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TOPICAL REVIEW

Assessing the impact of nature-based solutions on soil health in sub-Saharan Africa through farmer-centred methods

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Abstract

Soils underpin many ecosystem services, including food production, through functions such as organic matter decomposition. These functions are increasingly threatened by soil degradation, especially in climate-vulnerable regions, such as sub-Saharan Africa, where unstable soils are prone to severe erosion. As soils continue to degrade, farmers face multiple challenges; they cannot afford accurate tests to assess soil, their livelihoods are constrained by demand for food, fuel and water, and competition for valuable resources hampers farming. Hence, there is a pressing need for accessible tools to assess soil health and methods to provide tailored advice on resilient, climate-smart agricultural management and optimal use of resources. This narrative review offers a comprehensive overview of key issues and potential solutions. We highlight tools and approaches that can support farmers to improve soil and secure livelihoods. Practical indicators and field-ready tests are evaluated, with examples from Ethiopia, but tailored to support farmers and advisors across sub-Saharan Africa and other developing countries. A wide range of tests are reviewed, including physical, biological, chemical, function and service-related tests, drawing on scientific and farmers knowledge. Science-based tests require expertise, equipment and incur costs, while locally-derived tests are affordable and seamlessly applicable. We also review Nature-based Solutions for improving soil quality, and assess them against factors such as labour, costs, and crop production. There is no single universally applicable practice; suitability depends on farmers' priorities and circumstances. Therefore, we explore predictive methods—mechanistic, process-based soil models, data- and knowledge-driven Artificial Intelligence and systems models—to simulate the impact of practices on soil and farm dynamics. Promising approaches include hybrid approaches assimilating data, physics and knowledge through digital soil mapping.

Overall, this review emphasizes the need to empower farmers with accessible tools and methods to harness Nature-based Solutions, build climate resilience and secure sustainable futures for generations ahead.

1. Introduction

Humanity faces many global challenges that are closely interlinked and threaten human livelihoods, including environmental degradation, food insecurity and a changing climate. One specific component of many terrestrial ecosystems plays a significant role in all of these challenges; the soil [1–3]. More than 95% of the food produced depends directly or indirectly on soils [4, 5]. Despite this strong dependence of the human population on soil, this complex ecosystem is still relatively poorly understood [5, 6] and poorly managed in many regions [7]. Approximately 33% of the earth's soil are moderately to highly degraded as a result of different threats, many of which are influenced by human activities, including agricultural practices [2, 3, 8–10]. A common phenomenon worldwide is that topsoil (depth of 0–30 cm) has been almost entirely lost across substantial portions of currently or formerly intensively farmed land [8]. Future soil erosion rates are difficult to predict accurately and estimates can vary significantly. However, researchers strongly agree that rates will increase, particularly in the least developed economies, such as in many countries in sub-Saharan Africa (SSA), South America and Southeast Asia [8, 11–13]. While Africa's population is the fastest growing in the world, hunger and soil loss are simultaneously limiting the ability of African farmers to achieve long-term, sustainable food production [14, 15]. This phenomenon is referred to as *"the cycle of land degradation and social deprivation"*. It is characterised by a downward spiral in which severe land degradation, low farm productivity, poverty, low levels of education, inadequate infrastructure and social exclusion are inextricably linked [16–19]. In particular, many countries in SSA face considerable environmental and social challenges, and so find themselves at the core of this cycle. They are threatened by extreme soil degradation due to their climatically vulnerable regions and unstable soils [20]. For example, according to Nkonya *et al* [15], 85% of Ethiopia's soils are moderately to very severely degraded, with approximately 75% of the country being affected by desertification. Current rates of soil erosion on arable land in Ethiopia are estimated to vary between 42 and 300 t ha^{-1} y^{-1}. This wide range is attributable to complex spatial and temporal variations, and methodological difficulties in estimating rates. The most common causes of land degradation in Ethiopia are erosion by water, wind and tillage [21–23]. With approximately 80% of the Ethiopian population employed in rain-fed agriculture, the economic cost of land degradation, estimated at around \$4.3 billion y^{-1}, is a serious concern [15, 24]. If these issues are not addressed, degradation of land, and therefore, social deprivation, are estimated to become more severe across all of Ethiopia [25, 26]. Similar issues exist in many other countries in SSA. Breaking and potentially reversing this cycle requires a holistic approach based on established concepts related to soil [16].

1.1. Soil-related concepts

As outlined by Bünemann *et al* [27], the provision of services by the soil is entirely contingent on its underlying functions. These functions depend on the quality, health and fertility of the soil, which in turn are affected by the various soil threats.

1.1.1. Soil-based ecosystem services

Soil is not only vital for food, fuel and fibre production. It also provides other (soil-based) ecosystem services, such as biodiversity conservation, carbon (C) sequestration and erosion control [10]. In this context, ecosystem services are defined as *'the benefits which humans derive from ecosystems'* [28]. These can be grouped into provisioning (biomass production, water supply), regulating (climate regulation, pest, disease and erosion control, water quality, and biodiversity conservation), and cultural services [27, 29–31]. Given the significant challenges of food security across Africa, especially in low to middle income countries (LMICs), many with rapidly growing populations, the sustainable production of biomass is critical [32, 33]. However, services, such as biodiversity conservation, should not be neglected, as their feedback on soil functions affect the current state of the soil as well as biomass production [29, 32, 34].

1.1.2. Soil functions

Ecosystem services are underpinned by specific soil functions, including habitat provision, element cycling (including nutrient cycling), decomposition, soil structure maintenance, biological population regulation, water cycling (retention, percolation/infiltration) and organic matter cycling (humus formation and C sequestration) [27]. According to Glenk *et al* [35], these functions are composed of *'(bundles of) soil processes that support the provision of ecosystem services'* and are sometimes categorised as supporting ecosystem services.

1.1.3. Soil threats

The current state of soil, and consequently the provision of ecosystem services, is directly influenced by soil threats. These include erosion (e.g. through water or wind), soil organic matter decline, contamination (e.g. with heavy metals, such as copper or iron in Ethiopian soils [36]), sealing, compaction, biodiversity loss, salinisation, landslides and floods [27]. According to Baritz *et al* [37], '*soil threats are indicative circumstances which can damage or reduce a soil's capacity to provide ecosystem services*'.

1.1.4. Soil quality and soil health

In the literature, the terms '*soil quality*' and '*soil health*' are used more or less synonymously [27]. According to Doran *et al* [38, 39], soil quality is defined broadly as '*the capacity of a soil to function within ecosystem and land-use boundaries to sustain biological productivity, maintain environmental quality, and promote plant and animal health*'; here, human health is included in animal health. In contrast to this, Hannam *et al* [40] define soil health as '*the ability of soil to perform its functions and to deliver ecosystem goods and services. The range of functions and ecosystem services provided should reflect the different capabilities of different soils—a "healthy" soil is therefore one in which ecosystem services are provided at an acceptable level given inherent underlying constraints and the purpose of the land use*'. In essence, soil quality is more concerned with the soil's ability to meet specific human needs. Soil health, on the other hand, is focused on the long-term ability of the soil to support plant growth and maintain its functions [27]. In this paper, the term '*soil health*' is adopted because it more clearly reflects soil as a living organism [41, 42].

1.1.5. Soil fertility

The concept of '*soil fertility*' focuses mainly on crop yields. It is defined as '*the ability of the soil to supply essential plant nutrients and soil water in adequate amounts and proportions for plant growth and reproduction in the absence of toxic substances which may inhibit plant growth*' [27]. It is imperative to prioritise the interplay between soil fertility and soil health, because fertility is important for food production as a soil-based ecosystem service for the sustainable nutrition of the populations of countries in SSA [7, 16, 43].

1.2. Soil governance

In recent decades, considerable efforts have been made to address the numerous challenges facing humanity. These include the introduction of the Sustainable Development Goals and a range of citizen science initiatives.

1.2.1. Sustainable Development Goals and policies

As part of the United Nations' multilateral blueprint for the Sustainable Development Goals (SDGs), a total of 17 different goals are being targeted which are either directly or indirectly related to soil. For example, goals of ending hunger (SDG 1) or clean water and sanitation (SDG 6) are highly dependent on soil-based ecosystem services, such as biomass production [44–48]. In addition to these global initiatives, continental and national policies also play an important role as a driving force for sustainable development. These policies are largely in line with the SDGs, with specific adaptations to local circumstances [49–51]. In the context of SSA, national and local policies support the implementation of sustainable development by integrating them into political strategies, allocating relevant budgets, promoting investment, and facilitating collaborative and community-led efforts, as evidenced by initiatives in Ghana [52, 53]. However, while these measures aim to facilitate implementation, in some cases they can hinder progress. This may be due to inconsistent financing strategies, and lack of funding across sectors, leading to siloed approaches [54–56]. Without co-operation between different regulatory bodies and across multiple levels, from regulatory bodies to farmers, addressing human and environmental challenges appears to be less achievable.

1.2.2. Citizen science approaches

Alongside the interest and desire of high-level decision-makers, the commitment, participation, ownership and responsibility of citizens, specifically farmers as ground-level decision-makers, are becoming increasingly important [57, 58]. Regardless of the location, most farmers are interested in '*looking after*' their soil. This applies not only to current and near future crop production and therefore income, but also, if they own individual property rights, for passing on fertile land to their descendants. From day-to-day business, working on and with the land all year round and knowledge being passed down from ancestors, farmers generally hold extensive, localised knowledge, as well as personal memories of their land [45]. While their experience and knowledge can vary greatly, it is worth noting that these types of emotional relationships with the environment can be of similar value in tackling human challenges as international high-level initiatives [45, 59]. This arises because it is usually the responsibility of farmers not only to follow the guidelines '*handed down from above*' and adapt their farming practices, but also to maintain an acceptable income and feed their families. Therefore, the inclusion of farmers in community-based programmes (e.g. environmental monitoring, project design or implementation) [45] could be of great potential benefit. This can include large-scale initiatives, for example, where farmers can take in-field soil measurements themselves and contribute them to a database. Not only do farmers learn about their land from a different perspective and feel the health of their own soil, but they also provide data to projects, which rely on a large amount of data for critical scientific analysis and decision-making. Moreover, the involvement of farmers, as important stakeholders throughout a project enables tailored project development and the incorporation of local and indigenous knowledge into the decision-making process. This is particularly useful through participatory workshops and the creation of fuzzy cognitive maps [45, 59, 60]. Furthermore, the needs of farmers tend to outlast high-level initiatives and projects due to the nature of specific funding periods and their commitments, while farmers remain responsible for managing the land, producing food and generating income over the long-term [61]. The fight against poverty and hunger, the need to support the health of people and nature and the achievement of many SDG targets depend partly (directly and indirectly) on how the threats to soil health are addressed. Only with joined forces and integrative initiatives can soil threats be mitigated and soil health improved; this requires appropriate indicators and measures to be selected.

1.3. Improving food production and soil health

Reducing hunger and breaking the '*cycle of land degradation and social deprivation*' requires an understanding of the soil, its threats and services, and also the possible strategies to mitigate them. A deep understanding is extremely valuable for farmers when it comes to making appropriate management decisions. Soil health can be of benefit, not only to food production, but also to the wider environment. Here, food production is at the core, although sustainability aspects are no less important, as they aim to increase resilience to extreme weather events and halt degradation while ensuring a long-lasting sustainable biomass production.

1.3.1. Agricultural intensification

Short-term crop productivity could be improved through agricultural intensification (on a smaller area), characterised by widespread tillage and the use of external inputs. However, this approach can lead to significant loss of soil organic matter, depletion of soil nutrients, negative effects on other soil services and a catastrophic deterioration of soil health with lasting environmental pollution [62–65]. In addition, smallholder farmers from LMICs often have only limited access to external inputs due to financial and market-related restrictions. To maintain long-term food production without further depleting resources, and compromising soil health, quality and fertility, a different solution must be found to maintain productivity. A more accessible yet sustainable agricultural approach is needed for LMICs that does not compromise food production, particularly in countries already under pressure due to soil degradation or where sections of the population are suffering from malnutrition.

1.3.2. Sustainable agriculture

The concept of sustainable agriculture and the approaches and practices it entails appear to be a feasible way forward [66, 67]. It includes biophysical aspects, such as '*building healthy soil and preventing erosion, managing water wisely, minimising air and water pollution, storing C on farms, increasing resilience to extreme weather, and promoting biodiversity*', as well as socio-economic aspects, such as '*maintaining profitability to support farming families while contributing to their local economies*' [65, 68]. Improving soil health is a crucial part of many aspects of sustainable agriculture. A healthy soil is more resilient to soil threats and is better able to provide soil functions that contribute to ecosystem services, which in turn help to achieve the SDGs. There is compelling evidence in favour of sustainable practices, demonstrating that improving soil health yields substantial benefits, including increased crop production, while enhancing resilience to soil hazards [69–71]. Sustainable agriculture includes approaches, such as agroecology, nature-inclusive agriculture, organic farming, regenerative agriculture and climate-smart agriculture [66, 67]. These include several sustainable practices, such as crop rotation, crop diversification, cover cropping and intercropping. All of these have significant effects on the quantity and quality of organic inputs to the soil [72, 73]. These approaches and practices are in line with the three central pillars of sustainable development, i.e. environmental, social and economic sustainability [66].

1.3.3. Nature-based solutions

Valuable tools for sustainable development to reduce biodiversity loss and the threats to soil are Nature-based Solutions (NbSs) [67]. These approaches work by enhancing soil structure, improving nutrient cycling, increasing habitat diversity and restoring degraded lands, thereby reinforcing the ecological processes that support resilient and productive farming systems. NbSs are defined as '*actions to protect, sustainably manage and restore natural or modified ecosystems, which address societal challenges (e.g. climate change, food and water security or natural disasters) effectively and adaptively, while simultaneously providing human well-being and biodiversity benefits*' [59, 66, 74]. They are increasingly recognised in global sustainability agendas, including the United Nations SDGs and the United Nations Decade on Ecosystem Restoration, as key approaches to tackling interconnected environmental and societal challenges. The application of NbS in agriculture is relatively diverse. They can be used in different ecosystem conditions (natural, managed, modified or artificial) to simultaneaously deliver co-benefits that address diverse societal challenges, such as climate regulation, biodiversity conservation, food production, recreation and human health [75]. However, the adoption of NbS can also involve trade-offs, including potential short-term yield reductions, increased labour or management requirements, and competition for land, which must be carefully evaluated in each context. Furthermore, as with other management practices, long-term economic viability cannot be estimated precisely and must be assessed on a case-by-case basis using cost-benefit analysis. However, it is assumed that NbS tend to improve production as they are more affordable and sustainable than conventional approaches, which should benefit the viability and overall uptake of NbS in SSA [76].

The overarching concept of NbS comprises a variety of practices, including crop rotation, cover cropping, afforestation, agroforestry and watershed restoration. In many instances these practices have been used for decades, and are grounded in indigenous knowledge or were recognised under different frameworks of sustainable agriculture [59, 75, 77]. Although an extensive list of NbS for improving soil health and food production exists, there is no universally applicable solution. Every farmer requires tailor-made solutions for each individual field, depending on the climate, ecosystem type, regional context, geographical features and the farmer's socio-cultural conditions [45].

1.4. Research gaps, questions, objectives and contributions

In view of the pressing threats to soil, urgent measures are required to mitigate these challenges. To enhance soil health, it is first essential to determine the current condition of soil health and identify limiting factors. However, the poverty faced by farmers requires the availability of simple, low-cost tools to assess soil. Once tests are conducted, a multitude of NbS can be applied to restore and strengthen soil functions, but their specific benefits in relation to farmers' primary concerns, such as labour, costs, and crop yields, must be clearly communicated to encourage adoption. A further complication stems from the food–fuel–water nexus, where limited and valuable farm resources, such as livestock manures, cannot be used as soil ammendments because they are used for other purposes, such as fuel for cooking [78]. To ensure the optimal use of resources and the adoption of the most appropriate NbS according to the farmers' circumstances, predictive models can be used to simulate soil processes and farm dynamics. These tools can provide helpful guidance to farmers. However, numerous models are available to assess the potential effects of NbS on soil health and livelihoods. Their relevance needs to be clarified, as models should explicitly address ecosystem services that are most critical to farmers, including crop production and the prevention of soil erosion.

Despite the existence of literature that analyses available soil health assessment methods (e.g. [5, 79–81]) and approaches for improving (e.g. [44, 67]) and modelling soil health (e.g. [82–85]), these aspects are often disconnected from each other and do not offer a single, comprehensive solution to the problem. Previous research on farmer-based soil health assessment has often focused on conditions where farmers are not faced with such extreme soil degradation problems as seen in SSA and are therefore not so disadvantaged by poor soil health. Furthermore, these farmers often are not able to afford expensive and elaborate soil health test kits. In addition, the literature often fails to establish a clear link between the specific test for soil health, and the targeted soil functions and ecosystem services; this is essential to ensure the relevance and reliability of the test.

The present manuscript aims to address these knowledge gaps via a comprehensive, narrative literature review. The narrative (snowballing) approach offers the opportunity to cover a broad spectrum of relevant topics (see supplementary figure S1 for a systematic mapping of the literature across these topics), which would not be possible with other methods, such as the systematic review. The work combines a review of methodologies to assess and improve soil health and provide actionable advice to farmers and agricultural advisors in SSA. Therefore, the aim of this study is to answer the following research questions (RQs):

- **RQ1:** Which soil health assessment methods are available for use by farmers in SSA and how do these link to soil functions and ecosystem services?
- **RQ2:** What NbS can be used to improve soil health in farmlands in SSA?
- **RQ3:** What methods can be used to predict the impact of these NbS on soil health to enable actionable advice to farmers?

To address RQ1, relevant criteria for soil health metrics are discussed, highlighting their links to ecosystem services and pathways for interpreting and integrating soil health tests. Subsequently, agricultural approaches and practices for improving soil health are examined in order to answer RQ2. Thereafter, modelling methods available to assess the potential impact of agricultural practices on soil health are reviewed to answer RQ3. This study concludes with a discussion and a summary of the most suitable tests, approaches and models that could be used to assist farmers and agricultural advisors in making informed decisions.

1.5. Feasibility, constraints and challenges

The review includes tests and models that require the use of smartphones. These could offer significant advantages and potential solutions to the problem, now and increasingly in the future, as the availability of smartphones in SSA increases while their cost decreases [86]. The findings of this review are likely to remain valid in the coming years. However, at present, access to smartphone access is limited for smallholder farmers in SSA. The World Bank Group [87] reported that in the year 2018, approximately 16% of the rural population in Ghana, 14% in Kenya, 9% in Nigeria, 2% in Mozambique and only 1% in Rwanda owned a smartphone. In addition, network coverage across SSA is relatively sparse, with limited connectivity especially in remote areas [87–89]. Apart from the technological feasibility, other aspects, such as the financial resouces and the level and type of education of farmers vary greatly. According to reports by the World Bank Group and the Food and Agriculture Organization, in 2024 around 67% of the people in SSA were living in extreme poverty on less than 2.15 USD per person per day, while in 2017, around 60% of the rural household members in SSA earned less than 1 USD per day [90, 91]. This constrains the ability of rural households in many aspects of economic activity, beyond buying food, fuel or medicine. Household financial circumstances not only play a central role with respect to access to smartphones and material for soil tests, but also indirectly through education. This means that wealthier farmers are likely to be better able to benefit from the functions potentially made available through smartphones [87]. In addition to technological, financial and educational constraints, there are also political challenges that pose major obstacles to the transition from current agricultural practices to more sustainable approaches. This applies in particular to land ownership in many countries in SSA. For example in Ethiopia, farmers do not own the land, nor do they pass it on to their descendants. Instead, they lease it from the state for life, returning it after their death [92]. The state may then redistribute or lease the land to someone else. Consequently, the same land is not cultivated by the same family across generations. This can lead to the current owners placing less emphasis on soil health and longevity during their tenure than if they were passing it on to descendants who would also have to live off the land [92]. Furthermore, socio-cultural factors such as gender roles within predominantly patriarchal and hierarchical systems, which govern and influence power relationships within societies, traditional practices and mistrust towards new technologies could pose obstacles to the transition [93, 94]. These facts need to be considered when designing and deploying solutions.

2. Soil health assessment in the farmlands of sub-Saharan Africa

As Doran and Safley [42] in Pankhurst *et al* [41] stated in 1997, the '*assessment of […] soil health is invaluable in determining the sustainability of soil and land management systems and in evaluating their long-term effectiveness.*' Because of the complexity of soil, its' health cannot be measured easily, let alone directly; a singular metric or value is not sufficient to describe the level of soil health adequately. However, it is also not possible (or necessary) to measure all soil properties; this means that an appropriate balance in the number of soil properties used to assess soil health is required [95]. Soil health is usually assessed in relation to its functions, ecosystem services and threats. This means that measuring the health of the soil requires it to be examined from multiple angles. At the same time it is also important to repeat individual soil health measurements at sufficient locations across an entire field to characterise variability. This is particularly true when external factors, such as topography, are not homogeneous.

2.1. Static and dynamic soil properties, and extrinsic factors

All physical, chemical and biological properties of soil are influenced by extrinsic factors, e.g. parent material, climate, topography, hydrology, organisms, time and management. These properties are classified into relatively static (inherent) and dynamic (manageable) properties, although this distinction is not absolute [27, 96]. The classification also depends on the sensitivity of the soil property to external influences, such as weather, natural disturbances or agricultural management. For example, texture and stone content are relatively static soil properties, whereas organic C content, aggregate stability and nutrient availability are relatively dynamic properties, which change more quickly in response to changes in land-use or management practices [97]. Water content, temperature and nutrients change even more rapidly with time, affecting how soil health influences ecosystem services within a growing season. The differentiation in types of properties is important, as static properties provide a baseline for the potential of soils in terms of their functions and services. In contrast, dynamic soil properties vary more significantly on a small scale and are used to evaluate the actual state of the soil (i.e. soil health, relative to its potential) and to monitor temporal changes [98].

2.2. Criteria for choosing soil health indicators

Different dynamic soil properties could serve as reliable indicators for soil health assessment, depending on the extrinsic factors. Pankhurst *et al* [41] define the term '*indicator*' in this respect as a '*measurable surrogate for ecosystem services or soil functions*'. Such surrogates, usually physical, chemical or biological, provide information on the soil's ability to function. However, entire ecosystem services or soil functions can also serve as indicators, such as the crop yield (ecosystem service '*biomass production*') or the decomposition of standard organic amendments on the forest floor (soil function '*decomposition*'), which reflects the diverse fauna that would otherwise be challenging to measure [99]. One of the most commonly measured dynamic soil properties across all the categories is soil organic matter, often expressed as soil organic C (SOC). With respect to farmers in SSA, SOC is seen as the main indicator of soil health and fertility, and is crucial for crop growth and productivity, especially in

Table 1. T-shaped matrix showing the relationship between soil-based ecosystem services and soil functions as well as soil threats and soil functions adapted from Bünemann *et al* [27], CC BY 4.0, whereas a cross (X) marks a consistent, unweighted relationship between the corresponding row and the specific soil function in this column [95]. The green shaded columns 'biomass production' and 'erosion control' indicate the most urgent services to be targeted [32, 33] and the red shaded column 'erosion' indicates the greatest threat to soil in farmlands in SSA [21, 22]; SOM = soil organic matter; C = carbon; N = nitrogen.

Soil threats								Soil functions	Soil-based ecosystem services					
									Provision		Regulation			
Erosion	SOM decline	Contamination	Sealing	Compaction	Biodiversity loss	Salinization	Landslides & floods		Biomass production	Water quality & supply	Biodiversity conservation	Erosion control	Pest & disease control	Climate regulation
X	X	X	X	X	X	X	X	Habitat provision	X		X	X	X	
X	X	X			X			Element cycling (e.g. C, N cycling)	X	X				X
X	X		X	X		X		Soil structure maintenance	X		X	X		
	X				X			Biological population regulation	X				X	
X			X	X		X	X	Water cycling	X	X	X	X		X
	X	X	X			X	X	Organic matter decomposition	X	X		X		X

low-input, resource-limited agroecosystems of smallholder farmers [72, 100]. According to Pankhurst *et al* [41], the following criteria should be considered for selection of the most appropriate indicators:

- **Link:** An indicator should be linked via soil functions to relevant ecosystem services and soil threats, as shown in table 1;
- **Time:** An indicator should be time-effective to measure *in-situ* with respect to sampling, hardware, analysis and labour [101, 102];
- **Cost:** The indicator should be cost-effective to measure [101, 102];
- **Ease of use:** The indicator should be easy to measure [101, 102];
- **Sensitivity:** An indicator should be responsive to variations in management on a timescale of 1–3 years [101, 102], and not strongly influenced by short-term weather patterns [27].

In addition, Bünemann *et al* [27] report on some other requirements for soil health indicators/tests:

- **Correlation:** An indicator should be correlated to long-term responses of the soil;
- **Reliability:** An indicator should allow accurate and reliable measurements, with limited subjectivity [101, 102],
- **Interpretability:** A test should be clear (absolute) and easy to interpret [101, 102];
- **Redundancy:** An indicator should not overlap with other indicators.

Hughes *et al* [101] highlight the necessity for soil health indicators and tests to be practical for farmers, particularly considering the skills required and the associated costs. In addition, particular attention should be given to the applicability of the assessment methods to the present soil conditions and the destructiveness of the tests:

- **Applicability:** A test should be applicable in terms of the local pedological conditions.
- **Destructiveness:** A test should be as non-destructive as possible.

2.3. Assessment of soil health indicators

Any assessment of soil health should include the measurement of several indicators, including at least one indicator from each of the three categories: biological, physical and chemical properties [27]. Five different types of soil health indicator assessments exist, although the boundaries between them are not strict and assessments can sometimes be mapped to several types: (1) Laboratory assessment, often referred to as analytical assessment; (2) In-field analytical assessments that require specialist apparatus; (3) In-field visual or rapid assessments, e.g. field-based test kits for profile or spade methods; (4) Sensor-based assessment, including e.g. proximal and remote sensing; (5) Modelling, e.g. through pedotransfer functions. Furthermore, Artificial Intelligence-based approaches represent a state-of-the-art alternative to the conventional methods mentioned above. Laboratory, sensor-based, modelling and Artificial Intelligence based assessments usually yield quantitative (continuous) data, while in-field visual approaches mainly produce qualitative (categorical) data [81, 103].

2.3.1. Laboratory assessment

Quantitative methods that can be used to assess ecosystem services require analytical solutions, and these tend to be laboratory-based, such as the assessment of SOC through a standard method (for example loss on ignition) [104]. The results from the laboratory are usually more accurate than other approaches but tend to be costly and require more expert knowledge and time for analysis. They are accessible to farmers mostly at a relatively high cost, either directly or indirectly as part of an extension service.

2.3.2. In-field analytical assessment

Analytical field-based approaches that provide quantitative data generally require specialist equipment, such as for measuring water transport (infiltrometer), erodibility (rainfall simulator) or root growth mechanical restriction (penetrometer). Simpler versions of some of these tests exist, which are directly accessible to farmers for lower costs, but these are usually not as reliable.

2.3.3. In-field visual assessment

By contrast, the most accessible approaches for farmers to assess soil health are visual in-field methods. These use empirical indicators that are easy to learn and apply. Such visual approaches emphasise the educational aspect of soil health assessment, provide immediate results and can foster better communication between farmers, advisors and scientists [27]. Approaches could be as simple as counting earthworms, assessing soil colour, visually characterising soil structure, or estimating aggregate stability from dispersion upon immersion in water (e.g. Emerson test) [105]. Combined soil health tests can also be used, such as the Muenchberg Soil Quality Rating [106], or others [107–112], which tend to be more complex. As Hussain *et al* state [5], low-cost equipment, intuitive interpretation and immediate results are clear strengths of these field assessment methods. However, their scope is sometimes limited. For instance, they are unable to assess the status of biologically and chemically mediated soil ecosystem services, and the quality of the final results is highly influenced by the experience of the sampler [27, 113]. The assessments also do not provide quantitative data, such as on water transport/retention or nutrient status, so they are not directly transferable to assess ecosystems services.

2.3.4. Sensor-based assessment

Proximal sensors, such as hand-held devices, can be used in the field to estimate soil properties with greater accuracy than a visual assessment [114]. Examples of such sensors are spectroradiometers which measure the near-infrared reflection of the soil to assess factors, such as particle size distribution, water retention or soil organic matter content [115, 116]. Some sensors can also be placed directly in the soil, for example, to measure moisture or solar radiation [117, 118]. The use of such sensors by farmers has expanded considerably, but the costs make them inaccessible to most in SSA. Other technologies, such as satellites or drones, can perform similar measurements remotely (from a long distance), such as estimating soil moisture from satellite images [119]. The results of these measurements could be made available to farmers through smartphones.

2.3.5. Model-based assessment

In instances where the assessment of a particular indicator does not fulfil the requirements for a useful indicator, for example the ease and cost-effectiveness of the measurement, an attempt can be made to model a relationship to the indicator by measuring other properties. This can be done using pedotransfer functions, to provide a proxy value for a secondary soil property, as described by Greiner *et al* [27, 120, 121]. In this context, pedotransfer functions are '*simple to complex knowledge rules that relate available soil information to soil properties and variables*' [122].

A prominent use of pedotransfer functions is to infer the difficult-to-measure water retention curve from readily measured attributes, such as particle-size and bulk density [116, 123]. Most of the mathematical-statistical frameworks used as a basis for the pedotransfer functions are entirely empirical and purely data-driven, based on data from databases or look-up tables [122]. Consequently, the performance of a pedotransfer function is only as good as the data used for parameterisation, so for data-poor regions, such as SSA, their reliability can be compromised.

2.3.6. Artificial intelligence-based assessment

Artificial Intelligence (AI)-based models are increasingly being adopted to estimate soil health indicators and avoid the limitations of pedotransfer functions in terms of their accuracy and reliability [27]. The discipline of AI, which is defined as '*the science of making machines do things that would require intelligence if done by men*' [124–126], entails various methodologies of interest for assessing soil health. Solutions using AI can improve the efficiency of estimates while reducing the complexity of the approach, whether used in soil health assessment or in modelling the impact of management on soil health. This is achieved by establishing data-based relationships without the requirement for detailed knowledge about soils [127]. Based on the AI categories generally accepted in the literature [128–130], Wadoux [124] proposed a taxonomy of AI in soil science, encompassing the following three categories; reasoning and decision-making, learning and prediction, and sensing and interaction. The AI-based assessments of soil health indicators are mainly located in learning and predicting, as well as sensing and interacting. While the domain of learning and prediction involves applications, such as Machine Learning, data mining and

Table 2. A summary of selection methods, which are categorised according to their type, to reduce the number of soil health indicators and derive at a minimum data set.

Type	Method	Source(s)
Qualitative	Expert judgement	[38, 145]
	Participatory approach	[146]
	Logical-sieve approach	[146, 147]
Semi-quantitative	Decision trees	[142, 148]
	Bayesian Belief Networks	[149, 150]
Quantitative	Correlation analysis	[81]
	Analysis of Variance	[151]
	Partial least squares	[152]
	Principal component analysis	[153, 154]
	Redundancy analysis	[155]
	Regression analysis	[156]

pattern recognition, applications in sensing and interaction aim to establish a link between AI and the physical world, including robotics, computer vision and image processing.

An example of this is where the time-consuming and cost-intensive procedures of laboratory analyses can be streamlined through the application of AI models to analyse large data sets and potentially identify patterns more effectively than using manual analysis [131, 132]. Pedotransfer functions can also be supplemented with AI to bridge the gap between available and required data for predicting inaccessible indicators, utilising methods, such as neural networks [116, 119, 122]. A common computer vision-based approach used in soil science is the identification of patterns to predict soil properties from space through satellites, whereby environmental covariates from products (e.g. Normalized Difference Vegetation Index) or variables (e.g. topography or slope profile) are sourced to predict soil properties (e.g. pH) [127, 133, 134]. Another example of a sensor-based assessment, that greatly benefits from computer vision or other AI approaches, is proximal sensing, particularly when assessing soil properties in the field using a smartphone [135–137]. Here, models (e.g. neural networks) are used to extract information from images of the topsoil layer to estimate properties (e.g. SOC content), as demonstrated through the SOCit app [124, 127, 138–140].

2.3.7. Combined assessment

There are advantages and disadvantages to different assessment types, so combining them could be of great benefit [27, 141, 142]. Given the challenging circumstances of farmers in SSA, the options for assessing soil health are limited. Based on the above soil health indicator criteria, certain types of assessments are avoided, such as those that require laboratory analysis, as they are unlikely to provide the cost and time-efficient assessment that farmers in SSA require.

For farmers, in-field assessments are favoured because they are fast and cost-effective. In cases where technology is available, such as a smartphone, proximal sensors through phone cameras, data from satellite imagery and modelling can be integrated. This could significantly improve the accuracy of the in-field assessment in a relatively quick and inexpensive way [139]. Smartphones could be used to communicate educational aspects of soil health, as well as providing guidance about subsequent soil management.

2.3.8. Selection of assessment methods

An appropriate balance in the number of indicators and assessment methods is key. More measurements generally provides more information. However, the increase in the number leads to a greater chance of collinearity between the indicators. Too many indicators also increase the cost, the workload and the expertise required to assess soil health [27, 143]. Bünemann *et al* [6] and Rinot *et al* [81] identified different approaches to derive a minimum data set (table 2). The final number of assessment methods selected typically ranges from six to eight [27]. A number of studies [79, 144, 145] demonstrate that a small set of tests, carefully chosen based on expert opinion and participatory approaches, can provide adequate information for land management decisions while enabling a streamlined process [101].

2.3.9. Evaluation of assessment methods

This section highlights potential soil health indicators and their assessment methods, which are evaluated according to the criteria for suitability (section 2.2) for the example of Ethiopian farmlands. Although this assessment refers to suitability in the Ethiopian context, it is assumed that the soil health indicators and tests are equally applicable and effective in other SSA and LMIC contexts. This assumption is also supported by the fact that the list is compiled from resources focusing on science-based [27, 29, 45, 79, 80, 101, 113, 157] and farmer knowledge-based methods from across SSA [144, 158–166]. It does not include methods that are based solely on remote sensing techniques (see section 2.4.3) as this is outside the scope of this paper. However, it does include smartphone-based tests, which could partly be based on Earth Observation data, such as the SOCit app. Each method is linked to the corresponding soil functions to indicate its relevance for assessing an indicator of soil health. The legend for the heatmap evaluation can be found in table 3. The heat map, presented in the format of a traffic light system, shows favourable ratings in green (e.g. quick test), through to amber for less favourable ratings and then into red for those which are not favourable at all (e.g. time-consuming or unreliable test). In this way, the indicators and tests listed in table 4 can be compared effectively based on their advantages and disadvantages, using expert judgement, and then selected based on the frequency of the respective colours. Additional criteria mentioned in section 2.2, such as the redundancy with other tests for similar indicators, influence the final selection. The final selection of tests should be refined by involving farmers in the decision-making process through participatory approaches. To summarise the assessment given in table 4, based on the heat map and considering minimal redundancy of tests within each indicator category, a number of indicators offer particularly high value to Ethiopian farmers (RQ1). These are:

- Visual evaluation of soil structure (VESS),
- Colour,
- Penetration resistance,
- Beerkan test,
- Slakes app (Emerson test for farmers without smartphone access),
- pH test,
- SOCit app (colour, feel and smell test for farmers without smartphone access),
- Simplified tropical soil biology and fertility (TSBF) test
- Root development,
- Teabag index,
- Crop yield and
- Gully retreat.

Most in-field tests are associated with physical indicators, such as the VESS test. This test is widely used to assess soil structure, and can be adapted to Ethiopian conditions. A common test derived from farmers' knowledge is the analysis of the colour of the soil. This test can be carried out relatively quickly and reliably without any costs or expert knowledge required. To determine the degree of soil compaction caused by cultivation and the depth of the soil (static property), farmers can use a fencing wire to penetrate the soil. Another widely used method is the Beerkan test, which, using minimal equipment, helps farmers to assess the soil's ability to infiltrate water. The stability of soil aggregates could be determined using a smartphone and the Slakes app. If farmers do not have access to a smartphone, the Emerson test offers a suitable alternative with a similar approach, whereby water is added to soil aggregates and their dispersion is assessed. Evaluating chemical and biological indicators in-field appears to be limited. Some measurements, such as soil pH, require specialist equipment, but it is feasible to measure pH with relatively low-cost strips that could be provided to farmers. The assessment of pH is critical, due to its significant contribution to multiple soil functions and the importance of pH in regulating microbial activity and population size. The importance of SOC for biomass production and erosion control makes it another property that is crucial to assess. With limited reliability, farmers can get a sense of SOC from the colour, feel and smell of their soil without using a smartphone. Farmers can compare their agricultural land to parts of their farm under different land use, such as a home garden, which in Ethiopia tends to receive more organic inputs [226], or perennial planting, such as enset. If smartphones are available, moving to sensor-based solutions, such as the SOCit app, is highly recommended, as these provide a more reliable and interpretable SOC assessment at no extra cost or need for additional equipment.

In terms of biological indicators, mainly visual tests which account for soil fauna, e.g. termites or roots, are found to be applicable in Ethiopian farmlands, mostly because of the cost of other tests (see Head *et al* [79]). However, both tests listed in table 2 (the simplified TSBF test and assessment of root development) come with limitations, including time to conduct the test, reliability and the expertise required to interpret the results. Entire soil functions can alternatively be represented by indicators, such as the rate of decomposition, and assessed with tests such as the '*teabag index*'. Although other soil function tests, such as dung removal, toilet paper decomposition or the predation of seeds, also assess the biodiversity, they mainly target above-ground fauna [99].

Beyond this, wider ecosystem service assessments have also been noted, such as assessing the extent of weed infestation, relative crop yield or the rate of retreat of gullies. These can be derived from farmers' knowledge, and prove valuable for farmer-based soil health assessment. For example, the assessment to identify the retreat of gullies using pegs is relatively cost- and time-efficient as well as straightforward to interpret [224]. Once specific tests to assess soil on a one-off basis are selected, each test result must be contextualised and interpreted individually to fully understand changes in soil health.

2.4. Contextual interpretation of soil health indicators

To identify problems, monitor changes or make realistic predictions for agricultural management in relation to the soil, it is essential that the measured

Table 3. Heatmap legend using the traffic light system colours green (G), amber (A) and red (R) as adopted by [79] CC BY 4.0, indicating the suitability of the solution from high (G) to very low (R). The categories relate to the criteria outlined in section 2.2 with a short description including placeholders A and B (in italic). These placeholders are to be replaced by corresponding values appropriate for each classification, e.g. under disturbance, the test requires either no soil sample (G) or some soil (A). The threshold of USD3.0 is based on the poverty threshold highlighted by the World Bank in June 2025 [167]. Some criteria assume a training day to be held for farmers to get familiarised with the tests prior to independent usage.

	Time	Cost/Accessibility	Reliability	Ease of use	Interpretability	Applicability	Destructiveness	Sensitivity
	Measurement and interpretation either occurs only once a year and take *A* or occur multiple times annually and take *B* each time.	In addition to a spade, a trowel and a smartphone, the test requires A, which is readily accessible in Ethiopia.	*A* studies show *B* between the listed method and laboratory methods in terms of error and reliability in detecting changes.	After a training day, farmers require *A* help to conduct the test without compromising the accuracy and reliability of the results.	After conducting the test, farmers require *A* help to interpret the results without mistakes.	The test and its protocol can be used in Ethiopia *A* adaptations.	The test requires *A*.	The indicator and its test results change *A* in response to land-use changes or management practices.
Green (G)	$A = < 30$ min $B = < 15$ min	$A =$ no further equipment	$A =$ Several $B =$ no significant difference	$A =$ no	$A =$ no	$A =$ without	$A =$ no soil sample.	$A =$ within one year
Amber (A)	$A = < 60$ min $B = < 30$ min	$A =$ equipment not exceeding $3.0	$A =$ Several/Few $B =$ no significant difference/similar trends	$A =$ some	$A =$ some	$A =$ with few/small	$A =$ some soil that could be returned after the tests.	$A =$ within five years
Red (R)	$A = > 60$ min $B = < 60$ min	$A =$ equipment exceeding $3.0	$A =$ Several/Few $B =$ no agreement	$A =$ extensive	$A =$ extensive	$A =$ with significant	$A =$ digging a hole and extract an important amount of soil that disturbs the concerned area.	$A =$ not within five years

Table 4. Soil health indicators with corresponding science-based and farmer knowledge-based assessment methods. Each test is linked directly to soil functions (marked with a X) and thus to ecosystem services and threats in Ethiopian farmlands (see table 1). Indirect effects of indicators or tests on soil functions are not considered. The tests, which are mainly in-field assessments (see section 2.3.2), with the exception of the sensor-based Slakes and SOCit app (see section 2.3.3), are evaluated using a heatmap based on the criteria (see section 2.2) as shown in table 3. The costs of a spade/trowel and a smartphone are not considered under 'Cost' as these items can be used for other purposes. The tests are categorised into the most relevant indicators as described in section 2.2 due to the multitude of influences and overlaps. Tests based on farmers' knowledge are framed in black, and tests colour-coded according to their category offer Ethiopian farmers particularly high value. Indicators based on static soil properties are included for completeness and marked with *. VESS refers to visual evaluation of soil structure. TSBF test refers to tropical soil biology and fertility, compact. refers to compaction, stab. refers to stability, and decomp. refers to decomposition.

		Link								Criteria								
Category	Indicator	Habitat provision	Element cycling	Structure main.	Bio. pop. reg.	Water cycling	OM decomp.	Test	Farmer accessible kit	Time	Cost/Accessibility	Reliability	Ease of use	Interpretability	Applicability	Destructiveness	Sensitivity	Source(s)
Physical	Structure			X				VESS	Spade	A	G	G	G	G	A	R	R	[113, 168, 169]
				X				Bulk density	PVC ring, oven, phone, bag, knife, scale	A	R	G	R	G	G	A	R	[170–172]
				X				Workability	n/a	G	G	R	G	R	G	G	R	[161–163, 173–181]
	Colour			X				Colour	n/a	A	G	A	G	G	G	G	R	
	Stone content*			X				Stoniness	Spade	A	G	A	G	A	G	G	R	
	Depth*			X				Depth	Spade	R	G	A	G	G	G	R	R	
	Depth* (& compact.)			X				Penetration resistance	Fencing wire	G	A	A	G	A	G	G	R	[173, 182]
	Horizon* (& depth*)		X	X				Soil profiling	Spade	R	G	G	G	R	G	R	A	[183, 184]
	Texture*			X				Texture triangle test	Texture triangle, jar, tape measure, phone	G	A	A	G	A	G	A	R	[185–187]
				X				Ribbon test	Water	G	G	A	G	G	G	G	R	[188, 189]
	Infiltration			X		X		Beerkan test	PVC ring, marker, tape measure, bottle	A	A	G	G	G	G	G	R	[190–192]
	Aggregate stab.			X				Slake test	Spade, glass, wire mesh, phone	A	A	G	G	A	G	A	R	[193–195]
				X				Emerson test	Tray, water	A	G	A	G	A	G	A	R	[196–198]
				X				Slakes app	Tray, water, can, smartphone, app	A	G	G	G	G	G	A	R	[195, 199, 200]
				X				Drop shatter test	Spade, tray, plastic bag	A	G	A	G	A	G	R	R	[186]
Chemical	pH		X				X	pH test	pH strip	G	A	G	G	G	G	A	A	[201, 202]
			X				X	Vinegar test	Vinegar, baking soda	G	A	R	G	G	G	A	A	[202]
			X				X	SOCit app	Smartphone	G	G	A	G	A	G	R	A	[138, 139, 201, 203–205]
	SOC		X				X	SOCit app	Smartphone	G	G	A	G	A	G	R	A	
			X				X	Colour, feel, smell test	n/a	G	G	R	G	R	G	A	A	[206, 207]
			X				X	LOI field test	Spade, tray, scale, fan, oven, sieve, bowl, tin, tongs, stove	R	R	A	R	A	G	R	A	[79]
	Labile C		X				X	$KMnO_4$ test	Colour chart, glass, bottle, trays, spatula, dropper	A	R	A	A	A	G	G	A	[182, 208]

(Continued.)

Table 4. (Continued.)

		Link								Criteria								
Category	Indicator	Habitat provision	Element cycling	Structure main.	Bio. pop. reg.	Water cycling	OM decomp.	Test	Farmer accessible kit	Time	Cost/Accessibility	Reliability	Ease of use	Interpretability	Applicability	Destructiveness	Sensitivity	Source(s)
Biological	Soil fauna	X			X			Simplified TSBF test	Spade, tray	R	G	A	G	A	G	R	G	[209–211]
	Roots/Compaction	X		X				Root development	Spade	A	G	A	G	G	G	A	G	[103, 212, 213]
Function	OM decomp.						X	Teabag index	Marker, teabags, scale	G	A	G	G	A	G	G	G	[214–216]
							X	Levabag test	Marker, straw, nylon bag, scale	G	R	A	G	G	G	G	G	[217, 218]
							X	Fabric decomposition	Marker, fabric material	G	A	A	G	G	R	G	G	[219–221]
	Bio. pop. reg.				X			Bait lamina strips	Marker, bait lamina stripes, organic substrate	G	R	G	A	A	G	G	G	[222, 223]
Service	Pest & disease control	X			X			Weed infestation	n/a	A	G	A	G	A	G	G	G	
		X			X			Crop appearance	n/a	A	G	A	G	R	G	G	G	
	Biomass production	X	X	X	X	X	X	Crop yield	n/a	A	G	A	G	A	G	G	G	[161–163, 173–181]
	Erosion control	X		X		X	X	Rills & Gullies	n/a	A	G	A	G	G	G	G	A	
		X		X		X	X	Gully retreat	Pegs	G	G	G	G	G	G	G	G	[224, 225]

indicators are interpreted in a consistent and uniform way [42]. Analysing soil health can be compared to a medical examination of humans, where basic indicators, such as blood pressure should be within certain bands [41, 42]. This analogy can also be applied to the concept of soil health, where specific reference values, sometimes referred to as targets, baselines, thresholds or benchmarks [227], are used to establish specific ranges.

2.4.1. Benchmarks

Due to the large global variability of extrinsic factors influencing static and dynamic soil properties, it is considered impossible to establish absolute, universal reference values for soil health indicators. Hence, the development of benchmarks applicable across different scales, e.g. local level [228], across certain soil districts [229] or soil units [230], has gained increased traction in recent years. The reference values themselves within these districts, e.g. from a soil with maximum biomass production and/or environmental performance [27, 38], are then adopted to contextualise measured values and identify differences.

Matson *et al* [227] distinguish between four quantitative methods to evaluate soil health indicators: *(i) 'fixed', (ii) 'reference', (iii) 'distribution'* and *(iv) 'relative change'*. The fixed method (i) uses published, robust values to set a fixed target value. The reference method (ii) is based on a static value which is calculated as a percentage of what would be found in a single reference situation (such as the soil under natural conditions). The distribution approach (iii) is based on a value resulting from the distribution of multiple soils in the same region. The relative change approach (iv), which is the most feasible and widely used, requires less data and works on the basis of monitoring change relative to a target value, assuming a clear target direction for the value exists. An example of this is obtaining a desired pH value between six and seven for many soils so that crop productivity and other soil functions are optimised.

2.4.2. Calibration curves

After setting target or threshold values, many researchers apply them in standard non-linear scoring functions to evaluate soil health indicators against curves based on data from the literature and expert knowledge. By doing this, qualitative and quantitative attributes can be converted into unitless scores. The curves, sometimes referred to as calibration curves, usually take the form of (a) *'more is better'*, (b) *'optimal range'*, (c) *'less is better'* on a scale of 0–1 (or 0–100) [27]. For example, Lima *et al* [144] and Lenka *et al* [231] assigned the shape *"more is better"* (a) to indicators, such as SOC, meaning the higher the SOC the better. Furthermore, they assigned the *'optimal range'* (b) to pH as near neutral values usually optimise functions in agricultural soils. On the other hand, Lima *et al* [144] and Lenka *et al* [231] used the curve *'less is better'* (c) for bulk density as lower density, within reason, indicates better soil structure. The curve shapes are dependent on the targeted soil functions and the overall societal goals for a given landscape [42]. In contrast, some researchers also used linear scoring functions, where the measured indicators are divided by the maximum or minimum value, but these estimates are usually outperformed by the suitability of the non-linear approach [5].

Interpretation mechanisms, particularly universal approaches, are often controversial due to data scarcity and differing expert judgements [27]. Methods, such as relative change assessment, allow the need for changes in agricultural management to be quickly assessed; these are often urgent in many countries of SSA. In instances where data and information on relevant indicators from comparable sites are available, fixed, reference or distribution methods may be used for a more accurate analysis [232]. In cases of insufficient data, the relative change method should be used to prevent delays. Once the tests have been interpreted individually, they are integrated into a single result for easier communication.

2.5. Integrating soil health indicators

As multiple indicators and tests are needed to assess the health of the soil adequately, simply listing a multitude of numerical values of the indicators may be too overwhelming for non-soil experts to draw a conclusion about soil management. Moreover, the results may be difficult to assess or translate into something meaningful, such as mitigation concerns and options. Once the individual soil health indicators are interpreted, the results should be integrated or aggregated to effectively inform farmers about the impact of management practices on soil health. This integration can be done either numerically or graphically.

2.5.1. Numerical representation

According to Rinot *et al* [81], the integration of multiple quantitative indicators into a numerical soil health index can be achieved using either (i) additive or (ii) weighted-additive methods. Additive approaches, which yield a number between 1 and 10, treat each indicator as an equal contributor. However, this is not truly representative of the complexity of the soil [156, 233]. The more sophisticated approach is to assign specific weights to individual indicators, depending on (a) expert judgement, (b) the indicators' importance in contributing to a specific soil function or service, or (c) based on quantitative techniques used to derive the minimum data set [142, 145, 154]. Hussain *et al* [5] compared various soil health indicator integration methods. Common numerical methods include the Comprehensive Assessment of Soil Health [234], the Soil Management Assessment Framework [148], and others [201, 235–242]. Several visual soil examination methods can also be used to provide a soil health index, such as the Muenchberg Soil Quality Rating [106]. Despite all of these approaches, the creation of numerical soil health indices remains controversial. The aggregation of multiple indicators into a single index can result in the loss of detailed information. Given the vast array of functions provided by soils, the trade-offs and synergies between indicators would no longer be apparent. Huge threats, such as erosion, could be overlooked if the relevant indicators of aggregate stability or root biomass are combined into a single score alongside other indicators designed to assess different threats. Moreover, challenges arise when converting quantitative and qualitative, or continuous and categorical data points, as assigning absolute and exact values is subjective and can have a significant impact on the index [27].

2.5.2. Graphical representation

Instead of developing an overall soil health index, some studies use a mixed approach combining numerical and graphical representations of soil health. Here, the individual numerical values of the soil health indicators are supplemented by colour coding, e.g. according to a traffic light system in which the colours indicate low, sufficient or excessive values. Beyond the colour-coded numerical values, various types of diagrams are available for the simple visualization of individual soil health indicators, such as spider or amoeba diagrams, or parallel coordinate plots [243, 244]. These compact and concise ways allow individual indicators to be compared with reference values in a simple graphical manner without the need to summarise the indicators into indices. This might facilitate communication of the soil health assessment between diverse stakeholders without losing information, but might also be a source of confusion. The impact of management decisions on individual attributes can be readily conveyed through such diagrams, for instance, by comparing the area coverage of polygons in the spider diagram [27].

To summarise, this section covers requirements, indicators, interpretation and integration schemes. This study examines the latest, farmer-centred, soil health tests, and discusses tests that are more suitable for use by farmers. The in-depth analysis and comparison in table 4 summarises the current state of research on soil health tests suitable for farmers in SSA. While scientifically based tests tend to provide more accurate and reliable results, tests based on farmers' knowledge have advantages in terms of time and cost efficiency. Reflecting on the current challenges and limitations farmers face in SSA outlined in section 1.5 and the findings of this section, a significant research gap remains; the provision of more accurate yet accessible methods to enable farmers to assess soil health more reliably. This applies in particular to key soil health indicators, such as SOC.

3. Nature-based Solutions to improve soil health in sub-Saharan African farmlands

Once farmers have assessed the health of their soil, they must be able to make appropriate management decisions to maintain or improve soil health and biomass production. Alongside the amount of C input, agricultural management is considered the most important factor for SOC accumulation, which influences nutrient cycling, soil structure and plant growth. This is crucial for maintaining a healthy soil [67]. In order to enable sustainable development in SSA, agriculture must shift from unsustainable and intensive farming methods to accessible and sustainable NbS.

3.1. Benefits of Nature-based Solutions

As described by Seddon *et al* [59, 245], NbSs have the capacity to reduce the vulnerability of interconnected ecological and socio-economic systems to environmental shocks in three different ways; the reduction of exposure to climate hazards, the reduction of sensitivity to adverse impacts and the building of adaptive capacity [59, 246, 247]. These benefits have already been demonstrated in many case studies around the world. For example, farmers in Malawi increased yield and resilience to soil threats through intercropping maize with nitrogen-fixing trees at minimal cost, saving the equivalent of USD11.6 million annually in nitrogen-based inorganic fertiliser [248, 249]. A review of NbS in arid and semi-arid areas of Africa, including countries such as Ethiopia, Kenya and South Africa, highlighted the successful adoption of NbS in terms of socio-economic benefits, sustainable resource use, resource enhancement and conservation, as well as infrastructure sustainability and ecosystem resilience. The measures included solutions, such as water harvesting structures, afforestation and agroforestry, some of which were developed jointly with local communities, incorporating their indigenous knowledge through stakeholder engagement workshops. This involvement significantly increased the effectiveness of the NbS interventions [250]. These examples demonstrate that in the agricultural context, NbS can:

- offer low-cost solutions, especially to a vulnerable society [20, 245];
- maintain and enhance yield in drier, more variable climates [245, 251, 252];
- benefit the water supply [245, 253];
- benefit soil health, soil moisture and biodiversity [75, 254];
- reduce risks, such as flooding, erosion and water scarcity, mitigate climate change, and conserve land, water and biodiversity [254, 255];
- provide multiple other benefits [20, 44, 59, 67, 75, 248, 256–268].

When implemented appropriately, NbS can offer a 'triple-win' effect for people, planet and economy [20, 44, 245]. This makes NbS extremely valuable pathways for SSA farmers, both now and in the future.

3.2. Evaluation of Nature-based Solutions

Despite the variety of solutions and their numerous benefits, there is no single silver bullet that can increase farmers' resilience to all soil threats in isolation. Each location (in different climate zones, ecosystems or regions) and each farmer (with different pressures and priorities) requires specific practices; in essence, solutions which are suitable for a particular farm in Malawi may not be applicable elsewhere in SSA, or even for their nearest neighbour [44].

In order to identify the range of suitable, sustainable agricultural practices, table 5 lists criteria that are used to evaluate the practices [269]. The criteria reflect possible motivations and key aspects for farmers to implement NbS, also drawing on the soil-related ecosystem services from table 1. These criteria can be used to determine whether a practice can be classified as a NbS and what benefits it offers. Using these metrics, potential NbS, which are listed in table 6 and compiled from various resources ([268–271]), can be assessed. In this example for Ethiopia, each NbS is compared to the baseline, corresponding to conventional agriculture as usually practised by Ethiopian smallholder farmers. The baseline refers to mixed crop-livestock agricultural systems, where livestock mainly graze on communal land, and crop rotation is practised on arable land using a small amount of chemical fertilisers, herbicides and pesticides. In the baseline case, the work on the farm is carried out without bringing in external labour. Similar to the assessment of soil health tests, it can be assumed that, although this assessment refers to suitability in the Ethiopian context, NbS are equally applicable and effective in other SSA contexts. This assumption is supported by the fact that the sources provided in table 6 is compiled from literature sources that mainly cover SSA. Hence, there are multiple practices with great potential for farmers in SSA (RQ2), particularly those with strong advantages in terms of the categories labour, finance and biomass production in table 6. However, it must be emphasised that the most suitable solution for each individual farmer (and each individual field) depends on the farmer's circumstances, constraints and priorities. Accordingly, the choice is highly context-dependent.

If a household is short of labour, reduced tillage or residue retention are beneficial. The reduction of tillage to no or minimal tillage saves time compared to conventional agriculture and reduces erosion. Furthermore, the practice could benefit soil health, (above-ground) biodiversity conservation, and water quality and cycling. This improves the climate resilience of the farming system [275, 278, 279]. Countering this, however, is the value of tillage for weed control and the incorporation of organic residues that may otherwise be consumed by grazing livestock or surface fauna. Similar to the reduction of tillage, the retention of residues, e.g. straw incorporation, reduces the amount of labour needed and soil erosion. However, retaining residues in the field could lead to income losses, as feed and/or fodder for animals may have to be purchased externally [283, 317].

On the other hand, if a farming household is short of finances, mixed cropping, companion cropping, intercropping, terracing or biochar made on-farm using a soil pit should be prioritised. The use of mixed cropping systems provides farmers with numerous benefits, as has already been demonstrated in Ethiopia [318, 319] and Rwanda [320], ranging from higher crop and biomass yields to reduced erosion, and pest and disease control [271, 272]. Although additional crops or legumes would need to be purchased initially, seeds could be retained for subsequent years to reduce costs. When implemented appropriately, this type of NbS offers a unique opportunity to increase the resource use efficiency of the area, as other plants, such as legumes (e.g. clover or cowpeas), can be grown alongside main crops, such as maize, without requiring additional space or extensive nutrients. However, avoidance of competition between plants for resources, such as water, light and nutrients, requires careful selection of plants and appropriate cropping design [321]. If a household is short of finances and practices agriculture on (steep) hillsides, terracing could be particularly beneficial. Terraces do not require large investments, but do involve a considerable amount of work for construction and maintenance. The terraces are built by digging soil from down to upper slopes, in some cases stabilising them with stones or branches. They are of great benefit to the soil, reducing erosion, increasing water retention, regulating the climate and improving resilience through C storage [280–282]. Biochar can improve retention of water and nutrients, so improving crop yield. If biochar is made on-farm using a no-cost soil pit from unused residues, such as rice husks, it can significantly reduce the pressure on household finances. However, this also requires considerable labour to produce the biochar so more costly options might be preferred. In cases where financial resources are scarce, smallholders could draw on climate finance mechanisms or micro-credit programmes to support the introduction of NbS, thereby reducing upfront costs while improving climate resilience [322–324].

If the key priority is to maximise production, different methods can be considered depending on the availability of resources and location. Soil-conservation methods, such as terraces, offer advantages for a farm located in hilly terrain. In these locations, agroforestry systems could be of even greater benefit, not only reducing erosion, but also diversifying sources of income [34, 273]. These systems

Table 5. Heatmap legend indicating the suitability of NbSs. The suitability of the solutions is compared with a baseline. This baseline refers to mixed crop-livestock agricultural systems, where livestock mainly graze on communal land, and crop rotation is practised on arable land involving chemical/inorganic fertilizers, herbicides and pesticides. In the baseline case, the work on the farm is carried out without external assistance. The positive (P) and negative (N) category refer to solutions which provide advantages and disadvantages over the baseline, whereas a neutral (0) rating indicates same behaviour and a variable (V) rating an unclear behaviour compared to the baseline. The description (part 1) is to be combined with only one of the categories, either P, 0, N or V, and completed with description (part 2).

Category	Criterion	Description (Part 1)	Positive (P)	Neutral (0)	Negative (N)	Variable (V)	Description (Part 2)
Labour	Establishment time	The establishment of the practice	*reduces*	*does not affect*	*increases*	*reduces or increases*	the total working time (labour).
	Operating time	The operating of the practice	*reduces*	*does not affect*	*increases*	*reduces or increases*	the total working time (labour).
Finance	Establishment cost	The establishment of the practice	*reduces*	*does not affect*	*increases*	*reduces or increases*	the total cost excluding labour to avoid double-counting.
	Operating cost	The operating of the practice	*reduces*	*does not affect*	*increases*	*reduces or increases*	the total cost excluding labour to avoid double-counting.
	Net income	The practice	*increases*	*does not affect*	*reduces*	*increases or reduces*	total net income after costs.
Production	Crop production area	The practice	*increases*	*does not affect*	*reduces*	*increases or reduces*	the total area available for cropping.
	Crop yield	The practice	*increases*	*does not affect*	*reduces*	*increases or reduces*	the total crop yield across the farmed area.
	Biomass production	The practice	*increases*	*does not affect*	*reduces*	*increases or reduces*	the total biomass production, including crops, fruit, etc.
	Pest & disease control	The practice	*reduces*	*does not affect*	*increases*	*reduces or increases*	the chance of pest and disease.
	Climate resilience	The practice	*increases*	*does not affect*	*reduces*	*increases or reduces*	the farm's resilience to extreme weather events.
Soil & water	Soil health	The practice	*increases*	*does not affect*	*reduces*	*increases or reduces*	the health of soil.
	Erosion control	The practice	*reduces*	*does not affect*	*increases*	*reduces or increases*	the chance of erosion.
	Water quality & supply	The practice	*increases*	*does not affect*	*reduces*	*increases or reduces*	the quality, cycling and supply of water.
Environment	Biodiversity conservation	The practice	*increases*	*does not affect*	*reduces*	*increases or reduces*	the above-ground biodiversity.
	Climate regulation	The practice	*helps*	*does not affect*	*hinders*	*helps or hinders*	climate regulation through e.g. carbon sequestration.

Table 6. On-farm practices potentially considered as nature-based solutions in their specific setting evaluated against criteria relevant for the uptake of nature-based solutions in Ethiopian farmlands. The suitability of the solutions is compared with a baseline. This baseline refers to mixed crop-livestock agricultural systems, where livestock mainly graze on communal land, and crop rotation is practised on arable land involving chemical/inorganic fertilizers, herbicides and pesticides. In the baseline case, the work on the farm is carried out without external assistance. The positive (P) and negative (N) categories refer to solutions which provide advantages and disadvantages over the baseline, whereas a neutral (0) rating indicates same behaviour and a variable (V) rating an unclear behaviour compared to the baseline. The practices are sorted by their impact from top to bottom, with more positive and less negative impacts being better. The corresponding legend can be found in table 5.

	Labour		Finances			Production					Soil & water			Environment		
Potential nature-based solution	Establishment time	Operating time	Establishment cost	Operating cost	Net income	Crop production area	Crop yield	Biomass production	Pest & Disease control	Climate resilience	Soil health	Erosion control	Water quality & supply	Biodiversity conservation	Climate regulation	Source(s)
Mixed crop, companion cropping, intercropping	0 [1]	N [2]	0 [1]	0 [3]	P [4]	P [5]	P [6]	P [7]	P [8]	P [9]	P [10]	P [11]	P [12]	P [13]	P [14]	[271, 272]
Agroforestry	N [15]	P [16]	N [17]	P [18]	P [19]	N [20]	P [21]	P [22]	P [23]	P [24]	P [25]	P [26]	P [27]	P [28]	P [29]	[34, 273]
Crop diversification	0 [1]	0 [30]	N [31]	0 [31]	P [32]	0 [33]	P [34]	P [34]	P [35]	P [36]	P [37]	P [38]	P [39]	P [40]	P [41]	[274, 275]
Cover and catch crops	0 [1]	N [42]	0 [1]	N [42]	P [4]	0 [43]	P [44]	P [45]	P [8]	P [9]	P [10]	P [11]	P [12]	P [13]	P [14]	[276, 277]
No (zero-tillage) or minimal (conservation) tillage[a]	0 [1]	P [46]	0 [1]	P [46]	V [47]	0 [33]	V [48]	V [48]	V [49]	P [36]	P [50]	P [51]	P [52]	P [53]	P [54]	[275, 278, 279]
Soil-water conservation—Terraces	N [55]	N [56]	0 [57]	0 [57]	P [58]	P [59]	P [59]	P [59]	0 [60]	P [36]	P [61]	P [11]	P [62]	P [63]	P [41]	[280–282]
Biochar (made on farm)	0 [64]	N [65]	V [66]	0 [67]	P [68]	0 [33]	P [69]	P [70]	0 [71]	P [36]	P [72]	P [73]	P [74]	0 [75]	P [41]	[283–285]
Organic manure/compost (made on farm)	0 [76]	N [65]	0 [76]	V [77]	V [78]	0 [33]	P [69]	P [70]	0 [71]	P [36]	P [72]	P [73]	P [74]	0 [75]	P [41]	[286–288]
Residue retention	0 [1]	P [79]	0 [1]	N [80]	V [81]	0 [33]	P [69]	P [70]	N [82]	P [36]	P [72]	P [73]	P [74]	0 [75]	P [41]	[289, 290]
Water harvesting (e.g. ponds, tanks, gutters)	N [55]	N [56]	V [83]	0 [83]	P [84]	0 [85]	P [84]	P [84]	0 [60]	P [36]	P [86]	0 [87]	P [88]	P [89]	P [41]	[291–293]
Biochar (bought in)	0 [1]	N [65]	0 [1]	N [90]	V [91]	0 [33]	P [69]	P [70]	0 [71]	P [36]	P [72]	P [73]	P [74]	0 [75]	P [41]	[283–285]
Forestry	N [15]	P [16]	N [17]	P [18]	V [92]	N [20]	N [20]	V [93]	P [23]	P [24]	P [25]	P [26]	P [27]	P [28]	P [29]	[294, 295]
Organic manure/compost (bought in)	0 [1]	N [65]	0 [1]	N [90]	V [94]	0 [33]	P [69]	P [70]	0 [71]	P [36]	P [72]	P [73]	P [74]	0 [75]	P [41]	[286–288]
Field margins, buffer or grass strips	0 [95]	P [16]	0 [96]	P [97]	N [98]	N [20]	N [20]	N [20]	V [99]	P [100]	P [25]	P [11]	P [62]	P [28]	P [101]	[296, 297]
Soil-water conservation—Bunds, trenches	N [55]	N [56]	0 [102]	0 [102]	V [103]	N [104]	V [105]	V [106]	0 [60]	P [36]	P [61]	P [11]	P [62]	P [63]	P [41]	[280–282]
No herbicides/pesticides	0 [1]	P [107]	0 [1]	P [108]	N [109]	0 [33]	N [110]	N [110]	N [111]	N [112]	N [112]	N [112]	N [112]	P [113]	V [114]	[67, 298]
No inorganic fertilizer	0 [1]	P [107]	0 [1]	P [108]	N [109]	0 [33]	N [115]	N [116]	0 [117]	N [112]	N [112]	N [112]	N [112]	0 [118]	V [114]	[67, 299]

[a] Assuming increase in SOC

[1] No need for establishment

[2] More labour required to plant multiple crop species

[3] Different costs for seeds than if only monoculture is sown, but seeds can be retained for future years

[4] Higher biomass production and crop yield through improved soil health, water cycling and biodiversity

[5] Use of area between main crops which cannot be used otherwise

[6] Use of area between crops improves crop yield as well as the impact of additional crops on main crops

[7] Use of area between crops improves total biomass

(Continued.)

Table 6. (Continued.)

[8] Pest and diseases reduced through breaking up monoculture or arable crop cycles [29, 300]

[9] Increased OM inputs and storage of nutrients stabilise soils and improve their resilience against weather extremes

[10] Increased OM inputs and storage of nutrients allow soil structure to develop

[11] Reduce run-off during heavy rainfall periods

[12] Reduced evaporation and run-off through soil cover and therefore increased amount of infiltrated water to replenish groundwater

[13] Greater crop variety harbours more diverse flora and fauna

[14] Increased OM and nutrient input and reduced susceptibility to erosion lead to increased carbon storage

[15] Requires more labour to establish than with arable crops

[16] Less labour required to maintain than with arable crops

[17] Trees need to be purchased

[18] Forestry does not have annual fertilizer, seed or pesticide costs unlike arable farming

[19] Higher biomass production

[20] Arable land used up by non-arable areas or plants other than main crops

[21] Shading from trees can provide a better environment for crop growth as well as improving soil structure [252, 301, 302]

[22] Better crop yield and tree growth

[23] Blocks of forestry break up habitats for arable pest and diseases in surrounding arable land [294, 303]

[24] Deep roots and perennial growth of trees make them more climate resilient to e.g. droughts and floods, than annual crops

[25] Increased OM inputs and reduced disturbance through tillage allow soil structure to develop

[26] Roots stabilise soil structure [34, 303, 304]

[27] Trees increase water retention, reduce evaporation, increase water cycling and supply through deeper roots (depends on tree species, e.g. eucalyptus is water-hungry) [303, 305]

[28] Non-arable areas provide habitat for more species than arable monoculture

[29] Trees store carbon, both in plant and soil

[30] Similar labour required as for sowing usual crops

[31] Seeds bought in initially, but could be retained for following years

[32] Greater soil health supports growth of plants

[33] No impact on land available for cropping

[34] Greater diversity reduces erosion and improves soil health as well as reducing pests and diseases

[35] Greater diversity disrupts pest cycles from main crops

[36] Improved soil health

[37] Different root architectures stabilise soil structure and support belowground biodiversity

[38] Different root architectures stabilise soil structure

[39] Different root architectures and improved soil health support cycling of water

[40] Greater diversity provides habitat for more/different fauna

[41] Improved soil health supports carbon sequestration

[42] Higher labour and costs due to extra seed than if arable land were left fallow

[43] Crops grown sequentially with arable crops

[44] Capture of nutrients through cover/catch crops supports growth of main crops

[45] Improved crop yield

[46] Less equipment required than for conventional tillage

[47] Reduced operating time and cost as well as improved soil health can increase profit, however diseases such as weed can reduce short-term crop yield

[48] No direct impact, however potential indirect impact through greater weed infestation or positive impact on soil health

[49] With good management, reduced tillage could reduce pests and diseases, but can also result in increased weed infestation and harbour more pests [306, 307]

[50] Reduced soil disturbance and increased OM input through crop residue on surface allow soil structure to develop

(Continued.)

Table 6. (Continued.)

[51] Reduced soil disturbance allows soil structure to develop
[52] Reduced run-off improves water retention and reduces evaporation
[53] Crop residues left on the surface harbour fauna
[54] Reduced soil disturbance minimizes SOC to be released
[55] Initial implementation requires labour
[56] Maintenance of structures requires labour
[57] Constructed by digging soil from down slope to upper slopes, sometimes stabilised by stones from the field
[58] Potentially higher crop yield and biomass production and improved soil health benefits crop growth especially in the long-term
[59] Increases area available for cropping on steep slopes
[60] Minimal impact on pest and diseases
[61] Reduced run-off supports soil structure and therefore soil health
[62] Reduce run-off and therefore increased water retention and higher amount of infiltration
[63] Improved soil structure through reduced run-off provides more habitat for flora and fauna
[64] Requires minimal labour to set up biochar production, e.g. in biochar kiln or in soil pit
[65] Labour required for application
[66] Extra cost is required if biochar kiln is used, but not if biochar is prepared in soil pit
[67] Biochar made from material/residues on the farm not needed for other purposes (e.g.animal feeds)
[68] Increased crop production increases annual net income
[69] Increased OM input and cation exchange capacity improve crop growth by increasing the ability to hold more nutrients [308, 309]
[70] Increased crop growth improves biomass production
[71] No effect on pests and diseases
[72] Increased OM input supports soil health
[73] Increased OM input improves soil structure [286, 310, 311]
[74] Improved soil structure supports water cycling
[75] No direct impact on aboveground biodiversity
[76] Most composting methods do not require additional equipment
[77] No costs when applying manures/composts, but decreased benefits of using manures for other purposes
[78] Reduces options for other uses of manures, but improved soil health could improve crop yield especially in the long-term
[79] Reduced labour as crop residues remain on arable land
[80] Reduced benefits as residues cannot be used for other purposes
[81] Income could be reduced through not selling or using crop residues, but improved soil health could improve crop yield especially over the long-term
[82] Can results in increase in pests such as rodents [312]
[83] Tanks and guttering requires initial investment, but ponds are usually constructed by simply digging to impermeable layer, with subsequent operating costs likely to be minimal
[84] Collected water could be used to irrigate plants, thereby increasing crop yields
[85] Measures are usually built on communal ground, therefore they do not affect the land available for individual farmers

(Continued.)

Table 6. (Continued.)

86 Improved water supply increases plant growth and so also plant inputs increasing soil OM
87 No direct impact on erosion
88 Improved water cycling and supply through increased water availability, unless water is used for other means
89 Ponds harbour diverse flora and fauna, whereas water available from guttering could improve soil health and therefore harbour more/different flora and fauna
90 Purchase increases annual costs
91 Increased soil health and crop production can outweigh additional costs and labour, but this is not always the case (e.g. depends on economy, market, material etc.) [313]
92 Income from annual crop yield is reduced, however, trees provide a long-term investment; annual income could be increased if fruit trees are grown;
93 Annual biomass production could be more or less, depends on tree species, growth profile, and other factors
94 Costs of buying manure reduces income, but improved soil health could improve crop yield especially in the long-term
95 If sown, similar labour required as for arable crops
96 If sown, similar cost of seeds as for arable crops
97 If not ploughed up, no need for additional seeding in subsequent years
98 Lower biomass production
99 Strips could harbour pests or break up habitats to reduce pests in arable monocultures
100 Perennial plants are more resilient to climate extremes than annual crops
101 Reduced cultivated areas increases carbon storage
102 Compared to other water-related measures, they require only a small amount of material available on farms such as stones or branches for initial construction and maintenance
103 Reduced due to less land available for cropping or improved due to improved water retention, crop growth and additional biomass on bunds or in trenches
104 Takes away land from cropping
105 Less land available for cropping but improved water retention is likely to benefit crop growth
106 Less land available for cropping but improved water retention could benefit crop growth and additional biomass can be produced on bunds or in trenches
107 No application required
108 No need for annual purchases
109 Less money spent on fertilizers, but reduced crop production
110 Increased pests and diseases
111 No control of pests and diseases
112 Reduced crop growth results in lower organic inputs which breaks down soil structure
113 Other species are able to proliferate
114 Reduced carbon emissions due to fertilizer production but increased loss of carbon due to lower yields
115 Less nutrients available
116 Less nutrients available for crop growth
117 No direct impact on pests and diseases
118 Controlled manually, no direct impact of fertilizers [314–316]

provide benefits in all topographies by regulating field-scale microclimate, improving soil structure and reducing water evaporation. For example, agroforestry in Ethiopia has been observed to increase water infiltration and reduce catchment runoff by up to 81% [34]. In many cases in SSA, it is reported that trees increase the crop or livestock production, thereby improving nutrition and livelihoods [34]. Regardless of the terrain, cropping regimes, such as mixed cropping, companion cropping, intercropping, diversification of crops, or cover and catch crops, can help to improve crop yield and biomass production. Diversifying crops can make better use of the land area and provide alternative sources of nutrients, which has a positive impact on yield, water, soil and income [274, 275, 325]. Diverse crops might include underutilised, native or indigenous plants, which can have significant additional benefits for biodiversity [274, 275]. Crop diversification can require the purchase of additional seeds, so increasing costs in the first year, but retention of seeds in subsequent years can avoid these extra costs over the long-term. Cover and catch crops are grown between main crops, with cover crops avoiding bare soil, so reducing erosion and loss of nutrients, while catch crops grow rapidly to take up excess nutrients and prevent them from leaching into the groundwater [67, 326–328]. These practices help to reduce erosion, increase resilience to pests and diseases and can increase crop productivity, income, livelihoods, and climate resilience and regulation [329–331]. In addition to the various cropping regimes, organic fertilisers, such as biochar, manure or compost, can also lead to higher crop yields, thanks to healthier soil resulting from the supply of organic matter and nutrients [283–288]. If they are derived from unused wastes on-farm, this can be done with no additional cost to the farm. Despite the numerous advantages and their potential, studies show that organic resources are applied in insufficient quantites in SSA [332], and across a farm they tend to be applied more in home gardens where higher value crops are grown [226]. Further expansion of this practice could be challenging. This is because organic resources, such as manure, are often important energy sources in SSA [286–288, 332, 333], and so availability may be limited.

In addition to the nature-based methods listed in table 6, which are aimed directly at individual farms, there are also other valuable community level methods from which farmers can benefit indirectly. These include, exclosures on degraded non-productive arable land, and community ponds. These methods are often implemented on communal ground to benefit the entire village. Farmers can use water from the pond or might be given permission to collect biomass from exclosure areas to feed their animals during periods of extreme drought [334, 335].

Despite the many advantages of these nature-based practices, it is important to acknowledge that it is impossible to determine in advance whether these practices can be classified as NbS according to the IUCN's standard [67]. This is because the classification depends on the final implementation of each measure in a specific context. Sensitive aspects, such as cultural integrity, depend entirely on the respective community and its circumstances. For instance, valuable resources, such as organic manures, often remain unused in Borana, southern Ethiopia, because of cultural and traditional beliefs [336]. Accordingly, a practice must be designed to ensure the rights, values and knowledge of local and indigenous peoples are fully respected [59, 245, 337, 338]. This could potentially be achieved through co-design tailored to the specific needs of communities through participatory engagement, with scientists and community members working together to identify problems, assess causes and share knowledge in order to take action. This could lead to community-driven change in land management, as has been implemented in an agro-pastoral community in East Africa [339]. Conversely, the availability of necessary resources (e.g. specific tree seedlings for agroforestry systems) could influence the final selection of practices. Furthermore, the applicability and suitability of solutions, such as soil and water conservation measures, depend on how much erosion is taking place. In flat areas, for example, stone bunds are less suitable than other measures to improve soil health.

In conclusion, it is essential to determine the cultural integrity, availability and applicability alongside the criteria in table 5 for each practice in each individual location [44]. Beyond that, each farmer's socio-economic conditions require tailored solutions depending on factors, such as financial resources, available livestock and the amount of biomass used as fuel [44]. Reflecting on the threatened ecosystem services and the cycle of soil degradation and social deprivation described in section 1, as well as the findings from this section, methods must be found to identify the most suitable (set of) NbS for improving the soil for a farmer in advance. To this end, modelling the impact of NbS on soil and the entire farm can be extremely valuable. Provided it is technologically feasible and smartphones are available, the models could be used to advise farmers. If smartphones or similar devices are not available, the results of modelling exercises could be communicated to farmers through agricultural advisors.

4. Predicting the impact of Nature-based Solutions on soil health and farmers in sub-Saharan African farmlands

When selecting and implementing specific practices from a wide range of NbSs in LMICs, where vital services, such as long-term sustainable food production, are at stake, risks need to be minimised to the greatest extent possible. Therefore, it is valuable to predict the potential impact of a NbS before it is implemented. This enables the most suitable solution for a given situation to be identified in advance, therefore reducing the need for experimentation with different practices in each location. This can help farmers make more informed decisions by providing actionable recommendations on which sustainable agricultural practices to adopt. As a result, management risk is potentially reduced whilst environmental and social outcomes are improved. For NbS to be beneficial for long-term sustainability, not only environmental but also societal challenges need to be considered. Approaches that bridge benefits of mitigation strategies, with socio-economic and cultural impacts to farmers, are scant but an important step going forward [340]. This is because the demand for ecosystem services is primarily determined by socio-economic factors, and its quantification has mainly been attempted by economists [83]. However, the aim of this review is to identify ways to predict the effects of NbS on soil health and on ecosystem services and functions. Although purely socio-economic models are beyond the scope of this review, interdisciplinary models are considered here, as they could provide important information to the farmer.

4.1. Ecological modelling

The ecological impact of NbS can be obtained through a variety of models. These vary based on:

- ecosystem services and soil functions of main concern [82, 83, 341],
- soil health indicators of major concern,
- scale [82, 84, 341],
- underlying scope and formulation [82, 84, 341, 342],
- underlying principle [83, 343],
- contained environmental covariates.

The selection of suitable models depends primarily on the local context in terms of the targeted services, the modelling scale and the available soil health indicators. Therefore, models should address ecosystem services that are of central concern to farmers in SSA and are to be tackled by NbS. Models which relate to biomass production and soil erosion are of primary interest. Particularly, organic matter and element cycling models are of great relevance due to their importance in the production of biomass and erosion control [82, 84, 344].

The soil functions and ecosystem services dictate which soil health indicators are suitable for modelling. In turn, the methods available to farmers in SSA for assessing soil health indicators govern the selection of applicable models. For example, models, such as Agro-C [345], which require total soil nitrogen levels as input data, cannot be considered as it is difficult to estimate nitrogen using only simple methods. The models benefit from parameterisation with the simple soil health indicators that are accessible to farmers, alongside more quantitative approaches. By integrating data obtained from those soil health indicators assessed across multiple farms, improved regional decisions would be feasible, and could help to guide interventions and policy changes.

Beyond that, the modelling scale needs to be carefully considered to maximise the relevance of the models for smallholder farmers. Microsite, ecosystem, plot or field scale approaches allow for detailed modelling of processes in the field. By contrast, models on farm, landscape, catchment, regional, national or global scales offer assessments of large-scale dynamics, prediction of climate change with dynamic soil feedback and the simulation of global scenarios [85]. In this context, models on a scale up to the farm level are most relevant to smallholder farmers, in particular, those capable of considering processes across the entire farm.

While the aforementioned factors determine the range of models to be considered, the formulation of the models and the availability of data are decisive in identifying which models are ultimately considered most valuable.

4.1.1. Process-based models

In soil science, the term *'process-based models'* refers to models that are based on a conceptual understanding of soil mechanisms. Each important process is simulated, usually by one or more equations, and these equations are combined to provide an overall representation of the system. These mechanistic models serve to identify, extrapolate and predict long-term temporal and spatial changes in the soil based on internal, external, natural and anthropogenic factors [127]. For example, RothC is a process-based model, which simulates the carbon flows between different soil pools based on decomposition rates [346]. It can be used to predict SOC dynamics under different climate and land management scenarios [346]. A non-exhaustive compilation of such models can be found in table 7. Their application to represent ecological phenomena offers specific advantages in terms of transparency, physical consistency and suitability for specific cases [347]. However, due to the complexity of soil and computational efficiency, some process-based models are limited in their accuracy or generalizability, e.g. in predicting SOC changes over time on larger scale or across different climatic zones [127, 348–350]. In line with the rise in AI-based soil health assessment methods, the adoption of AI methods for modelling has gained notable momentum in recent years.

Table 7. Selection of process-based models to assess the ecological impact of nature-based solutions on soil health and soil-based ecosystem services and soil functions, in the context of soil organic carbon (SOC), crop yield, erosion, nitrogen (N) and phosphorus (P), based on Vereecken et al [83], Neil et al [341] and Aitkenhead [82]. To assess the potential for meeting the needs of Ethiopian farmers, models are selected based on their age, stage of development, specificity with respect to soil, their use cases, the spatial and temporal scale and the required soil health indicators as inputs for modelling.

	Use case					
Model	SOC	Crop yield	Erosion	N	P	Source
APSIM		X		X		[351]
CANDY	X			X		[352]
CENTURY	X			X	X	[353]
CERES		X				[354]
CN-SIM	X			X		[355]
DAISY	X	X		X		[356]
DAYCENT	X	X		X		[357]
DNDC	X	X		X		[358]
ECOSSE	X			X		[359]
EPIC	X	X	X	X	X	[360]
EUROSEM			X			[361]
ICBM	X					[362]
KINEROS2			X			[363]
LISEM			X			[364]
MONICA		X		X		[365]
N14C	X			X		[366]
RothC	X					[346]
RUSLE			X			[367]
SOMKO	X					[368]
STICS	X	X		X		[369]
SUNDIAL	X			X		[370]
WEPP			X			[371]
YASSO	X			X		[372]

4.1.2. Models based on artificial intelligence

In contrast to the soil health assessment, most of the AI-based methods for modelling the changes of soil health indicators belong to the category of learning and predicting. Algorithms in this category are purely data-driven approaches [124].

4.1.2.1. Data-based artificial intelligence algorithms

This type of model is trained solely on data, e.g. to recognise patterns or establish relationships between independent and dependent variables, and do not take into account any inherent understanding of the underlying processes. The training of such models depends heavily on the architecture of the model. The data is used to adjust selected parameters to minimise the difference between the predicted and the actual data values. If the model architecture and the selected parameters provide a good representation of the system, the model can be used for predictions on unseen data. A wide range of such methods have been employed, including statistical models (e.g. generalised additive models)), widely used Machine Learning approaches (e.g. random forest), and Deep Learning models (e.g. neural networks) for a range of different uses as shown in table 8 (alongside many others not mentioned here) [373–378]. A multitude of models have been implemented to predict changes in crop yield or erosion severity in different locations across different spatial and temporal scales. Furthermore, data-driven AI models, such as random forest, support vector machines and neural networks, and can be used to predict the dynamics of SOC, nitrogen and phosphorus. In many cases, AI methods are reported to be promising approaches for future research [379]. Some researchers have demonstrated greater prediction performance in classification and regression tasks [347, 348, 375, 380] through data-based AI methods compared to process-based methods. Others observe better computational efficiency in approximating behaviour of complex systems, enabling fast virtual experimentation [127, 375]. The simplicity, the uniformity in application across different tasks and the greater flexibility in architecture and parameterisation are key advantages of AI models, such as neural networks, over process-based methods when dealing with large amounts of data [126, 127, 381]. Machine Learning-based methods often operate within non-linear domains, establishing relationships between variables based solely on data rather than information derived from potentially inaccurate or incomplete process-based models. As a result, they avoid making unrealistic and/or linear assumptions. They can also infer missing data based on patterns in existing data and avoid the need for time-consuming expert annotations through automation and training methods, such as self-supervised learning [382].

However, AI that is purely based on data mostly overlooks the underlying soil processes (which could reveal new insights) [127]. It is worth noting that the performance of these AI algorithms strongly depends on the size and quality of the dataset [348]. Lastly, the limited interpretability of advanced, data-driven

Table 8. Selection of data-driven AI models to assess the ecological impact of nature-based solutions on soil organic carbon (SOC), crop yield, erosion, nitrogen (N) and phosphorus (P). The selection of widely used AI models in soil science, such as tree-based methods such as decision trees or random forests, through to neural networks, is narrowed down based on their ability to simulate various impacts of NbS on key aspects such as SOC.

	Use case				
Model	SOC	Crop yield	Erosion	N	P
Decision tree		X [383]			
Random forest	X [384]	X [373, 383, 385, 386]	X [380]	X [387]	X [388, 389]
Quantile regression forest	X [390]				
(Boosted) regression trees			X [391]		
Support vector machine	X [384]			X [387]	
Support vector regression			X [392]		
Multiple linear regression		X [373]	X [391]		
Logistic regression				X [387]	
Neural network	X [384, 393]	X [385]	X [391, 394]	X [387]	X [395]

AI methods, such as neural networks (sometimes referred to as a '*black box*') poses a significant challenge [126]. However, they constitute a powerful toolbox, particularly due to their multimodal capabilities and the integration of systems, such as large language models.

4.1.2.2. Knowledge-based artificial intelligence algorithms

A rather unexplored area for AI-supported modelling of soil health indicators, but one that promises great potential for improving the interpretability of AI methods, is the domain of reasoning and decision making [83, 124, 127]. Unlike data-based approaches, which analyse statistical patterns, knowledge-based models are rooted in logic and rely heavily on tacit and explicit knowledge. This area includes conceptual schemes, such as symbolic rule inference and expert systems. Here, knowledge is captured in the form of facts and rules that are used to construct a (partially) fixed knowledge graph model [396] or neuro-symbolic AI models [397]. A common approach is the integration of diverse knowledge into graphs, including scientific as well as local and indigenous knowledge. This could be achieved through participatory and collaborative workshops between indigenous peoples and researchers documenting lived experiences or traditions, which are usually not captured in text but rather in cultural practices, such as stories, songs, dance and lore. These are then systematically translated into formalized rules [398, 399]. The graph can then be used to classify unknown data and make informed predictions according to its logic. One of the few applications of knowledge-based systems with respect to soil health is the recognition of patterns through fuzzy logic to assess soil erosion in Ethiopia [400]. This approach aims to rank the potential for erosion rather than model potential changes resulting from erosion. Another example is the application of a conceptual model to incorporate prior knowledge into the model development for predicting the soil bulk density [401]. Again, the approach is not intended to model the changes of soil bulk density based on external or internal influences over time and/or space, but it promises to provide a more interpretable and rational form compared to classical data-mining techniques [401]. A key benefit of such approaches over classical methods is that they can typically be trained using smaller datasets, as the embedded domain knowledge restricts the search space of the optimisation task [402].

4.1.2.3. Hybrid modelling

The idea behind hybrid models is to combine different aspects, often theoretical foundations and interpretable components of physical models with the adaptability of AI methods, making them extremely relevant and versatile [403–405]. Previous research has already shown that the assimilation of biophysics and data in models is advantageous, e.g. in physics-informed neural networks or soil science-informed Machine Learning models [116, 124, 127, 347, 390, 403], differentiable programming [347], structural equation modelling [406], Bayesian belief networks [407] and geographically weighted regression kriging models [350, 408]. There are also specific applications of soil erosion models, such as the Revised Universal Soil Loss Equation (RUSLE), combined with random forests and neural networks [409], long short-term memory networks [377] or extreme gradient boosting [376]. Other models include APSIM in conjunction with random forests and multiple linear regression [373] and RothC with random forests [350, 410]. The combination of process-based and AI models could also serve as an emulator for regional crop yield changes. This allows issues, such as limited upscaling of process-based models and hallucinations of AI models, to be overcome [411, 412]. Although there is no literature currently available on the combination of process- and knowledge-based models, let alone the combination of all three (process, data and knowledge), integrating expert knowledge into modelling could be extremely valuable to future applications, especially in the expanded use of AI [124, 127, 348]. This could enable the use of previously untapped sources of information, such as the knowledge of soil scientists, but also, more importantly, the knowledge of farmers. This could be simple information about crop productivity in different agricultural areas, which could be used to evaluate process-based models or to supervise the training of data-based AI methods. It could also yield profound insights from the experiences of predecessors regarding specific practices.

The application of ecological models, including process-based models and AI models, whether data- or knowledge-based or hybrid models, offers certain advantages in terms of their accuracy and suitability for specific processes. However, their perception is limited, as soil management practices and measures are determined by overarching conditions for the entire farm. Therefore, models must consider the different flows within the farm, such as food production, animal production, labour and income. To holistically determine entire feedback loops and interrelationships, as well as effects on the soil, models should be applied in an interdisciplinary manner.

4.2. Interdisciplinary modelling

The necessity to evaluate the impact of NbS, not only in terms of specific ecosystem services, such as crop production or soil erosion and C cycling, but also on the entire agricultural operation in a so-called '*system model*', is based on the strong interrelationships between the different parts of a system. Each part of the farming system affected by management decisions is modelled, usually using very simple approaches. The impacts of one part of the system on another are described explicitly, allowing the wider consequences of decisions to be understood. For instance, the implementation of NbS to enhance soil health through the incorporation of organic matter or modifications in tillage practices influences the use of organic material or the labour available in other parts of the farm [413]. In resource-limited households, such as many smallholder farms in SSA, this influence can lead to conflicts over resources. For example, the increased use of organic fertiliser versus the amount available for other purposes, including use as fuel for households [414]. In turn, this can result in perceived or actual costs which may prevent farmers from following recommendations to improve their soils [340, 415].

Smith *et al* [340] identified a number of different modelling frameworks linking multiple modules in order to represent cross-sectional relationships. However, most of these remain focused on crop and/or livestock production [416–419]. To close this research gap, Smith *et al* [340] developed the ORATOR model, which aims to reflect household decision-making and its consequences in other areas of smallholder farms. Modified versions of the process-based models, RothC and ECOSSE, combined with other climate, water and nutrient models, establish links between soil, plant and animal production, and their joint impact on water and fuel consumption. The aforementioned factors are conditioned by and condition (i.e. bi-causal relationship) both on-farm and off-farm labour, which in turn lead to external expenditures and the total income of the farm [340].

In summary, in order to predict the impacts of NbS on soil health (RQ3), a range of models could be used. The analysis provided in this section highlights specific strengths and limitations of different models. While process-based models can provide accurate simulations within certain boundaries as they incorporate physical laws and soil processes, they are often limited in their scalability and generalizability due to incomplete description of processes. Although data-driven AI models can solve these issues by making use of large datasets, they often overlook underlying processes and are usually more difficult to interpret than process-based models. Knowledge-based models can offer greater interpretability and transparency and can be trained with smaller datasets by incorporating knowledge, but may demand time-consuming knowledge acquisition to ensure their reliability. System models are valuable methods as they integrate biophysical and socio-economic factors affecting the overall farm management, but they can be over-complex and inevitably require more assumptions to be made that affect the accuracy of modelling.

In view of the pressing need to enhance soil health, taking into account the constraints and socio-economic challenges for farmers outlined in section 1 and the findings of this section, a specific gap needs to be addressed promptly; the provision of accurate, scalable and interpretable models to predict the impact of NbS on soil and the entire farm.

5. Potential future research directions

Farmers in SSA urgently need readily accessible and affordable soil health assessments, coupled with actionable advice for NbS to enhance soil health and livelihoods. As demonstrated in previous sections, a vast landscape of potential tools and methods is available. Nevertheless, notable constraints and research gaps remain within individual domains, that need to be tackled to deliver tailored assistance to farmers.

5.1. Soil health assessment

To resolve the research gap identified in section 2 concerning the provision of more accurate yet accessible methods to assess soil health in SSA, this study outlines two prospective research directions that hold considerable promise to resolve the issue.

The first is the exploration of so far untapped indigenous knowledge. Since many of the soil health tests listed in table 4 are based on indigenous or farmer knowledge, there may be many other indicators that have yet to be recorded that could prove helpful. This argument is supported by the fact that centuries ago, indigenous communities had already adopted sustainable land management practices as systems, such as observed in Terra Preta soils [420]. Similary, there is likely to be an equally extensive body of knowledge about accurate, accessible tests to assess soil health indicators that has simply not yet been discovered or documented.

The second is the use of intelligent, holistic and technological solutions for future applications. Given the predicted increase in the availability of smartphones and similar devices, there is also a compelling rationale for exploring the potential of these tools. There are a few successful examples, such as the virtual agronomist [421], which demonstrate the potential use of smartphones in agricultural contexts to improve the soil management together with farmers in SSA. Table 4 lists solutions that could be used to assess individual soil indicators with a reasonable degree of accuracy. If smartphones become more widely available in SSA, such solutions should assess multiple indicators rather than just single factors to enable a streamlined approach and holistically assess soil health.

5.2. Use of models to inform soil health improvement through Nature-based Solutions

To successfully fill the research gap in the provision of accurate, scalable and interpretable models to predict the impacts of NbS on soils and the farm (section 4), a range of perspectives and conditions must be considered. Therefore, the ecological model of soil health should be embedded within a socio-economic framework to describe the impacts on the whole farm. This will allow soil health to be linked to social and economic factors to ensure that quantifiable benefits outweigh costs. Ideally, the ecological modelling component itself would consist of a suite of methods with different functions, including process-based models (see table 7) and AI methods based on data (see table 8) and farmers' knowledge. Such a hybrid modelling approach allows the weaknesses of individual methods to be mitigated and their strengths to be combined.

The gaps outlined in the assessment and the modelling of soil health can, of course, be addressed in isolation. However, the farmers need to gain a holistic understanding by the results of their own soil health assessment being fed directly into the models to provide actionable recommendations for improving overall soil health. This study therefore suggests that research should focus on the assessment and modelling of soil health as components of a holistic decision-support framework [421–423]. With access to smartphones, such a framework could facilitate participatory soil testing for site-specific diagnoses and long-term impact assessments, giving farmers greater autonomy. In instances where farmers lack access to smart devices, agricultural advisors could provide assistance to provide recommendations for farmers.

6. Conclusion

Soils provide a wide range of ecosystem services that are of great importance to humanity, such as biomass production, C sequestration, erosion control and climate change mitigation. Soils around the world are at risk, especially in many countries in SSA, which are threatened by severe soil degradation due to factors including climate change, soil erosion and suboptimal land management. The health of soil needs to be improved to ensure long-term, sustainable crop production and livelihoods. Nature-based solutions offer significant benefits for soil health while also improving crop production and livelihoods.

A series of steps must be taken to translate the findings of this review into actionable policy directives and advice for farmers and other key stakeholders. This can only be achieved through long-term integrative and participatory initiatives involving farmers, agricultural advisors, non-governmental organisations and policymakers. To start this process, farmers must first be able to easily assess soil health; this could be done using the tests described in this study. When combined with modelling, this could provide farmers with actionable, farm-specific recommendations for improving soil health. This process should be facilitated through governments and researchers by providing farmers with practical field guides containing simple instructions on tests and NbSs, or offering support in using smartphones for soil assessment and improvement. In order to guarantee fair and appropriate environmental as well as social outcomes, interdisciplinary studies should be conducted to establish an evidence base for the impacts of recommended practices.

First and foremost, the focus on farmer-oriented soil health tests should serve to advance decision-making regarding sustainable management practices and raise awareness of the importance of soil health. Beyond that, the subsequent adoption of NbSs is likely to bring a number of key benefits. Primarily, there is the potential to improve soil health, which in turn increases crop yields and reduces soil erosion. These effects lead to improved food security and climate resilience, respectively. Last but not least, the introduction of NbS contributes to both climate change mitigation and adaptation. This overview aims not only to facilitate the use of sustainable and climate-resilient NbSs, but also to improve farmers' livelihoods, particularly in SSA and other LMICs worldwide.

Data availability statement

No new data were created or analysed in this study.

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