Tracking Soil Health: Monitoring and Modeling the Soil-Plant System

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Abstract

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Abstract:

The assessment of soil health has evolved from focusing primary on agricultural productivity to an integrated evaluation of soil biota and biotic processes that impact soil properties. Consequently, soil health assessment has shifted from a predominantly physico-chemical approach to incorporating ecological, biological and molecular microbiology methods. These methods enable a comprehensive exploration of soil microbial community properties and their responses to environmental changes arising from climate change and anthropogenic disturbances. Despite the increasing availability of soil health indicators (physical, chemical, and biological), a holistic mechanistic linkage between indicators and soil functions across multiple spatiotemporal scales has not yet been fully established. This article reviews the state-of-the-art of soil health monitoring, focusing on understanding how soil-microbiome-plant processes contribute to feedback mechanisms and causes of changes in soil properties, as well as the impact these changes have on soil functions. Furthermore, we survey the opportunities afforded by the soil-plant digital twin approach, an integrative framework that amalgamates process-based models, Earth Observation data, data assimilation, and physics-informed machine learning, to achieve a nuanced comprehension of soil health. This review delineates the prospective trajectory for monitoring soil health by embracing a digital twin approach to systematically observe and model the soil-plant system. We further identify gaps and opportunities, and provide perspectives for future research for an enhanced understanding of the intricate interplay between soil properties, soil hydrological processes, soil-plant hydraulics, soil microbiomes, and landscape genomics.

1. Introduction

Healthy soils are indispensable for sustaining life on our planet. They provide vital provisioning, supporting and regulating ecosystem services (Babaeian et al., 2016; Vereecken et al., 2016). Soils are fundamental for the production of safe and nutritious food and they also provide essential raw materials, such as fibre and biofuels, for various human needs. Soils support nutrient cycling, which is crucial for plant growth and therefore overall (agri-)ecosystem productivity. They also support a diverse range of organisms, thereby preserving biodiversity and maintaining healthy ecosystems. In addition, soils play a crucial role in storing and purifying water, regulating water flows, and recharging aquifers. They act as a natural buffer against droughts and floods, contributing significantly to climate adaptation. Additionally, soils sequester carbon from the atmosphere, which helps mitigate greenhouse gas emissions.

It has been assessed that 60-70% of soils in Europe are in an unhealthy condition (European Commission, 2023a). This situation may likely worsen as climate change and intensified land use will make it harder to maintain healthy soils. For instance, warming of the Earth System will enhance plant growth and therefore increase litter inputs into the soil, as well as will accelerate the mineralization of soil carbon, leading to increased CO_2 emissions from soil respiration. Adding to the complexities, there are uncertainties about how elevated atmospheric CO_2, warming, and altered precipitation patterns will influence the soil carbon balance, considering nutrient limitations to primary production, microbial respiration, microbial thermal acclimation and adaptation (Hartmann and Six, 2023; Philippot et al., 2024; Robinson et al., 2019; Sullivan et al., 2022). Similarly, agriculture intensification will result in more soil compaction, surface sealing, runoff and contamination of adjacent environmental compartments such as groundwater and the atmosphere (Rillig et al., 2023). Soil-related issues such as erosion, salinization, and fertility loss, along with water management challenges, deforestation and habitat destruction, are identified as the primary environmental drivers that historically contributed to the collapse of societies (Anderson, 2005). These same problems persist today and pose significant environmental threats.

Recognizing the importance of soil health, the European Commission (EC) has launched 'A Soil Deal for Europe' mission (European Commission, 2023b) with the goal of pioneering, showcasing and accelerating the transition to healthy soils by 2030, in alignment with Green Deal commitments. This mission includes establishing a robust, harmonised soil monitoring framework (EU Soil Observatory) (Panagos et al., 2022). The concept of 'soil health' is gaining traction, highlighting soils as a crucial yet overlooked societal asset and public good (Panagos et al., 2024).

The term 'Soil Health' was introduced by Haberern in (1992), two decades after 'Soil Quality' was coined by Mausel in (1971). Since then, these two terms have often been used interchangeably (Laishram et al., 2015). However, soil health has been distinguished from soil quality, with most scientists concurring on its definition as "the continued capacity of a soil to function as a vital living ecosystem that sustains plants, animals, and humans," as defined by the U.S. Department of Agriculture Natural Resource Conservation Service (USDA-NRCS) (Norris et al., 2020). Additionally, soil health is described as "the continued capacity of soils to support ecosystem services"(European Commission, 2023b), encompassing both the intrinsic and dynamic properties of soils to function sustainably and provide ecosystem services (Bünemann et al., 2018; Lehmann et al., 2020).

It is essential to monitor soil health using a set of measurable and sensitive indicators that can reflect a soil's capacity to deliver ecosystem services (European Environement Agency, 2023; Greiner et al., 2017). This monitoring should be carried out through effective and ideally low-cost strategies that enable sufficiently high spatio-temporal monitoring frequencies. Despite the growing acceptance of the concept of soil health among scientists and policymakers, selecting relevant soil health indicators, and interpreting them in the context of soil physico-chemical and biological properties, is not straightforward (Banerjee and van der Heijden, 2023).

1.1 Soil Health Indicators

Soil health and its indicators have been studied for over three decades (Gregorich and Acton, 2012; Lehmann et al., 2020; Lehmann and Kleber, 2015). However, the definition and classification of soil health indicators (SHI), as well as their systems for sampling, measuring and evaluation, remain diverse (European Environement Agency, 2023; Moinet et al., 2023). In light of monitoring soil threats and supporting policy development, a set of common SHIs is considered for assessing soil condition, degradation, resilience, and valuable services (see Figure 1). These indicators consist of eight main categories (European Commission, 2023b): 1) presence of soil pollutants, excess nutrients and salts; 2) soil organic carbon; 3) soil structure; 4) soil biodiversity; 5) soil nutrients and pH; 6) vegetation cover; 7) landscape heterogeneity; and, 8) area of forest and other wooded lands. It is noteworthy that recent advancements in proximal and remote sensing of the land surface (Manfreda and Dor, 2023; Wang et al., 2023) have significantly improved the assessment of SHIs.

Among these indicators, SHI-1 through SHI-5 can be directly obtained from measurable soil properties mostly through field and laboratory experiments on soil samples (European Environement Agency, 2023). SHI-6 through SHI-8 are indicators related to drivers of change in soil health at landscape scales and can be operationally monitored using remote sensing techniques (spaceborne, airborne, proximal) (Angileri et al., 2023). Nevertheless, these SHIs are not always clearly distinguishable from each other, as many indicators reflect multiple soil processes, and vice versa. For instance, soil aggregation (or soil structure, being a physical indicator) results from chemical parameters (e.g., soil organic matter), mineral type (Ben Dor et al., 2022) and biological processes (Totsche et al., 2018a), as well as land use and management (as expressed by vegetation cover). Similarly, the evaluation on a soil's potential to produce biomass depends on root zone water and nutrient availabilities, the capacity for root water and nutrient uptake (a function of soil texture/structure), and the fraction of absorbed photosynthetically active radiation (external drivers, non-soil indicators) (Wang et al., 2021a; Yu et al., 2020a). Additionally, estimating soil erosion in one place and deposition of soil materials elsewhere requires a model with (non-)soil parameters and indicators such as climatic and vegetation inputs and a Digital Elevation Model (Borrelli et al., 2023).

Once measured, these SHIs are expected to be compared with specific threshold values that define soil as either 'healthy' or 'unhealthy', thereby furnishing crucial insights into soil function (Maharjan et al., 2020). Nonetheless, prominent reviews by Bünemann et al. (2018) and Lehmann et al. (2020) underscore a persisting deficiency in mechanistic links (e.g., through process-based modelling) between SHIs and soil functions (Vogel et al., 2019). Furthermore, Fierer et al. (2021) delved into the ongoing discourse surrounding the utility of soil microbial diversity and activity in assessing soil health. While an ongoing debate questions whether soil health disproportionately emphasizes either soil microbiology or physicochemical properties, the inherent synergy between the two realms remain inadequately explored (Bünemann et al., 2018; Coyne et al., 2022).

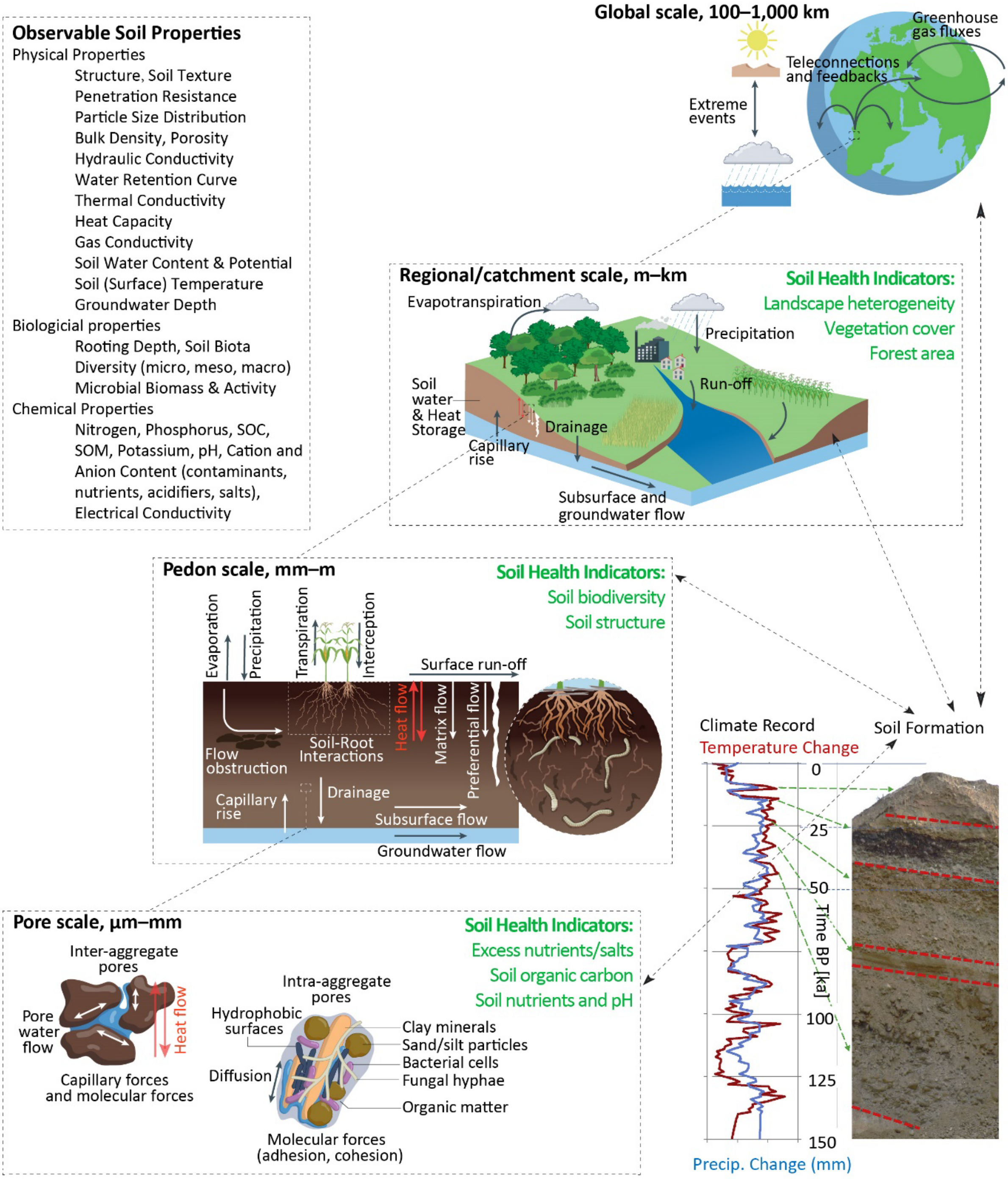


Figure 1 Soil properties, microbiome, soil hydrological processes at pore-scale, to pedon, regional (weather), and global (climate) scale (adapted from (Vereecken et al., 2022)*). Conversely, climate together with internally/externally driven deposition/erosion processes shape the soil formation: the soil column on the bottom right shows how the climate record (temperature (red) and precipitation (blue)) correlates via depositional events to sedimentary units (adopted from (Veldkamp et al., 2017)). At the same time, the specific soil formation will feed back to the local land-atmosphere interactions. The double arrows show the continuous cross-talks between soil formation and soil properties, vegetation (root development), soil fauna, as well as climate. The observable soil (physical, biological, and chemical) properties are listed (top left). The eight soil health indicators adopted by European Commission's Soil Mission* (European Commission, 2023b) *are listed with the diagrams representing the scales at which these indicators are measurable.*

1.2 Soil microorganisms as “bedrock-to-atmosphere” exchange agents

Soil formation and soil structure

Soil is a surface layer of Earth made up of mineral and organic substances and shaped by the interaction of soil-forming factors: climate, organisms, topography, parent material, time and human activities. Soil formation is a critical process in global elemental cycling through the interactions of water, minerals, and microorganisms during rock weathering (Dignac et al., 2017). This process begins with the development of porosity from the transformation of rock-forming minerals, enabling microorganisms to colonize mineral surfaces. These microbial primary colonisers include autotrophs and heterotrophs that fix carbon, and then when they die, their necromass contributes to organic matter build up and helps the forming soils to hold moisture that allow higher plants to colonize (Banwart et al., 2019). These microorganisms also accelerate the chemical dissolution of rock-forming minerals, making essential nutrients like phosphorus, magnesium, potassium, calcium, and nitrogen bioavailable for plant colonization. As plants establish themselves on rock surfaces, their roots and symbiotic mycorrhizal fungi extend into the rock's micropores, connecting photosynthetic production directly to bedrock weathering (Dignac et al., 2017) and linking plant-soil-microorganism interactions to solar energy (Wild et al., 2022).

As plants grow, they capture more solar energy and convert it into photosynthate, which supports the growth of roots, mycorrhizal fungi, and the rhizosphere microbiome, as well as the dissolution of parent rock minerals (Dignac et al., 2017). This process leads to the formation of fine-grained particles such as primary clay and organo-mineral complexes. These particles, combined with particulate organic matter (POM) from plant litter and root fragments, are bound by root and microbial exudates and fungal hyphae to form macroaggregates, microaggregates and silt-clay sized compound particles (Giannakis et al., 2017b). The stability of such soil structure is dynamically influenced by (bio)physical processes (such as, root penetration), (bio)chemical processes (such as, mineral dissolution, POM decomposition, production and consumption of exudate 'glues'), and microbial interactions (Sullivan et al., 2022; Wilpiszeski et al., 2019).

Soil microorganisms can influence the reorganization of soil particles and pores through their involvement in both the formation and destruction of soil macroaggregates (Sullivan et al., 2022). An increase in soil microbial necromass compounds can lead to pore clogging, whereas the decomposition of soil organic matter can create new soil pores (Cao et al., 2024). As a result, the soil microbiome can alter soil properties and processes, and consequently the “bedrock-to-atmosphere” exchange and feedback processes. For instance, pore clogging can reduce soil hydraulic conductivity and decrease water infiltration, while stable aggregates and micropores can enhance water retention. These changes in soil hydrological processes will inevitably affect the ecosystem water, energy, and carbon fluxes at the land-atmosphere interface. In turn, the local (micro)climate can influence the composition of soil microbial species (Bickel and Or, 2020).

Mechanistic linkages of the soil-microbiome-plant continuum

The biogeographic distribution of soil microbial communities is shaped by environmental factors such as climate conditions, vegetation cover, soil-type dependent physiochemical properties of microhabitats, as well as land use and management (Sokol et al., 2022). For example, diverse plant traits in mixed vegetation can shape the abundance and structure of belowground soil communities, via providing organic matter input as plant litter or root exudates with distinct substrate and energy resources (Coban et al., 2022). On the other hand, the heterogeneous soil microbiome impacts vegetation by modulating the bioavailability of soil nutrients for plant growth (Philippot et al., 2024). For instance, direct interactions include beneficial symbiotic relationships between plant and mycorrhizal fungi, which enhance plant nutrient uptake and formation of soil aggregates (Cao et al., 2024). These linkages within the soil-microbiome-plant continuum reflect the mechanistic connection between aboveground and belowground communities, which have been increasingly recognized as key drivers of soil and ecosystem functions, as well as their community dynamics (Faucon et al., 2017).

1.3 Soil microbiome and soil health

Soil microbial metrics

Assessing soil health often involves measuring the abundance and composition of certain microbial taxa of interest, quantifying processing rates of microbial activities, or evaluating microbial pools and their enzymatic potentials, but their mechanistic interpretation can vary significantly based on the specific context and conditions of the soil (Fierer, 2017). For example, potential activities of extracellular enzymes are often measured to infer nitrogen and phosphorus availability. However, the measured enzymatic activities could suggest either nutrient limitation or greater nutrient availability (Schloter et al., 2018). Similarly, measuring soil microbial biomass or the ratio of microbial biomass to soil organic carbon may not provide straightforward insights into soil health, given the numerous biotic and abiotic factors influencing microbial biomass changes (Cao et al., 2024).

These established microbial metrics may have utility in certain contexts; however, the mechanistic understanding supporting their application is frequently not conclusive for providing definitive guidance for management and policy decisions (Lajoie and Kembel, 2019). For instance, fungal-to-bacterial ratios have been used widely to understand nutrient cycling efficiency at ecosystem scale, even though there is limited evidence supporting clear differentiation between fungal- and bacterial-dominated pathways (Philippot et al., 2013). Therefore, the choice of biological indicators to evaluate soil health depends on available scientific evidence and mechanistic understanding, as well as the soil and the specific soil health aspects under consideration. This requires a shift from relying on a universal set of indicators to adopting a more targeted approach, choosing metrics that align with specific management or policy goals (Jansson et al., 2023).

Trait-based approach for soil microbiome

Changes in soil microbial communities can reflect variations in soil processes and alterations in biotic and abiotic factors, such as shifts in nutrient availability, soil pH, moisture and temperature, as well as soil organic carbon pools. These factors, in turn, can modify the structure of the soil microbiome. Such interactive effects illustrate the interdependent nature between the soil-microbiome-plant continuum and its environmental and climatic conditions (Hartmann and Six, 2023). It is, therefore, expected that soil microorganisms' community structure and dynamics can be inferred from measurable environmental characteristics (as functional traits) at landscape/ecosystem scales, which is termed landscape genomics (Dauphin et al., 2023; Yang, 2021). With the revolution of high-throughput molecular (multi-omics) technology, the characteristics of soil microorganisms can now be measured at the gene/enzyme, genome, guild, and community levels (Lahlali et al., 2021). Via such 'high-resolution' microbial functional traits, together with enzymes and morpho-physio-phenological traits, as well as the emergence of landscape genomics, we are now at an opportunity edge to apply trait-based approach for assessing, understanding, and managing soil health.

Functional traits of specific microbial taxa can be identified via their roles in soil processes, such as nitrification, denitrification, aggregate formation, and particulate organic matter (POM) degradation (Dauphin et al., 2023). This approach aids in developing trait-based biogeochemical cycling models (Crowther et al., 2019). While there is growing recognition of the importance of microbial functional traits in understanding environmental changes and predicting biogeochemical processing rates, there is still a significant challenge in accurately assessing and managing soil and ecosystem functions across a wide range of soil and ecosystem types.

Achieving this goal requires sequencing, cataloging, and characterizing soil microbial genomes worldwide (Lewin et al., 2022). Additionally, comprehensive, cross-site analysis of environmental impacts on microbial functional traits and the influence of microbes on biogeochemical processes is necessary. The global need for data on microbial functional traits across the globe mirrors the development of soil spectral libraries (SSLs), which collect hyperspectral measurements of soil properties (Viscarra Rossel et al., 2016). The premise is that a sufficiently diverse SSL could encompass the spectral signatures of all soil types across various climatic and biogeographical regions, allowing for the calibration of any independent soil spectral measurements to infer physical, chemical, and biological properties.

1.4 Soil structure and soil functions

Soil structure as the engine of soil functions

The formation and destruction of soil aggregates create reactive, porous interfaces that regulate the exchange of water, solute, energy, and carbon among the atmosphere, biosphere, hydrosphere, and lithosphere. Furthermore, soil structure controls the potential for microbial interactions, including gene transfer and other ecological interactions like competition and predation (Cao et al., 2024). Consequently, soil aggregates serve as the driving force behind the delivery of soil functions (Vereecken et al., 2016). This soil structure-facilitated interface exhibits dynamic behavior across multiple timescales, ranging from long-term regolith transformation, to seasonal shifts in vegetation inputs of organic matter, and hourly variations in water-, heat- and gas flows and solute transport. It also extends across a range of spatial scales, from nanometric-sized clay particles to landscape-scale ecosystem fluxes (Sullivan et al., 2022) (Figure 1).

Within inter- and intra-aggregate soil pores, internal abiotic and biotic processes occur, creating heterogeneous physiochemical conditions for microbial habitats. These processes can break down minerals and build mineral structures (Philippot et al., 2024), creating internal surfaces that accumulate sorbed substances and attached microbial communities (Totsche et al., 2018b), and transforming nutrients and pollutants (Hartmann and Six, 2023). At the scale of the soil-plant system, a healthy soil structure can be conceptualized as an efficient 'biogeochemical reactor' that facilitate the abiotic and biotic processes mentioned above. This reactor establishes a mechanistic link between the aboveground vegetation and belowground soils, via connecting soil to microbiome, plant and atmosphere, as well as to ground waters that receives discharge passing through soil (Ebrahimi and Or, 2018; Kravchenko et al., 2019).

Soil structure modeling

There are currently two fundamentally different approaches to model soil structure: the pore perspective and the aggregate perspective. The pore perspective emphasizes the structure of the pore network framed by soil particle surfaces, while the aggregate perspective focuses on the formation, stability, destruction, and reformation of soil aggregates (Vogel et al., 2022).

Models based on the aggregate perspective include the Coupled Carbon, Aggregation and Structure Turnover (CAST) model (Stamati et al., 2013), AggModel (Segoli et al., 2013), and the Cellular Automaton Model (CAM) (Zech et al., 2024). These models are characterized by the dynamic, self-organized re-arrangement of solid building or functional units such as particulate organic matter (POM) and aggregates based on surface interactions (Zech et al., 2022). On the other hand, models based on the pore perspective include the BODIUM model by König et al. (2023) and the soil structure model by Meurer et al. (2020). These models focus on the dynamic interactions among soil organic matter storage and turnover, soil porosity, and pore size distribution. However, they do not consider individual soil aggregates as explicit building units and tend to overlook the biological processes that contribute to the generation of aggregation pore-space.

There is a growing consensus that both pore and aggregate perspectives provide complementary insights into soil structure. Ultimately, soil functions such as water retention, carbon sequestration, elemental cycling, and the movement of fluids and matter are influenced by the spatial organization of particles, particulate organic matter (POM), pores, and the characteristics of biogeochemical interfaces (such as topography and heterogeneity) across various scales (Totsche et al., 2024).

Modelling hydro-biogeochemical consequences of soil structure

Understanding the mechanistic link between soil structure and soil function involves simulating soil structural changes and their hydro-biogeochemical impacts across various spatial scales and complexities. This requires consideration of the impact of soil-intrinsic forces such as dynamic root growth or earthworm activity, and external forces such as raindrop impact and tillage activities. These forces, single or in unison, will affect pore generation, pore collapse, pore clogging, and ultimately pore-size distribution. In turn the spatial arrangement of pore networks will determine soil's physical, chemical and biological properties (Yu et al., 2020c).

The aggregate-based CAST model has been incorporated into the critical zone model 1D-ICZ to simulate dynamic soil structure and its effects on soil functions, including plant and biomass production, soil biodiversity, carbon and nutrient turnover and sequestration, water filtration and groundwater recharge (Giannakis et al., 2017a). The comprehensive capacity of 1D-ICZ model stems from its integrative model structure, which includes flow, transport, and bioturbation modules (HYDRUS-1D and SoilGen), a chemical equilibrium and weathering module (BRNS chemical equilibrium model coupled with SAFE chemical weathering module), the C/N/P dynamics and structure module (CAST), and the plant productivity module (PROSUM based on theoretical production ecology principles) (Banwart et al., 2019; Giannakis et al., 2017b). While 1D-ICZ accounts for root exudates' influence on soil weathering processes, it does not explicitly express the mechanic processes of root exudation, nutrient absorption, and associated microbial activities. The Root Exudation in Watershed-Scale Transport (REWT) model addresses this shortcoming but simplifies other processes considered in the 1D-ICZ model (Sullivan et al., 2022).

Similarly, the pore-perspective-based soil structure model by Meurer (2020) has been integrated into the soil-crop model USSF (Uppsala model of soil structure and function). USSF simulates interactions between soil structure dynamics and soil hydrological processes, influencing crop production and organic matter cycling at the soil profile scale in the soil-plant-atmosphere continuum (Jarvis et al., 2024). The model accounts for matrix porosity composed of textural pore structure and aggregation porosity, along with bioporosity, tillage porosity, total macroporosity, percolating macroporosity, and soil bulk density. These soil structure dynamics influence soil processes via their impacts on root growth and turnover, soil organic matter turnover, and soil hydraulic properties (Jarvis et al., 2024).

These advanced soil function models demonstrate that the understanding of the link between soil structure and soil functions can only be achieved through modelling the chain of impacts from the microbiome scale to soil aggregates, pedon, watershed, regional, continental, and global scales (Sullivan et al., 2022; Vereecken et al., 2022) (Figure 1). Simulating this complex cascade of processes requires careful integration of all key mechanisms and processes within the soil-microbiome-plant continuum, as well as their roles in regulating the 'bedrock-to-atmosphere' exchanges.

1.5 The digital twin approach

Digital twin technology, initially developed for engineering and industry, has now been widely adopted in various fields, including Earth system science (Bauer et al., 2021a). A digital twin is essentially a digital replica (in silico representation) of real-world systems and processes, synchronized at a specified frequency and fidelity using model-data fusion techniques to enable the two-way data/information flows (Tao and Qi, 2019). One notable application of Digital Twin in Earth system science is the European Union's Destination Earth (DestinE) program (Hoffmann et al., 2023), which seeks to create the most accurate digital replica of our planet by combining Earth system models and Earth Observation data with data assimilation techniques, in conjunction with artificial intelligence (e.g., physics-informed machine learning and deep learning) (Bauer et al., 2024).

The fundamental characteristics of a digital twin include (Tsakiridis et al., 2023): a) a highly precise and high-fidelity digital replica of its physical counterpart; b) near-real-time accurate measurements; c) lifecycle data management for both measurements and model simulation results; and d) model-data fusion to optimally combine observations and models, either by updating the model system's parameters or states. This 'self-evolving' nature allows the digital twin to simulate and predict system states and parameters that progressively align with physical reality. Additionally, computational science is another key element of digital twins to support human interaction with digital twins, transforming complex data into actionable information for decision-making in a data/information-streaming manner (Bauer et al., 2024).

The integration of digital twin technology in soil function research, particularly soil monitoring, has been limited and primarily conducted at small scales (Tsakiridis et al., 2023). However, the rapid expansion of soil observation data, including spectro-microscopy with tomography and multi-omics (Amelung et al., 2024), hyperspectral imaging of soil's electromagnetic reflectance across visible, near-infrared, and thermal infrared spectra (Ben-Dor et al., 2019), and microwave data (Wigneron et al., 2017), has created a vast and rapidly growing repository of soil function data. This wealth of soil data establishes soil science as a 'big data' discipline and opens new possibilities to apply digital twin technology for soil health monitoring. The use of digital twin technology is anticipated to advance soil structure and soil function models by integrating dynamic structural components into soil modeling (Fisher and Koven, 2020; Sullivan et al., 2022). By combining algorithms grounded in physical, chemical, biological, and ecological principles with big soil data, we can improve our understanding of soil structure-function relationships, as well as enable scenario-based spatiotemporal projections of soil health for better management practices under current and future environmental conditions .

1.6 Structure of This Review

It is critically important for acquiring process-level insights into soil health to grasp the multifaceted functions performed by soils. Addressing this imperative necessitates the monitoring and prediction of soil health amidst mounting challenges posed by unsustainable soil management practices and the impacts of climate change. Interactions in the soil system, involving soil properties, hydrological processes, soil-plant hydraulic parameters, soil-root interactions, soil microbiomes and land management practices are ever-present. Thus, monitoring soil health mandates a comprehensive approach that encompasses the entire soil-plant system across diverse spatiotemporal scales, as it is only through such holistic monitoring endeavors that a contextual understanding of soil health can be attained.

This review aims to explore the following scientific inquiries:

- What are the mechanistic linkages between soil health indicators and soil functions?

- How do soil-microbiome-plant processes contribute to changes and dynamics in soil properties and subsequent alterations in soil functions?
- How can process-based models, Earth Observation data, data assimilation, and physics-informed machine learning be integrated to monitor and predict soil health and its responses to environmental and climatic changes across spatiotemporal scales?

Particularly, this article will scrutinize the current state-of-the-art soil properties and processes considered in soil health monitoring, review the effectiveness of existing approaches, and pinpoint potential gaps to be addressed. This will involve reviewing the representation of soil microbiomes (Section 2) and soil hydrological processes (Section 3) in Earth system models to comprehend the mechanistic linkages between SHIs and soil functions. The emphasis on these two sets of processes is mainly driven by the pivotal role of soil microbiomes in linking microbial activities at the microscale to large-scale soil processes (e.g., water infiltration and distribution, or increased greenhouse gas emissions) through biochemical and structural alterations to the soil.

Recent advancements in molecular methods for soil microbiology will be reviewed, alongside the examination of trait-based approaches that integrate microbial processes into soil biogeochemical modelling. Furthermore, recent developments in remote sensing will be surveyed for their applicability in landscape genomic approaches for understanding below-ground soil properties, which remain largely underexplored. The article will also delve into the principles of mapping and remote sensing of observable soil properties (Section 4), as well as the current challenges associated with monitoring and predicting subsurface soil properties.

We expand beyond these aspects by also reviewing the “vegetation as a root-zone soil sensor” approach for monitoring and predicting subsurface soil properties from remote sensing (Section 5). The evolution of this innovative technique, e.g., linking soil-plant processes to satellite observables, is poised to stimulate and propel a new research paradigm within the domain of ‘soil health’. Last but not least, the digital twin approach, synergizing advanced remote sensing, field and laboratory measurements, and model representation of soil-plant processes, coupled with data assimilation and machine learning, is reviewed for its applications in soil health monitoring, and in comprehending the intricate interplay between soil properties, soil hydrological processes, soil-plant hydraulics, soil microbiomes and landscape genomics (Section 6).

Soil health will be a major theme of the coming decades, and will require the use of growing Earth Observation data, soil microbial analyses and microbial trait data, model developments, and a digital twin approach. This review aims to prompt the opportunity for companies, governments, non-profit organizations, farmers, research institutes and universities to collaborate to produce continuous, harmonized and standardized data and models to foster soil health monitoring for sustainable soil management for future generations (Section 7).

2. Soil Microbiomes and Soil Properties

Indicators of soil health related to biological properties encompass both the 'visible' components (e.g. the macrofauna) and the 'invisible' components (e.g. the microbiome). While established guidelines often include 'visible' indicators, such as the diversity and abundance of earthworms and nematodes (as outlined in ISO 11268), indicators for assessing the status of the soil microbiome remain scarce (Schloter et al., 2018). The soil microbiome is the belowground ‘engine’ governing biogeochemical cycling of macro-/micro-nutrients and other elements for delivering key soil functions, including nitrogen transformation (Crowther et al., 2019), plant growth and resilience to abiotic stresses (Trivedi et al., 2020), pest and disease control (Hu et al., 2018), pollutant degradation (Teng and Chen, 2019), as well as regulating functions related to soil structure and soil hydrological processes (Hartmann and Six, 2023).

Soil functions are primarily governed by three groups of beneficial microorganisms (Coban et al., 2022): plant growth–promoting rhizobacteria (PGPR), nitrogen-fixing bacteria, and two major types of mycorrhizal fungi: arbuscular mycorrhizal fungi (AMF) and ectomycorrhizal fungi (EMF). PGPR refers to microorganisms that colonize the rhizosphere or endosphere and enhance plant growth and stress tolerance (Trivedi et al., 2020). Nitrogen-fixing microorganisms (i.e., diazotrophic bacteria and archaea that can be both plant-symbionts or free-living) convert atmospheric nitrogen gas into ammonia, adding new nitrogen to the soil. In addition, the nitrogen-mineralization microorganisms decompose organic matter to release plant-available inorganic nutrients via various transformation processes (Hartmann and Six, 2023). AMF establish a symbiotic relationship with vegetation by penetrating the cortical cells of the roots of vascular plants to enhance access to nutrients and water, and to stimulate root hair growth (Bayanati et al., 2024). EMF form symbiotic relationships with woody plant species, making this relationship the dominant symbiotic plant-fungal interaction in forest ecosystems. Ectomycorrhizas drive nutrient cycling and enhance water transfer between plants through their hyphal network, thereby increasing plant drought resilience (Martin et al., 2016).

The functioning of soil microorganisms is highly context-dependent and governed by the composition of soil microbial communities and the abundance of its individual members (i.e., termed as the community structure) (Bickel and Or, 2020; Sokol et al., 2022). For example, the relative abundances of major bacterial and archaeal taxa can vary dramatically depending on the soil (Crowther et al., 2019). Composition of the soil microbiome is influenced by the spatial variability in the soil environment, which can differ significantly over micrometers to millimeters. These small-scale variations encompass distinct biotic and abiotic characteristics, microbial abundances, and rates of microbial activities (O’Brien et al., 2016). Furthermore, aboveground plant communities can shape belowground microbial communities, which is particularly true for mycorrhizal fungi, fungal plant pathogens and some nitrogen-fixing bacteria (Trivedi et al., 2020). Although there are associations between plant communities and soil microbial communities, many other factors can be involved (e.g., climate, plant species, microbial taxa, and soil habitat properties) (Evans et al., 2022; Vahedifard et al., 2024), which render the direct prediction of soil microbial community structure from the plant species not straightforward.

2.1 Characterizing the soil microbiome

Currently, 20 to 50% of the variation in the mineralization rates of carbon and nitrogen across terrestrial ecosystems can be explained by climate, plant, and edaphic factors (Jansson and Hofmockel, 2020; Li et al., 2019). The remaining unexplained variation in elemental processing rates across the globe is assumed to be determined by the structure and function of soil microbial communities (Fierer, 2017; Sokol et al., 2022). Therefore, it is critical to generate a predictive understanding of the global variation in soil community structure to allow for reliable prediction of future changes in key soil functions. There are four emerging categories to characterize the functional biogeography of soil microbial communities: global patterns in biomass and abundance, functional group composition, taxonomic diversity and composition, and functional trait expression (Crowther et al., 2019).

Biomass and abundance

One common assumption is that the biomass or abundance of soil organisms reflects the functional potential of the soil microbiome, since they influence the turnover rates of soil organic matter (SOM) (Basile-Doelsch et al., 2020; Dignac et al., 2017). However, this relationship can behave unexpectedly depending on climate conditions. For example, the soil biomass has a general trend of increasing with latitude, indicating a negative relationship between soil microbial biomass and SOM turnover rate at the global scale (i.e., the greatest soil organism abundance is in Arctic and Sub-Arctic regions, where the metabolic rates of heterotrophic organisms are low) (van den Hoogen et al., 2019). However, for regions under equivalent climate and environmental conditions, larger soil microbial communities generally drive faster SOM turnover. This highlights the fact that using indicators from the soil biological perspective alone is not enough to comprehend the soil functioning and its health status.

Functional group composition

The microbial biomass or abundance is frequently used as a so-called 'black-box' metric of soil health, since it does not provide information on which taxa are present. Also, estimates of the total microbial biomass can vary, depending on methods used and soil physicochemical properties (Fierer et al., 2021). The partitioning of the soil microbiome into broad organismal groups can provide a more detailed understanding of soil functioning. Different kingdoms of soil organisms (i.e., fungi, bacteria, archaea, protists, and animals) have different structural, morphological, and biochemical properties, which affect dramatically their impacts on the rates of carbon and nitrogen mineralization (Coban et al., 2022). According to Bahram et al. (2018), slow-growing high plants are generally associated with fungi-dominated communities that decompose more recalcitrant organic carbon than grasslands that are typically dominated by bacteria driving rapid nutrient cycling. Therefore, the ratio between the relative biomass of fungi versus bacteria (F:B ratio) has been used as an indicator associated with the C:N ratio of soil and biogeochemical process rates (Malik et al., 2016). Nevertheless, F:B ratios can vary for many reasons, and these two organismal groups often have overlapping niches and functions in soil, which make the interpretation of this indicator difficult (Fierer et al., 2021).

A further delineation of the broad organismal groups into key functional groups (or guilds) can reveal valuable mechanistic insights into soil functioning. For instance, the differences in the nutrient cycling rates of AMF and EMF can be used to infer the SOM turnover rates (Steidinger et al., 2019). This is because AMF rely on inorganic forms of nitrogen and tend to dominate fast nitrogen-cycling ecosystems while EMF can degrade and acquire organic nitrogen directly and are more dominant in slow nitrogen-cycling systems (Philippot et al., 2013). As such, the AMF:EMF ratio represents differences between fast and slow elemental cycling systems, as well as reflecting fast and slow energy channels in soil ecology (Malik et al., 2016). Therefore, the relative abundance of AMF over EMF can provide essential insights into the stability of soil microbial communities and soil health. Research efforts have been invested to generate spatially explicit data about the relative abundances of functional groups of different kingdoms at a global scale for characterizing and incorporating such mechanisms into Earth System Models (ESMs) (Steidinger et al., 2019).

Taxonomic diversity and composition

Within each of these functional groups the soil-dwelling species can be divided into different soil microbial taxa to provide refined understanding of soil functioning. DNA metabarcoding has revolutionized the way by which we categorize the relative abundance of different microbial taxa (Bahram et al., 2018; Bouchez et al., 2016). Despite the immense diversity of soil microbial taxa, Bahram et al. (2018) demonstrated that only a relatively few taxa are dominant in soil microbial communities (Bahram et al., 2018; Tedersoo et al., 2014). Such a hyperdominance structure of soil microbial communities is also observed in many plant communities (McGill et al., 2007). Given this similarity, one might wonder whether the spatial variation in the structure of soil microbial communities can be represented by the spatial distribution of aboveground plant communities (Fierer et al., 2012).

Growing evidence suggests that there are consistent edaphic and biotic factors that are predominantly shaping the diversity and abundance of soil microbial taxa, including soil pH, C:N ratios, soil moisture and temperature, soil texture and structure, climate (i.e. precipitation and air temperature), as well as vegetation types and plant species (Bahram et al., 2018; Delgado-Baquerizo et al., 2018; Fierer, 2017; Sullivan et al., 2022). It turns out that we can use the relationship between these environmental factors and soil microbial taxa to infer the functional potential of soil taxa at broad spatial scales (Fierer, 2017; Sokol et al., 2022). For example, Delgado-Baquerizo (2018) shows that commonly available environmental information can be deployed to predict global distributions of bacterial clusters.

Nevertheless, despite the increasing amount of data and studies advancing the characterization of dominant soil microbial taxa, it is still very challenging to link these diverse species with the functional biogeography of soil communities. This is mainly because taxonomic information, while providing valuable insights into the evolutionary relationships and genetic relatedness of microorganisms, does not always directly correlate with functional traits. Additionally, soil microbial processes integrate a myriad of metabolic pathways carried out by a diverse range of taxa, including active, dormant, and relatively inactive microorganisms. This complexity makes predicting functional traits based on taxonomy challenging (Blagodatskaya and Kuzyakov, 2013). Furthermore, most of DNA sequencing-based approaches can only quantify the relative abundance of taxa or functional genes in soil, while soil microbial processes are governed by the absolute numbers of taxa and the functional traits of soil organisms, together with the knowledge of specific enzyme kinetics as well as the environmental constraints on the relevant taxa (Fierer et al., 2021). It is to note that there are now approaches to obtain absolute abundance from sequencing data (Zhang et al., 2022), although these methods have not yet become mainstream.

Functional traits of soil organisms

The functional traits expressed by individual soil organisms in soil communities, instead of their taxonomic diversity and composition, govern the integrated soil functioning (Crowther et al., 2014). Functional traits include structural, morphological, biochemical, and genetic characteristics of soil organisms, which determine the performance of individuals in elemental processing rates and beyond (Lennon et al., 2012). Microbial molecular techniques provide the highly-resolved level of understanding of the functional profile of entire soil microbial communities, including metagenomics (estimating the genetic composition of microbial communities, providing insights into phylogenetic diversity and functional potential), metatranscriptomics (identifying active functions under certain environmental constraints), and metaproteomics (examining the protein synthesis and targeting responsible enzymes) (Bouchez et al., 2016).

The direct measurements of these traits can facilitate the mechanistic understanding of soil microbial community assembly. For instance, broad-scale measurements on the traits of individuals have revealed the trade-off mechanisms of expressing either stress-tolerance traits or competitive traits across broad environmental gradients. Stress tolerance traits dominate in cold or dry regions, while competitive traits dominate in tropical moist regions (Fierer, 2017). Such mechanisms hold across fungi and bacteria, and facilitate the mechanistic understanding of the biogeographic patterns of soil functioning, which differ between biomes and are governed by interactive effects of climate and edaphic characteristics (Maynard et al., 2019). Therefore, the increasing number of ‘omics’-based measurement methods provides a window of opportunity to establish the relationship between the genetic and functional diversity of soil microbial communities, and integrated soil functioning, following the trait-based concepts developed by plant ecologists (Sokol et al., 2022).

2.2 Soil microbiome, soil aggregate, and soil processes

Soil microorganisms are not only responsible for nutrient and carbon transformations but they also shape their physical soil habitat through either biogeochemical and/or biophysical mechanisms

(Gregory, 2022; Sullivan et al., 2022). On the other hand, biologically altered soil properties can influence the abundance and composition of soil microbial communities across space and time. There are eco-coevolutionary relationships between the soil microbiome and soil properties/processes due to the complex network of causation and feedback effects (Hartmann and Six, 2023).

Soil microorganisms and physiochemical properties

Microbial processes related to nutrient and carbon cycling are the most notable biogeochemical processes generating protons and hydroxyl ions that affect soil pH (Huet et al., 2023), which in turn primarily structures soil microbial communities. The microbial release of protons or organic acids contribute to the biological weathering of minerals (such as granitic bedrock and silicates) (Jongmans et al., 1997), which increases the solubility and bioavailability of nutrients needed by soil microorganisms and plants. This release of elements from rocks changes the geochemical and mineralogical conditions of soil environments, which can facilitate the bio-silicification process that takes up silicic acid from the soil (Sommer et al., 2013). On top of mineral dissolution and formation, bacterial and fungal activities also induce the precipitation of carbonate minerals (i.e., microbially induced carbonate precipitation, MICP), which can alter directly soil physical and mechanical properties, e.g. causing reduced hydraulic conductivity and enhanced shear strength (Vaksmaa et al., 2017).

Soil microorganisms and soil aggregates

Soil microorganisms have direct effects on the formation, stabilization, and disintegration of soil aggregates (or soil structure), since microorganisms can affect the 3D arrangement of soil particles and pores. For instance, microorganisms can stabilize the architecture of soil aggregates with their cells and metabolic products, while they can disintegrate the aggregates via catabolizing the binding agents that hold together soil particles (Wilpiszeski et al., 2019). Both bacteria and fungi have dominant influences on the formation of soil aggregates (Angst et al., 2021), via producing binding agents, such as the gel-like water-rich macromolecular organic mixtures – extracellular polymeric substances (EPS).

The EPS plays an Important role in binding soil particles with carbonates, metal oxides, and organic matter into organo-mineral complexes forming silt-sized aggregates (<50 μm) or microaggregates (50 – 250 μm), while the complexes of roots and fungal hyphae can enmesh and physically entangle these smaller aggregates into larger and less stable macroaggregates (>250 μm) (Costa et al., 2018). It is to acknowledge that the dominant theory of aggregate hierarchy is that microaggregates might from within macroaggregates (Six et al., 2000). Soil microorganisms interact with soil aggregates from the smallest scale (for instance, microbial processes involved in mineral weathering or MICP), via intermediate scales (for instance, enmeshment and entanglement via fungal hyphae), to the largest scale (for instance, AMF-induced changes in the aboveground plant community reshape soil structure and its interactions with microorganisms) (Philippot et al., 2024).

Soil microorganisms and soil hydrological processes

It is intuitive to reason that the interaction between soil microorganisms and soil processes is via the intermediate soil properties such as the size and stability of soil aggregates. As detailed above, microorganisms can alter the 3D arrangement of soil particles and pores (or pore-size distribution), as well as the cohesion of the soil structure, which can increase the volume of soil micropores, thus directly influencing the water holding capacity of the soil (Rabot et al., 2018). Growing evidence suggests that mycorrhizal fungi can facilitate water movement between plants along their hyphae, via water redistribution through the soil profile, to mitigate drought impacts on plant productivity. The contribution of water transport by AMF has been reported to account for more than 30% of transpiration of their host plants (Kakouridis et al., 2022), and AMF can improve soil hydraulic conductivity by up to 50% to allow root to extract more soil water in the plant available moisture range

(Bitterlich et al., 2018). Nevertheless, the microbial secreted EPS and MICP can also decrease soil hydraulic conductivity by clogging macropores and slow down soil evaporation rates by introducing soil hydrophobicity (Philippot et al., 2024; Querejeta, 2017). For instance, fungi can produce compounds like hydrophobins to render soil particle surfaces hydrophobic. Such development of hydrophobicity attenuates soil rewetting rates but it maintains the continuity of the liquid phase in micropores under extremely dry conditions (Or et al., 2007). Furthermore, soil microorganisms in rhizosheath are also known to be drought-resilient and can improve plant drought tolerance (Etesami, 2021).

2.3 Soil-microbiome-plant continuum and trait-based approaches

Soil-microbiome-plant continuum

The soil-microbiome-plant interactions occur at soil-root interface (rhizosphere) and root-shoot interface, via a series of complex plant-microorganism and microorganism-microorganism interactions (Trivedi et al., 2020). For example, the plant roots exudes organic acids, sugars, and secondary metabolites, serving as signals to attract microbial colonization (Xu et al., 2018) attached to the root surface (Levy et al., 2018). Root-secreted compounds and signals not only produce biofilms but also influence the architecture of the biofilm. For instance, under either biotic or abiotic stress conditions, plant roots can alter their exudation patterns to selectively recruit beneficial stress-tolerant microbiomes from the soil (Giauque et al., 2019). These root-associated microbial processes can benefit plants through promoting growth with enhanced nutrient uptake, controlling stress by the modulation of plant hormones, and warding off pathogens and pests via antagonism (Trivedi et al., 2020).

It is expected that these belowground microbial processes occurring during plant growth will modify the soil properties/functions in the rhizosphere (e.g., soil pH, soil aggregates, water and nutrient uptake). Other than releasing low-molecular-mass compounds (such as, sugars and organic acids) and secondary metabolites, roots also exude a complex mixture of polymeric substances (e.g. polysaccharides) that make up the mucilage, root border cells and dead root cap cells (Philippot et al., 2013). These rhizodeposits are important carbon sources for soil microorganisms. It has been reported that root exudation can account for approximately 25% of the carbon allocation to the roots in grasses and cereals (Jones et al., 2009). On the other hand, rhizosphere microbiota are responsible for the plant loosing photosynthate via rhizodeposition, imposing a significant cost on plant fitness, since microbial biodegradation of exudates drives passive transport of the exudates from inside the root to outside, which creates the concentration gradient driving the loss via diffusion (Gregory, 2022; Martin et al., 2016; Philippot et al., 2013). Rhizosphere microbiotas can influence the competitiveness of plant species and thus also influence plant community diversity (Wardle et al., 2004). Such effects of belowground-aboveground interactions on the plant community composition have been reported by an increasing number of plant-soil feedback experiments (Jiang et al., 2024; Van der Putten et al., 2013).

Trait-based approaches

Plant-soil feedback studies have led to the rapid proliferation of trait-based approaches to understand soil-microbiome-plant interactions, assuming that changes in environmental conditions can exert strong selection pressures on fitness-related phenotypic traits. The trait-based approach integrates environmental and ‘omics’ data to investigate spatiotemporal variations in the abundance and metabolic activity of belowground microorganisms (Dauphin et al., 2023). One of the most recognized advantages of trait-based approaches is that they improve our mechanistic understanding of the genetic basis of phenotypic traits that impact organismal fitness across environmental gradients and species (Lajoie and Kembel, 2019), without directly measuring fitness, because that is difficult to assess.

A widely used trait-based approach is genotype-environment associations (GEA), also called landscape genomic analysis, which typically relies on four key components (Li et al., 2017): (a) the sampling design considering intraspecific genetic diversity and relevant environmental differences; (b) environmental data describing the putative selective pressures of interest; (c) high-quality genome-wide data; and, (d) statistical methods to correlate the targeted response variable (that is, genomics) with the predictor (environmental) variables.

The biotic and abiotic environmental predictors needed by the GEA approach can be obtained from in-situ measurements, remote sensing, or model-observation-derived gridded datasets. With the current trend of increasing our understanding of the global biogeography of soil communities, geo-referenced, interpolation-based, gridded environmental datasets (e.g., from remote sensing or climate/land reanalysis) have been intensively used in landscape genomics (Bahram et al., 2018; Crowther et al., 2019; Tedersoo et al., 2014). Nevertheless, despite soil properties being an essential predictor for understanding genetic patterns and molecular mechanisms of local adaptation of individuals, global datasets of below-ground physical, chemical, and biological soil factors are still largely missing, which hinder the application of GEA analyses for evaluating soil health (Dauphin et al., 2023; Lajoie and Kembel, 2019; Leigh et al., 2021).

Making the most of landscape genomics for understanding soil health requires the most informative and largely independent predictors that can capture complex environmental conditions and intraspecific genetic variation. It also demands sound statistical methods to investigate and describe the genetic response to environmental variations (Li et al., 2017). Moreover, expert knowledge of predictors related to selective pressures or species information is needed to select the most relevant factors that our statistical models should focus on (Dauphin et al., 2023). Yet, GEA methods suffer from various issues, such as collinearity, model overfitting, or the confounding effects of demographic history of soil microbiomes on the genetic signature (Lajoie and Kembel, 2019). Machine learning and deep learning algorithms have been deployed to remedy these issues, facilitating detailed characterization of environmental conditions, and to account for the nonlinear genomic responses to biotic and abiotic environmental predictors (Leigh et al., 2021).

2.4 Remote sensing for soil-microbiome-plant continuum

Traditional field-based soil investigations, obtained via an appropriate sampling design, is of crucial importance in landscape genomic research (Dauphin et al., 2023). However, repeated acquisitions of soil samples to determine their physical, chemical, and biological properties can be laborious, especially on a large scale. As a result, field-obtained soil information is often slow, expensive, and limited in space. Remote sensing technology, based on radiative properties (e.g., reflectance, emissivity, absorbance, and transmission) of land surfaces, can serve as an effective alternative to acquire low-cost information at high spatiotemporal resolution (Su et al., 2020a). For instance, soil moisture is a widely-used indicator for total soil microbial biomass. Yet, its field-collection is highly time- and resource consuming, which has led to the clustering of in-situ stations in the northern hemisphere midlatitude regions (Dorigo et al., 2021). On the other hand, recent rapid developments in remote sensing have enabled the daily retrieval of soil moisture at global scales (Han et al., 2023; Zeng et al., 2016; Zhang et al., 2021; Zhuang et al., 2020).

Remote sensing data can be classified based on different sensor types (passive or active), platforms (ground-, air-, and space-borne), electromagnetic spectrum regions (optical, thermal infrared, and microwave), as well as spectral resolutions (panchromatic, multi-spectral, super-spectral and hyperspectral) (Babaeian et al., 2019; McCabe et al., 2017; Su et al., 2020a). Based on this plethora of remote sensing data, a comprehensive set of soil information can be retrieved from the spectral response of soil, which is characterized by distinct soil properties. Depending on targets, remote sensing-derived soil properties can be categorized as direct indicators (e.g., soil mineral composition, soil texture, organic matter/content, soil surface roughness, soil moisture and temperature), and indirect/proxy factors (e.g., vegetation indices, topography, and land use/land cover) (Abdulraheem et al., 2023; Wang et al., 2023). These indicators are then used to evaluate soil health via assessing soil erosion, salinization, desertification, and contamination, based on empirical relationships established with statistical regression models that are like those used in the trait-based approaches (such as, PLSR - Partial Least Squares Regression) (Dauphin and Peter, 2023; Francos et al., 2021).

While these correlation-based analysis frameworks offer valuable insights into the connection between soil properties and soil health assessment, there remains a gap in our mechanistic understanding of the intricate interplay among plant-soil-microbial interactions, soil structure dynamics, soil functioning, and their ecological consequences (Adewopo et al., 2014). Soil-microbiome-plant interactions entail complex networks of causation and feedback, within which previously adapted/selected microorganisms are driving soil environmental changes (e.g., formation of soil aggregates) (Fierer, 2017). As a consequence, soil microbiome-driven shifts in soil properties will subsequently shape the structure of microbial community in terms of its composition, abundance of individuals, as well as affect the fitness of the modifying soil organisms themselves. As such, if these reciprocal modifications between plant-soil-microorganisms are persistent in time, microorganisms can influence selective pressures across generations with possible adaptive evolutionary trajectories (Philippot et al., 2024).

Given the intricate interconnected nature of the soil-microbiome-plant continuum, unraveling the fundamental mechanisms governing soil functions poses a significant challenge when employing reductionist methodologies that isolate individual factors. Progressing in this field necessitates an integrative framework that merges insights from soil science, microbiology, biogeochemistry, ecology, hydrology and climatology (Coban et al., 2022; Hartmann and Six, 2023; Ma et al., 2021). This advancement can be facilitated by leveraging advancements in microbial molecular techniques, multi-omics analyses, field-based sampling methods, and trait-based approaches to bridge the gap between laboratory experiments and field conditions (Leigh et al., 2021; Martin and van der Heijden, 2024). Furthermore, capitalizing on advancements in Earth observation science, such as the proliferation of (spatiotemporal and spectral) high-resolution satellite sensors, the continual refinement of process and observation models, and the integration of machine and deep learning algorithms, in conjunction with the emergence of Digital Twin Earth, promises a substantial amplification of our understanding of this complex continuum (Su et al., 2020a; Zeng and Su, 2024).

2.5 Digital twin approach and microbial processes

The concept of Digital Twin Earth (DTE) is rapidly evolving, revolutionizing Earth system science through its multifaceted approach and advanced digital technologies (Bauer et al., 2021b). Its importance is increasingly acknowledged for its ability to agilely and accurately forecast extreme climate events and predict environmental impacts (Bauer et al., 2021a; Bi et al., 2023). At the core of DTEs are four main pillars: physics-based models, machine learning and deep learning algorithms, data assimilation techniques, as well as the associated need of digital technologies that facilitate the supercomputing and data-handling capabilities. The ‘knowledge heart’ of DTE is the high-quality science input from the optimal synergy between physics first-principle-based models and Earth observations via data assimilation (Li et al., 2023), which create physics-based reference and training data for the hybrid physical equation-data driven DTE system (Bauer et al., 2024; Vance et al., 2024). The above digital twin approach can be generalized to build DTE components, including DTE-Climate (Bauer et al., 2021a), DTE-Hydrology (Brocca et al., 2024), as well as Digital Twins for other subsystems/processes, such as, a digital twin of soil-plant system (Zeng and Su, 2024), or a digital twin of the soil-microbiome-plant continuum.

Recent years have witnessed significant strides in the integration of diverse processes into Earth System Models (ESMs) (Blyth et al., 2021). These advancements span various domains, including biogeochemical cycles (Fisher and Koven, 2020; Yu et al., 2020a), plant hydraulics (Kennedy et al., 2019; Sabot et al., 2020; Wang et al., 2021b), coupled moisture and heat transfer (Garcia Gonzalez et al., 2012; Yu et al., 2020b; Zeng et al., 2011b), freeze-thaw dynamics (Yu et al., 2018), groundwater flow and beyond (Condon et al., 2021). Despite advancements, ESMs continue to lack a thorough depiction of microbial processes, essential for the long-term projected responses of soil organic matter and carbon storage to global warming (Wieder et al., 2013, 2015). This deficiency arises from our incomplete understanding of soil biota distribution and abundance on a global scale, compounded by the complexity of microbial ecology and the challenges associated with in situ measurements. These factors are essential for conceptualizing and parameterizing biogeochemical model structures intended to simulate microbial processes explicitly.

A promising avenue for advancing biogeochemical modeling involves integrating microbial community properties through trait-based approaches (Fierer, 2017). This approach is viable because trait information can be observed as phenotypes, such as growth rates, substrate assimilation efficiency, and microbial substrate uptake, or inferred directly from genomic proxies, such as optimal growth temperatures and minimum generation times (Reed et al., 2014). By adhering to fundamental thermodynamic principles (Calabrese et al., 2021), physiological and biophysical trade-offs can be quantified as the benefits and costs to an organism for each functional trait. These trade-offs govern microbial fitness and trait distributions in both space and time (Lajoie and Kembel, 2019). Together with these traits and multi-omics data, the microbial model considering biophysical trade-offs related to substrate acquisition, energy generation and stress tolerance can provide tangible predictions of how microbial-mediated ecosystem processes, such as carbon-use efficiency, nitrogen fixation and nitrate reduction, and microbial biomass turnover, vary through time and space (Sokol et al., 2022).

2.6 Microbial processes within a Digital Twin Framework

Despite significant progress in trait-based microbial models, most soil biogeochemical models still fail to incorporate the dynamic variations of the physical and chemical soil environment. These fluctuations within the highly heterogeneous soil microhabitats are pivotal in shaping the distribution and activities of soil microorganisms (Fierer, 2017), yet they remain inadequately linked with microbial processes.

For instance, when plant residues enter the soil system, they are colonized by microbial decomposers under the presence of favorable conditions for microbial activity, such as soil moisture and temperature. This then initiates a process where fungal hyphae, microbial metabolites, and root exudates bind soil particles into macro-aggregates around particulate organic matter (POM) (Hartmann and Six, 2023). Subsequently, the macro-aggregated POM undergoes decomposition and fragmentation, producing smaller micro-aggregates as well as silt-clay sized aggregates (Wilpiszeski et al., 2019). The further decomposition of incorporated organic matter leads to decreased microbial growth and reduced stability of macro-aggregates, causing the release of stabilized micro-aggregates, silt-clay sized aggregates, and highly decomposed residual POM. This macro-aggregate destruction process is influenced by the availability of decomposable materials and the “glue” (e.g. EPS) that holds the aggregates together, as well as the micro soil environment (Wilpiszeski et al., 2019). The microbial processes involved in the life-cycle of soil aggregates therefore modify ‘intermediate’ soil properties (e.g., re-organization and binding of soil particles that affect hydraulic conductivity, micropore volume, and hydrophobicity), which have soil hydrological consequences on soil water infiltration/retention capacity, and desiccation/rehydration rates (Philippot et al., 2024).

Therefore, a digital twin of the soil-microbiome-plant continuum should integrate soil microbial processes and their impacts on soil aggregates, as well as the cascade effects on soil hydrological processes. It should capture the complex interactions between these elements, which ultimately govern ecological processes and soil functions at landscape and ecosystem scales (Cao et al., 2024; Little et al., 2008). Only with such a mechanistic process-based approach, together with the trait-based landscape genomics method, combined with remote sensing observations and data assimilation techniques, microbial processes are then deemed embedded within a digital twin framework.

3. Soil Hydrology and Soil Properties

Soil hydrological processes are governed by the physical, chemical, and biological properties of soils. These properties influence how soil water is allocated between evaporation, deep drainage, percolation, or uptake by roots to support transpiration (Vereecken et al., 2022; Wang et al., 2021a; Yu et al., 2016, 2020a). Soil hydrological dynamics are shaped by a combination of soil characteristics such as texture, organic matter content, structure, and surface condition, as well as vegetation type and climate. Together, these factors modulate the effects of climate change on terrestrial ecosystems and control feedback mechanisms within the water, energy, carbon, and nutrient cycles (Fatichi et al., 2020; Vereecken et al., 2015). Consequently, soil hydrological processes, together with soil microbiomes, create the links between pore-scale soil properties and broader regional and global climate processes (Figure 1) (Vereecken et al., 2022).

Quantifying soil hydrological parameters and processes is essential for assessing soil health indicators, including the presence of pollutants, excess nutrients and salts, soil nutrients and pH, and soil biodiversity. As noted in the previous section, indicators such as soil structure and soil organic matter have a strong influence on soil hydrology, affecting various land surface processes and Earth system components, including vegetation, groundwater, and the atmosphere.

At the pore scale, capillary and molecular forces, such as hydrogen bonding, van der Waals forces, and other electrical attractions, act on soil water (Luo et al., 2022). These forces influence the heat and energy stored in the soil or transferred through it, including the heat of wetting or condensation (Edlefsen and Anderson, 1943). At the soil profile scale, soil hydrological processes involve infiltration, runoff, internal and deep drainage, evapotranspiration, soil water storage, and capillary rise from the groundwater table. Water flows primarily through the soil matrix or along preferential flow paths, such as macropores and biopores (Vereecken et al., 2019). At the regional scale, water flow within and on top of the soil is spatially connected and routed across the landscape. At the global scale, large-scale atmospheric processes, such as droughts, floods, and convective rainfall events, interact with soil physical processes (Taylor, 2015).

Furthermore, across all the mentioned scales, land-atmosphere feedbacks interact with soil hydrological processes within the Soil Plant Atmosphere Continuum (SPAC) (Stephens et al., 2023). These interactions also influenced the formation of soils throughout Earth’s history, shaping the present-day landscapes, landforms, and soils (Veldkamp et al., 2017) (Figure 1). Soil hydrological processes, along with their interactions with vegetation and climate, continue to impact soil properties, functioning, and development. Changes to the soil system can occur at an accelerated rate due to human activity and climate change. Therefore, accurately representing soil hydrological processes and properties in Earth system models is crucial, as the pace of soil hydrological changes (e.g., acceleration or deceleration) can serve as a key indicator of soil health and sustainability (Yang et al., 2011).

In this section, we review and discuss the representation of soil properties in Earth System Models (ESMs) and explore ways to improve their parameterization. We consider static basic soil properties such as soil texture and mineralogy, along with the variable basic soil property of soil structure, particularly in the soil surface layer. We also examine secondary non-static properties, including hydraulic and thermal properties such as soil hydrothermal conductivities. These properties directly depend on the basic soil properties, both static and variable. We have intentionally excluded the event-based impacts (e.g., fires, volcanic ash deposition, severe erosion, or eolian deposition) on soil properties (Doerr and Cerdà, 2005; Furtak and Wolińska, 2023; Lubis et al., 2021; Massman, 2021).

3.1 Soil Structure and its representation in ESMs

Mineralogical, biological, and chemical interactions influence soil structure and related properties by causing primary particles to bind and form clay-sized or silt-sized organo-mineral complexes. These complexes can cluster into microaggregates, macroaggregates, or peds (Totsche et al., 2018a). Over time, macropores form between macroaggregates and peds, often induced by shrinkage and swelling of clays due to soil drying-wetting and freezing-thawing cycles. Additionally, natural soil structure formation in many terrestrial ecosystems is driven by root systems and burrowing soil fauna, which create biopores (Robinson et al., 2019).

The voids within and between aggregates are typically small (up to a few micrometers in diameter) and exhibit high tortuosity (Peth et al., 2008, 2014). In contrast, macropores are much larger in diameter (up to several millimetres or even centimetres) with low tortuosity and can connect the soil surface with the subsoil, sometimes reaching several meters in depth (Katuwal et al., 2015). These characteristics of soil pores and their size distribution significantly impact infiltration capacity and soil water storage, as well as soil thermal conductivities and associated water and heat flow processes within the soil matrix.

While it can take decades or even centuries for natural soil structure to form (Banwart et al., 2019; Veldkamp et al., 2017), a single tillage or erosion event can easily disrupt this structure, compromising soil functionality and carbon storage. For instance, tillage disrupts pore continuity, causes loss of biopores, and creates compacted plough pans that hinder root growth and vertical water movement (Or et al., 2021). Additionally, tilled soil surfaces are vulnerable to crust formation during heavy rainfall, which can negatively impact water infiltration rates (Francos et al., 2021).

Land-use practices, agronomic management, and tillage can significantly alter soil properties and structures, as well as related hydrological and thermal behaviours. Conversely, numerous studies have shown that "no-till" practices enhance soil structure stability, preserving against erosion and improving water storage within the soil body (Mondal and Chakraborty, 2022). These benefits, along with other notable impacts on various chemical and biological parameters, contribute to a significantly higher soil health status under no-till practices compared to conventional tillage (Aziz et al., 2013).

In addition to texture and mineralogical composition, non-static soil structure and related hydrothermal properties can evolve over extended periods, ranging from decades to millennia (Figure 1). Capturing these slow, ongoing soil-forming processes, including the melting of permafrost and the reduction of soil organic matter, is critical in ESMs, especially for long-term climate predictions (Robinson et al., 2019).

Furthermore, soil scientists and agronomists increasingly recognize soil systems and their properties as dynamic on sub-seasonal to seasonal timescales (Bonetti et al., 2021; Fatichi et al., 2020; Vereecken et al., 2022). Soil physical properties can vary due to land use and management activities, freeze-thaw cycles, vegetation growth, fires, and environmental and climate changes. These short-term changes in soil systems influence land-atmosphere interactions and feedbacks, as well as land hydrological and thermal memories, which have significant implications for Earth System modelling up to seasonal scales (Rahmati et al., 2023). Simulating the Earth System at the kilometre scale also presents challenges in representing within-grid cell heterogeneity of soil and related vegetation properties (e.g., through scaling techniques) (Montzka et al., 2017). Addressing these complexities is essential for improving the accuracy and relevance of ESMs.

Current ESMs rely on static data such as soil texture to derive soil hydrothermal parameters using pedotransfer functions. These parameters feed into the mathematical functions that model hydraulic functions, including the water retention and hydraulic conductivity curves, within soil hydrological sub-models. These functions implicitly describe the soil matrix's pore-size distributions and sometimes account for dual porosity soils, allowing for preferential flow. However, ESMs often overlook the impact of sudden and gradual changes in soil structure, which can alter the parameters used in hydraulic functions. This limitation arises from a lack of understanding regarding the turnover timescales of aggregates and macropores (Vereecken et al., 2022). A recent study (Zhao et al., 2022b) found that the absence of soil structure representation in ESMs (CMIP6) leads to a 50% underestimation of drought-driven increases in evapotranspiration, particularly in drier regions. These drought-driven increases in evapotranspiration are concerning because they can rapidly deplete water resources, leading to flash droughts and acute stress on ecosystems. These challenges are not adequately captured by CMIP6 predictions for the future of the Earth (Zhao et al., 2022b).

3.2 Pedotransfer functions

Directly measuring soil hydraulic properties at regional and global scales is impractical due to the significant time and labor required (Van Looy et al., 2017). Pedotransfer functions (PTFs) offer an alternative by linking easily accessible soil characteristics, such as texture, bulk density, and organic carbon content (Hengl et al., 2017; Poggio et al., 2021), with soil hydraulic and thermal parameters needed to model soil water and heat flow, as well as biogeochemical parameters for carbon and nutrient cycles (Dai et al., 2019a; Van Looy et al., 2017). Despite their widespread use in land surface modeling, the selection of hydraulic PTFs can introduce significant uncertainties in estimates of soil water infiltration and surface evaporation (Weihermüller et al., 2021). These uncertainties stem from the following limitations (Van Looy et al., 2017; Vereecken, 2023; Vereecken et al., 2022):

i) Different measurement methods and instruments used to assess basic and hydraulic soil properties can introduce systematic biases (Vereecken et al., 2010);
ii) PTFs often have region-specific limitations. For instance, many PTFs are derived from arable land in temperate zones and may not perform well in fine-textured soils of tropical and subtropical regions (Ottoni et al., 2018);
iii) PTF development typically relies on textural information, bulk density, and soil carbon content, without explicitly accounting for the impact of soil structure (Romero-Ruiz et al., 2018);
iv) Most PTFs assume homogeneity and unimodality of pore size distributions using simplified models like van Genuchten-Mualem, overlooking variations in rock fragments, mineralogy, chemical, and biological properties (Lehmann et al., 2021);
v) While dual-modal and multimodal hydraulic functions have been created, they are yet to be integrated into land surface models (LSMs). Additionally, reliable PTFs for these functions remain undeveloped (Durner, 1994);

vi) There are significant data gaps for developing multiscale PTFs, ranging from soil profile to global scale, especially for soils formed under natural vegetation in varying climatic conditions (Vereecken et al., 2022).

3.3 Towards a Harmonized PTF for LSMs

Weihermüller et al. (2021) advocate for harmonizing PTFs in model intercomparison studies to clarify the distinction between impacts from PTF choice and model structures. According to personal communications within the GEWEX-ISMC SoilWat initiative (Zeng et al., 2021), some land surface modelers express concern that PTF harmonization might diminish model diversity, potentially collapsing the ensemble spread of LSM simulations and leading to biases. While this concern is valid, it should not impede the adoption of more physically based soil hydraulic and thermal property models or the enhanced representation of temporally variable soil processes in LSMs. These considerations are especially important in model intercomparison studies that aim to better understand model structural differences. Without harmonizing PTFs, it is challenging to ascertain whether divergences in model outputs stem from model structure and physics or from different PTF choices, a situation further complicated by the inconsistent use of soil maps, which are the necessary input data for PTFs (Zhao et al., 2018).

If the goal is to understand how variations in model physics (such as infiltration, coupled or uncoupled soil heat and water transfer, vapor transfer enhancement, soil-root hydraulics, and plant hydraulics) contribute to model diversity and influence the process-level understanding of land-atmosphere interactions, it is crucial to use a consistent set of PTFs and soil property maps (Zeng et al., 2021). In this context, the SoilWat – SPMIP (Soil Parameter Model Intercomparison Project) has been proposed to examine how much of the LSM spread is due to soil hydraulic properties. This will involve controlled multi-model experiments with coordinated inputs of basic soil properties and PTFs (Lukas and Cuntz, 2016).

Vereecken et al. (2022) advocate for closer collaboration between soil hydrology scientists and global land surface and climate modellers to enhance the representation of soil hydrological processes in PTF-aided LSMs. Further theoretical work is needed to unify soil hydraulic, thermal, biological, and gas flow properties for a consistent depiction of interactions and feedback mechanisms among soil water balance, thermal regime, and carbon fluxes in LSMs (Luo et al., 2022). This integrated approach would also aid in the development and harmonization of PTFs. Vereecken et al. (2022) propose two potential pathways forward: i) Developing multiscale PTFs that can be applied seamlessly from soil profile to global scales. For example, multiscale Bayesian neural network-based PTFs enable the upscaling and downscaling of soil hydraulic parameters (Jana and Mohanty, 2011); ii) Most LSMs rely on a single set of PTFs (e.g., for Van Genuchten Mualem or Brooks-Corey hydraulic equations), which can lead to bias and overconfidence in PTF predictive ability. It is recommended to use ensemble PTFs that combine multiple PTF sets (Dai et al., 2019a; He et al., 2020).

3.4 Soil Property Maps for ESMs

Soil property maps serve as inputs for pedotransfer functions (PTFs) to estimate soil hydraulic and thermal characteristics in ESMs. A fundamental question to consider is how these soil property maps are initially generated. There are two main approaches to soil mapping: a) pedologically-based approach: rooted in traditional soil surveys, this method disaggregates general soil-type maps (typically in the form of polygon maps) into high-resolution grids with specific soil properties (Stoorvogel et al., 2017); b) statistically-based technique (Digital Soil Mapping - DSM): this method identifies relationships between soil properties and soil covariates or environmental factors such as climate, DEM, parent material, land cover, and land use density (Hengl et al., 2017; Poggio et al., 2021).

Soil maps derived from the pedological approach cannot be directly applied in ESMs due to several limitations (Dai et al., 2019b; Schoorl and Veldkamp, 2016; Wielemaker et al., 2001): a) mapping units or soil polygons are often described as soil complexes or associations, while ESMs require gridded soil data; b) traditional maps ignore spatial variations between polygons, resulting in abrupt transitions at soil polygon boundaries; c) Soil types are used to represent regional soil variability, explaining only a limited range of actual variation in soil properties and lacking quantitative information.

To address these issues, Stoorvogel et al. (2017) proposed the S-World methodology, which integrates landscape properties with soil types to generate global grids of soil properties for use in ESMs. However, this approach assumes that the influence of landscape properties (e.g., topography, land cover, rainfall, and air temperature) on specific soil properties is consistent across different soil types. In reality, these landscape impacts are specific and dynamic for each landscape property, soil type, and soil property, which complicates the use of S-World approach in certain contexts.

The DSM utilizes an ensemble of machine learning models to generate high-resolution soil property maps by leveraging a wealth of auxiliary data and soil profile databases at regional and national levels, such as SoilGrids250m (Hengl et al., 2017). This approach explains variations in soil properties across different soil types, linking them to soil formation covariates like climate, relief, living organisms, water dynamics, and parent material, in line with the Catena concept (Jenny and Amundson, 1994; Pennock and Veldkamp, 2006; Schoorl and Veldkamp, 2016).

Although SoilGrids250m addresses the limitations of the pedological approach, both methods face uncertainties due to the use of different analytical methods for the same soil property across various soil profile databases (Dai et al., 2019b). Additionally, since both approaches rely on legacy soil profile data that were not collected probabilistically, the spatial uncertainty estimates of the resulting soil property maps are significantly limited (Stoorvogel et al., 2017).

In addition to topsoil properties extending a few meters below the surface, ESMs also require information on soil properties down to the depth of bedrock (DTB) (Shangguan et al., 2017). However, due to a lack of reliable data, creating an accurate global DTB map remains challenging. While applying DTB data to define the lower boundary of ESMs requires caution, Huscroft et al. (2018) developed a two-layer global hydrogeology map that provides permeability data for shallower (unconsolidated, based on DTB data) and deeper (consolidated, defined as up to 100m) layers. Despite inherent uncertainties due to limited regional and national permeability data, the two-layer global permeability map presents an opportunity to simulate deeper groundwater flow processes at a global scale (de Graaf et al., 2017), although such a simulation is not yet considered in ESMs (Condon et al., 2021).

There are several soil processes and properties that are not yet fully represented in ESMs. For example, the presence of gravel significantly impacts soil hydrothermal properties (You et al., 2022), yet there is a lack of PTFs to account for the effects of gravel on a global scale. Additionally, there is no global map of temporally variable soil properties, which would recognize that soils evolve and change over time (Pennock and Veldkamp, 2006; Schoorl and Veldkamp, 2016). Soil surveys in areas such as the Netherlands indicate that agricultural practices have substantially altered soil physical and chemical properties (Sonneveld et al., 2002). Similarly, studies of sediment flux dynamics in fluvial systems reveal the occurrence of centennial sediment waves in eroding river channels, where dynamic sedimentation zones shift both upstream and downstream (Schoorl et al., 2014). These relationships between land use, landscape dynamics, and soil properties can be explored through soil-landscape process modelling, such as with the LAPSUS model (Landscape Process Modelling at Multi-dimensions and Scales) (Schoorl et al., 2000, 2014; Schoorl and Veldkamp, 2016).

Given these complexities, integrating ESMs with soil-landscape models is essential for simulating soil formation processes, including the soil microbiome and soil aggregation as discussed earlier. This coupling allows ESMs to account for temporal changes in soil properties, leading to more precise and nuanced predictions (Dai et al., 2019b; Pelletier et al., 2015).

Current global soil maps are derived from a combination of legacy and newly available soil profiles. The World Soil Information Service (WoSIS) hosts a comprehensive dataset with 196,498 geo-referenced profiles collected between 1920 and 2020 (Batjes et al., 2020). The dataset includes 18.2% of data from before 1980, 47.7% from between 1981 and 2020, and 31.9% with unknown collection dates. Although these soil profiles can be time-stamped, the spatial coverage varies significantly across different time periods, making the available soil profiles insufficient for generating statistically reliable global soil maps for each period. For instance, in WoSIS, only 0.7% of profiles were sampled before 1920, 0.1% between 1921 and 1940, and 3.9% between 1941 and 1960 (Batjes et al., 2020).

To address these data constraints, data assimilation (DA) techniques have been utilized to integrate process-based knowledge from soil-landscape models with limited soil profile data. This approach generates continuous space-time soil maps at a catchment scale (Heuvelink et al., 2006). DA employs recursive optimization algorithms to update the soil map by projecting one timestep ahead based on the predicted soil map from the previous timestep and incorporating measurements from the current timestep. The data assimilation (DA) approach for updating soil maps aligns closely with the Digital Twin methodology (Bauer et al., 2021b, 2021a; European Commission, 2021), which can simulate and analyse past and present soil formation processes, as well as predict future changes. This approach can potentially create maps of temporally variable soil properties if ample time-stamped and geo-referenced soil profile data are available.

Remote sensing has been utilized in soil surveys for quite a long time, and modern air- and space-borne hyperspectral imagery has been extensively applied for mapping soil properties with success (Chabrillat et al., 2019; Lagacherie and Gomez, 2018; Viscarra Rossel et al., 2022). With the increasing availability of remote sensing products and other big data in Earth system science (Li et al., 2023), when combined with the DA approach, the challenge of data scarcity for producing global maps of temporally variable soil properties can be effectively addressed.

4. Remote Sensing of Observable Soil Properties

4.1 Soil Remote Sensing

Given the multifaceted nature of the soil health, soil monitoring must accurately measure inputs and outputs, external pressure and drivers (e.g., climate zones, vegetation covers). It should also capture biological, chemical, and physical transformations and processes related to water, matter, and energy cycles. This holistic approach to soil monitoring is crucial for providing all relevant soil health (and non-soil) indicators for soil health assessment to prevent soil degradation and sustain soil ecosystem services in the long term, supporting sustainability goals (European Environement Agency, 2023).

The adoption of a ‘holistic monitoring’ approach has been advocated to promote the ‘checks by monitoring’ (CbM) approach as a key control system for paying agencies under the EU’s Common Agricultural Policy (CAP) (Angileri et al., 2023) (hereafter as CbM-CAP). The remote sensing-based CbM-CAP approach is employed to monitor plot- or farm-based policy measures aimed at enhancing environmental and climate performance, promoting sustainable management of natural resources (such as soil and water), and safeguarding biodiversity, landscapes and associated ecosystem services. This approach, along with other remote sensing methods, encompasses three aspects (Devos et al., 2021): 1) land-use practices, which involve human activities on a unit of land and their impact on altering the biophysical characteristics of the soil-plant system; 2) Earth Observation of the soil-plant system and the land cover manifestations linked to land-use practices; 3) meeting the information need of end-users, such as those related to the new CAP's Eco-schemes (European Commission, 2022), which support farmers in transitioning towards more sustainable farming practice by adopting climate adaptation measures to minimize the negative impacts of agriculture.

The abovementioned remote sensing-based approach introduces the concept of a fundamental physical monitoring unit known as "tegon," derived from the Latin "tegere," meaning "to cover". Tegon describes the vertical relationship between vegetation cover and soil. The tegon is defined as the smallest monitoring unit of vegetation cover, consisting of various layers with uniform biophysical and life cycle characteristics. These layers exchange material and energy with one another, as well as with the atmosphere above and the soil below (Devos and Milenov, 2013). Thus, the tegon-pedon pair (Figure 2) represents the three-dimensional elementary components of the SPAC, which can be monitored with remote sensing.

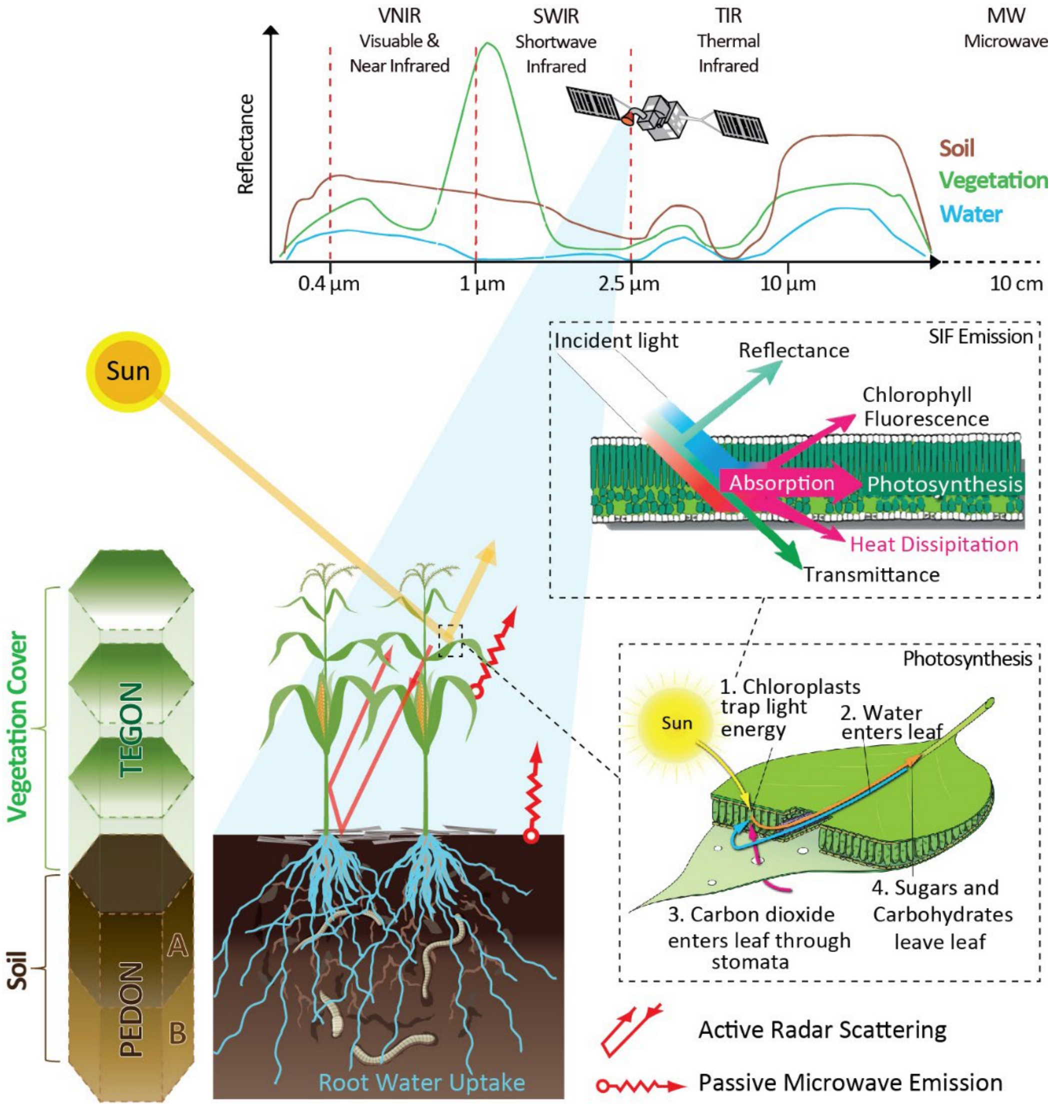


Figure 2 The "Tegon-Pedon" pair as the three-dimensional elementary unit of the soil-plant-atmosphere continuum (SPAC), whose biophysical characteristics can be observed with remote sensing across the VNIR-SWIR-TIR-MW domains of the electromagnetic spectrum (VNIR – Visible and Near Infrared [0.4–1.0 µm] , SWIR -Short Wave Infrared [1.0–2.5 µm], TIR - thermal infrared [3–12 µm], MW – microwave [0.5-100 cm]). In the top panel, the spectral reflectance characteristics of soil, vegetation,

and water can be observed by multi- and hyperspectral sensors (e.g., Sentinel-2, EnMAP). The active radar scattering and passive microwave emission from the "Tegon-Pedon" pair can also be monitored from microwave sensors (e.g., Sentinel-1, SMAP, SMOS). The photosynthesis process at leaf level is also illustrated: energy from sunlight is absorbed by the plant photosynthetic pigments (i.e., chlorophyll and carotenoids) in chloroplasts and converted into energy-rich carbohydrates. When illuminated, leaves reflect, transmit, and absorb light, as well as re-emit light as chlorophyll florescence (i.e., solar-induced chlorophyll florescence, SIF). The FLEX mission (Drusch et al., 2017) *is dedicated to measure SIF, which serves as a proxy of photosynthesis and is an integrative observable of soil-plant-atmosphere (or SPAC) dynamics. It should be pointed out that recent progress in drone technology can provide high spectral separation and temporal resolution of large fields. These are pivotal advances in the context of high-resolution soil health monitoring* (Manfreda and Dor, 2023).

While remote sensing is widely recognized an innovative technique for soil health monitoring, few review articles and reports elaborate how to apply remote sensing technique for monitoring soil health, e.g., not only providing spatial information of soil properties and land cover characteristics, but also assessing soil- and land-management practices that can be related to soil functions via physically-based modelling. Such a linkage between SHIs and soil functions, considering the synergy between soil biological and physico-chemical properties, requires the combined use of process-based model, Earth Observation data, data assimilation and physics-informed machine learning, which has been coined as the digital twin approach (Bauer et al., 2021b, 2021a; Zeng and Su, 2024).

4.2 Challenges of soil remote sensing

In 2019, the European Space Agency (ESA) hosted the World Soil User Consultation Meeting to discuss the steps needed to establish a soil monitoring system that combines space-based Earth observation (EO) data with in-situ data and modeling (http://worldsoils2019.esa.int/index.php). There are currently operational passive and active remote sensing platforms that can be used to observe soil properties such as soil organic content, clay, particle size, soil roughness, and other soil attributes, as well as state variables like near-surface soil moisture. These platforms include passive optical (multi-spectral and hyperspectral), thermal, and microwave systems, as well as active synthetic aperture radar (SAR) and LiDAR systems (Ben-Dor et al., 2019).

Although remote sensing techniques for soil monitoring are available, their application in retrieving soil properties and variables is challenged by the fact that most pixels represent a mix of bare soil, non-photosynthetic vegetation (such as alpine tundra, wetland, fallow cropland and crop residues), and photosynthetic vegetation. This necessitates refining retrieval models capable of distinguishing signals from mixed pixels (see Figure 2, top panel). Other complicating factors include the condition of the soil surface (sealed or non-sealed) and soil moisture content, which influences absolute soil reflectance. Additionally, satellite radiance reflectance can be affected by atmospheric conditions, such as gases, clouds, aerosols as well as viewing geometry (Chabrillat et al., 2019).

Despite challenges, soil spectroscopy methods for estimating soil properties have improved significantly over the years due to their cost-effectiveness (e.g., costing one-tenth of a chemical analysis) and high reliability (repeatable and reproducible results) (Viscarra Rossel et al., 2022; Viscarra Rossel and Bouma, 2016). This progress has produced impressive outcomes using laboratory measurements and refined protocols. Consequently, many soil spectral libraries, such as the LUCAS SSL and the world soil SSL (Leenen et al., 2022; Viscarra Rossel et al., 2016), have been established to advance remote sensing-assisted soil monitoring.

New orbiting sensors like PRISMA and EnMAP, with over 200 spectral bands across the visible, near-infrared (VNIR), and shortwave infrared (SWIR) regions, have already demonstrated their ability to capture Earth's surface reflectance information. Upcoming missions from the Copernicus Programme, such as LSTM (Land Surface Temperature Monitoring Mission) and CHIME (Copernicus Hyperspectral Imaging Mission for the Environment), will further enhance monitoring soil properties through their extensive spectral coverage. In this context, it's noteworthy to mention NASA's planned 2027 launch of the SBG hyperspectral sensor. The Surface Biology and Geology (SBG) initiative aims to acquire global spectroscopic (hyperspectral) imagery across visible to shortwave infrared (VSWIR; 380–2500 nm) and multispectral midwave and thermal infrared (MWIR: 3–5 µm; TIR: 8–12 µm) wavelengths at high spatial resolution (~30 m in the VSWIR and ~60 m in the TIR) and sub-monthly global temporal resolution (Cawse-Nicholson et al., 2021).

Terrestrial spectral libraries play a critical role in analyzing hyperspectral remote sensing data. These libraries contain spectral profiles of various soil materials from different horizons, along with detailed metadata such as location, pedogenic characterization, and measurement protocols for both field and laboratory settings (Nocita et al., 2015). This information can be applied for retrieving soil information from multispectral sensors, via resampling the SSL spectral resolution to match the multispectral measurements. Ben Dor and Banin (1995) pioneered this approach, which remains widely used today (Fongaro et al., 2018; Silvero et al., 2021). It should be noted that the laboratory SSL are developed with soil samples from the field with demolished soil surface. However, based on image spectra or from a 'field-lab' apparatus (Ben-Dor et al., 2017), SSL can be established based on in-situ measurements with undisturbed soil surface. Common soil attributes in spectral libraries include textural composition (clay, silt, and sand content), organic matter, carbonate, iron oxides, hygroscopic moisture, and specific surface area (as in the LUCAS SSL and global SSL) (d'Andrimont et al., 2020; Ben Dor et al., 2022). SSLs provide a foundation for developing proxy models for quantifying, classifying, mapping, and monitoring soil properties. Therefore, they should be closely integrated with the advancement of remote sensing technology for effective soil monitoring (Ben-Dor et al., 2019).

4.3 Soil Reflectance and Soil Properties

While factors such as vegetation cover, soil moisture, and soil sealing are often seen as constraints for soil monitoring, they can also be viewed as opportunities to gather information on land surface properties and state variables through soil reflectance data (Ben-Dor et al., 2019). Given that soil samples consist of a mixture of mineral particles, air, water, and organic matter, each element influences reflectance and transmittance, shaping the soil spectrum.

Spectral responses of soils can be directly related to physical or chemical soil properties (e.g., absorption features of water molecules) or correlated with other properties (e.g., specific surface area being associated with the type of clay minerals). Often, the spectral features related to a specific soil property overlap with signals from other properties, making direct assessment challenging. However, a thorough understanding of the radiative transfer process within the soil-plant system (Tegon-Pedon pair) and its interactions with soil state variables and properties can help resolve specific spectral signals (Ben-Dor et al., 2019; Chabrillat et al., 2019) (Figure 2).

Recent advancements in field-based soil measurements under laboratory conditions, e.g., SoilPRO (Ben-Dor et al., 2017, 2023), have supported the application of soil reflectance to derive surface water infiltration rates (Francos et al., 2021, 2023). Spectral transfer functions (STFs) can estimate soil hydraulic properties by combining soil physio-chemical properties with spectral measurements (Francos et al., 2021; Su et al., 2020a). However, the effectiveness of STFs depends on the similarity between the spectral data used to develop them and the data to which they are applied (Romano et al., 2023). Babaeian et al. (2015) derived STFs to predict parameters of the van Genuchten-Mualem and Brooks-Corey models based on VNIR-SWIR spectral data. These STFs have shown that predicted parameters of soil hydraulic models can realistically describe the dynamics of measured soil water content profiles (Babaeian et al., 2016). Alternatively, STFs can predict basic soil properties such as soil texture and organic matter content, which can then be used as inputs to pedotransfer functions for deriving soil hydraulic parameters (Romano et al., 2023; Su et al., 2020a).

4.4 Soil sensors in the space

The concept of Image Spectroscopy (IS also terms hyperspectral), which involves creating a 'spectral cube' composed of numerous spectral bands, has been employed to capture cognitive (imaging) spectral views of soils. This process allows for the information extraction of a spectrum representing the spectral features of the soil for each pixel in a spectral image.

Currently, there are several spaceborne IS sensors available, such as EnMAP, PRISMA (PRecursore IperSpettrale della Missione Applicativa), HUSUI (Hyperspectral Imager Suite) deployed on the International Space Station (ISS), and SHALOM (Spaceborne Hyperspectral Applicative Land and Ocean Mission). Other global missions, like CHIME and LSTM, are currently in the design phase. This expanding availability of high signal-to-noise ratio spaceborne spectral data is anticipated to support global monitoring of soils, provided the spectral response/transfer function (i.e., a regression function between spectral signal and observable soil properties) is known, soils are well-exposed and homogeneously distributed (i.e., bare soil pixels), and local ground data are accessible (e.g., from soil spectral libraries). However, utilizing this technology for routine global soil monitoring is challenging due to mixed pixels, atmospheric attenuation, geometrics and optical distortions, and BRDF (Bidirectional Reflectance Distribution Function) effects. Furthermore, optical remote sensing is limited to sensing the top 50 µm – 1mm of the soil body in the VNIR-TIR domains (Ben-Dor et al., 2019; Dupiau et al., 2022).

Developing unmixing solutions at high spectral and spatial resolutions is key to deriving pure soil pixels when there is coverage of photosynthetic and non-photosynthetic vegetation. Gallo et al. (2018) and Rogge et al. (2018), in separate studies, successfully resolved the contributions of vegetation cover (photosynthetic vegetation) and litter cover (non-photosynthetic vegetation) on the soil spectrum by utilizing temporal coverage of an area and summarizing the exposed pixel of bare soil. They assumed that in a dynamic agricultural area, there would be at least one point in time when the soil is not vegetated. By using indices to account for non-photosynthetic and photosynthetic vegetation, they generated a ‘soil-free’ (or pure soil) image.

Though optical remote sensing cannot penetrate the soil surface, spectral images combined with electromagnetic methods using smart techniques (such as a spectral penetrating-probe assembly) (Ben-Dor et al., 2009) can yield soil profile maps. Another promising avenue is utilizing vegetation as a ‘root zone’ sensor for soil monitoring. For instance, Zuzana et al. (2013) inferred various soil types, topsoil, and substrate properties using spectrally measured leaf properties such as chlorophylls a and b, carotenoids, and relative water content. Paz Kagan et al. (2015) proposed a biological assay to evaluate soil health by assessing the condition of selected standard vegetation as an indicator for probing the root zone soil health using imaging spectroscopy. This approach can extend the application of (multi-/hyper-)spectral remote sensing beyond topsoil monitoring to include soil profiles when combined optimally with other EO technologies dedicated to vegetation monitoring.

5. Vegetation-as-a-Soil-Sensor

5.1 Remote Sensing of Vegetation Properties and Functioning

EO-based optical vegetation indices (VIs) are widely utilized to monitor plant health, reflecting various biophysical, biochemical, and physiological properties of vegetation. The most well-known VI is the

Normalized Difference Vegetation Index (NDVI). However, VIs often face challenges such as data gaps caused by long revisit times and cloud cover, which can affect the quality of information they provide. The reliability of VI-based data depends on the satellite sensors used, quality control processes, compositing algorithms, atmospheric and geometric corrections, as well as soil conditions (Zeng et al., 2022). For instance, wet exposed soil may cause NDVI to incorrectly classify soil as vegetation.

Analyses of VI data products are mostly limited to the Light Use Efficiency framework, focusing on structural properties such as Leaf Area Index (LAI), and to a lesser extent, on vegetation functioning (e.g., greenness parameters are used to estimate Fraction of Absorbed Photosynthetically Active Radiation and Gross Primary Production) (Pierrat et al., 2022). The recent advancements in satellite remote sensing of solar-induced chlorophyll fluorescence (SIF), such as the Fluorescence Explorer (FLEX) mission, offer new opportunities for assessing vegetation functioning and understanding photosynthetic changes to quantify early pre-visual impacts of soil water stress (Buitink et al., 2020; Drusch et al., 2017). SIF can thus serve as a satellite observable for using vegetation as a root-zone sensor to monitor subsurface soil properties or state variables (such as soil moisture content).

SIF remote sensing enables the acquisition of detailed information about photosynthetic light response curves and steady-state behaviors in vegetation for evaluating photosynthesis and stress effects across various biological, spatial, and temporal scales (Mohammed et al., 2019a). Nevertheless, SIF retrieval can be influenced by confounding factors at the leaf and canopy levels that are unrelated to the photosynthetic activity of plants (Porcar-Castell et al., 2021). As such, SIF modeling involves two main approaches: leaf physiological models that describe fluorescence emission and its relationship with electron transport and photochemistry in leaves (Busch et al., 2020; van der Tol et al., 2016; Yin et al., 2021)(Busch et al., 2020; Yin et al., 2021), and radiative transfer models that describe the effects of canopy structure on absorption and scattering (Verhoef et al., 2007). Nevertheless, both methods simplify the relationship between soil water availability and vegetation functioning (Joshi et al., 2022; Wang et al., 2021a).

As a result, water-stress effects may only become apparent in SIF signals when soil water deficits affect the optical or thermal appearance of the vegetation. This 'invisibility' of water stress effects limits the potential of SIF satellite data to accurately capture vegetation health status and its relationship with root zone soil moisture content. Consequently, this disconnect between water stress and vegetation functioning hinders the use of vegetation as a soil sensor in the context of SIF observations, unless a forward observation simulator can be employed to account for this water stress effect and link the belowground soil processes to aboveground top-of-canopy reflectance and SIF (Figure 3).

5.2 Satellite Observables for Soil-Plant Water Content

Microwave remote sensing products of surface soil moisture (SSM) and root zone soil moisture (RZSM) have long been utilized for drought monitoring (Zhang et al., 2021; Zhuang et al., 2020). Most microwave SSM data products operate at regional scales (around 25 km) and use a fixed root zone depth of 1 m globally (Reichle et al., 2017). However, in reality, root growth is dynamic, and the depth of root water and nutrient uptake varies throughout the growing season. Currently, there is a range of SSM products available at a 1 km resolution generated through machine learning algorithms (Han et al., 2023). Nevertheless, reliable, physically consistent sets of SSM and RZSM at field and plot scales are still needed for effective tracking of soil water stress and its impacts on ecosystem functioning (Carranza et al., 2018; Du et al., 2021; Zhuang et al., 2020).

Satellite-based SSM and RZSM data, when integrated with land surface models via data assimilation techniques, can be used to estimate soil texture and hydraulic properties (Pinnington et al., 2021; Santanello et al., 2007). However, both SSM and RZSM data are derived from satellite products using retrieval algorithms that simplify radiative transfer processes and depend on ancillary datasets (e.g., land use/land cover classification, vegetation indices, soil attributes, meteorological variables, etc.) (Colliander et al., 2017, 2022; de Rosnay et al., 2020; Su et al., 2013; Zeng et al., 2016). This simplification and reliance on ancillary data can introduce uncertainties (Su et al., 2018; Zeng et al., 2015, 2019) in estimating soil hydraulic properties through the assimilation of SSM and RZSM data, particularly when soil attributes are part of the ancillary data. To address these challenges, forward observation simulators, in which process-based models are coupled with either emission models (Han et al., 2014; de Rosnay et al., 2020) or discrete emission-scattering model (Zhao et al., 2021), have been developed to directly assimilate brightness temperature to retrieve soil properties (Zhao et al., 2023).

The ability to track liquid water in vegetation using hyperspectral remote sensing was first demonstrated by Gao and Goetz (1990), allowing for the mapping of vegetation burn potential (Robichaud et al., 2007). Furthermore, changes in vegetation water content (VWC) are directly linked to ecosystem functioning, including water-energy-carbon fluxes (Konings et al., 2021). Therefore, quantifying VWC can enhance our understanding of ecosystem responses to drought, especially when coordinated with SSM/RZSM dynamics.

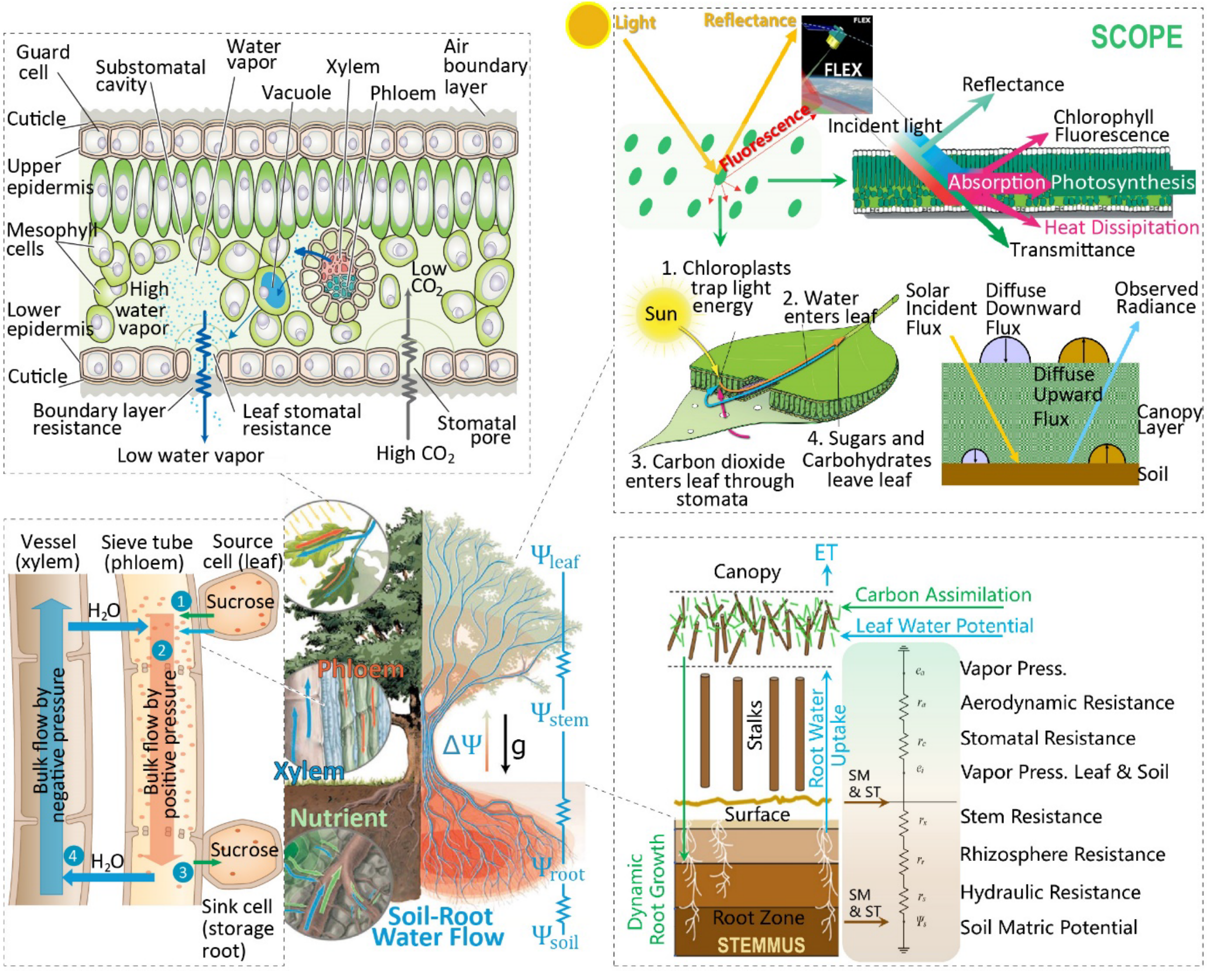
Microwave radiometry-derived vegetation optical depth (VOD) correlates with VWC and biomass, depending on sensor wavelengths, plant type, and structure (Frappart et al., 2020a). Given microwave remote sensing's capabilities to observe day and night regardless of cloud cover, along with penetration beyond the top few millimeters of plant canopies, microwave sensors such as AMSR-E, SMOS, and SMAP have been widely used to provide long-term, coarse-resolution VOD observations (25-50 km) for monitoring regional soil-plant water status (Konings et al., 2017b). However, existing VOD products struggle to capture dynamic VWC changes from seasonal and interannual variations in phenology and biomass in tropical woodlands (Tian et al., 2018) or sub-daily plant physiological processes (Wigneron et al., 2021). These sub-daily processes influence water-energy-carbon exchanges and the hydraulic connections across the SPAC continuum (Xu et al., 2021).

5.3 Satellite Observables for Soil-Plant Hydraulics

Currently, there is a growing trend towards incorporating soil-plant hydraulics into Earth System Models. However, the focus primarily remains on xylem vulnerability, while the explicit roles of soil and root hydraulics are often overlooked. Carminati and Javaux (2020) illustrate that xylem vulnerability does not trigger a plant's drought response (i.e., stomatal closure) in medium-wet to dry soils. Instead, soil hydraulic conductivity loss is the key driver of a plant's drought response. This is because plants adapt the hydraulic conductivity of their roots and the surrounding soil (the rhizosphere) to match the soil conditions and atmospheric water demand. For instance, roots may shrink as soil dries, creating air gaps between root hairs and the soil matrix. These gaps lead to a drop in the hydraulic conductivity of the soil-root system, imposing a primary hydraulic limitation along the soil-plant continuum (Carminati and Javaux, 2020).

Such regulation of plant water status, root zone soil hydraulic properties, and transpiration can be predicted based on the theory of the coupled soil-plant hydraulic system. This leads to an “$E - \Psi_{leaf} - \Psi_{soil}$” framework for interpreting a plant’s drought response, taking into account both above- and below-ground hydraulic traits (E represents evaporation, Ψ_{leaf} represents leaf water potential, and Ψ_{soil} represents soil water potential).

The interpretation framework of soil-plant hydraulics offers a mechanistic approach to infer belowground soil water potential (Ψ_{soil}) from aboveground leaf water potential (Ψ_{leaf}), which closely correlates with vegetation water content (VWC). The non-linear relationship between Ψ_{leaf} and VWC is known as the pressure-volume curve, which is analogous to the soil water retention curve. Measurements of the pressure-volume curve across plant species are becoming more accessible (Konings et al., 2021), generating interest in collecting more data (Novick et al., 2022). Advances in in-situ measurement techniques for water potentials across the SPAC continuum (Conesa et al., 2023; Jain et al., 2021; Lakso et al., 2022) are also emerging. With the increasing availability of in-situ soil-plant water content and water potential data, it will become feasible to develop methods to derive Ψ_{leaf} from remote sensing VWC data. This capability could enable the use of vegetation as a soil sensor to detect Ψ_{soil}, leveraging the connections within the soil-plant hydraulic system (Figure 3).



① Loading of sugar (coral dots, being the output of photosynthetic activities) into the sieve-tube at the source (a mesophyll cell in a leaf) reduces water potential inside the sieve-tube elements, causes a water potential gradient between the vessel and the sieve tube, and induces water flow from the vessel to the tube.

② The water uptake by the sieve-tube generates a positive pressure that forces the sap to flow along the tube.

③ This positive pressure is relieved by the unloading of sugar to sink cells (e.g., root, organ), which inverses the water potential gradientbetween the vessel and the sieve-tube, and causes the consequent loss of water at the sink.

④ In the leaf-to-root phloem translocation, xylem recycles water from sink to source, and also uptake water from soil via root hairs.

Figure 3 It illustrates the soil-plant hydraulic system. Left panel: water potential across the SPAC continuum connects the root zone soil to the leaf, impacting the flow of water through xylem. This connection also affects the water vapor density in the substomatal intercellular airspace of leaves, which in turn influences gas exchange, photosynthesis, energy balance fluxes, and radiative transfer at leaf and canopy levels; Right panel: An example of a digital replica of the soil-plant system, known as the STEMMUS-SCOPE model. The SCOPE model simulates leaf-to-canopy reflectance and SIF spectra in observation directions. It also models photosynthesis and evapotranspiration based on leaf optical properties, canopy structure, and micrometeorological conditions. STEMMUS simulates the *simultaneous transfer of liquid, vapor, dry air, and heat, and calculates soil moisture, soil temperature, and soil water potential in a coupled manner. The model uses these soil state variables to compute the hydraulic resistances across the soil-plant hydraulic system.*

Remote detection of subsurface Ψ_{soil}, combined with remotely sensed SSM and RZSM data, can facilitate the retrieval of parameters necessary for soil hydraulic property models and water retention curves. Additionally, remote sensing-based Ψ_{leaf} and Ψ_{soil} can be directly assimilated into a suitable soil-plant model within a data assimilation framework. This integration can help estimate both vegetation properties and various soil properties such as soil thermal properties, soil organic content, and soil texture (Wang et al., 2021a; Zhao et al., 2023).

6. Towards Sub-daily Soil-Plant Monitoring

6.1 Multifaceted Nature of the Soil-Plant System

In previous sections, we discussed the ongoing interactions between soil properties, vegetation, climate, and land management and their complex relationship with the soil-plant hydraulic continuum. Therefore, monitoring soil goes beyond focusing solely on the soil itself, it also encompasses the intricate physical and biogeochemical processes that drive the water, energy, and carbon cycles within the critical zone. These interplays, along with their responses to climate extremes such as droughts, are both spatially and temporally complex (refer to Figures 1 and 3).

Over time spans of years to decades, average VWC measurements can quantify ecological dynamics, including biomass and structural changes at biome, continental, and global scales (Bueso et al., 2023). For example, information on the impact of disturbances such as fire, extreme drought, and land use changes (e.g., tillage practices) can be gleaned from VWC's sensitivity to aboveground biomass (Zhang et al., 2018). Consequently, remotely sensed VWC, SSM, RZSM, and SIF (hereafter, these four variables are called as soil-plant hydraulics variables, SPHVs) can help identify disturbances in soil properties on large scales. This is due to the cohesive coordination within the soil-plant hydraulic system, as illustrated in Figure 3, which links soil properties to satellite observations of soil-plant hydraulics.

At sub-seasonal to seasonal timescales (weeks to months), interactions between SSM, RZSM, xylem hydraulic functions, and VWC (Figure 3) can assess the risk of drought-induced mortality and fire risk (Konings et al., 2019). During this time frame, SPHVs data can also provide insights into regional soil properties. At sub-daily timescales, measurements of SPHVs reflect the coordinated responses of root-xylem hydraulics and stomatal conductance to drying soil and air. Consequently, these data can detect water stress before it becomes apparent through other leaf properties (Wang et al., 2021a). Therefore, sub-daily monitoring of SPHVs holds promise as an early warning system for drought risks.

By monitoring the soil-plant system via satellites, we can retrieve sub-daily leaf water potential and soil water potential, with the latter at the core of soil hydrological processes. This ultimately facilitates the estimation of soil hydraulic and thermal properties, enhancing our understanding of the soil-plant hydraulic system.

6.2 The Need for Sub-Daily Monitoring System

The necessity for sub-daily observations of the SPHVs is evident in Figure 4. Figures 4a and 4b demonstrate the sub-daily variations in leaf water potential and SIF, both influenced by root zone soil moisture via the WSF (water stress factor). This is evident by the fact that the variation of leaf water potential is regulated by WSF (Figure 4a). Figures 4c demonstrate that the SIF-Ψ_{leaf} relationship exhibits a sub-daily hysteresis loop with a negative linear relationship under water-stressed conditions (Wang et al., 2021b). Such linear relationship provides an opportunity to derive Ψ_{leaf} from SIF remote sensing data. To enhance our understanding of drought responses in plants and ecosystems across multiple spatiotemporal scales, we need simultaneous sub-daily monitoring of SPHVs using Earth observation (EO) technologies. These span optical (e.g., for SIF, SSM) (Dupiau et al., 2022; Porcar-Castell et al., 2021), thermal infrared (e.g., for SIF, SSM) (Paruta et al., 2021), and microwave (e.g., for VWC, SSM and RZSM) domains (Konings et al., 2019; Zhuang et al., 2020).

Although this type of monitoring may seem complex, current constraints are largely due to the availability of sensors rather than technological limitations (Damm et al., 2018; Konings et al., 2021; Mohammed et al., 2019b; Novick et al., 2022). Gaining a deeper understanding of sub-daily drought response and enhancing the monitoring of SPHVs will pave the way for the development of methodologies that use vegetation as a soil sensor. Currently, there is no dedicated spaceborne system designed to systematically observe SPHVs at sub-daily intervals to capture the dynamic physiological responses of plants to water stress. However, greenhouse experiments under controlled conditions have demonstrated the potential of hyperspectral technology to track the daily evapotranspiration cycle (Weksler et al., 2020), suggesting high spectral resolution technology could be used to detect VWC.

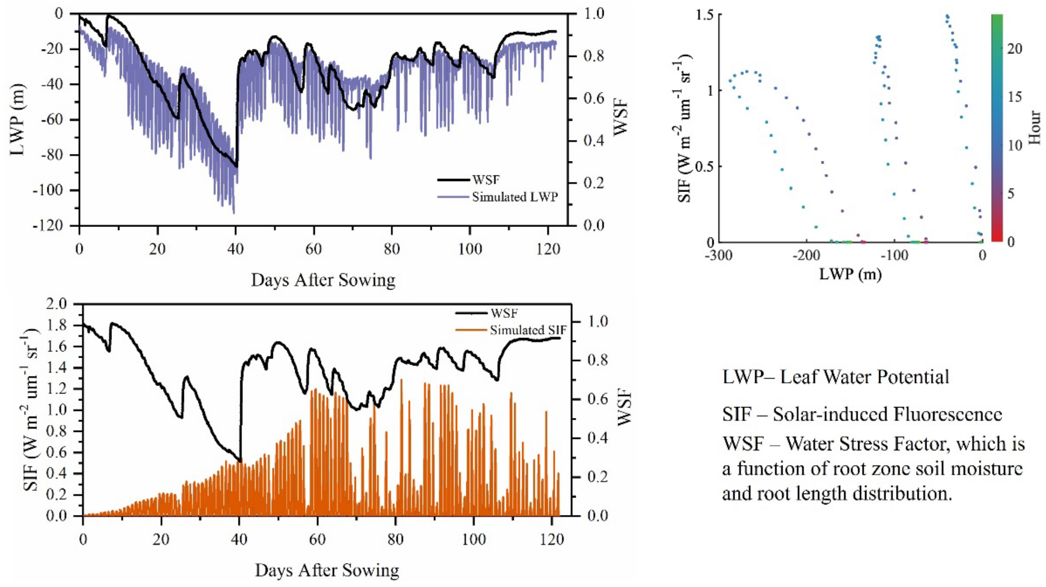


Figure 4: The sub-daily (half-hourly) variations in (a) leaf water potential (Ψ_{leaf}*) and water stress factor (WSF). It shows the coordinated variation between leaf water potential and water stress factor, which is a function of root zone soil moisture and root length distribution. WSF=1 means there is no stress, while WSF=0 means there is no plant-available water content to be uptake by roots; (b) solar-induced fluorescence (SIF). The SIF is also regulated by water stress factor, Since the WSF in STEMMUS-SCOPE is imposed on the maximum carboxylation rate and the maximum electron transport rate, which determines the SIF yield* (Wang et al., 2021a). *(c) the SIF-LWP relationship under stressed and not stressed conditions. Under stressed condition, SIF has a positive relationship with LWP. Such positive relationship provides an opportunity to derive LWP from SIF remote sensing data.*

Existing and planned passive microwave radiometers (e.g., AMSR-E, SMAP, SMOS, CIMR, and AMSR-3) offer long-term, near-daily (1–3 days) coarse resolution (25 km) observations to monitor the water status of soil-plant systems at regional scales, including VWC, SSM and RZSM. The active microwave scatterometers (e.g., ASCAT, ROSE-L), however, provide high spatial resolution (<1 km) synthetic aperture radar measurements on a weekly basis (Bueso et al., 2023; Frappart et al., 2020b; Wigneron et al., 2021). Recent advancements, such as RapidScat on the International Space Station, have shown the feasibility of tracking VWC and, consequently, SSM and RZSM dynamics throughout the day (Konings et al., 2017a). For SIF, the Orbiting Carbon Observatory 2/3 (OCO-2/3) have been used to generate SIF data at a biweekly interval with ~2 km resolution. Additionally, TROPOMI provides daily SIF observations at a coarser 5 km resolution, which can be further downscaled to 500 m for limited regions such as the continental United States (Sun et al., 2023).

Therefore, the ability to obtain sub-daily observations of SPHVs is currently limited more by the orbital configurations of existing sensors than by the inherent sensitivity of optical, thermal, and microwave observations. This suggests that a geostationary multi-sensor platform is required to enhance our understanding of drought responses in the soil-plant system across various spatial scales, ranging from plant-level (1-10 m, sub-daily) to field-level (10-60 m, weekly), landscape-level (60-300 m, weekly-monthly), and regional-level (>1 km, monthly-annual).

Gaining insights into the soil-plant system at these scales will support monitoring soil properties from point to global scales, especially when integrated with soil reflectance measurements from laboratory to airborne platforms (Francos et al., 2021). Alternatively, a constellation of CubeSats with different daily observation times and sensors spanning the visible, near-infrared, shortwave infrared, thermal infrared, and microwave domains could potentially achieve the necessary spatiotemporal resolutions. To integrate observations across multiple electromagnetic frequencies for deriving consistent SPHVs at different scales, a process-based model linking satellite observations in the visible, near-infrared, shortwave infrared, thermal infrared, and microwave domains with above- and below-ground water-energy-carbon processes is required (Zhao et al., 2022a) (Figure 2 and Figure 3).

6.3 The Need for a Soil-Plant Digital Twin

The collection of sub-daily measurements of soil reflectance and SPHVs across various spatiotemporal scales will enhance our understanding of drought responses in agricultural and (semi-)natural ecosystems, as well as the soil properties at different scales (Figure 3 and Figure 4). However, extracting process-level insights from these measurements requires the development of a Digital Twin for the soil-plant system, encompassing a process-based model integrated within a data assimilation framework (Bauer et al., 2021b). A soil-plant digital twin should facilitate a continuous two-way data/information flow between the digital replica and the physical system, and should enable users to interrogate the soil-plant system with future climate scenarios for scenario analyses and for proposing potential adaptation and mitigation measures (Zeng and Su, 2024). This soil-plant digital twin will enable the evaluation of plant evolution and health, as well as their interactions with soil properties, through the optimal fusion of multi- and hyperspectral, VNIR-SWIR-TIR-MW data from satellite missions, drone surveys, and in situ measurements, as well as the application of machine learning algorithms (Su et al., 2020a).

A digital twin is essential because satellite sensors cannot directly observe belowground soil properties. For instance, optical sensors cannot penetrate the soil profile, although microwave sensors can capture signals from both soil and vegetation. Remote sensing (VNIR-SWIR-TIR-MW) signals related to specific soil properties often overlap with those from other soil or vegetation properties (Figure 2 top panel). However, by mathematically modelling and solving soil-plant processes and the associated radiative transfer within the soil-plant system (e.g., scattering, emission, and reflection processes at the vegetation canopy, within the canopy, on the soil surface, and within the top soil layer), we can resolve and unmix remote sensing signals (satellite observables) to assess the specific soil and vegetation properties in question (Bai et al., 2017; Lv et al., 2022; Su et al., 2020b; Zhao et al., 2021, 2022a).

The integration of soil-plant processes with radiative transfer processes connects the digital model of the soil-plant system to satellite observations. This linkage between physical SPAC processes and satellite observations is a key aspect of the soil-plant digital twin, allowing direct assimilation of remote sensing data into process-based models, facilitating the two-way data/information flow. Traditional point-based sampling methods are neither feasible nor economical for large-scale quantification of soil health indicators. Instead, the soil-plant digital twin, combined with multi-scale observations (from points to air- and space-borne sensor footprints), provides an innovative approach for monitoring and predicting soil health indicators with comprehensive spatial coverage (Abdulraheem et al., 2023).

7. Conclusions

7.1 Gaps and Opportunities

The physical, chemical, and biological properties of soils play a central role in regulating soil processes, particularly those related to the soil microbiome and hydrology. These properties shape the formation of soil structure, which in turn influences soil hydrological and thermal processes. Consequently, soil structure and soil hydrological process connect pore-scale water and heat flow, biogeochemical processes, and soil-root interactions to regional landscape land-atmosphere interactions and global climate cycles (such as water, energy, and carbon cycles) (Vereecken et al., 2022). Climate also plays a significant role in soil formation within an intricate feedback cycle (Figure 1) (Veldkamp et al., 2017). It is evident that continuous interactions occur among soil properties, soil-forming processes, and land management. Therefore, monitoring soil health extends beyond soil alone to include the soil-plant system, as soil acts as the interface between the atmosphere, biosphere, geosphere, and hydrosphere.

To effectively model soil hydrological and biogeochemical processes in the Earth system and gain a better understanding of the comprehensive interactions between soil properties and Earth system processes, we need to obtain accurate soil hydraulic, thermal, biological, and gas flow properties (Baatz et al., 2021; Van Looy et al., 2017; Vereecken et al., 2022; Zeng et al., 2011a, 2011b). Although state-of-the-art field and laboratory methods are available to measure these properties at specific locations, extending these measurements to a global scale remains challenging. In recent decades, pedotransfer functions (PTFs) have been developed to link readily available basic soil properties (such as soil texture, bulk density, and organic carbon content) to hydrothermal and biogeochemical parameters (Van Looy et al., 2017; Montzka et al., 2017) essential for estimating water, energy, and carbon cycles in LSMs. However, significant data gaps hinder the development of seamless multiscale PTFs, from soil profile to global scale. These functions should account for the influence of variable soil structure over time, including the occurrence of dual or multimodal pore systems (Lehmann et al., 2021). This underscores the need for stronger collaborations between soil hydrology scientists and global land surface and climate modelers to enhance the physical realism of PTFs used in LSMs (Vereecken et al., 2022; Zeng et al., 2021).

From a technological standpoint, remote sensing of soils through image spectroscopy, combined with regional and global soil spectral libraries, offers significant potential for monitoring soil properties using spectral transfer functions (Francos et al., 2021; Romano et al., 2023; Su et al., 2020a). However, the application of spectral imagery for soil monitoring faces limitations, such as the need to perceive soil as a continuous surface and separate vegetation data to extract information from the soil body. Although soil spectroscopy approaches often treat the vegetation signal as noise, vegetation could potentially serve as a root-zone sensor for gathering information on subsurface soils with the trait-based approach. Furthermore, using vegetation as soil sensor is achievable by coupling a process-based soil-plant model with a radiative transfer model, effectively linking the belowground and aboveground processes to satellite observables across VNIR-SWIR-TIR-MW domains.

Current remote sensing-based vegetation indices primarily assess plant structure properties, using greenness parameters to estimate fAPAR and GPP. These indices focus on foliage and biomass while overlooking the influence of root zone soil water content on plants' drought responses and soil-root interactions. Therefore, these vegetation indices alone may not be suitable to be applied to detect below ground soil properties. Recent advances, however, involve using satellite-derived SIF as a soil-plant proxy to understand photosynthetic changes associated with water-stress impacts. This approach offers a promising observable that can be linked to subsurface soil properties (Porcar-Castell et al., 2021; Wang et al., 2021a), particularly when considering the hydraulic connections across the soil-plant-atmosphere continuum.

Remote sensing of soil-plant hydraulics involves satellite observables across various electromagnetic domains (VNIR, SWIR, TIR, MW), capturing root zone soil moisture, surface soil moisture, vegetation optical depth, vegetation water content, and SIF. These observables are interconnected through water potentials across the soil-plant system, including water potential in soil, root, stem, and leaf (Figure 3). Advances in remote sensing technologies, such as the use of microwave sensors to retrieve vegetation water content and the growing availability of in-situ water potential data for soil, stem, and leaf, have opened the door to deriving leaf water potential from space (Novick et al., 2022). There is significant potential to subsequently infer soil water potential from leaf water potential when remote sensing-based vegetation water content and leaf water potential are integrated with a process-based soil-plant model that explicitly accounts for plant hydraulics (Sabot et al., 2022; Wang et al., 2021a).

Using vegetation as a root zone soil sensor necessitates understanding the multiscale spatiotemporal dynamics of the soil-plant system, ranging from the plant level (1–10 m, sub-daily scale) to the field (10–60 m, weekly scale), landscape (60–300 m, weekly to monthly scale), and regional (greater than 1 km, monthly to annual scale) scales. Sub-daily observations of soil-plant state and flux variables can reveal plants' immediate physiological responses to water and nutrient stress (Figures 3 and 4). These soil-plant processes are crucial for quantifying soil health indicators, including metrics related to soil organic content, soil structure, soil biodiversity, landscape heterogeneity, and forest and woodland area (Panagos et al., 2022).

A soil-plant digital twin is essential for linking soil-plant processes with satellite observations across multiple spatiotemporal scales. This digital twin enables the monitoring and prediction of soil health evolution across various scales and local conditions, soil types, and climates. It also allows for exploring "what-if" scenarios to assess the impacts of future climate change or sustainable land management strategies on soil health (Bauer et al., 2021a). For example, by applying a spatially explicit biogeochemical model, one can examine the effects of converting global cropland to organic farming with or without the use of cover crops and plant residue on soil carbon inputs and soil organic content stocks (Gaudaré et al., 2023). Additionally, the soil-plant digital twin's ability to quantify multiple soil functions concurrently facilitates comprehensive assessments and helps identify optimized synergies for sustainable soil health tailored to specific local contexts.

7.2 Assessment of Soil Health

It is anticipated that measurements of soil health indicators (SHIs) will be specific to soil type and dependent on location and climate. These measurements will reveal distinct characteristic ranges of values across different soil types, land uses and climate zones. For instance, the significance of a given value of soil organic content can vary greatly depending on soil characteristics: an organic carbon value of 1.5% may be considered low for soils with over 40% clay, yet relatively high for sandy soils with less than 10% clay content, particularly in temperate arable soils in England and Wales (Verheijen et al., 2005).

Aggregating multiple Soil Health Indicators (SHIs) into a single metric for assessing soil health is a complex task. The European Union Soil Observatory (EUSO) has implemented a dashboard to visualize soil degradation across Europe using a convergence of evidence approach and the "number of soil degradation processes" as an indicator (European Environement Agency, 2023; Veerman et al., 2020). However, most existing soil assessment systems and frameworks treat all SHIs as equally important (Lehmann et al., 2020), which may not accurately reflect the varied significance of different soil properties.

Soil properties can exhibit dynamic responses to management practices and disturbances, such as fluctuations in soil organic matter content, nutrient levels, vegetation cover, and topsoil condition. On the other hand, some intrinsic, static qualities, such as parent material, soil texture, mineralogy, and subsoil structure, remain largely unaffected by management (European Environement Agency, 2023). Recognizing these distinctions is essential for developing more precise and meaningful assessments of soil health.

Soil health assessment enables the alignment of SHIs with specific soil quality standards or thresholds relevant to protection targets, such as those related to water, food, and energy security. This alignment requires an understanding of the relationship between soil dynamics and critical limits for soil protection in the context of climate change. Such insights facilitate the evaluation of healthy and degraded soils, support the achievement of policy goals such as the EU Soil Strategy 2030, and guide precautionary and preventative measures (European Environement Agency, 2023).

Converting critical thresholds for soil protection—such as those impacting water quality, plant production, ecosystem functioning, and climate—into measurable soil properties that affect SHIs is essential. When a soil exceeds a certain threshold, it may necessitate actions or measures to reduce inputs (e.g., nitrogen) to the soil or mitigate the impacts of changes in land use (e.g., soil sealing, net land take, or declining soil fertility) (Hartemink et al., 2008).

Soil health management aims to boost multiple soil ecosystem services, but enhancing one service may unintentionally compromise others. For example, while organic farming seeks to increase soil organic carbon stocks in croplands, extensive adoption of organic practices (with cover crops and plant residue) might limit the soil's overall carbon sequestration potential, due to large nutrient deficiency (Gaudaré et al., 2023). Moreover, increasing nutrient inputs can improve carbon sequestration in agricultural soils, but it may also result in elevated greenhouse gas emissions and nitrogen leaching into groundwater (Carpenter et al., 1998; Hijbeek et al., 2019; Paustian et al., 2016). Thus, efforts to improve one ecosystem service may have unintended effects on other aspects of the Earth system. To optimize synergies and maximize soil sustainability, a holistic assessment of soil health that considers multiple soil functions simultaneously is essential (Moinet et al., 2023). This comprehensive approach ensures a balanced perspective on soil health and ecosystem service trade-offs, highlighting the need to track soil health by monitoring and modeling the soil-plant system.

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Open Research

Data in Figure 4 is available from (Wang et al., 2021a), the software used for generating this data is available on Github: https://github.com/EcoExtreML/STEMMUS_SCOPE.

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