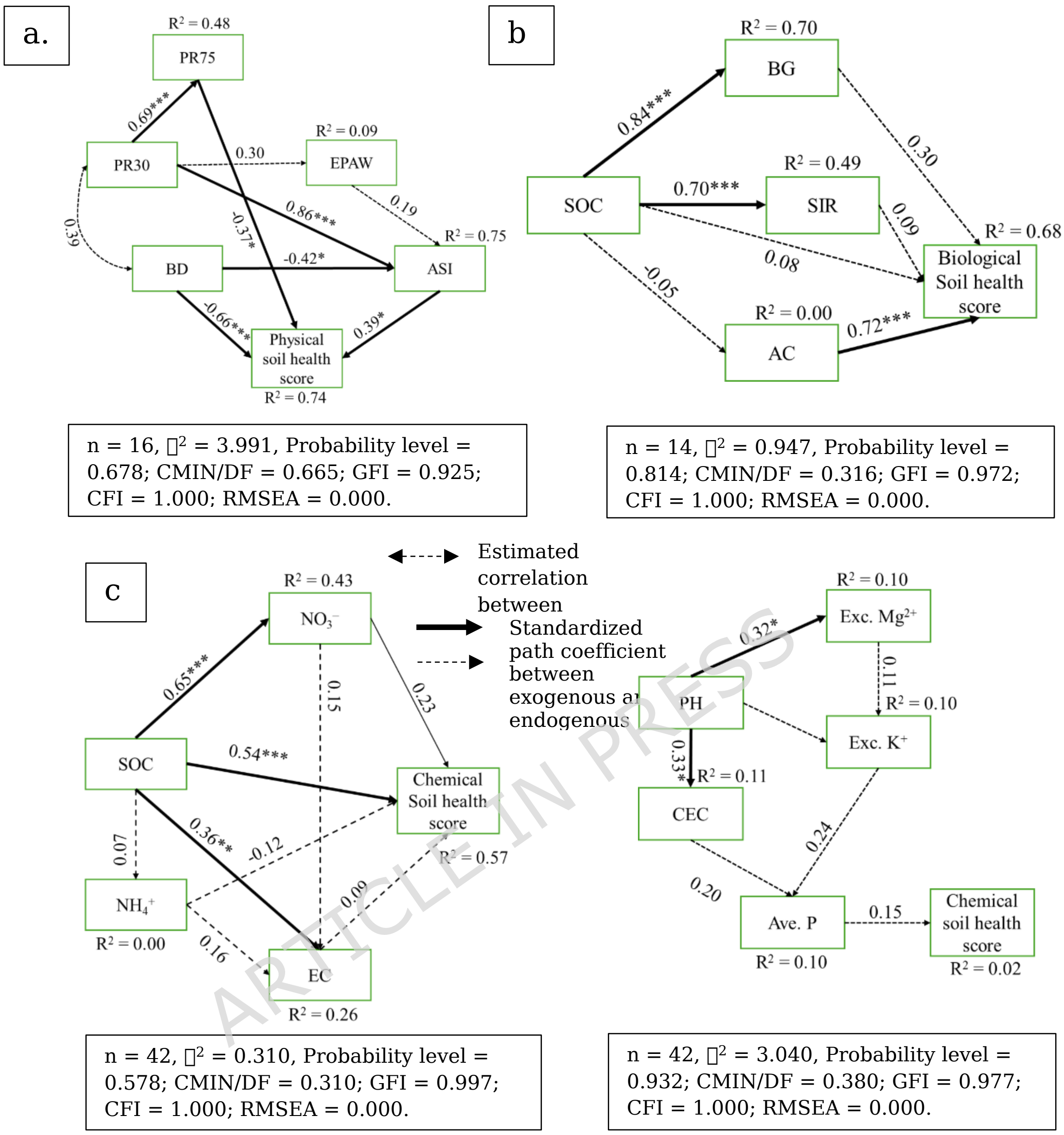


Fig. 3 The contribution of several soil health indicators based on pathway analysis on: a. physical, b. biological, and c. chemical soil health score. *, **, *** = the relation between variables are significant at $p < 0.05$, $p < 0.01$, $p < 0.001$; BD = bulk density; PR30 and PR75 = soil penetration resistance at 0–30 cm and 30–75 cm; EPAW = easily plant available water; ASI = aggregate stability; SOC = soil organic carbon; AC = active carbon; SIR = substrate induced respiration; pH = soil acidity; CEC = cation exchange capacity; Exc. K^+ = exchangeable potassium; Exc. Mg^{2+} = exchangeable magnesium; Ave. P = available phosphate; NO_3^- = nitrate nitrogen; NH_4^+ = ammonium nitrogen; EC = electrical conductivity; R^2 = coefficient of

determination; n = sample size, χ^2 = Chi-square; CMIN/DF = the ratio of chi-squared degrees of freedom; GFI = goodness-of-fit index; CFI = comparative fit index; RMSEA = root mean squared error of approximation.

the modest sample size warrants cautious interpretation. Based on the SEM, the physical soil health score was significantly influenced by soil BD, which exhibited a direct negative correlation with the physical soil health score ($p < 0.05$). Additionally, soil BD indirectly influenced the physical soil health score through the mediation of ASI ($p < 0.05$). ASI was also directly influenced by the PR at 0–30 cm ($p < 0.05$). Both BD and PR at 0–30 cm were significantly correlated, affecting the aggregate stability in different directions ($p < 0.05$). Notably, PR at 30–75 cm also directly affected the physical soil health score ($p < 0.05$) but in a negative direction. Similarly, the path analysis of biological SHIs in relation to the biological soil health score also revealed an exceptionally strong model fit ($\chi^2 = 0.947$, DF = 6, p = 0.814) with the CMIN/DF = 0.316, further also confirming the adequacy of the model. Additional fit indices reinforced this result, the GFI = 0.972, CFI = 1.000, and RMSEA = 0.000. These results demonstrate that the biological SHIs are highly coherent with the biological soil health score, validating the structural specification of the model despite the modest sample size (n = 14). According to the SEM, direct effect of SOC on the biological soil health score was not found ($p > 0.05$), but active carbon (AC) directly affects the biological soil health score ($p < 0.05$). Although, the SOC also directly influenced soil BG ($p < 0.05$)

and SIR ($p < 0.05$). The specified pathway did not adequately account for the mediation effects of BG, SIR, and AC in relation to SOC and the biological soil health score. In addition, SOC influenced the chemical soil health score both directly and indirectly. SOC significantly increased NO_3^-, EC, and the chemical soil health score ($p < 0.05$); however, the indirect effect of SOC on the chemical soil health score through NO_3^- and EC was not statistically significant ($p > 0.05$). The pathway of chemical SHIs in relation to the chemical soil health score also yielded an excellent model fit ($\chi^2 = 0.310$, DF = 8, p = 0.578). The CMIN/DF = 0.310; GFI = 0.997; CFI = 1.000 and the RMSEA = 0.000. The chemical soil health score was also influenced by the soil pH, although the effect was relatively minor. Soil pH significantly affected CEC and exc. Mg^{2+} ($p < 0.05$) and indirectly influenced the chemical soil health score through two pathways. First, pH altered CEC ($p < 0.05$) and av. P. Second, pH influenced exc. Mg^{2+} ($p < 0.05$), exc. K^+, and av. P. However, both pathways were not statistically significant ($p > 0.05$). This pathway was also deemed satisfactory fit (□^{2} = 3.040, DF = 1, p = 0.932; CMIN/DF = 0.380; GFI = 0.977; CFI = 1.000; RMSEA = 0.000). These results demonstrate that the chemical SHIs are highly consistent with the chemical soil health score, validating the structural specification of the model with a relatively larger sample size (n = 42). Furthermore, SOC stock significantly contributed to improving the overall soil health score ($p < 0.05$) (Fig. 4), which exhibited a negative correlation with the net global warming potential (GWP) in 2021 ($p < 0.05$) (Fig. 5).

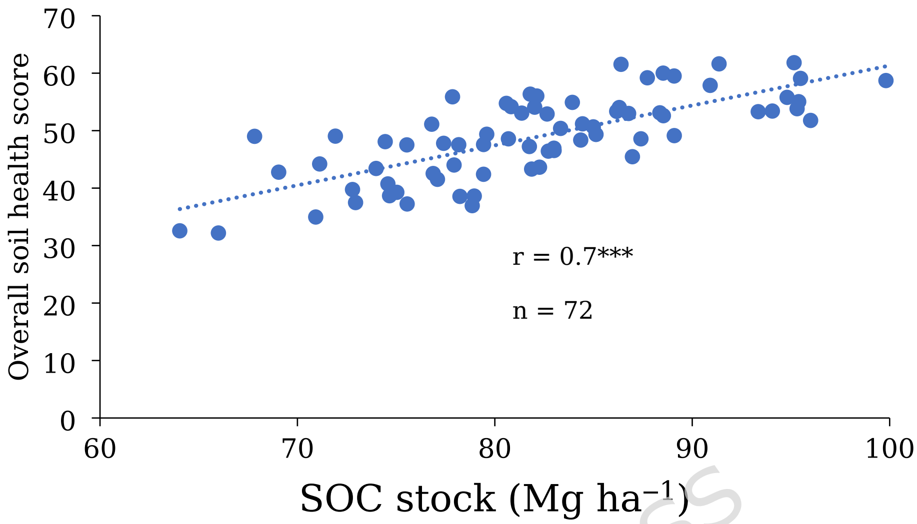


Fig. 4 Soil organic carbon (SOC) stock contribution to overall soil health score. r = Pearson correlation, n = sample size; *** indicate correlation between the two variables statistically significance at $p < 0.001$.

A positive correlation was also observed between the overall soil health score and CC biomass; however, the effect was only statistically significant in 2020 ($p < 0.05$) (Fig. 6). Conversely, no significant relationship was found between the overall soil health score and soybean production, including both dried biomass and yield ($p > 0.05$) (Supplementary Figs. 3–4). Although the overall soil health score was significantly higher under NT than under RT and MP from 2020 to 2022 ($p < 0.05$), the soybean yield decreased across all tillage treatments. In 2021, NT had the lowest soybean yield compared to RT and MP ($p < 0.05$). However, in subsequent years, soybean yields in the NT and MP treatments were comparable ($p > 0.05$) and remained higher than those in the RT treatment ($p < 0.05$) (Supplementary Fig. 5). This indicates interannual variability; thus, yield improvements under NT may be possible.

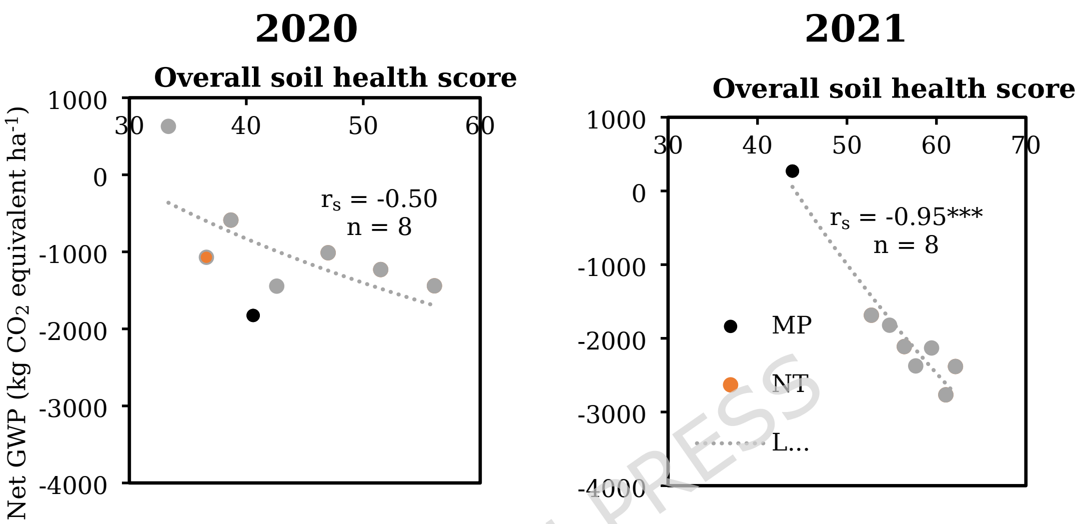
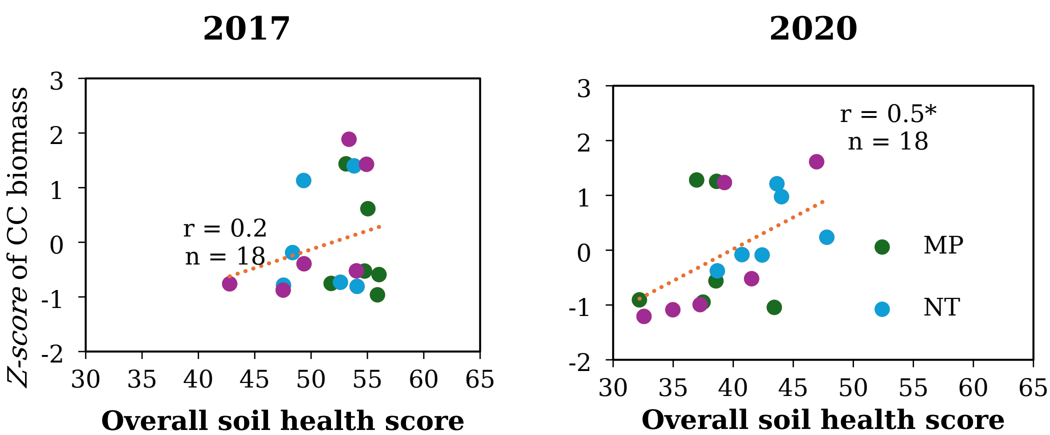


Fig. 5 Overall soil health score relative to net global warming potential (GWP). r_s = Spearman correlation, n = sample size; *** indicate correlation between the two variables statistically significance at $p < 0.001$; NT, MP = no-tillage, moldboard tillage, respectively.



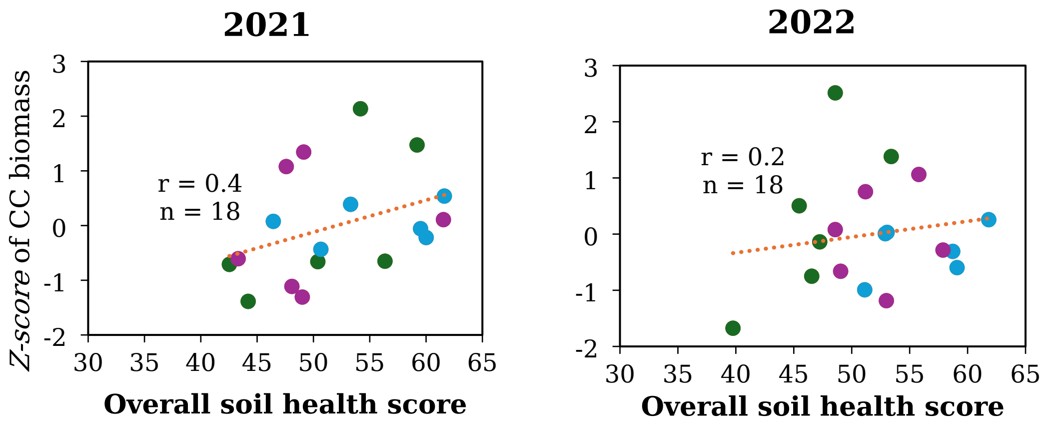


Fig. 6 Overall soil health score relative to cover crop biomass in different years. r = Pearson correlation, n = sample size; CC = cover crop; * indicate correlation between the two variables statistically significance at $p < 0.05$; NT, RT, MP = no-tillage, rotary tillage, and moldboard tillage, respectively.

3. Discussion

3.1 Development of a new scoring function for upland Andosols

Andosols constitute the second-largest cultivated land area in Japan[7], making it essential to develop a new scoring function for evaluating SHS. Andosols are characterized by high SOC and low BD, which influence the physical, biological, and chemical properties of the soil. SOC accounts for more than 50% of soil organic matter[28]; therefore, it can be difficult to determine soil health accurately when relying solely on global soil health assessment tools. In the assessed soil samples, the mean SOC content was approximately 3.7%, which is relatively higher than the global average for different soil types (1–2% SOC). According to CASH, the mean organic matter content for the scoring function is 3.99% for fine-textured soils, 3.07% for medium-textured soils, and 2.01% for coarse-textured soils, corresponding to SOC values of 1.99%, 1.5%, and 1.01% respectively[7]. An SOC content of 2% in Ultisols of the southeastern U.S. is considered high and would receive a high SOC score. However, in Midwestern Mollisols of the U.S., the same SOC content would be considered low and assigned a correspondingly low score[6]. Contrastingly, the organic matter content of Andosols in Colombia can be 4.7%–29.8% with mean of 17.4% or equal to 2.35%–14.9% with mean 8.7% of SOC[26]which is exceptionally high, making conventional scoring functions unable to capture differences in soil health status. Similarly, the mean of SOC content of Andosols we examined in this study was 3.7%, although the values were still lower than those reported for Colombian Andosols. Although both soils are classified as Andosols, differences in SOC content are attributed to local conditions and land-use patterns. Agroforestry systems tend to maintain higher SOC levels, while cultivated lands generally exhibit lower SOC levels. In this study, we established the threshold for a new scoring function using soil samples that represent the local conditions of upland Andosols under soybean production. Given that SOC plays a key role in determining the physical, chemical, and biological properties of soil, the newly developed scoring function provides an initial assessment of soil health in upland Andosols, particularly in soybean production systems that rotate with CCs. However, this scoring function is specific to local soybean production in upland Andosols. Despite its limitations, it represents a significant first step toward developing more comprehensive benchmarks for soil health assessment. A broader range of soil samples from Andosols in different regions of Japan, covering various crop production systems, is necessary to refine and improve the scoring function for broader applicability.

3.2 Soil health score and its relationship with soil function

The new soil health scoring function effectively distinguished differences in SHS among agroecosystems with varying tillage and CC management practices in the long-term soybean field experiment. Although no significant differences were observed in SHS across agroecosystems in 2017, the scoring function detected variations in 2020, 2021, and 2022. NT has been reported to significantly influence soil BD and SOC in the surface layer (0‒7.5 cm) due to organic matter accumulation[29]. Differences in SHI values and scores reflected variations in tillage and CC practices. Although SHS demonstrated sensitivity, it sometimes failed to detect subtle but important changes resulting from improved land management practices (Supplementary Tables 2‒6).

Intensive tillage led to the deterioration of SHS despite the application of CC rotation and biochar, ultimately reducing SHS under certain farming management practices. In contrast, SHS remained more stable under NT compared to MP and RT. Moreover, biochar application enhanced SHS in NT HV, NT RY, and RT HV systems.

Intensive tillage negatively impacted biological soil properties, whereas NT helped preserve biological activity by minimizing soil disturbance. This experimental field has been managed organically since 2018. Long-term soil health was maintained under minimal or no soil disturbance for a more extended period than under intensive tillage. The integration of CC increased soil organic matter content, which contributed to improvements in the chemical and physical properties of the soil. Under NT with CC management, the accumulation of organic matter, particularly in surface soil, increased SOC content and maintained lower soil BD, which in turn improved easily plant-available water. Thus, organic conservation management can effectively restore soil function by enhancing physical stability, improving soil structure, and regulating water retention. Biological indicators, including high SOC, SIR, and BG activity, showed annual improvements under NT. The combination of NT and CC rotation enhanced nutrient cycling more effectively than other tillage systems. Higher biological activity under NT contributed to improved soil biodiversity and enhanced the productivity of soil organisms.

Furthermore, sustainable farm management can help reduce greenhouse gas (GHG) emissions[30]. The accumulation of organic matter under NT with CC management and biochar amendment gradually increased SOC stock and improved SHS, contributing to the mitigation of net global warming (Fig. 5). Although the relationship between soil health score and net GWP is correlational, it is mechanistically consistent with established understanding that SOC accumulation under reduced tillage promotes carbon stabilization and may reduce nitrogen-related emissions. In regenerative organic farming-based NT systems, reduced soil disturbance minimizes the oxidation of organic matter, thereby promoting carbon stabilization within soil aggregates[31]. As a result, soils managed under NT exhibit higher SOC storage compared to conventional tillage systems. Elevated SOC levels contribute to carbon sequestration, effectively offsetting greenhouse gas emissions. Improved soil health under NT enhances nutrient cycling efficiency, which reduces nitrogen losses and mitigates N_2O emissions—a potent contributor to agricultural GWP as reported by Huang et al. (2024)[30] that the net CO_2 retention of the combined NT–RY–WB fully offsets the non-CO_2 emissions, resulting in a net negative GWP. NT farming techniques, CCs, polycultures, intercropping, and perennially selected crops have been demonstrated to positively impact SOC and other physical and chemical soil processes and functions[30, 32]. Although we have not yet established a direct relationship between SHS and soybean production, the overall soil health score significantly increased CC biomass (Fig. 6). When CC biomass is incorporated into the soil, it enhances soil health and gradually improves crop production, ultimately optimizing the primary productivity of the soil. Recent research on conservation agriculture reported that a 21% increase in soil health can sustain crop production levels even after long-term warming, compared to conventional agriculture[33].

Plant productivity depends not only on the soil status but also on various other factors that influence plant growth and development. A regression model from a 14-year long-term study on spring wheat in Orthic Dark Brown Chernozem (Typic Boroll) under semiarid conditions showed that 20 g SOC kg^{-1} (2% SOC) is a critical threshold. Below this level, soil productivity decreased significantly, whereas above this threshold, no further yield response was observed[32, 34]. Given its critical role in improving sustainable agriculture, CC management must be optimized to balance food security with environmental protection. These optimized practices are expected to enhance the multifunctionality of agroecosystems by 1.25%, corresponding to annual gains of 97.7 million metric tons in cereal production, 21.7 billion metric tons in carbon dioxide sequestration, and 2.41 billion metric tons in soil erosion reduction[35]. Notably, occasional soil health evaluations do not contribute to reducing global warming, whereas regular soil health assessments play a crucial role in promoting practical farming practices that enhance both production and environmental sustainability.

In summary, the soil health score of each indicator in this study aligned with the original values of the indicators, confirming that the new scoring function is valid and sensitive to farming management. Sustainable agricultural approaches, such as eliminating tillage, implementing crop rotation, and incorporating soil amendments (e.g., biochar), enhance soil health. Conversely, intensive tillage degrades soil health. However, intensive tillage can still rapidly alter soil conditions when combined with CC rotation and organic matter amendments. Regular soil health assessments using an appropriate scoring function tailored to local conditions are recommended. Finally, implementing sustainable farm management practices can help maintain soil functions and support the provision of multiple ecosystem services.

3.3 Role of specific SHIs

In this study, we highlight the critical role of individual SHIs for maintaining overall SHS, including physical, chemical, and biological properties. The path analysis of the individual SHIs and their respective soil health scores deemed satisfactory based on the standard model fit criteria (Fig. 3). This outcome highlights the robustness of the selected physical, biological, and chemical indicators as integrative measures of soil health. The consistently strong fit indices across all three domains provide strong support that the indicators capture the latent construct of soil health in a coherent manner. Nevertheless, the relatively small sample sizes employed in the physical and biological models raise the possibility of model overfitting, which should be acknowledged as a limitation. While the chemical model benefits from a larger sample size (n = 42), caution is warranted in generalizing the findings.

Regular measurements of soil BD, PR, ASI, and SOC in upland Andosols are recommended. Physical soil quality in upland Andosols is influenced by PR, BD, and ASI in the top 30 cm of soil, emphasizing the importance of surface hardness in determining physical soil properties. Soil BD and PR influence seedling emergence, root development, crop yield, porosity, and water infiltration, among other factors[36]. Lower soil BD is associated with higher aggregate stability, indicating increased pore space, which benefits root growth, water infiltration, and air movement. Changes in ASI can also influence the severity of soil erosion and the protection of soil C and nutrients at both macroscale and microscale levels[36]. Soil aggregation serves as a key physical indicator of SOC stability[37]. Additionally, soil BD and ASI are considered SHI relevant to water storage and transport[13]. Soils with lower BD and higher aggregate stability generally exhibit superior health and productivity.

This study also revealed that SOC and SIR are the most significant biological SHIs in upland Andosols. SOC clustered with active C and soil BG, showing a strong positive correlation with soil biological activity. An increase in SOC enhances active C and soil BG, improving SHS. In addition, SIR was identified as a key indicator of soil microbial activity. Although the mediation effects of soil BG, SIR, and active C on the biological soil health score by SOC were not significant, SOC strongly influenced BG and SIR, while active C significantly affected the biological soil health score. SOC, active C, and BG are related to

C pools and cycling, which are responsive to management practices[13]. Active C represents the readily decomposable organic fraction available to soil microbes[7]. Soil BG activity, dependent on SOC levels, is sensitive to diverse management practices across various climates, soil types, and soil textures. This enzyme plays a crucial role in breaking down plant material and providing simple sugars for microbial populations[38]. Additionally, microbial activity is influenced by SOC. Soils with higher SOC typically support increased microbial biomass and activity, leading to higher SIR values[39]. These findings highlight the significant role of SOC in sustaining microbial life and enzyme activity, reinforcing its importance in soil biological health.

Our study findings suggest that SOC enhancement improves nitrogen availability in upland Andosols. Soil fertility is primarily determined by the availability of essential nutrients[13]. The pathway model revealed that SOC directly affects the chemical soil health score, indicating that SOC is a strong predictor of chemical soil properties. Additionally, soil pH directly influenced CEC. Higher soil pH promotes macronutrient availability, although its overall effect on soil chemical properties was less pronounced. CEC plays a crucial role in nutrient retention and buffering against acidification. Both pH and CEC primarily reflect inherent soil characteristics[13], which are shaped by parent material, native vegetation, climate, topography, and other soil-forming factors[40]. Since this study was conducted on similar soil types, variations in pH and CEC were difficult to detect, limiting conclusions on their response to management practices. This study confirmed that while soil pH did not directly affect the chemical component of the soil health score, it strongly influenced CEC and exc. Mg^{2+} (Fig. 3). Conversely, SOC directly reflected soil health, underscoring its role in maintaining chemical soil properties.

It's important to select indicators that primarily reflect the soil health and avoid redundant measurement[13]. However, it's also imperative to note that the selection of soil health indicator is dependent on the purpose. Different purposes may lead to different soil health indicators; thus, the additional soil health indicator can be added on the evaluation such as to conduct the soil fertility management, the macro nutrient status in the soil need to be assessed. SOC is crucial in maintaining soil health, influencing physical, chemical, and biological properties. It enhances soil quality by improving water and nutrient retention, leading to increased plant productivity in natural ecosystems and agricultural settings. Given its fundamental role in soil function, SOC emerged as a highly influential indicator within this specific agroecosystem, although soil health remains a multidimensional construct that cannot be fully represented by a single variable. Beyond its impact on soil properties and plant nutrition, SOC also contributes to regulating carbon exchange between land and atmosphere[41].

4. Conclusions

This new soil health scoring function is site- and system-specific, applicable to upland Andosols under soybean-based organic management in Japan. It serves as an initial benchmark for evaluating soil health in this area, though further validation and recalibration are required before broader application. Expanding research across multiple upland Andosols sites in Japan is necessary to refine the scoring function. The scoring function assesses soil function—including primary productivity and multiple environmental services—and emphasizes the importance of regularly measuring key SHIs such as soil BD, PR, ASI, and SOC. Notably, SOC emerged as a highly responsive indicator in this system, reflecting an integrative role across physical, chemical, and biological domains. NT soybean cultivation combined with CC rotation may help maintain organic matter input, resulting in increased SOC accumulation. Additionally, biochar amendment further increases SOC and improves soil health. Improving soil health may contribute to climate change mitigation. While NT-based agroecosystems may not maximize yields, this regenerative organic farming supports long-term environmental conservation, promoting sustainable agricultural production.

5. Materials and methods

5.1 Site description and experimental design

The study was located at experimental fields of the Faculty of Agriculture, Ibaraki University (36◦02′ N, 140◦12′ E). Soil health evaluation was conducted in the long-term field experiment on different tillage and CC management systems, established in 2002. The soil is classified as Andosol with a sandy loam soil texture[14]. Initially, the field was used for upland rice cultivation during the summer (2002–2007) before being converted to soybean production (2008–present). The experiment included three tillage systems—MP, RT, and NT—as the main plot factor, combined with CC management as the subplot factor. The CC treatments consisted of HV (*Vicia villosa*), RY (*Secale cereale*), and FA (local weeds). The experiment followed a split-plot design with four replications. Tillage was applied before soybean and CC cultivation, with depths of 30 cm for MP, 15 cm for RT, and 0 cm for NT. Soybean was planted in July and harvested in November, while CC was planted in November and terminated around May of the following year. Fertilizer application was managed within each plot as a sub-sub-plot factor. Nitrogen (0 and 100 kg ha^{-1}) was applied for upland rice (2002–2007) and at 0 and 20 kg ha^{-1} for soybean[36]. From 2018 to 2023, no fertilizer was applied, but from 2020 to 2023, rice husk biochar was added at rates of 0 Mg ha^{-1} (no biochar) and 8 Mg ha^{-1} (with biochar) before tillage for soybean cultivation[37]. Plot sizes were 6 × 12 m^2, 6 × 6 m^2, and 3 × 6 m^2 for the main plots, subplots, and sub-sub-plots, respectively.

5.2 Farming management history

The field was used for upland rice and soybean production during the summer, followed by CC rotation. Before soybean cultivation, tillage was performed in the MP and RT plots, followed by soil harrowing to prepare the seed bed. However, the NT plot remained undisturbed. The CC residue and biochar were incorporated into the soil during tillage at depths of 25–30 cm for MP and 15 cm for RT. In NT plots, CC residue and biochar were left on the surface and mixed with the soil using a mower to prepare the seed bed. Soybean (50 kg ha^{-1}) was sown using an NT seeder in all plots, while CC was hand-sown at rates of 50 kg ha^{-1} and 100 kg ha^{-1} for HV and RY, respectively. The soybean seeds used in this study were obtained from JA (Japan Agricultural Cooperative) in Ibaraki Prefecture. Phosphorus (100 kg P_2O_5 ha^{-1}) and potassium (100 kg K_2O ha^{-1}) were applied at soybean seeding from 2008 to 2016. The field has been under organic management since 2018.

5.3 Soil sampling and measurement

The soil samples were collected from the experimental fields of the Faculty of Agriculture, Ibaraki University. The measurement of soil health indicators consists of physical, biological, and chemical soil health indicators. Indicator selection followed an established framework[7]. Although some redundancy among variables may exist, dimensionality reduction was not employed, as the primary objective was to assess functional components rather than to maximize predictive efficiency.

5.3.1 Physical indicators

Soil BD and PR were used as physical soil indicators. Soil samples were collected using a soil core sampler (diameter: 5 cm) at 0‒30 cm depth to measure BD in May 2018, October 2020, and October 2021. Samples were oven-dried at 105°C until a constant weight was achieved, and BD was calculated as the ratio of oven-dried weight to soil volume[29]. Soil PR was measured directly in the field in November 2018 and 2021 using a hand-held electronic cone penetrometer (CP40II, Cone Penetrometer, RFM Australia Pty Ltd.) at 0‒75 cm depth. In 2021, additional physical indicators, such as aggregate stability and easily plant-available water, were incorporated using a dataset from Hashimi et al. (2023)[31], which was reanalyzed.

5.3.2 Biological indicators

SOC, SIR, and BG were measured to assess soil biological health. Soil samples for SOC were also collected using a soil core sampler at 0‒30 cm soil depth. The oven-dried soil that already sieved through 2 mm sieve was analyzed for SOC using the dry combustion method with a CN analyzer (JM 3000, J-Science Lab, Japan)[42]. SOC stock was then determined using the equivalent soil mass method. Soil samples from a 0‒5 cm soil depth were collected in May 2019, October 2021, and April 2024 for SIR analysis. SIR was evaluated by measuring CO_2 emissions from soil microorganisms after activation with a readily decomposable C substrate (glucose) for 1 h. Fresh soil samples, sieved through a 2 mm mesh and adjusted to 30 ± 1% moisture, were stored in airtight containers for CO_2 emission measurements using a portable

CO_2 meter at a controlled room temperature of 25 °C[39]. In 2021, active C was added as a chemical indicator using a dataset from Hashimi et al.[31]. For BG activity, soil samples from the 0–5 cm depth were collected in October 2023. Enzyme activity was analyzed using fresh soil samples and expressed in µg p-nitrophenol h^{-1}. It involves extraction and colorimetric determination of the p-nitrophenol released when 1 g of soil is incubated with 5 ml of buffered p-nitrophenyl glycoside solution at 37°C for 1 h [43].

5.3.3 Chemical indicators

Soil samples were collected in October 2017, 2020, 2021, and 2022 from 0–30 cm depths using a soil core sampler (diameter: 5 cm). Each sample was further divided into four depth intervals: 0–2.5 cm, 2.5–7.5 cm, 7.5–15 cm, and 15–30 cm. Samples were air-dried at room temperature, ground, and sieved through a 2 mm mesh before chemical analysis. The following soil chemical parameters were measured: pH, EC, NO_3^-, NH_4^+, av. P, exchangeable cations (exc. K^+, Ca^{2+}, and Mg^{2+}), and CEC. Soil pH and EC were measured using a hand-held pH meter (PH72-S2.01; Yokogawa, Japan) and a conductivity meter (B-173, Horiba, Japan), respectively, in a 1:8 soil-to-water solution. NO_3^- was extracted using distilled water[44], while NH_4^+ and av. P were measured using the indophenol blue and Bray I methods, respectively[45]. A spectrophotometer (SPCA 6210, Shimadzu, Japan) was used to analyze NO_3^-, NH_4^+, and av. P. Exchangeable Ca^{2+}, Mg^{2+}, and K^+ were extracted using neutral normal ammonium acetate[45] and analyzed through atomic absorption spectroscopy (SPCA 6210, Shimadzu, Japan). CEC was estimated by collecting NH_4^+ from a KCl extract, followed by washing with 1 N ammonium acetate and 80% ethanol. NH_4^+ content was measured using a spectrophotometer (SPCA 6210)[46], and CEC content was calculated. Chemical parameters (NO_3^-, NH_4^+, ave–P, exc. cations, and CEC) were estimated using bulk soil samples collected at a depth of 0–30 cm through the equivalent soil mass method[47]. The 2003 soil mass was used as a reference to adjust subsurface soil depth (15–30 cm).

5.4 Crop biomass and yield

CC biomass was randomly collected using a 50 cm × 50 cm quadrant before termination. Samples were placed in net bags, initially dried in a greenhouse, and then oven-dried at 60°C until a constant weight was reached. Total C content in CC was determined using the dry combustion method. C accumulation was calculated based on the oven-dried weight of aboveground biomass produced in each plot and its C concentration. The dried biomass was then recorded and converted to a hectare basis. Soybean biomass was collected from a 30 cm × 100 cm area. Yield was determined after separating the grains.

5. 5 Global warming potential

Greenhouse gas emissions, including N_2O and CH_4, were analyzed to calculate net GWP. Gas samples were collected weekly between 9:00 and 11:00 AM from June 2020 to May 2022 using the static chamber method[48, 49]. Net GWP (kg CO_2-equivalent ha^{-1} $year^{-1}$) was calculated using Eq. 1[30].

Net GWP = 298 × annual N_2O emission + 34 × annual CH_4 emission − annual net CO_2 retention ………………………………………………………………………… Eq. 1

5.6 Development of a scoring function for soil health indicators

We developed a soil health scoring approach for soybean production in upland Andosols. The scoring system was based on a long-term soil dataset (19 years) from different tillage and CC management practices, incorporating physical, biological, and chemical indicators following the CASH[7, 26]. A cumulative normal distribution (CND) function, using mean (m) and standard deviation (s), was applied to normalize soil data and generate SHI scores. This approach provides the probability ($0 < x < 1$) that a given SHI measurement (x) falls within the distribution (Eq. 2). Scores were then multiplied by 100 to standardize values on a 0–100 scale, translating measured laboratory values into unitless percentile scores:

$$CND(x,m,s) = 1/2[1 + \mathrm{erf}((x - m)/(s\sqrt{2}))] \times 100$$
………………………………. Eq. 2

Here, *erf* denotes the error function.

The cumulative normal distribution (CND) was selected for its empirical robustness and interpretability. It can accommodate variability across datasets, offers stable statistical properties, and is resistant to the influence of outliers. Moreover, the CND transforms raw indicator values into a 0–1 (percentile-like) scale (in this study, it transforms to 0–100), making results easier to interpret as probabilities or relative positions. This enables different indicators to be compared on a common standardized scale, even when their raw units differ. In addition, the CND emphasizes average values, aligning with how practitioners typically interpret SHS. A nonlinear equation was then constructed using a Boltzmann sigmoidal fit curve with specific fitting constants to enhances reliability by aligning the scoring function with empirical data patterns, thereby reducing dependence on strict distributional assumptions. The Kolmogorov–Smirnov normality test validated the assumption of normality of the CND function ($p > 0.05$). Scoring functions were categorized into three types: "less is better," "more is better," and "optimum range" (Supplementary Table 1). SHI scores were classified into five categories: very low (0–20), low (20–40), medium (40–60), high (60–80), and very high (80–100) following the existing CASH benchmark[18]. These categories were illustrated in red, orange, yellow, green, and dark green, respectively (Supplementary Fig. 1–2). The overall soil health score was calculated as the mean of physical, chemical, and biological SHI scores[50]. Equal weighting was used for simplicity and transparency. This scoring function was then used to evaluate SHS under different tillage and CC management practices, as well as the addition of fertilizer (2017) and biochar (2020, 2021, and 2022).

5.7 Statistical analyses

An analysis of variance (ANOVA) was conducted to analyze the effects of different farming management practices on specific SHIs in each year. Since treatment effects were evaluated independently within each year and measurements were not modeled as repeated observations across years, separate ANOVA analyses were conducted for each year following the split-plot design structure. Normality and residual diagnostics were conducted prior to the ANOVA. The normality test was conducted with Kolmogorov–Smirnov. Linear regression and Pearson's correlation analyses were employed to evaluate the association between the overall soil health score and key agronomic indicators, including soil organic carbon (SOC) stock, crop biomass, and crop production. These approaches allowed for quantification of the strength and direction of linear relationships between soil health and productivity-related variables. In contrast, the relationship between the overall soil health score and net GWP was assessed using non-linear regression models, reflecting the complex and potentially non-linear dynamics between soil quality and greenhouse gas fluxes. To complement this, Spearman's rank correlation was applied to examine monotonic associations, providing a robust non-parametric measure of correlation that does not assume linearity or normal distribution of the data. The statistical analyses were conducted using OriginPro®.

Furthermore, a multiple regression path analysis was conducted using SEM with IBM© SPSS Amos 28 Graphics to assess the direct and indirect effects of individual SHIs on physical, biological, and chemical soil health scores. The significance of indirect effects was tested using the Sobel test. The maximum likelihood method was used to estimate model parameters. The chi-square (χ^2) test was used to assess general model fit, where a good fit was indicated if the null hypothesis was not rejected (p > 0.05). Additional model fit criteria included the chi-square degrees of freedom ratio (CMIN/DF), goodness-of-fit index (GFI), comparative fit index (CFI), normed fit index (NFI), and root mean squared error of approximation (RMSEA). A good fit was indicated by CMIN/DF < 3, RMSEA < 0.1, and values for GFI, CFI, and NFI close to 1[27, 51].

Data availability

The research data supporting the results of this manuscript are available from the corresponding author upon reasonable request. Due to institutional regulations, the dataset cannot be made publicly available.

References

1. Doran, J. W. Soil health and global sustainability: translating science into practice. *Agric. Ecosyst. Environ.* **88**, 119–127 (2002).

2. United States Department of Agriculture (USDA). Soil Health | Natural Resources Conservation Service.

https://www.nrcs.usda.gov/conservation-basics/natural-resource-concerns/soils/soil-health (2018).

3. Landmark. Soil functions concept - Landmark2020. http://landmark2020.eu/soil-functions-concept/ (2020).

4. Hughes, H. M. *et al.* Towards a farmer-feasible soil health assessment that is globally applicable. *J. Environ. Manage.* **345**, 1–10 (2023).

5. Chang, T., Feng, G., Paul, V., Adeli, A. & Brooks, J. P. *Soil Health Assessment Methods: Progress, Applications and Comparison*. *Advances in Agronomy* vol. 172 (Elsevier Inc., 2022).

6. Andrews, S. S., Karlen, D. L. & Cambardella, C. A. The Soil Management Assessment Framework. *Soil Science Society of America Journal* **68**, 1945–1962 (2004).

7. Moebius-Clune, B. N. *et al. Comprehensive Assessment of Soil Health – The Cornell Framework Manual, Edition 3.1*. *Cornell University, Geneva, NY* (2016).

8. Liebig, M. A., Miller, M. E., Varvel, G. E., Doran, J. W. & Hanson, J. D. AEPAT: Software for assessing agronomic and environmental performance of management practices in long-term agroecosystem experiments. *Agron. J.* **96**, 109–115 (2004).

9. Chu, M. *et al.* Soil Health and Soil Fertility Assessment by the Haney Soil Health Test in an Agricultural Soil in West Tennessee. *Commun. Soil Sci. Plant Anal.* **50**, 1123–1131 (2019).

10. Bosarge, T. A Soil Quality Index for Alabama. (Auburn University, 2015).

11. Congreves, K. A., Hayes, A., Verhallen, E. A. & Van Eerd, L. L. Long-term impact of tillage and crop rotation on soil health at four temperate agroecosystems. *Soil Tillage Res.* **152**, 17–28 (2015).

12. Franco, H. H. S., Guimarães, R. M. L., Tormena, C. A., Cherubin, M. R. & Favilla, H. S. Global applications of the Visual Evaluation of Soil Structure method: A systematic review and meta-analysis. *Soil Tillage Res.* **190**, 61–69 (2019).

13. Bagnall, D. K. *et al.* A minimum suite of soil health indicators for North American agriculture. *Soil Security* **10**, 1–9 (2023).

14. Kanda, T. *et al.* New soil maps of Japan based on the comprehensive soil classification system of Japan - First approximation and its application to the world reference base for soil resources 2006. *Jpn. Agric. Res. Q.* **52**, 285–292 (2018).

15. Eswaran, H., Berg, E. V. A. N. D. E. N. & Reich, P. Division S-5 Notes. *Soil Science of America Journal* **57**, 192–194 (1993).

16. Matus, F., Rumpel, C., Neculman, R., Panichini, M. & Mora, M. L. Soil carbon storage and stabilisation in andic soils: A review. *Catena (Amst).* **120**, 102–110 (2014).

17. ISRIC. ANDOSOLS (AN) Summary description of Andosols. https://www.isric.org/sites/default/files/major_soils_of_the_world/set3/an/andosol.pdf (2016).

18. Hatano, R., Shinjo, H., Takata, Y. & Ihara, H. Soil priorities in Japan. *Geoderma Regional* **28**, 1–3 (2022).

19. Hashimoto, Y., Kang, J., Matsuyama, N. & Saigusa, M. Path Analysis of Phosphorus Retention Capacity in Allophanic and Non-allophanic Andisols. *Soil Sci. Soc. Am. J* **76**, 441–448 (2012).

20. Chevallier, T. *et al.* Short-range-order minerals as powerful factors explaining deep soil organic carbon stock distribution: The case of a coffee agroforestry plantation on Andosols in Costa Rica. *Soil* **5**, 315–332 (2019).

21. Matsui, K. *et al.* Soil carbon and nitrogen stock of the Japanese agricultural land estimated by the national soil monitoring database (2015–2018). *Soil Sci. Plant Nutr.* **67**, 633–642 (2021).

22. Hairiah, K. *et al.* Soil health indicators, farmer concepts and carbon market standards in agroforestation of underutilized lands in West Sumatra (Indonesia). *Soil Advances* **3**, 1–18 (2025).

23. Avilés-Junco, C. *et al.* Integrated multiscale assessment of andosol degradation after conversion from grasslands to agriculture. *Catena (Amst).* **250**, (2025).

24. Takahashi, T. The diversity of volcanic soils: focusing on the function of aluminum–humus complexes. *Soil Sci. Plant Nutr.* **66**, 666–672 (2020).

25. Ishikura, K., Fueki, N. & Niwa, K. Progress in “Clean Agriculture” for Nitrogen Management to Enhance the Soil Health of Arable Fields and Its Application by Remote Sensing in Hokkaido, Japan. *Agriculture (Switzerland)* vol. 15 Preprint at https://doi.org/10.3390/agriculture15111192 (2025).

26. Rekik, F., van Es, H., Hernandez-Aguilera, J. N. & Gómez, M. I. Soil health assessment for coffee farms on andosols in Colombia. *Geoderma Regional* **14**, 1–7 (2018).

27. Schermelleh-Engel, K., Moosbrugger, H. & Müller, H. Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *MPR-online* **8**, 23–74 (2003).

28. Pribyl, D. W. A critical review of the conventional SOC to SOM conversion factor. *Geoderma* **156**, 75–83 (2010).

29. Wulanningtyas, H. S. *et al.* A cover crop and no-tillage system for enhancing soil health by increasing soil organic matter in soybean cultivation. *Soil Tillage Res.* **205**, 1–14 (2021).

30. Huang, Q., Dewi, R. K., Gong, Y., Hashimi, R. & Li, P. Triple impact : Biochar , no-tillage , and cover crops for soil carbon enhancement and climate resilience in soybean farming. *Pedosphere* 1–28 (2024) doi:10.1016/j.pedsph.2024.10.002.

31. Hashimi, R., Huang, Q., Dewi, R. K., Nishiwaki, J. & Komatsuzaki, M. No-tillage and rye cover crop systems improve soil water retention by increasing soil organic carbon in Andosols under humid subtropical climate. *Soil Tillage Res.* **234**, 1–13 (2023).

32. Meena, R. S. *et al.* Significance of soil organic carbon for regenerative agriculture and ecosystem services. in *Biodiversity and Bioeconomy: Status Quo, Challenges, and Opportunities* (eds. Singh, K., Ribeiro, C. M. & Calicioglu, Ö.) 217–240 (Elsevier, 2024). doi:10.1016/B978-0-323-95482-2.00010-9.

33. Teng, J. *et al.* Conservation agriculture improves soil health and sustains crop yields after long-term warming. *Nat. Commun.* **15**, 1–12 (2024).

34. Zvomuya, F., Janzen, H. H., Larney, F. J. & Olson, B. M. A Long-Term Field Bioassay of Soil Quality Indicators in a Semiarid Environment. *Soil Science Society of America Journal* **72**, 683–692 (2008).

35. Qiu, T. *et al.* Optimizing cover crop practices as a sustainable solution for global agroecosystem services. *Nat. Commun.* **15**, 1–14 (2024).

36. Blanco-Canqui, H. & Ruis, S. J. No-tillage and soil physical environment. *Geoderma* **326**, 164–200 (2018).

37. Yang, J., Li, A., Yang, Y., Li, G. & Zhang, F. Soil organic carbon stability under natural and anthropogenic-induced perturbations. *Earth. Sci. Rev.* **205**, (2020).

38. Stott, D. E., Andrews, S. S., Liebig, M. A., Wienhold, B. J. & Karlen, D. L. Evaluation of β-Glucosidase Activity as a Soil Quality Indicator for the Soil Management Assessment Framework. *Soil Science Society of America Journal* **74**, 107–119 (2010).

39. Nakamoto, T. & Wakahara, S. Development of Substrate Induced Respiration (SIR) method combined with selective inhibition for estimating fungal and bacterial biomass in humic andosols. *Plant Prod. Sci.* **7**, 70–76 (2004).

40. Zuber, S. M., Veum, K. S., Myers, R. L., Kitchen, N. R. & Anderson, S. H. Role of inherent soil characteristics in assessing soil health across Missouri. *Agricultural and Environmental Letters* **5**, 1–5 (2020).

41. Yang, X. *et al.* Characteristics of greenhouse gas emissions from farmland soils based on a structural equation model: Regulation mechanism of biochar. *Environ. Res.* **206**, 1–11 (2022).

42. Van Moort, J. C. & De Vries, D. Rapid carbon determination by dry combustion in soil science and geochemistry. *Geoderma* **4**, 109–118 (1970).

43. Eivazi, F. & Tabatabai, M. A. Glucosidases and galactosidases in soils. *Soil Biol. Biochem.* **20**, 601–606 (1988).

44. Griffin, G. *et al.* Recommended Soil Nitrate Tests. *Delaware Agric. Exp. Stn. Bull. 493.* 22–29 https://www.udel.edu/content/dam/udelImages/canr/pdfs/extension/factsheets/soiltest-recs/CHAP4.pdf (2009).

45. Motsara, M. R. & Roy, R. N. *Guide to Laboratory Establishment for Plant Nutrient Analysis. Fao Fertilizer and Plant Nutrition Bulletin 19* (FAO, Rome, Italy, 2008).

46. Ciesielski, H. & Sterckeman, T. A comparison between three methods for the determination of cation exchange capacity and exchangeable cations in soils. *Agronomie* **17**, 9–16 (1997).

47. Ellert, B. H. & Bettany, J. R. Calculation of organic matter and nutrients stored in soils under contrasting management regimes. *Can. J. Soil Sci.* **75**, 529–538 (1995).

48. Dewi, R. K. *et al.* Addition of biochar decreased soil respiration in a permanent no-till cover crop system for organic soybean production. *Soil Tillage Res.* **237**, 1–14 (2024).

49. Gong, Y., Li, P., Sakagami, N. & Komatsuzaki, M. No-tillage with rye cover crop can reduce net global warming potential and yield-scaled global warming potential in the long-term organic soybean field. *Soil Tillage Res.* **205**, 104747 (2021).

50. Cherubin, M. R. *et al.* A Soil Management Assessment Framework (SMAF) Evaluation of Brazilian Sugarcane Expansion on Soil Quality. *Soil Science Society of America Journal* **80**, 215–226 (2016).

51. Gama-Rodrigues, A. C. *et al.* An exploratory analysis of phosphorus transformations in tropical soils using structural equation modeling. *Biogeochemistry* **118**, 453–469 (2014).

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Author contributions

Ratih Kemala Dewi: Methodology, Investigation, Formal analysis, Data curation, Writing an original draft. Qiliang Huang: Investigation, Data curation and review. Rahmatullah Hashimi: Investigation, Data curation and review. Soh Sugihara: Data curation and review. Junta Yanai: Data curation and review. Nobuo Sakagami: Data curation and review. Masakazu Komatsuzaki: Conceptualization, Methodology, Supervision, Review & editing, and Validation. All authors contributed to concept and development, data interpretation, and writing.

Competing interests

The authors declare no competing interests.

Additional information

Supplementary information.

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