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Review

From Indicators to Integration: Soil Health Assessment and the SMAF Framework

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Abstract

Soil health refers to the combined physical, chemical, and biological properties of soils that allow them to function as a living system that sustains life. While numerous reviews summarize several methods to measure soil health, this review critically evaluates how the Soil Management Assessment Framework (SMAF) performs across diverse ecosystems, including croplands, agroforestry, coastal mangrove, and rangelands. We explore the evolutionary shift from single indicators to integrated assessment frameworks, tracing how targeted management practices, such as conservation tillage, crop rotation, cover cropping, organic amendments, and water management, alter physical, chemical, and biological indicator performance. The SMAF framework and scoring system are outlined using examples from around the world. This synthesis concludes that while SMAF provides an exceptionally rigorous, non-linear platform for quantitative Soil Quality Index (SQI), its practical execution remains deeply constrained by data-intensive requirements, selection of appropriate indicators, and adaptation to local contexts. To close this gap, we outline critical future directions, integrating the framework with AI and machine learning, real-time Internet of Things (IoT) field sensors, and dynamic digital twins. Ultimately, this work aims to shift soil monitoring from descriptive reporting to predictive, automated intelligence to provide the exact data needed for sustainable land management decisions.

Keywords: SMAF; soil health; soil quality; indicators; soil management

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1. Introduction

Healthy soils are dynamic, living systems that sustain crop production, buffer agroecosystems against climate shocks, and drive global biogeochemical cycles. Moving beyond the view of soil as a mere growing substrate, Doran and Parkin [1] defined soil health as the ability of a soil to perform within the ecosystem constraints to support biological productivity, environmental quality, and promote plant and animal health. Because soil properties interact in complex, non-linear ways, the subsequent literature establishes that no single test can capture whole-soil functionality; instead, indicators vary dynamically across divergent soil types, climates, and management histories [2,3].

Meanwhile, the extent of soil degradation is becoming hard to ignore. Productivity and ecosystem stability continue to decline as soils are eroded, depleted of nutrients, salinized, and gradually decline in organic matter [4]. With the FAO [5] estimating that over one-third of global soils are moderately or severely degraded, there is an urgent need for monitoring frameworks that are practical, comparable across sites, and highly sensitive to management-induced changes.

Soil is a multifunctional matrix, and hence, evaluating its health requires a multi-indicator approach combining physical, chemical, and biological data [6]. However, a universal definition of soil health remains debated, often oscillating between priorities of crop productivity and broader ecosystem services [7,8]. Researchers widely agree that effective assessments must integrate physical, chemical, and biological indicators [7,9].

Physical indicators such as texture, structure, porosity, and bulk density influence the water movement, aeration, and ease with which roots can penetrate through the profile. Soil chemical indicators, such as pH, available nutrients, salinity, and organic matter content, give an idea of soil potential fertility and buffering capacity. Biological indicators, such as microbial biomass, activity of enzymes, and soil fauna, are involved in the processes of decomposition of organic matter and nutrient cycling [10]. These indicators are all connected to each other: for instance, soils with good structure facilitate water infiltration, which affects nutrient mobility and microbial activity [11]. Consequently, single indicators can successfully identify specific limiting factors on individual farms [12,13]. However, evaluation of the relative performance of different land uses or management systems requires an integrated assessment with numerical scores to facilitate land use decision-making and manage trade-offs [14].

From a broader perspective, the Soil Management Assessment Framework (SMAF) of Andrews et al. [15] is a commonly used tool to translate a set of soil indicators into a normalized Soil Quality Index (SQI). SMAF scores for indicators can be presented as scoring curves to enable relative ranking of indicators to evaluate trade-offs between different services across systems and ecoregions. Integrating physical, chemical, and biological properties allows land managers to make evidence-based decisions that optimize soil function, long-term productivity, and environmental sustainability [16].

Current research on the Soil Management Assessment Framework (SMAF) remains confined to localized agricultural settings, leaving its multi-regional adaptation strategies fragmented. This review provides a much-needed cross-ecosystem evaluation of the framework, analyzing its performance across croplands, mixed agroforestry, and sensitive mangrove zones. Beyond mapping these ecological boundaries, we critique SMAF's internal mathematical constraints, such as indicator selection vulnerabilities and additive scoring errors. Finally, we offer a forward-looking roadmap to modernize the framework by integrating it with emerging digital assets, specifically machine learning, hyperspectral proximal sensing, and cloud-based GIS, bridging the gap between theoretical soil science and practical, global land management.

2. Indicators of Soil Health

Soil health is generally assessed by measuring several soil indicators chosen for their overall potential to assess several key ecosystem functions. Doran and Safley [1] recommended that soil health indicators should: (1) respond to specific soil management practices; (2) relate to specific soil functions; and (3) be measurable with little loss of precision. Soils have three groups of indicators measured during soil health assessments (Table 1): physical, chemical, and biological soil properties [3,17,18].

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Table 1. Major physical, chemical, and biological soil health indicators and their main functions.

Indicator (Unit)	Typical * Range	Healthy * Range	Functional Interpretation	Reference
Physical Bulk Density (Mg m^{-3})	1.0–1.8	<1.4 (Clay) <1.6 (Sand)	Soil compaction, root restriction, porosity.	[19,20]
Available Water Capacity (AWC) (cm cm^{-1})	0.05–0.25	>0.15	Water retention for plant uptake, drought resilience.	[21,22]
Water Stable Aggregates (WSA) (%)	10–80	>50	Resistance to erosion, infiltration.	[23,24]
Penetration Resistance (MPa)	0.5–4.0	<2.0	Restricts root growth.	[25,26]
Infiltration Rate (mm h^{-1})	1–100+	>15–30	Runoff, erosion, porosity, structure.	[27]
Chemical Soil pH	3.5–9.0	6.0–7.5	Nutrient availability, microbial activity.	[28,29]
Electrical Conductivity (EC) (dS m^{-1})	0–16	<2.0	Salinity, osmotic stress.	[30,31]
Extractable Nutrients (P, K) (mg kg^{-1})	P: 5–50 K: 50–300	P: 10–30 K: 100–200	Macronutrient availability.	[32,33]
Cation Exchange Capacity (cmol(+) kg^{-1})	3–40	<20 (Clay) <5 (Sand)	Nutrient holding capacity: buffers against acidification.	[34]
Biological Soil Organic Carbon (SOC) (%)	0.5–5.0	>2.5	Biological activity, nutrient cycling, structure, water retention.	[15,21]
Active Carbon (POXC) (mg kg^{-1})	200–1000	>600	Labile carbon: a rapid indicator of management changes.	[35,36]
Soil Respiration (mg kg^{-1} d^{-1})	5–100+	>50	Microbial activity, OM turnover, nutrient mineralization.	[37,38]
Microbial Biomass C (mg C kg^{-1})	100–1500	>300	Active microbial pool.	[39,40]
Potentially Mineralizable N (PMN) (mg N kg^{-1} soil)	2–30	>10	Available N supply capacity.	[41]
Soil Protein (Glomalin) (mg g^{-1})	2–15	>6–8	Organically bound nitrogen pool, aggregate stability.	[42,43]
β-Glucosidase (mg pNP kg^{-1} h^{-1})	50–500	>150	C cycling enzyme.	[44,45]
Enzyme Activities (General) (μmol g^{-1} h^{-1})	0.5–100	2–40	Nutrient cycling potential.	[46,47]
Earthworm Density (individuals m^{-2})	0–400	>100	Soil fauna activity, soil structure, aeration.	[48,49]

Note: * Values represent generalized global baselines. Optimal ranges are highly context-dependent and must be calibrated to local pedo-climatic conditions, including climate, parent material, soil order, and soil texture. The typical and healthy ranges provided in this table apply exclusively to mineral soils and are not representative of organic soils (e.g., Histosols).

The best assessment of soil health is achieved by measuring a number of these indicators together, rather than in isolation.

2.1. Physical Indicators of Soil Health

The basis of healthy soil is provided by its physical properties or processes. The physical attributes of soil regulate several key processes, including water movement, aeration, root expansion, and activity of the soil biota. Important indicators of physical soil health are soil structure, texture, infiltration, porosity, aeration, and bulk density.

Information on how management practices affect these indicators is crucial to long-term soil and crop productivity [8,11,50].

2.1.1. Soil Structure and Aggregation

Soil structure, in particular the formation, cohesion, and stability of soil aggregates, is a key physical soil health attribute. Stable soil aggregates promote plant growth and ecosystem production by enabling deeper root growth, increased water infiltration, and improved soil aeration [11].

Several parameters overlapping with water erosion factors affect aggregate stability, such as microbiological activity, organic matter content, and intensity of tillage. However, these factors may negatively affect soil structure. Heavy or frequent tillage disrupts soil aggregates, reduces the porosity, and can result in a surface crust, which in turn results in less infiltration after irrigation or rain events [11]. Conservation tillage, which minimizes soil disturbance, can speed up the long-term process of building or maintaining soil structure [50]. Soil organic matter acts as a natural glue, holding soil aggregates together and making them more resilient and less prone to erosion [51].

Other microorganisms magnify these effects, since most of them produce extracellular polymeric substances that encrust soil particles, reinforcing their structure [11].To protect the soil structure, it is necessary to search for balance: a minimum amount of tillage; the regular addition of organic amendments, crop residues, and belowground biomass inputs to the soil; and environmental conditions conducive to the soil microbial processes, which in the long term, result in a stable and resilient soil structure.

2.1.2. Water Infiltration and Retention

Soil water holding capacity is an important indicator since it is highly related to plant growth, nutrient cycling, and the stability of an ecosystem. Infiltration rate of water, which is the rate of water penetration into the soil, is influenced by texture, structure, and the content of organic matter. Coarse-textured soils exhibit high infiltration rates, which may be decreased by compaction or the lack of aggregation even in the sandy soils [11]. On the other hand, well-aggregated soils with high organic matter content increase the infiltration rate, decrease runoff, and erosion [52].

Water retention, the ability of soil to retain water against gravitational forces, depends on the texture and organic matter. Small pore spaces of fine-textured soils, such as clays, retain more water, whereas organic matter enhances the retention through the formation of micropores (<30 μm in diameter), which are responsible for retaining plant-available water against gravity [52,53].

Conservation tillage, mulching, cover crops, and organic amendments can increase the connectivity of pores and maintain hydrological balance, which in turn guarantees that nutrients are available at an adequate level and roots can access moisture [52,53].

2.1.3. Soil Aeration and Porosity

Root respiration, the metabolism of microorganisms, and nutrient transformations require adequate soil aeration, which is provided in part by soil porosity (i.e., the proportion of pore space in the soil) [54]. The intensive agricultural practices cause compaction, which decreases porosity, diffusion of oxygen, and prevents root growth and the activity of microbes [11]. Aeration also slows down the decomposition of organic matter and mineralization of nutrients, reducing soil fertility [51].

However, there are certain management practices that could mitigate these impacts. Conservation tillage and organic residue incorporation could be useful in retaining pore connectivity as well as forming aggregates that promote soil aeration [51]. The addition of organic matter enhances macroporosity, which enhances the exchange of gases and the growth of microbes [11]. To maximize aeration, it is important to reduce mechanical compaction, control irrigation to avoid waterlogging, and periodically add organic substances, all of which are crucial to the maintenance of soil productivity and ecological activity [54].

2.1.4. Bulk Density and Porosity

The bulk density (mass of dry soil divided by the unit volume) and porosity (volume fraction of the pore space) are interconnected and can give significant information regarding soil compaction and structure [55,56]. High bulk density is frequently an indicator of compaction, which inhibits root length, water infiltration, and gas exchange [55,57]. On the other hand, the high porosity of the soil means that it is highly organized with smooth movement of air and water [56]. These parameters can be easily determined by the usual laboratory techniques and provide significant diagnostic data to assess the physical state of soil. The possibility of monitoring bulk density and porosity over time helps identify structural degradation early enough and helps to evaluate the management practice that ensures the maintenance of soil functionality and long-term sustainability.

The combination of these parameters indicates the physical strength of the soil system. While high bulk density specifically points to soil compaction, the soil's overall structural stability is best measured using indices like Mean Weight Diameter (MWD) and the percentage of Water Stable Aggregates (WSA). When severe compaction is paired with poor aggregate stability, it restricts gas exchange, limits root growth, and limits biological activity, which ultimately drives down productivity. Fortunately, these physical conditions can be actively improved through practices like conservation tillage, retaining crop residues, and applying organic amendments [58,59].

2.2. Chemical Indicators of Soil Health

Chemical indicators have been considered inevitable parameters used to evaluate soil nutrient levels and geochemical balance, which are subsequently important for sustaining plant growth, increasing microbial activity, and maintaining environmental quality (Table 1). They coordinate nutrient bioavailability, maintain the pH, and develop the overall chemical environment that supports biological and ecological processes. Key indicators include the soil pH, organic matter content, nutrient cycle, soil salinity, and heavy metal concentration. The chemical content of soils is due to both natural pedogenic processes and an overall result of anthropogenic management activities, such as fertilization, liming, and the use of organic amendments [52,60,61]. Therefore, maintaining optimum chemical conditions is a priority in maintaining balanced nutrient cycling as well as increasing soil productivity and developing robust agroecosystems.

2.2.1. Soil pH and Nutrient Availability

Soil pH, a quantitative measure that represents the level of soil acidity or alkalinity, serves as an overarching control of nutrient solubility, the movement of metals, microbial activity, and the overall chemistry of the soil. Each nutrient and microbial group is considered to have an optimal performance range [55]. As an example, phosphorus has maximum bioavailability in slightly acidic to neutral substrates (pH 6.0–7.0), whereas micronutrients, like iron (Fe) and manganese (Mn), have increased solubility in acidic conditions. In the case of over-acidic soils, toxic levels of aluminum (Al) and manganese ions might be mobilized, thus inhibiting root development and the absorption of nutrients; on the contrary, alkaline soils often trigger the deficiency of essential micronutrients, especially zinc (Zn) and iron (Fe) [61].

Crop production practices and soil pH are intimately related. Ammonium-based fertilizers, which are acid-producing, decrease soil pH, whereas liming and some organic residues increase it [61]. Therefore, to maintain an optimal environment for plant growth and the plant/soil microbiome, monitoring soil pH, adequate fertilization, and liming are important considerations.

2.2.2. Soil Organic Matter and Carbon Sequestration

Soil organic matter (SOM) is the foundation of chemical and biological soil health. It improves soil structure, has a temporary hold on water, and permanently stores nutrients [62]. In the long term, it is a store of energy and carbon [52]. Decomposing organic matter releases vital macronutrients such as nitrogen, phosphorus, and sulfur. Also, its colloidal properties aid soil aggregation and increase water infiltration. This is in addition to the fact that SOM maintains a constantly acting microbial habitat, which coordinates nutrient and organic matter cycling [52].

SOM also plays a central role in sequestering carbon so that it can mitigate climate change: it sequesters atmospheric CO_2 and stores it in stable organic forms [63]. As a result, healthy soils serve as large carbon sinks and reduce the level of greenhouse gases, which is the basis of global climate regulation [51]. Conservation tillage, cover crops, retention of residue, and organic amendments are management practices that enhance SOM accumulation, fertility, erosion control, and soil resiliency and carbon storage capacity.

2.2.3. Nutrient Cycling and Availability

Nutrient cycling refers to the process of transformation and flux of elements in the soil–plant–microbe system, which provides the biochemical basis of soil fertility and productivity [64]. During the process of mineralization, organic nutrients are transformed into available nutrients such as nitrate (NO_{3-}), phosphate (PO_4^{3-}), and potassium (K+) ions [65]. Important microbial-mediated processes in nutrient cycling are the fixation of nitrogen, nitrification, and decomposition of organic matter [64].

Organic fertilizers such as compost and manure increase nutrient cycling by increasing microbial activity and improving soil structure [52,66]. Excessive and improper use of inorganic fertilizers, on the other hand, can disrupt nutrient cycling processes and cause nutrient leaching, soil acidification, and pollution [67,68]. Optimal nutrient management includes a combination of both organic and inorganic fertilizers.

2.2.4. Soil Salinity

One of the major chemical constraints that limit the growth of plants and microbial processes is soil salinity or the build-up of soluble salts. High salinity also goes down in osmotic potential, which subsequently hinders water and nutrient uptake in plants [69]. Salinity may also be measured through the electrical conductivity (EC) of soil extracts as an indication of the level of soluble salts [70,71].

Management of salt-affected soil requires precise diagnosis, controlled irrigation, proper drainage, and salt-tolerant crops. Measurement of EC can detect the onset of salinization and the appropriate measures to prevent further degradation through leaching or reclamation before the process reaches irretrievable levels of soil degradation [72].

2.2.5. Heavy Metal Contamination

Heavy metals such as cadmium, lead, mercury, chromium, and arsenic alter soil chemistry, crop production, and food safety [73]. All of them are mostly introduced into the terrestrial systems due to industrial emissions, wastewater irrigation, excess use of phosphate fertilizers, and municipal waste disposal.

These contaminant types are normally quantified using either atomic absorption spectrophotometry (AAS) or inductively coupled plasma mass spectrometry (ICP-MS) with high sensitivity and reliable and reproducible concentrations [74]. The resultant data can only be interpreted considering factors of total and bioavailable contents, toxicity dose, and site factors, which are specific to the place. Some of the common remedial strategies that are normally used as a way of reducing mobility and bioavailability include phytoremediation, liming, and the use of organic amendments, all of which are used to reduce the uptake of metals by plants and the overall resilience of the soil.

2.3. Biological Indicators of Soil Health

Biological indicators are critical for monitoring the health of soils since they reflect living components within soils and their functional capacity (Table 1). They are made up of microbiological populations within soils, fauna (macro/mesofauna), and enzymes in soils, which are involved in nutrient cycling, organic matter decomposition, and structure stability [7,75]. The reason why monitoring these indicators are vital is that life within soil supports a wide range of functions required for sustainability, meaning that monitoring these provides a dynamic functionality status within soils.

Biological indicators are extremely sensitive to land use changes, land management practices, and environmental stressors. Thus, they provide early diagnostic indicators when it comes to imminent ecosystem change and degradation.

2.3.1. Soil Microbial Communities

The most active and diverse biological factor in the soil ecosystems is soil microbial communities: bacteria, fungi, archaea, and protists. These microorganisms also control the major ecological processes, including nutrient cycling, decomposing, and suppressing soil-borne pathogens [7]. Due to the soil texture, the organic matter, temperatures, moisture, and management practices, their diversity, abundance, and composition are impacted [75]. A high level of microbial diversity can be associated with soil resilience and redundancy in functions, which leads to the rapid processes of soil restoration after environmental or anthropogenic disruptions [76].

Nitrogen-fixing microorganisms, such as Rhizobium and Azotobacter, convert atmospheric nitrogen into a bioavailable form for plants, while decomposer microorganisms mineralize organic residues to available nutrients [64]. Mycorrhizal fungi establish symbiosis with plant roots and promote root nutrient and water uptake, thereby rendering plants more tolerant to environmental stress [77]. As microbes are highly responsive to farm management as well as environmental practices and conditions, the community structure and functional potential of soil microorganisms can provide good information on soil health. The use of modern molecular technologies, such as metagenomics and 16S rRNA sequencing, as well as phospholipid fatty acid (PLFA) profiling, will allow accurate characterization of microbial diversity and activity and a better understanding of biological processes in soils [75].

2.3.2. Soil Fauna and Invertebrates

Soil fauna play significant roles in maintaining the soil environment through their activities in soil structure, soil fertility, and ecosystem equilibrium. The major macrofaunal components are earthworms and other small fauna such as nematodes, arthropods, etc. [78]. Earthworms are referred to as ecosystem engineers because they change environmental conditions in fundamental ways by modifying materials and environments. Through burrowing, feeding, and casting activities, earthworms can increase soil aeration, enhance water infiltration, and improve soil structure [78]. Earthworm bioturbation can affect nutrient distribution and organic matter decomposition rate and therefore can have a direct impact on soil productivity [79].

For most nematode species, the plant parasite form receives attention for its role as a plant pest, but many species have forms that are beneficial to plants by regulating microbial populations and mineralizing nutrients [7]. Arthropods (e.g., insects, Acari, Chilopoda, Diplopoda) and microarthropods (mites, beetles, springtails) break down complex organic materials into fragments of greater surface area that can be attacked by microorganisms, decomposed, or turned over for nutrient use [54]. The diversity and relative abundance of soil fauna are affected by soil texture, soil moisture content, organic materials, and human activities such as tillage and the use of pesticides [79]. High faunal diversity is an indicator of a well-balanced soil food web and good ecosystem function [11,54]. The composition, relative abundance, and trophic organization of the soil fauna are of importance as indicators of biological integrity and environmental quality.

2.3.3. Soil Enzymes and Microbial Activity

Soil enzymes, which are produced mainly by microorganisms and plant roots, stimulate key biochemical reactions that regulate nutrient changes and degradation of organic matter [11]. Enzyme activity is a functional proxy (ones that represent other factors such as soil biochemical health) for microbial metabolism and soil biochemical health. Specific enzymes correspond to specific nutrient cycles: dehydrogenase activity is representative of total microbial respiration and metabolic intensity deficit; phosphatase activity is the mineralization of phosphate and bioavailability of this element; and urease, β-glucosidase, and arylsulfatase activities are indicative of nitrogen, carbon, and sulfur cycling, respectively [80].

While measuring standalone enzyme behaviors (such as urease, phosphatase, or β-glucosidase) offers an isolated view of single nutrient pathways, modern soil health assessments increasingly rely on integrated enzymatic indices [81]. Rather than evaluating isolated reactions, advanced frameworks now utilize multi-enzyme mathematical integrations, such as the Total Enzyme Activity Index (TEI) or the geometric mean of enzyme activities (GMea), to provide a holistic, robust metric of overall microbial metabolism and the soil's biochemical buffering capacity [82,83].

The fluctuation in enzyme activity is often parallel to changes in the microbial biomass, substrate availability, or environmental management [11]. Due to the rapid response of enzyme activities to disturbance in soil due to contamination or restoration, they can be used as early warning signals of soil degradation or soil recovery. A combination of enzyme tests, microbial, faunal, and chemical tests allows the complete evaluation of soil functionality and health [67].

2.3.4. Soil Resilience Indicators

Soil resilience indicators provide important insights into soil health by showing how well soil systems can withstand environmental disturbances and restore their essential functions after stress [84]. These indicators are often evaluated by observing changes in key biological processes, such as substrate-induced respiration, microbial activity, and nitrification potential, before and after disturbance events like drought, compaction, or salinity stress [85]. Assessing soil resilience involves understanding both how effectively soils maintain their functions during periods of stress and how quickly and completely they recover to their original state over time [86].

In summary, biological indicators are useful for providing a holistic approach to assessing the function of soils by relating microbial processes, activities of fauna, and enzyme transformations. Integration of these elements within the frameworks for assessing soil health, e.g., the Soil Management Assessment Framework (or SMAF), will result in enhanced diagnostic precision and increase our ability to interpret and manage the performance of the soil ecosystem.

2.4. Integrating Indicators into Functional Assessment

A big challenge is to be able to integrate different measurements into a consistent representation of the soil functionality. Some key indicators of soil and their typical range and the corresponding ecosystem services are summarized in Table 1. Many articles have shown that the relationships between the indicators are non-linear, e.g., that microbial activity strongly increases with soil organic carbon (SOC) till a point of saturation (≈4–5% SOC in loam soils) beyond which SOC benefits are flattened [58,87–89]. Hence, integrative frameworks like SMAF use scoring curves instead of simple linear relationships for expressing optimum ranges of performances [15,90].

3. Management Practices Influencing Soil Health Indicators

Agriculture management practices have a profound effect on soil health by changing its physical, chemical, and biological quality. The combination of management intensity, soil type, and climatic conditions is what dictates whether these changes amplify or degrade the functions of soils. A growing body of literature shows that sustainable management approaches that include conservation tillage, use of organic amendments, diversification of crops, and agroforestry can result in restoring degraded soils, becoming more resilient and improving an integrated Soil Quality Index (SQI) measured by frameworks such as SMAF [3,51,91]. Figure 1 presents a simple conceptual model that connects management practices such as tillage, crop rotation, and the use of organic amendments with changes in soil indicators and, in the end, ecosystem functions.

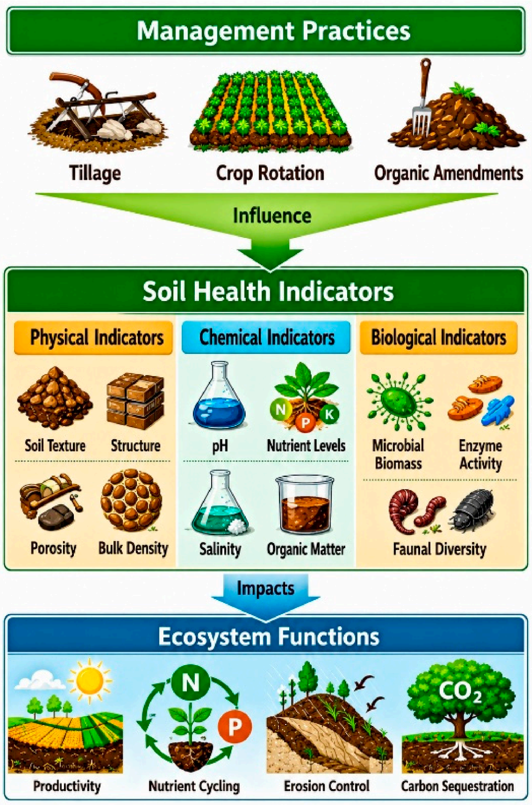

Figure 1. A simple conceptual model that connects management practices with changes in soil indicators and, in the end, ecosystem functions.

3.1. Tillage Practices

Tillage operations affect soil structure, porosity, and the ecosystem of soil microorganisms in both immediate and persistent ways. While conventional tillage breaks soil aggregates, increases erosion risk, and rapidly oxidizes organic matter, conservation tillage and no-till systems facilitate changes to soil structure, promote carbon sequestration, and enhance soil biological activity [58,59]. Long-term field investigations [51,90] reported that microbial biomass and soil organic carbon (SOC) were 10–25% greater under no-till than under conventional tillage systems (Table 2).

Table 2. Comparative effects of conventional, reduced, and no-till systems on selected soil indicators.

Indicator	Conventional Tillage	Reduced Tillage	No-Till
SOC (%)	↓ 10–30%	↑ 5–10%	↑ 15–25%
Aggregate Stability	Low	Moderate	High
Bulk Density	Low (initially) → High (later)	Stable	Moderate
Microbial Biomass	Reduced	Slightly increased	Enhanced
Infiltration Rate	Variable	Improved	Strongly improved

Source: Adapted from [51,58,90]. Symbol keys: ↑ = increase; ↓ = decrease.

3.2. Fertilization and Nutrient Management

Fertilization influences the chemical balance as well as the biological activity of soils. Inorganic fertilizers provide immediate, targeted plant-available nutrients; however, unregulated or prolonged application, particularly of ammonium-based or high-analysis synthetic fertilizers, runs the risk of acidifying the soil, reducing microbial diversity indices, and disrupting natural soil nutrient cycling mechanisms over time [67]. Organic amendments, such as compost, manure, and green manure, are nutrients of N, P, and K that improve soil structure, stimulate soil enzymatic activity, and maximize SOC sequestration [52,92].

Integrated Nutrient Management (INM) techniques, or a combination of organic and inorganic supplements, have been known to achieve maximum nutrient use efficiency with sustained long-term fertility [93]. The studies in both maize and wheat systems demonstrate that INM can increase the microbial biomass of C and N by 20–40% compared with the sole application of chemical fertilization [94].

3.3. Crop Rotation and Cover Cropping

Crop rotation and cover cropping are important conservation techniques that help to improve the soil's health by diversifying biological inputs into the soil and reducing pest pressure. Crop rotation (alternation of one crop with another across seasons) enhances soil fertility, disrupts the cycle of pests and diseases, and contributes to the balance of nutrients [11]. Including legumes as a form of rotation is advantageous because it has the capacity to fix nitrogen, thus decreasing the use of synthetic nitrogen fertilizers [52].

Cover crops that grow between cash crops prevent soil erosion and weeds, and enhance nutrient retention [95]. Leguminous cover crops also increase the level of nitrogen and promote microbial activity [96]. The choice of suitable cover crop species, depending on the climate, the type of soil, and the goal of the cropping, is important. Moreover, diverse cover crop mixtures provide greater soil biodiversity and multifunctionality as they support more soil organisms [97]. These practices combine to improve soil structure, increase soil fertility, and provide greater resilience to environmental stress.

3.4. Organic Amendments and Compost Applications

Use of organic residues such as farmyard manure, biochar, or compost can supply soil with organic carbon and increase the functionality of the microbial community. Biochar has been reported to increase the cation exchange capacity of soil and decrease the leaching of nutrients [98]. Application of diverse organic residues, ranging from broad agricultural composts [55] to specific agro-industrial byproducts like brewers' spent grain [62], has been shown to increase soil organic carbon, particularly in coarse-texture soils, and to increase microbial biomass and soil enzymatic activity.

Long-term experiments show that organic amendments can reverse soil microbiological damage and redress loss of soil organic carbon [99]. However, the rate at which these amendments are applied, as well as their compositions, need to be regulated to avoid nutrient imbalance and the accumulation of heavy metals in the soil [68].

3.5. Agroforestry and Soil Health

Agroforestry is the combination of trees or bush lands with agriculture and/or livestock production. There are many potential benefits of agroforestry in improving soil health and sustainability. Trees and bushes can decrease evapotranspiration, increase water infiltration, and provide additional organic inputs, such as leaf litter and root turnover [100]. This additional organic matter enhances soil structure by promoting the formation and stabilization of soil aggregates through biological and physicochemical binding mechanisms. These stable aggregates increase soil porosity, improve water infiltration and retention, enhance aeration, reduce compaction, and provide a favorable environment for root growth and microbial activity [101]. Agroforestry can prevent soil erosion and promote biodiversity and nutrient cycling [100].

Soil health measurements using SMAF in agroforestry systems were greater than their corresponding monoculture systems [16]. The increase in SQI was largely contributed by the indicators of the biological and structural SQI. Tree–crop interactions in agroforestry systems thus promote sustainable long-term soil–plant–microbe interactions.

Well-designed and managed agroforestry has great potential to enhance crop productivity and reduce environmental degradation by minimizing competition for crops and trees for light, nutrients, and water. Managed and well-designed agroforestry also has great potential to enhance long-term soil health and carbon storage and to achieve sustainable use of these resources [102–105].

3.6. Irrigation and Water Management

Water management in agricultural production systems affects soil aeration, soil salinity, and several biological processes. Over-irrigation could result in soil compaction and nutrient leaching, while under-irrigation could impede some microbial and enzymatic processes [69]. New technologies such as precision irrigation technologies and soil moisture monitoring (e.g., tensiometers, capacitance probes) make it possible to apply water site-specifically, ensuring optimal soil moisture conditions, without salinization. Integrating remote sensing information with SMAF frameworks is a promising way for large-scale assessment of irrigation impacts [106].

3.7. Pesticide Use and Soil Biota

Excessive use of pesticides can also affect microbial diversity, enzyme activity, and faunal composition of soil [79]. Conversely, the use of biopesticides and integrated pest management (IPM) offers an environmentally friendly and minimum damage approach for the control of pests for crop protection. Monitoring enzyme activities such as dehydrogenase and phosphatase under different pesticide programs may thus give early warnings on possible adverse effects to the soil ecosystem [107].

Collectively, sustainable management practices restore soil multifunctionality by improving indicator performance across all domains.

3.8. Modern and System-Level Soil Management Approaches

For soil health assessments to be globally scalable, frameworks must evaluate holistic agricultural systems rather than isolated field practices. Adopting these system-level strategies fundamentally shifts the baseline thresholds for physical, chemical, and biological indicators:

- **Regenerative Agriculture:** Rather than focusing solely on crop yield, regenerative agriculture actively restores soil health through closed-loop nutrient cycling and enhanced biodiversity [108]. By maintaining continuous living roots and minimizing chemical inputs, these systems accelerate organic matter accumulation and build long-term ecological resilience [109].
- **Conservation Agriculture (CA) Packages:** CA relies on three integrated pillars: minimum mechanical disturbance (no-till), permanent organic cover, and diversified crop rotations. When applied together, these practices create structural synergies that stabilize macroaggregates, improve water infiltration, and maximize carbon retention far better than isolated interventions [110].
- **Biochar Applications:** Applying pyrolyzed biomass (biochar) offers a more permanent alteration to the soil matrix than traditional organic amendments. Its highly porous architecture and large surface area significantly increases cation exchange capacity (CEC), boost water retention in coarse soils, and provides a protective physical habitat for microbial communities [111].
- **Precision Agriculture:** Moving away from uniform field treatments, precision agriculture uses variable-rate technology (VRT) and real-time sensors to apply inputs exactly where and when they are needed [112]. This targeted approach prevents over-application, drastically reducing the risks of artificial acidification, nutrient leaching, and biological toxicity [113].
- **Controlled Traffic Farming (CTF):** To combat severe mechanical compaction, CTF uses GPS-guided tracking to confine heavy machinery to permanent lanes, leaving up to 80% of the crop bed completely undisturbed [114]. Preserving this undisturbed zone protects natural soil structure, maintains macro-porosity, and ensures optimal aeration and root elongation pathways [115].

3.9. Climate Change, Soil Resilience, and Adaptive Functionality

The accelerating pace of global climate instability poses significant risks to terrestrial ecosystem functions, making it necessary to evaluate how soil infrastructure responds to environmental stress [116]. Rather than acting as a passive substrate, healthy soil serves as a dynamic biophysical buffer that can actively dampen or amplify regional climate shocks by regulating surface energy balances, moisture retention, and greenhouse gas fluxes [117].

- **Soil Health under Extreme Weather:** Extreme weather events, including prolonged heat waves and high-intensity precipitation anomalies, directly accelerate structural soil degradation pathways [118]. Soils with degraded physical properties or depleted organic carbon reserves suffer from rapid surface crusting, slaking, and severe accelerated erosion during heavy rainfall events. Conversely, structurally sound soils possessing well-developed macroaggregate architectures cushion agroecosystems against the destructive forces of both excessive water runoff and severe, prolonged droughts by maximizing water infiltration rates and subsurface storage capacity [111].
- **Drought Resilience:** The capacity of a soil system to maintain biological and crop productivity during severe moisture deficits depends heavily on its water retention characteristics and pore network connectivity [119]. Sustainable management practices that build and protect stable macroaggregates prevent internal structural collapse under intense drying stress. This structural stability preserves the critical micropore and mesopore networks that store plant-available water, maintaining essential hydrological balance and supporting microbial activity when surface layers dry out [120].
- **Carbon Sequestration:** Terrestrial soils represent one of the largest active sinks for atmospheric carbon on Earth [121]. Soil organic matter (SOM) plays a vital dual role: it acts as a dynamic biological energy pool, fueling the soil food web while simul-

taneously stabilizing atmospheric CO_2 into organo-mineral complexes and chemically protected matrices, directly contributing to long-term global climate change mitigation [18].

- **Climate-Smart Agriculture (CSA):** Mitigating modern climate pressures requires transitioning away from high-disturbance management toward integrated CSA frameworks [122]. Combining low-intensity tillage, leguminous cover crop mixtures, and multi-layered agroforestry practices restore degraded profiles, enhance continuous organic carbon inputs, and create resilient soil–plant–microbe systems capable of withstanding extreme environmental disruptions [123].
- **Soil Health Indicators Sensitive to Climate Change:** To track climate impacts effectively, monitoring frameworks must prioritize dynamic indicators that provide early warning signals of environmental degradation rather than relying on slow-to-change bulk metrics [123,124]. Physical and biological metrics, specifically water-stable aggregation (WSA), microbial biomass carbon (MBC), soil respiration rates, and labile permanganate oxidizable carbon (POXC), exhibit high sensitivity to subtle temperature and moisture variations, making them vital tools for tracking climate-induced soil alterations over short temporal scales [35].

4. Soil Health Assessment Frameworks

Assessment and monitoring of soil systems require the use of meaningful indicators and their integration into an index for monitoring, comparison, and management of soils. In the last decades, many quantitative methods for the assessment and monitoring of soils have been developed to provide specific indicators for decision-support tools for sustainable land use [3,15,125]. These frameworks include assessment of soil use status with a scoring system and assigned weights of different indicators to form a unique index of the soil health status [126]. However, a lack of global standardization still exists and reveals the need for further improvement and standardization of assessment protocols between regions and soil types.

These frameworks vary in scope, data requirements, and computational methodology (Table 3, Figure 2) but share a common goal: to be able to transform raw measurements into their useful form of interpretive scores that represent soil functionality.

Table 3. Comparative synthesis of global soil health assessment frameworks.

Framework	Indicator Selection	Scoring Method	Advantages	Limitations
SMAF (Soil Management Assessment Framework)	Flexible Minimum Data Set (MDS) including physical, chemical, and biological properties.	Unitless normalization (0–1 scale) using non-linear, scoring curves.	Highly rigorous; accounts for non-linear dynamics and allows precise regional calibration.	Highly data-intensive; requires robust baseline data sets; lacks standardized crop codes.
CASH (Comprehensive Assessment of Soil Health)	Standardized suite of physical, chemical, and biological metrics.	Cumulative normal distribution functions (0–100 score) based on regional soil texture.	Commercialized; direct lab-to-field advice.	Primarily optimized for temperate zones; scoring thresholds can affect results in weathered tropical soils.
SHAPE (Soil Health Assessment Protocol and Evaluation)	Dynamic properties include wet aggregate stability, POXC, and microbial respiration.	Non-linear scoring curves combined with peer group benchmarking using local climate and texture.	Advanced peer group comparison capabilities; fully compatible with existing SMAF model structures.	Heavily dependent on the availability of massive, pre-existing empirical regional databases.

Table 3. *Cont.*

Framework	Indicator Selection	Scoring Method	Advantages	Limitations
SHI (Soil Health Indices)	Variable; typically selected based on project-specific goals and local data availability.	Additive indexing, weighted averages, or multivariate algorithms like PCA.	Highly flexible and well suited for high-level project monitoring.	Prone to bias; can mask critical trade-offs between parameters if weights are poorly justified.
SHC (Soil Health Card)	Restrained to basic chemical properties (NPK, pH, OC, EC).	Qualitative, color-coded status brackets (low, medium, high).	Cost-effective; simple for smallholders.	Missing biological indicators; variable field protocols.
ISHM (Integrated Soil Health Management)	Dynamically pairs biophysical MDS with localized management metadata (tillage, history, inputs).	Combines biophysical soil data with management practices for holistic indexing.	Transitions directly from diagnostics to action.	Difficult to standardize across different labs.

Source: Adapted from [15,16,52,93,127–131].

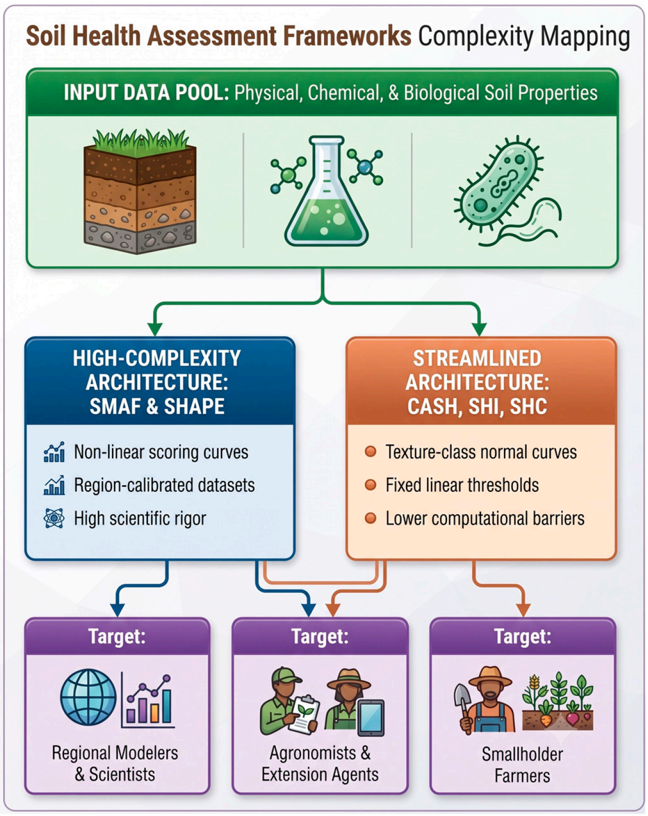

Figure 2. Conceptual workflow and operational complexity mapping of prominent global soil health assessment frameworks.

4.1. Principles of Integrated Soil Health Assessment

A sound soil health framework should meet three basic requirements [1,17].

Sensitivity: Indicators should respond to changes in management and climate over reasonable time frames.

Universality: Core indicators should have universality and adaptability across different soil types and regions.

Functionality: Score should reflect relationships to ecosystem services such as productivity, nutrient cycling, or water regulation.

To reach these goals, frameworks are needed that typically start with a Minimum Data Set (MDS) of a selection of representative indicators. These indicators can be chosen in a multivariate or expert-based approach [12,15].

A composite index, e.g., the Soil Quality Index (SQI), a Soil Health Index (SHI), is produced by normalizing the value of the indicators using their scoring algorithms and then aggregating these (often by weighted addition and/or principal component analysis).

4.2. Soil Health Indices (SHIs)

Soil Health Indices (SHIs): for handling several indicators at the same time to obtain a single score for assessing complex soil data [52,131]. The SHI construction consists of three steps: (i) selection of indicators, (ii) weighing of the indicators according to their importance, and (iii) calculating a single score (index value) using an algorithm (e.g., weighted average, principal component analysis) [52]. The choice for indicators and weighting methods is based on the goals of the research and local soil and climatic specificities.

SHI frameworks provide a very convenient approach for temporal monitoring and comparison of soil. For example, Singh et al. [131] reported high sensitivity of SHIs to conservation management with significant improvement in infiltration, aggregate stability, and soil enzyme activity. SHIs have the advantage of easy interpretation and understanding, but results could get distorted due to inherent trade-offs between individual indicators if the factors governing weights are not justified.

4.3. Soil Health Card (SHC)

Soil Health Card (SHC) is an applied extension of the soil testing program to promote farmers' participation and management for enhancing soil health [130]. The SHC indicates the nutrient, pH, salinity, and organic carbon status of soil in color and provides specific management recommendations. SHCs have some advantages like simplicity to interpret the results for farmers and establishing a direct link between laboratory analysis of soil and field decisions. There are limitations to SHC, including the need for a laboratory, variability in protocols for sampling, and the lack of biological indicators. However, SHCs are an important communication tool that translates scientific information into practical field guidance [129].

4.4. Integrated Soil Health Management (ISHM)

Integrated Soil Health Management (ISHM) focuses on the circular process between diagnosis, management, and monitoring [93]. It brings together soil testing, ecological knowledge, and participatory planning under an adaptive management framework based on farmers' feedback.

ISHM frameworks often have four steps:

- Evaluation of the soil health at the baseline level.
- Identification of constraints (i.e., low SOC, compaction).
- Implementation of corrective practices (e.g., compost addition, cover crops).
- Re-assessment to make judgments on improvements.

Through a combination of scientific and practical knowledge, ISHM ensures that management interventions are evidence-based and locally relevant [128].

4.5. SHAPE: Soil Health Assessment Protocol and Evaluation Tool

Soil Health Assessment Protocol and Evaluation (SHAPE), newly standardized by Nunes et al. [127], has included both lab and field observations of soil properties in its scoring system. SHAPE contains dynamic properties such as stability in wet aggregate, permanganate oxidizable carbon (POXC), and microbial respiration.

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Important innovations are:

- Peer group comparisons based on comparable climatic and textural conditions.
- Non-linear scoring functions based on large empirical data sets.
- Regional soil calibration in the United States and worldwide.

This enables the user to identify "soil health opportunity gaps" and addresses quantitative management improvement targets. SHAPE has been successfully integrated with SMAF scoring curves, and compatibility between frames has been established [127].

4.6. Digital Agriculture, Remote Sensing, and AI-Driven Approaches

In recent years, advances in technology have enabled evaluations of soil health to transcend point measurements. Mapping of indicators for soil health, including organic carbon, moisture content, and vegetation indices, is now possible through remote sensing, GIS, and machine learning approaches (Figure 3) [106,132].

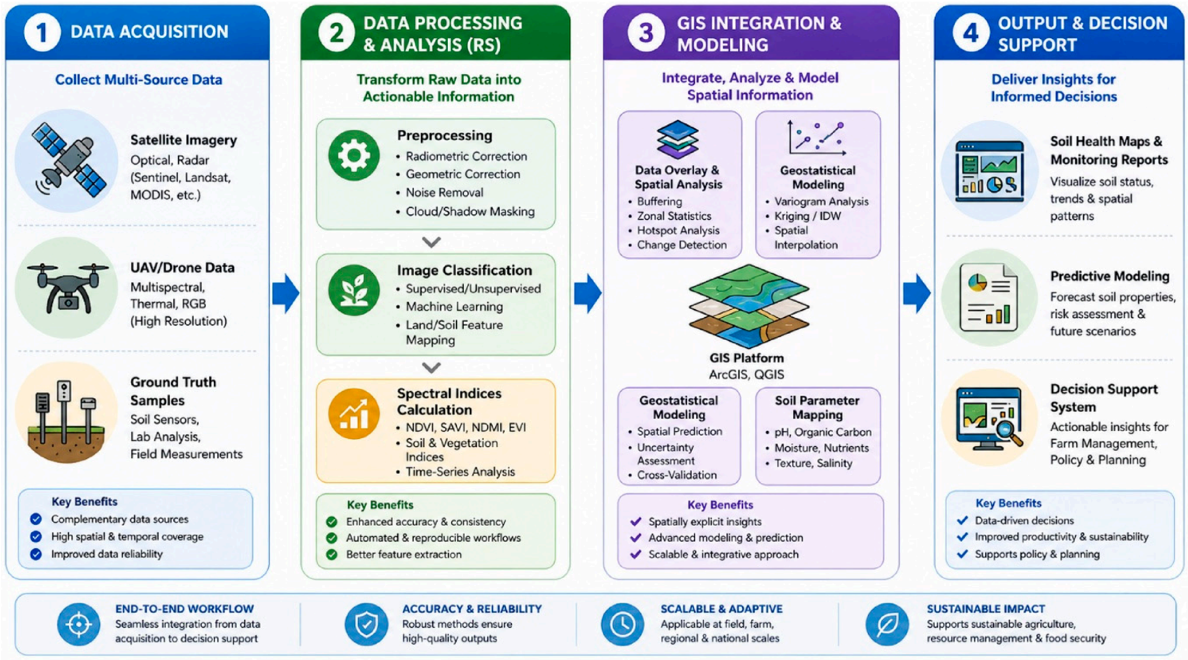

Figure 3. Illustrative workflow: The process of using remote Sensing and GIS for monitoring soil health.

Multispectral or hyperspectral imagery can be used to estimate SOC, clay, or even microbiome proxies [56]. Such data are often incorporated into GIS analysis software and can be extremely useful in regional planning, precision agriculture, and in the calibration and testing of SMAF models in various environments [106]. Good ground-truthing data can allow a well-tuned SMAF model to be applied to a variety of soils and cover types.

Modern soil health assessment has moved past static, point-source laboratory measurements to embrace high-throughput, multi-scale digital infrastructure (Figure 3) [133,134]. Integrating frameworks like SMAF into digital workflows allows for the automated, real-time spatialization of soil quality indices over large geographic extents [135]. This digital modernization is driven by seven key technological pillars:

- **Artificial Intelligence (AI) and Machine Learning (ML)**: Traditional indexing models rely heavily on linear assumptions that mask biological synergies. AI and advanced ML algorithms such as random forests (RFs), support vector machines (SVMs), and artificial neural networks (ANNs) excel at modeling complex, non-linear interactions among physical, chemical, and biological indicators to automate indexing without losing the subtle multivariable dependencies inherent in soil matrices [136].

- **Unmanned Aerial Vehicles (UAVs):** UAVs bridge the spatial resolution gap between localized field sampling and satellite imaging by delivering centimeter-scale imagery with flexible repeat-flight schedules [137]. Drones equipped with advanced payloads (such as multispectral and LiDAR sensors) capture micro-topographical variations and high-resolution crop canopy feedback that correlate closely with underlying physical soil constraints, including localized soil compaction and altered drainage pathways [138].
- **Hyperspectral Sensing:** Utilizing narrow, continuous spectral bands across the electromagnetic spectrum allows hyperspectral assets to map distinct, continuous surface soil signatures rather than broad, aggregated bands [139]. This optical approach enables the non-destructive estimation of sensitive topsoil attributes, including highly reactive active organic carbon (AOC) fractions [140] and surface moisture variations [141], directly from a distance.
- **Proximal Sensing:** Field-scale proximal tools, including electromagnetic induction (EMI), gamma-ray spectroscopy, and portable mid-infrared (MIR) sensors, provide rapid, non-destructive, on-the-go data collection [142]. By bypassing intensive, time-consuming laboratory preparation steps, these systems allow researchers and agronomists to instantly characterize and map high-resolution soil texture, salinity, and bulk density patterns across entire production fields [143].
- **Digital Soil Mapping (DSM):** DSM combines discrete field-sampled observations with continuous environmental covariates (such as digital elevation models and climate grids) via advanced geostatistical modeling and spatial interpolation algorithms, including regression-kriging and machine learning hybrids [144]. This predictive framework allows researchers to scale up localized, point-source SMAF indicator scores into continuous, high-resolution regional soil health maps that capture true landscape-scale variability [145].
- **Digital Twins:** Representing the absolute cutting edge of soil intelligence, digital soil twins are virtual, dynamically updated replicas of physical field systems [146]. By continually streaming data from ground-based IoT sensors, real-time weather feeds, and satellite imagery pipelines, digital twins simulate daily soil performance, organic matter turnover dynamics, and predictive changes under variable future climate scenarios [147].

Consolidating these remote and proximal sensing arrays directly into the SMAF scoring architecture represents a vital pathway toward scalable, data-driven land management decisions and automated global soil health monitoring [148].

4.7. Spectroscopic Techniques

Spectroscopy, in particular, mid-infrared (MIR) and near-infrared (NIR) spectroscopy, is a non-destructive, high-throughput, and fast technique of analyzing various soil properties [56,149]. The techniques can predict SOC, nutrient levels, and texture simultaneously with minimal chemical reagents and can take advantage of large-scale soil surveys.

The spectral libraries, such as the Spectral Library of Soil Health of the USDA, have contributed to the comparability between the regions, even though there are calibration challenges [127]. Integration of spectroscopic data in systems such as SMAF and SHAPE allows the efficacy and the reliability of assessments to be improved.

4.8. Soil Management Assessment Framework (SMAF): Overview

The Soil Management Assessment Framework (SMAF) is the most rigorously scientific of all frameworks and is versatile. SMAF, which was developed by Andrews et al. [15] in the USDA, takes data of soil indicators and converts them into standardized scores using empirically derived scoring curves that represent optimal functional ranges. These are then combined to compute a Soil Quality Index (SQI), which reflects the overall soil performance (Figure 4).

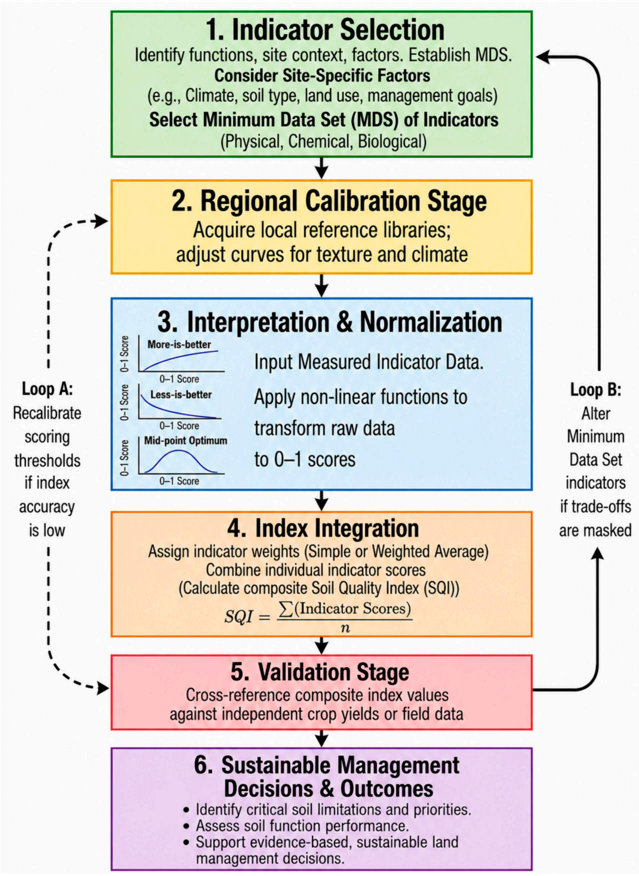

Figure 4. Soil Management Assessment Framework (SMAF) workflow.

SMAF is not comparable with more fundamental indices because of:

- Adding dynamic soil processes (nutrient cycling, water management, biodiversity).
- The use of indicator-specific scoring curves, instead of arbitrary thresholds.
- Enabling regional calibration (soil type, climatic, land use calibration).

The flexibility of the framework has resulted in its use in both agricultural and forestry environments, as well as in coastal ecosystems [14,16,150].

5. Structure and Methodology of the Soil Management Assessment Framework (SMAF)

SMAF is one of the most validated and quantitative methods of measuring soil health. It integrates physical, chemical, and biological indicators into one Soil Quality Index (SQI), which enables the consistent interpretation of the multiple data sets in other areas and systems of management. SMAF, in contrast to strictly empirical indices, is a combination of scientific knowledge of how soils should work and statistically determined scoring algorithms to indicate performance with respect to functional optima [3,14].

5.1. Conceptual Framework

SMAF works under the assumption that the functions of the soil, i.e., nutrient cycling, water, and biological productivity, can be measured using measurable indicators. Indicators such as standardized, scored, and combined are measured to create a total SQI (0–1 scale) [14], which is the capacity of the soil to carry out a variety of functions under certain management and environmental conditions.

The framework aids in making comparative assessments of management systems, performing time-based tracking of soil enhancement or deterioration, and conducting the determination of limitations that are function-specific [16].

5.2. Indicator Selection and the Minimum Data Set (MDS)

The first step is to select a suitable Minimum Data Set (MDS) of indicators of major soil processes [150]. Selection is based on:

- Significance to soil functions, e.g., soil structure, fertility, and biological activity.
- Receptiveness to management or environmental change.
- Ease and cost of measurement.

SMAF incorporates a Minimum Data Set (MDS) consisting of crucial soil indicators that embody physical, chemical, and biological soil functions [150]. The indicators used depend on the type of ecosystem, the goal of management, and land use. As an illustration, in mangrove ecosystems, an MDS can involve the pH, available phosphorus, bulk density, and soil organic carbon [150]. Alternative larger data sets can be used in an agricultural setting and include microbial biomass, enzyme activity, water-holding capacity, and aggregate stability [14,94].

The choice of indicators must also be related to scientific significance and local soil limitations to guarantee the accuracy of the assessment concerning the specific environment [151].

Multivariate statistical methods, especially principal component analysis (PCA), are also common to identify indicators that describe the maximum variance of soil properties [12]. This guarantees that unnecessary variables are eliminated and the framework is parsimonious as well as diagnostic.

5.3. Scoring Curves and Normalization Procedures

To translate heterogeneous raw data sets into a uniform metric, SMAF utilizes a non-linear data normalization procedure [15]. This framework converts measured field data into a unitless, standardized score (S) scaled continuously from 0.00 to 1.00. This is mathematically executed using a generalized logistic function [15]:

$$S = \frac{a}{1 + e^{-b(x - x_0)}}$$

where:

S is the unitless standardized indicator score (0 to 1).

a is the maximum asymptotic score limit (typically 1.00).

b represents the slope parameter, derived from empirical data, which dictates the curve's sensitivity to change.

x is the raw experimental value of the soil indicator.

x_0 is the inflection point where the score equals exactly 0.50.

To accurately reflect specific biophysical soil functions, SMAF dynamically alters this architecture into three distinct functional curve patterns [15,152]:

More-is-Better: Programmed for parameters where higher levels indicate optimal performance (e.g., soil organic carbon, cation exchange capacity). Using a positive slope factor, the score climbs toward 1.00 as concentration increases until reaching a biochemical saturation plateau.

Less-is-Better: Utilized for indicators where increasing values directly signify degradation (e.g., bulk density, electrical conductivity). Applying a negative slope factor causes values to decline rapidly toward 0.00 past localized disruption limits.

Mid-Point Optimum: Configured for metrics exhibiting performance restrictions at both low and high extremes (e.g., soil pH). This profile links two opposing logistic curves to establish a peak optimal plateau near neutral ranges, dropping steeply toward 0.00 under hyper-acidic or alkaline conditions.

These curves are governed by the following explicit mathematical equations [15]:

- More-is-better function:

$$S(x) = \frac{1}{1 + e^{-b(x-c)}}$$

- Less-is-better function:

$$S(x) = \frac{1}{1 + e^{b(x-c)}}$$

- Mid-point optimum function (segmented two-sided logistic) [15]:

$$S(x) = \begin{cases} \frac{1}{1+e^{-b_1(x-c_1)}} & \text{for } x \leq x_{\text{opt}} \\ \frac{1}{1+e^{b_2(x-c_2)}} & \text{for } x > x_{\text{opt}} \end{cases}$$

where:

- $S(x)$ represents the final unitless normalized score bounded explicitly by the constraint: $0.00 \leq S(x) \leq 1.00$.
- x is the raw field or laboratory measurement of the target indicator.
- b, b_1, b_2 are slope coefficients empirically calibrated to establish the curve's sensitivity to management changes.
- c, c_1, c_2 define the inflection cross-over coordinates where the normalized score maps to exactly 0.50.
- x_{opt} represents the optimal threshold or range plateau where the soil property reaches peak functional capacity, scoring a perfect 1.00."

The curves are either empirically obtained based on long-run data sets or calibrated by experts. As an example, pH 1 equals close to neutral soils (6.5–7.0), but decreases drastically further below 5.0 or further above 8.0 [152]. A set of common SMAF scoring curves is shown in Figure 5.

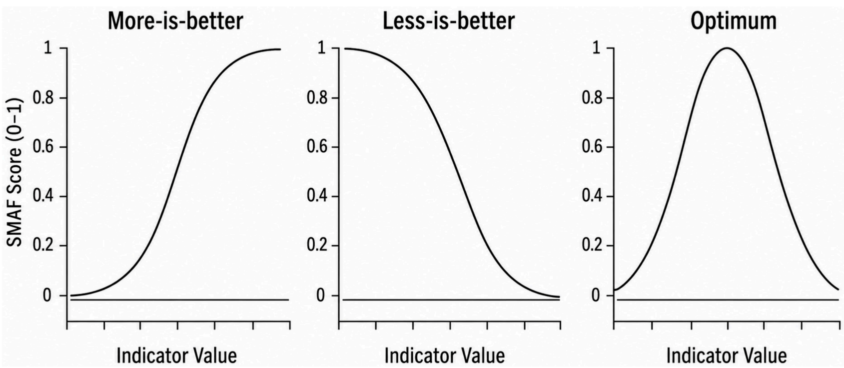

Figure 5. Example of SMAF scoring curves shapes: more-is-better function (e.g., SOC, microbial biomass, CEC), less-is-better function (e.g., bulk density, salinity, compaction), and mid-point optimum function (e.g., pH, soil aeration capacity).

The normalization method of SMAF enables a direct comparison of indicators that have different units, magnitudes, and directions of response. It is also easy to incorporate it into digital decision-support tools.

5.4. Weighting Frameworks and Indicator Integration

Once individual parameters are normalized, they are aggregated into a single composite Soil Quality Index (SQI) using an additive integration model [153]:

$$SQI = \sum_{i=1}^{n}(S_i \times W_i)$$

where S_i represents the normalized score of the indicator, W_i is the unique relative weight assigned to that indicator, and n is the total count of properties included in the Minimum Data Set (MDS). The assignment of the weight parameter (W_i) is conventionally executed via two distinct methods:

Expert-Based Equal Weighting: Indicators within the MDS receive identical weighting factors ($W_i = 1/n$), ensuring each parameter contributes equally to the total SQI value [153].

Principal Component Analysis (PCA): Weights are derived empirically from total data variance. Indicators are grouped into orthogonal principal components (PCs) with eigenvalues ≥ 1. The percentage of variation explained by each PC assigns data-driven weights, minimizing subjective investigator bias [153,154].

Crucially, regardless of the methodology chosen, the cumulative sum of all weights across the system must satisfy the baseline mathematical constraint: $\sum_{i=1}^{n} W_i = 1.00$ [153,155].

5.5. Calibration, Validation, and Regional Adaptation

The advantage of SMAF is its ability to be calibrated regionally. Original empirical scoring functions were created on the soils of the Midwest of the U.S. but have since been recalibrated on a variety of soil orders and climates, such as tropical Oxisols [14], Mediterranean Alfisols [152], and mangrove sediments [150].

Calibration involves the local relationships between the scoring and the soil functions that are usually validated using the yield of crops, respiration, or hydrological response data. This is to make sure SMAF scores show the exact ecological context.

The sensitivity of SMAF to management effects was proven by validation studies and is superior to single-indicator or non-weighted index systems [16,90].

5.6. Algorithm Development

SMAF algorithms combine the process of scoring and weighting to produce the final SQI. The flexibility of the framework allows the incorporation of new indicators and other weighting schemes and statistical refinements [14]. Its ability to detect the changes in soil quality across varying land use and land management practices underlines its role in evidence-based soil management [16].

5.7. Methodological Execution and Worked SQI Demonstration

To demonstrate the quantitative mechanics of the framework, we outline a step-by-step mock evaluation of a sandy loam agricultural soil. We establish a representative three-indicator Minimum Data Set ($n = 3$) evaluated under an equal-weighting allocation matrix ($W_i = 0.33$):

- Indicator 1: Soil Organic Carbon (SOC)—*More-is-better.*
- Indicator 2: Bulk Density (BD)—*Less-is-better.*
- Indicator 3: Soil pH—*Mid-point optimum.*

Step 1: Compilation of Field-Sampled Experimental Values

Field and laboratory evaluations yield the following raw data set:

- Raw SOC = 1.8%.
- Raw BD = 1.25 g cm^{-3}.
- Raw Soil pH = 6.5.

Step 2: Algorithmic Score Normalization (S_i)

Passing these raw observations through regionally calibrated SMAF scoring curves standardizes the metrics into unitless coefficients [15]:

- SOC: Passing 1.8% through the texture-specific curve yields a standardized score of S_1 = 0.65.
- Bulk Density: Submitting 1.25 g cm^{-3} into a curve calibrated for coarse soils yields an excellent physical score of S_2 = 0.92.
- Soil pH: Inserting a pH of 6.5 places the soil directly within the maximum functional range, resulting in an optimal score of S_3 = 1.00.

Step 3: Mathematical Weight Indexing and Aggregation

Applying the normalized scores and equal weights to the additive integration function yields the final composite profile:

$$SQI = (0.65 \times 0.33) + (0.92 \times 0.33) + (1.00 \times 0.33) = 0.85$$

Step 4: Qualitative Interpretation of the Output

The quantitative execution yields a total Soil Quality Index of 0.85. Cross-referencing this against standard SMAF classification scales maps this plot into the "Very Good / Excellent" bracket, signifying optimal soil functioning [15] (Table 4). However, isolating the individual scoring matrix clearly flags the soil organic carbon pool (0.65) as the primary limiting constraint, advising the land manager to integrate targeted organic amendments to further maximize whole-system productivity.

Table 4. Interpretation of Soil Management Assessment Framework (SMAF) scores.

SMAF Score *	Interpretation	Meaning
0.00–0.20	Very Poor	Severely degraded soil, major constraints
0.21–0.40	Poor	Multiple limitations, low function
0.41–0.60	Moderate/Fair	Average quality, some constraints
0.61–0.80	Good	Healthy soil functioning
0.81–1.00	Very Good/Excellent	Optimal soil functioning

* These ranges are widely used in SMAF-based studies [15,156,157].

6. Applications of SMAF

SMAF has been extensively utilized in diverse ecosystems and agricultural activities worldwide to establish the effects of land use and land management practices on soil health (Table 5). This quantitative and versatile nature enables the comparison of the quality of soils between opposing environments and time periods [14,16,150]. The following subsections give a brief description of the significant SMAF applications in various systems.

Table 5. Representative applications of SMAF across ecosystems and management contexts.

Region	Ecosystem Type	Management Practice	Key Findings	Reference
Brazil	Agricultural Oxisols	Conservation tillage vs. conventional tillage	SMAF detected improvements in structure and SOC under conservation management	[14]

Table 5. *Cont.*

Region	Ecosystem Type	Management Practice	Key Findings	Reference
USA (Midwest)	Agroforestry systems	Tree species selection and fertility source variation	Enhanced soil health with species-specific effects	[16]
Peru	Mangrove restoration	Reforestation and organic matter enrichment	SMAF effectively tracked the recovery of soil physical and biological functions	[113]
Nepal	Mountain forests and cropland	Land use type comparison	Protected forests exhibited the highest Soil Quality Index (SQI)	[119]
USA (Rangelands)	Degraded grasslands	Biosolid application	Improvement in SMAF indices linked to nutrient restoration	[120]

6.1. Agricultural Systems

SMAF can be used to assess the status of agricultural soils and monitor the impacts of management practices on physical, chemical, or biological indicators of soil health status. SMAF has been used to assess tillage systems, fertilization practices, and cropping systems assessments [94,152,158]. SMAF was applied to evaluate the health status of agricultural soils in agricultural areas in Northern Spain [152]. Results from this study indicated that conservation tillage increased SOC and aggregate stability and improved SQI of 0.15–0.25 compared with conventional tillage systems. Results from long-term trials in Iowa and Missouri, USA, demonstrated increases in the scores of the biological and chemical indicators for the no-till practice, especially for β-glucosidase activity and SOC [86].

According to Miner et al. [94], SMAF was used to compare organic manure and synthetic nitrogen fertilizers in continuous maize regimes. The treatments with manure provided better SQI values (0.78) compared with the inorganic treatments (0.62), and significant changes in the microbial biomass, enzyme, and structural stability were observed. However, because these scores are specifically calibrated for temperate climates and local crop needs, they should be viewed as regional benchmarks rather than universal standards. On the same note, Cherubin et al. [14] examined long-term conversion of native vegetation to croplands, which showed deterioration in the soil quality in correlation with intensive cultivation. In the long-term organic agriculture systems, SMAF scores have a high level of correlation with the stability of crop yield and the efficiency of nutrient cycling [52]. Short-term studies also have shown that SMAF is sensitive to changes associated with tillage intensity, residue management, and cover cropping [14]. Collectively, these findings support the utility of SMAF in detecting the minor variations in the soil functionality under farming (Table 6).

Table 6. Illustrative effects of management on SMAF soil health indicators. The table indicates typical responses of representative indicators to different practices. This is a conceptual example to show how integrated indicators reflect land use.

Indicator	Natural/Native System	No-Till + Cover Crop	Intensive Monoculture	Organic Input (Manure/Compost)
Bulk Density (Bd)	→ (optimal)	↓ (looser soil)	↑ (compact soil)	↓ (improves structure)
Aggregate Stability	↑ (high)	↑	↓	↑
Soil Organic Carbon	↑ (high)	↑	↓	↑
pH (if neutral base)	~ optimal	→	→ or ↑ (from fertilizer)	→
Available N (PMN)	→ (balanced)	↑	↑ (fertilizer)+/−	↑ (added N)
Microbial Biomass C	↑ (rich biology)	↑	↓	↑ (food source)
β-Glucosidase (BG)	↑ (high activity)	↑	↓	↑

Note: (→) indicates minimal change, as the baseline is already healthy; (↑) = increase; (↓) = decrease; (~) approximately stable or maintained, and (+/−) highly variable.

6.2. Agroforestry Systems

The multi-layered structure and the improved organic matter cycling in agroforestry systems make them a special environment in which SMAF can be used. In a study in Northwest Arkansas [16], SMAF was applied to measure responses to soil health in relation to different tree species composition and sources of fertility. The outcomes showed that the framework can capture ecosystem synergies, in which an average of 20% of the Soil Quality Index (SQI) is observed to be high in tree-crop systems in comparison with the monocultures located nearby. Moreover, it was determined that the properties of specific species (e.g., nitrogen-fixing or non-fixing) had a substantial effect on the microbial biomass and carbon pools of soil microbes. These results show the potential of SMAF to aid species selection and maximize soil fertility in complex and mixed land use systems.

In another study [159], SMAF was used in Western Nepal to evaluate soil quality under various land use systems. They have recited the greatest Soil Quality Index (SQI) in the protected forests, then the agricultural lands and grasslands, and this has resulted in the importance of the vegetation cover in sustaining soil health.

SMAF has also been applied in land use conversion studies, which give an insight into the influence of deforestation or reforestation on soil functionality. SMAF was utilized to assess Brazilian Oxisols that were developed out of the original Cerrado vegetation as croplands [14]. The findings indicated a sudden decrease in SQI scores with a decrease in the total SQI of 0.85 (forest) to 0.59 (cropland); this specific tropical-calibrated model means the score reflects severe localized degradation rather than a baseline norm. On the other hand, reforestation and perennial vegetation recovery enhanced SQI by 25–35%, which validated the sensitivity of SMAF to the long-term land use alterations and its appropriateness in monitoring restoration processes.

6.3. Coastal and Mangrove Ecosystems

More recently, SMAF has been used to determine the health of soil in mangrove ecosystems and especially in Brazilian mangrove restoration projects [150]. The initial attempt was to adapt SMAF to coastal areas. The research revealed that the framework could effectively capture any changes in the quality of the mangrove soil in terms of restoration activities, which were mainly manifested in the increase in biological and physical indicators [150].

This innovative contribution widens the applicability of SMAF from agricultural and terrestrial systems to ecologically sensitive coastal environments, where it is necessary to monitor soil health to rehabilitate the ecosystem and evaluate its resilience.

6.4. Rangelands and Grazing Systems

SMAF has been employed to evaluate management-intensive grazing (MIG) and restoration treatments in semi-arid rangelands. For instance, SMAF was used to assess overgrazed rangelands amended with biosolid and found a significant increase in organic carbon, aggregate stability, and enzyme activity after five years of management [160]. SMAF provides a powerful tool for determining the end-point of land and soil rehabilitation.

Similarly, Shawver et al. [158] used SMAF to track the soil health in management-intensive grazing systems in Colorado. They discovered that the score of biological indicators was better with rotational grazing, whereas compaction was a limiting element, which highlights the significance of combining physical remediation plans.

6.5. Global and Multi-Regional Studies

Nunes et al. [161] synthesized 456 SMAF applications in all climates and management regimes in the United States in a comprehensive meta-analysis. This study concluded that

SMAF was a reliable indicator of improvements in SOC, microbial biomass, and aggregate stability in all conservation-oriented systems. It also, however, highlighted the necessity of region-specific recalibration of some indicator scoring curves (e.g., pH and enzyme activity) to increase cross-site comparability.

Fine et al. [12] also showed that the use of regional adjustments can enhance the interpretative accuracy of SMAF scores, which is as high as 18% in support of the use of local calibration data sets.

6.6. Summary Insight

The studies reviewed confirm that SMAF is a reliable and versatile instrument to evaluate the health of soil under a wide variety of ecosystems. The most convenient aspect is that it can be used to understand which soil functions are limiting and to what extent each of them contributes to the overall SQI. According to many researchers, biological alterations (e.g., changes in enzyme activity or microbial biomass) are often found in SMAF scores long before any changes are reflected in the chemical or physical indicators. It is also possible to compare the performance of management in extremely different systems using the framework, and when SMAF is combined with data on spatial or long-term monitoring, it becomes a powerful tool to track trends and make more specific management decisions. While the literature suggests that SMAF could still benefit from region-specific calibration, choice of indicators, and improvements to the scoring algorithm, all studies comment that SMAF represents a middle ground between the purely scientific scenario of soil management and the real-world scenario of soil management and is a useful tool for measuring the long-term sustainability of restoration efforts.

7. SMAF Regional Variations and Adaptations

Despite the successes in the adoption of the Soil Management Assessment Framework (SMAF) in various soil ecosystems, its effectiveness is highly reliant on the local calibration and adaptation. The indicators of soil health are not uniform when relating to the climates, soil textures, and land applications; therefore, the curves of scoring region-specifically and the algorithm refinements are important to provide a reliable interpretation [12,162,163].

7.1. Need for Regional Calibration

The original SMAF models were trained using the data of the U.S. Corn Belt, which is mostly Mollisols and Alfisols [3,15]. Later developments showed that these scoring functions can either under- or overestimate the performance of soil through the application to different regions. As an example, optimum SOC and bulk density in temperate loams vary considerably from those in tropical Oxisols or arid Vertisols [14].

Calibration involves the estimation of local data by functional relationships using regression modeling or hand-based thresholds. For the thermic region of the Southern Great Plains, uncalibrated SMAF curves averaged 18% less than corresponding biological measurements. Modifying the scoring curves to reflect enzyme activities and microbial biomass improved the relationship with crop yield and respiration values.

7.2. Climatic and Soil-Type Variability

Climate and parent material differences in the region affect the dynamics of soil functions (that is, adaptive scoring will be required):

- Tropical soils (Oxisols, Ultisols): highly weathered, with low cation exchange capacity (CEC); organic carbon is a major factor controlling the quality of soil. SMAF adaptation in Brazil has done this by increasing SOC weighting [14].

- Temperate soils (Mollisols, Alfisols): freeze–thaw and tillage processes put structural indicators (aggregations and porosity) in the first place [12].
- Arid and semi-arid soils: salinity and the rate of infiltration are critical, and it is necessary to add electrical conductivity (EC) and sodicity as further indicators [69].
- Coastal and mangrove soils: additional factors might include oxidation reduction potential, dynamics of sulfur compounds, and organic carbon pools [150].
- Arid-zone soils: In dry, wind-prone regions, the framework must prioritize physical indicators like aggregate stability and water infiltration [164]. Because high temperatures accelerate carbon breakdown, the standard "more-is-better" carbon scoring curve should also be lowered to establish a realistic baseline for these environments [157,164].
- Saline soils: To accurately reflect the osmotic stress caused by high salt levels, rigid electrical conductivity (EC) thresholds must be replaced with dynamic, crop-specific "less-is-better" curves [157]. The minimum data set should also incorporate the Sodium Adsorption Ratio (SAR) to monitor for structural degradation [165].
- Calcareous soils: Because these soils naturally buffer at highly alkaline pH levels (7.5 to 8.5), the standard "mid-point optimum" pH curve must be shifted to the right to avoid unfairly penalizing an unchangeable regional trait [157]. Chemical scoring functions must also be adjusted, as high calcium carbonate levels lock up essential nutrients like phosphorus [165].

Different variations were tested to show that SMAF is not a generic model and needs to be specifically adapted to the pedo-climatic zone where it is being used.

8. Strengths, Challenges, and Limitations of SMAF

SMAF is currently one of the most scientifically advanced methods for quantitative assessment of soil health. Its modular framework, empirical basis, and adaptability to current data systems mean that SMAF is one of the major platforms for future monitoring systems for soil.

Although SMAF has demonstrated flexibility and applicability, certain practical and methodological concerns are currently impeding its successful adoption and application in different regional contexts.

8.1. Strengths

- **Integration of Multiple Indicators:** SMAF excels at consolidating disparate physical, chemical, and biological soil metrics into a single, cohesive framework, preventing individual parameters from being interpreted in isolation.
- **Standardized Scoring System:** By converting raw data with varying units into unitless scores ranging from 0 to 1, the framework allows direct mathematical comparison across highly divergent soil properties.
- **Flexibility Across Ecosystems:** The modular nature of the framework allows it to scale effectively, demonstrating high functional sensitivity when transitioning from standard croplands to complex agroforestry and coastal mangrove environments.

8.2. Limitations of SMAF

- **Subjectivity in Indicator Selection:** SMAF results are highly determined by the choice of indicators [151]. Although the most efficient over the long term, the Minimum Data Set (MDS) methodology may lack the multidimensionality of soil health, especially in a specific ecosystem or in non-conventional managed systems [150]. There is still a persistent argument on the best indicators, proportionality, and availability of data, particularly in resource-constrained areas [93].

- **Algorithmic Vulnerabilities (The Masking Effect):** The primary technical vulnerability of the SMAF is its linear additive aggregation model. Because the framework assumes indicators function independently or with linear weights, it fails to represent complex, non-linear interactions among soil properties. Consequently, a severe deficiency in a single critical parameter (such as extreme salinity) can be mathematically masked by an artificially high score in another parameter (such as total SOC), potentially generating an overly optimistic composite Soil Quality Index (SQI) [124].
- **Financial and Accessibility Barriers:** Executing a comprehensive MDS requires substantial, multidisciplinary data sets that are often expensive and time-consuming to acquire [93]. While traditional chemical testing is cost-effective, advanced biological and physical metrics (e.g., microbial sequencing) require specialized instrumentation. These high data and fiscal requirements severely restrict the framework's accessibility for smallholder farmers and resource-constrained research institutions globally [166]. However, emerging proximal and remote sensing methodologies (e.g., spectral estimates of SOC) may help bridge this adoption gap if validated against SMAF data [56,167].
- **Ecosystem Transferability and Calibration Limits:** The accuracy of SMAF scoring functions relies entirely on regional baseline data. Scaling the framework outside of its foundational temperate agricultural baselines highlights severe transferability limits. Applying uncalibrated equations optimized for traditional row-crop monocultures to specialized systems, such as tropical soils, arid regions, or multi-layered agroforestry, frequently yield skewed performance profiles. These unique environments require entirely new, site-specific scoring architectures [166].
- **Temporal and Seasonal Variability:** Soil health indicators operate on vastly different timelines. While physical parameters change slowly over years, dynamic biological metrics fluctuate rapidly due to recent rainfall, temperature shifts, or fertilization. This dynamic variability risks misinterpreting a temporary seasonal spike as a permanent shift in long-term soil function [168].
- **Lack of Standardization in Codes and Protocols:** The framework's global interoperability is limited by a lack of standardization across two fronts. First, the absence of standardized taxonomical crop and ecosystem codes [16] complicates comparing land use types (e.g., a specific SOC score functions differently in a rangeland versus an orchard). Second, the lack of universally standardized laboratory protocols presents a barrier to cross-site data comparison; processing identical soil samples through different extraction techniques can yield divergent normalized scores [124]. The creation of a standardized taxonomical framework of crop codes, which is associated with soil functional baselines, would aid in the cross-regional assessment and the meta-analyses. USDA-NRCS and the North American Soil Health Assessment Network are striving to fill this gap in their ongoing efforts [127].
- **Data Uncertainty and Variance Amplification:** Field-scale spatial heterogeneity and minor variations in laboratory execution introduce inevitable measurement errors. When SMAF aggregates these independent metrics, these errors cascade through the non-linear scoring curves, potentially propagating substantial mathematical uncertainty into the final composite score [15].

9. Future Directions for SMAF

Due to the increasing global challenges, such as soil degradation, climate change, and food insecurity, new technological and conceptual developments are transforming the ways of measuring and managing soil health [169]. The potential of SMAF's further development is high. It could go in the direction of digitalization, advanced analytics, and monitoring in participatory approaches or global harmonization. However, future development should focus on methodological improvements, integration, and accessibility of data.

- **AI-Assisted SMAF Modeling:** Future frameworks must transition from simple statistical scoring curves toward advanced artificial intelligence (AI) and machine learning (ML) models [170]. Utilizing artificial neural networks (ANNs), random forests (RF), and gradient-boosted regression trees allows for the automatic, data-driven weighting of dynamic indicators [171]. These advanced computational architectures excel at capturing the complex, highly non-linear biological, chemical, and physical synergies within the heterogeneous soil matrix that traditional linear index models routinely mask [136].
- **Remote Sensing Integration:** Overcoming localized, point-source data limitations requires integrating multi-temporal remote sensing data streams directly into cloud-based indexing workflows [172]. Combining high-resolution satellite imagery (e.g., Sentinel-2, Landsat-9), Unmanned Aerial Vehicle (UAV) arrays, and on-the-go proximal measurements via advanced data fusion technologies allows continuous, real-time spatial tracking of critical indicators across vast regional and continental scales [173].
- **Leveraging Spectral Libraries:** Expanding the operational deployment of near-infrared (NIR) and mid-infrared (MIR) spectroscopy offers a rapid, highly cost-effective, and non-destructive pathway to estimate multiple biophysical parameters simultaneously [142]. Calibrating dynamic SMAF scoring models against large-scale, open-access repositories, such as the global infrared soil spectral libraries and the USDA-NRCS soil health repositories, is critical to eliminating cross-site laboratory bias and improving index comparability between highly divergent geographic regions [56].
- **Real-Time Soil Monitoring and the Internet of Things (IoT):** Moving from delayed, destructive laboratory analysis to active, in-field diagnostic models relies heavily on the strategic deployment of localized IoT sensor arrays [174]. Continuously streaming real-time, in-situ data from soil moisture probes, solid-state tensiometers, and microfluidic electrochemical sensors create a highly dynamic platform for tracking immediate, localized biophysical updates and micro-environmental shifts [83].
- **Carbon Credit and Carbon Accounting Applications:** As global climate action initiatives and voluntary carbon markets expand, standardized indexing frameworks are increasingly vital for robust measurement, reporting, and verification (MRV) protocols [175]. Modernizing SMAF algorithms to precisely track and model soil organic carbon (SOC) fraction dynamics and mineral-associated organic matter (MAOM) saturation ceilings supports the rigorous validation necessary for sustainable land management incentives and corporate climate compliance [176].
- **Global Standardization of Soil Health Frameworks:** Resolving the historical lack of global standardization requires harmonizing indicator definitions, analytical sampling protocols, and open-source software interfaces across continents [177]. Integrating the empirical, curve-based architecture of SMAF with other prominent conceptual platforms, such as the Soil Health Assessment Protocol for Europe (SHAPE), the FAO's Global Soil Partnership (GSP) initiatives, and regional visual Soil Health Cards, establishes a uniform, cross-compatible data language essential for guiding international land use policies and sustainable development goals [124].
- **Building a Global Soil Intelligence Network:** The ultimate convergence of these technologies lies in creating a cloud-based, edge-collaborative Global Soil Intelligence Network [178]. This digital ecosystem will dynamically feed real-time remote sensor streams, hyperspectral spectral libraries, and localized machine learning predictions into highly intuitive decision-support dashboards. By synthesizing complex multi-variable metrics into clear operational insights, it makes advanced soil diagnostics and

adaptive management alerts directly accessible to smallholder farmers, agricultural extension agents, and regional land managers worldwide [179].

- **Improving Score Curve and Integration with AI and Machine Learning:** Future work should include optimization and validation of the SMAF scoring curves on different soils and climates [152]. Using region-specific data, moving from simple statistical models to strong machine learning models, and incorporating domain knowledge into the curves should improve the accuracy and strength of the SMAF scoring curves.
- Since machine learning and artificial intelligence (AI) can determine non-linear and multidimensional relationships between soil indicators, they can be used to improve the predictive properties of SMAF [167]. Some of the techniques that can be used to weight indicators automatically and integrate complex data sets include random forests, neural networks, and regression trees.
- **Development of Standardized Crop Codes:** Soil scientists, agronomists, and data experts will need to work together to develop standardized crop codes [16]. The codes must be based on field information and expert opinion to make them uniform and applicable to various cropping systems and agroecological regions.
- **Integration with Other Frameworks:** The increasing number of soil health frameworks across the globe highlights the necessity of standardized procedures. The empirical basis of SMAF makes it a good fit for harmonization with other emerging frameworks, including Open Soil Index (OSI), Global Soil Partnership (GSP), Soil Health Card (India), and SHAPE (USA) [126,127].

Including SMAF scoring operations in existing soil health assessments will enable international comparisons and the establishment of standards of soil health globally. Efforts are being made to harmonize soil indicator definitions, sampling approaches, and data sharing across continents [127].

- **Development of User-Friendly Tools:** The development of software interfaces or applications for mobile devices for easy data entry, SQI calculation, and interpretation could further enhance the SMAF application [14]. This would make SMAF more accessible to farmers, extension agents, and decision-makers without the need for specific skills.
- **Addressing Data Scarcity:** Integrating remote sensing and proximal sensing and applying data fusion technologies can address various data limitations relevant to SMAF [167]. Local and traditional knowledge about soil should be integrated into soil health measurement approaches to improve the representativeness of measurements [128]. Such approaches will be useful for SMAF users in areas with limited lab facilities [93].
- **Expanding the Scope of SMAF:** Future development of SMAF could focus on extending its application to non-conventional land systems such as agroforestry, rangelands, urban soils, and restoration sites [150]. This could involve the development of ecosystem-based indicators and significant changes to the framework to account for the different soil functions and management objectives.
- **Towards a Global Soil Intelligence Network:** The future of SMAF could end up in a Global Soil Intelligence Network consisting of a network of data streams, machine learning models, and decision-support tool dashboards.

This Global Soil Intelligence vision aligns with the Sustainable Development Goals of the United Nations, in particular SDG-2 (zero hunger—food security), SDG-15 (life on land—land degradation neutrality), and SDG-13 (climate action). Connecting science, technology, and governance, SMAF can be a diagnostic engine as well as a decision-support platform of sustainable soil management in the 21st century.

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10. Conclusions

Soil health is crucial to the long-term sustainability of agricultural production and ecosystem function. Recently, the focus has shifted from simple parameter measurement of soil to more integrated function-based assessment methods. In this paper, one of the frameworks, the Soil Management Assessment Framework (SMAF), is reviewed. SMAF is a scientifically sound, quantitative, and flexible tool for utilizing complex soil data to obtain performance indicators for ecosystem health and make sustainable management decisions. This paper describes the framework in terms of physical, chemical, and biological indicators, score and index development methods, and their combinations. SMAF is an analytical tool for comparing the quality of soil management, tracking changes in soil quality over time, and comparing soils under different management systems. SMAF is a multidimensional language of soil quality diagnosis that is universally applicable if suitably calibrated.

SMAF is management-sensitive, particularly in scenarios where conservation is accompanied by improvement practices such as conservation tillage, cover crops, organic amendments, and agroforestry. However, it is necessary to regionally calibrate it with robust data sets and with novel indicators such as microbial diversities and the regulation capacity of water in soil. Future applications of SMAF will be digital- and machine learning-optimized. SMAF will be integrated with remote sensing, artificial intelligence, and big data to generate real-time soil health intelligence. The dynamic nature of SMAF index values and integrated monitoring framework will allow for ongoing monitoring of soil changes. SMAF can be further refined to integrate into global frameworks and monitoring efforts to monitor progress towards the Sustainable Development Goals (SDG-2, -13, and -15).

SMAF provides quantitative insights into the impacts of soil stewardship for climate change mitigation, food security, and biodiversity. For policy practitioners and decision-makers, SMAF offers evidence-based information to support planning and decision-making. For scientists, SMAF is a flexible dynamic model that can be expanded to include microbiome, carbon accounting, and uncertainty quantification.

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