Monitoring and modeling the soil-plant system toward understanding soil health

Article

Published Version

Zeng, Y., Verhoef, A. ORCID: https://orcid.org/0000-0002-9498-6696, Vereecken, H., Ben-Dor, E., Veldkamp, T., Shaw, L., Van Der Ploeg, M., Wang, Y. and Su, Z. (2025) Monitoring and modeling the soil-plant system toward understanding soil health. Reviews of Geophysics, 63 (1). e2024RG000836. ISSN 8755-1209 doi: 10.1029/2024RG000836 Available at https://centaur.reading.ac.uk/120416/

To link to this article DOI: http://dx.doi.org/10.1029/2024RG000836

Publisher: American Geophysical Union

AGU ADVANCING EARTH AND SPACE SCIENCES

Reviews of Geophysics®

REVIEW ARTICLE
10.1029/2024RG000836

Key Points:

- The mechanistic link between soil health indicators and soil functions across spatiotemporal scales has not yet been fully established
- Soil-microbial-plant interactions cause and respond to changes in soil properties and subsequent alterations in soil functions
- The digital twin approach linking soil-plant processes to satellite observables propel a new research paradigm for monitoring soil health

Correspondence to:
Y. Zeng and Z. Su,
y.zeng@utwente.nl;
z.su@utwente.nl

Citation:
Zeng, Y., Verhoef, A., Vereecken, H., Ben-Dor, E., Veldkamp, T., Shaw, L., et al. (2025). Monitoring and modeling the soil-plant system toward understanding soil health. *Reviews of Geophysics*, *63*, e2024RG000836. https://doi.org/10.1029/2024RG000836

Received 31 MAY 2024
Accepted 24 DEC 2024

Monitoring and Modeling the Soil-Plant System Toward Understanding Soil Health

Yijian Zeng[1], Anne Verhoef[2], Harry Vereecken[3], Eyal Ben-Dor[4], Tom Veldkamp[1], Liz Shaw[2], Martine Van Der Ploeg[5], Yunfei Wang[1], and Zhongbo Su[1]

[1]ITC Faculty of Geo-Information Science and Earth Observation, University of Twente, Enschede, The Netherlands, [2]Department of Geography and Environmental Science, Soil Research Centre, The University of Reading, Reading, UK, [3]Agrosphere (IBG-3), Institute of Bio- and Geosciences, Forschungszentrum Jülich, Jülich, Germany, [4]The Remote Sensing Laboratory, Department of Geography and Human Environment, Faculty of Exact Sciences, Porter School of Environment and Earth Sciences, Tel Aviv University, Tel Aviv, Israel, [5]Hydrology and Environmental Hydraulics Group, Wageningen University, Wageningen, The Netherlands

Abstract The soil health assessment has evolved from focusing primarily 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 physicochemical approach to incorporating ecological, biological and molecular microbiology indicators. This shift enables 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) and data, a holistic mechanistic linkage has not yet been fully established between indicators and soil functions across multiple spatiotemporal scales. 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 microbiome, and landscape genomics.

Plain Language Summary Soil health refers to the ability of soil to function as a vital ecosystem that supports plants, animals, and humans. Traditionally, soil health assessments focused mainly on agricultural productivity. However, modern assessments now consider the soil's living organisms and their driving processes, which affect soil properties. This shift has expanded soil health evaluations to include ecological, biological, and molecular microbiology methods. Despite the growing number of indicators to measure soil health, including physical, chemical, and biological factors, there is still a need to fully understand how these indicators relate to soil functions over different times and places. This article reviews the latest methods for monitoring soil health, particularly how soil-microbiome-plant interactions cause and respond to changes in soil properties and functions. It also explores the promising approach of the soil-plant digital twin, which combines various models and data sources to understand soil health better. The review highlights future directions for monitoring soil health using digital twin technology to observe and model the soil-plant system systematically. It identifies current knowledge gaps and opportunities and suggests areas for future research to improve our understanding of the complex interactions between soil properties, water processes, plant interactions, 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 (Keesstra et al., 2016; Lal et al., 2021; Vereecken et al., 2016). Soils are fundamental for the production of safe and nutritious food and they also provide essential raw materials, such as fiber and biofuels, for various human needs (Adhikari & Hartemink, 2016). Soils support nutrient cycling, which is crucial for plant growth and therefore overall (agri-) ecosystem productivity (Cao et al., 2024; Manzoni & Porporato, 2009). They also support a diverse range of organisms, thereby preserving biodiversity and maintaining healthy ecosystems (Bardgett & Van Der Putten, 2014). 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 (Vereecken et al., 2022). Additionally, via vegetation's assimilation of CO_2 and subsequent decomposition of plant materials, soils sequester carbon from the atmosphere, which helps mitigate greenhouse gas emissions (Minasny et al., 2017). All these above-mentioned soil functions are dependent on soil health.

It has been assessed that 60%–70% of soils in Europe are in an unhealthy condition (European Commission, 2023). Globally, the Food and Agriculture Organization of the United Nations (FAO, see Appendix Table A1 for abbreviations) reported that 5,670 million ha of land is undergoing degradation, of which 29% is attributed to human activity (FAO, 2022). This situation may likely worsen as climate changes and land use intensifies. For instance, warming of the Earth System will enhance plant growth and therefore increase litter inputs into the soil, as well as accelerate the mineralization of soil carbon, leading to increased CO_2 emissions from soil respiration. Adding to the complexities, there are significant uncertainties regarding how elevated atmospheric CO_2, global warming, and altered precipitation patterns will impact soil carbon balance, as well as nutrient limitations to primary production, microbial respiration, microbial thermal acclimation and adaptation (Hartmann & Six, 2023; Philippot et al., 2024; Robinson et al., 2019; Sullivan et al., 2022). Similarly, agriculture intensification and deforestation, without sustainable land management practices, will result in more soil compaction, surface sealing, runoff, soil erosion, and contamination of surface and ground waters and the atmosphere (Borrelli et al., 2023; Panagos et al., 2015; Panagos, Vieira, et al., 2024; Rillig et al., 2023). Soil-related issues are identified also 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, 2023; Panagos, Borrelli, et al., 2024) with the goal of pioneering, showcasing and accelerating the transition to healthy soils by 2030, in alignment with the Green Deal commitments. This mission includes establishing a robust, harmonized soil monitoring framework (European Union Soil Observatory, EUSO) (Panagos, Montanarella, et al., 2022; Panagos, Broothaerts, et al., 2024). Similarly, the North American Project to Evaluate Soil Health Measurements (NAPESHM) has been initiated to investigate widely applicable soil health measurements for soil health assessment using over 30 soil health indicators (SHIs) and 124 long-term agricultural research sites (including both conventional and regenerative systems) (Norris et al., 2020). Furthermore, in China, the third national soil survey was launched in 2022 to understand and protect soil health toward food security, as well as China's peak carbon and carbon neutrality targets (G. L. Zhang et al., 2022). These developments emphasize the concept of “soil health” is gaining traction, highlighting soils as a crucial yet overlooked societal asset and public good (Panagos, Borrelli, et al., 2024).

Haberern (1992) first introduced the concept “Soil Health,” two decades after Mausel (1971) coined the term “Soil Quality” that refers to “the ability of soils to yield corn, soybeans and wheat under conditions of high-level management.” While soil quality emphasizes agricultural production, soil health considers “the capacity of a living soil to function, within natural or managed ecosystem boundaries, to sustain plant and animal productivity, maintain or enhance water and air quality, and promote plant and animal health” (Doran, 2002). Since then, “soil health” and “soil quality” 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 describes “the continued capacity of soils to support ecosystem services” (European Commission, 2023), and more specifically as “the physical, chemical and biological condition of the soil, determining its capacity to function as a vital living system and to provide ecosystem service” in the first-ever EU Soil Monitoring Law. This comprehensive definition of soil health encompasses both the intrinsic and dynamic properties of soils to function sustainably and provide ecosystem services (Bünemann et al., 2018; J. Lehmann et al., 2020).

To keep track of a soil's health under ever changing conditions, it is essential to monitor a set of measurable SHIs that can reflect a soil's capacity to deliver ecosystem services (European Environment Agency, 2023; Greiner et al., 2017). This monitoring should consist of effective and ideally low-cost strategies that enable sufficiently high spatio-temporal monitoring resolutions. Despite the growing acceptance of the concept of soil health among scientists and policymakers, selecting relevant SHIs and interpreting them in the context of soil physico-chemical and biological properties remains a challenge (Banerjee & van der Heijden, 2023).

For example, prominent reviews by Bünemann et al. (2018) and J. Lehmann et al. (2020) underscore a persisting deficiency in mechanistic links (e.g., through process-based modeling) 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 these two realms remains inadequately explored (Bünemann et al., 2018; Coyne et al., 2022).

Box 1. Soil Health Indicators (SHIs).

Soil health and its indicators have been studied for over three decades (Gregorich & Acton, 2012; J. Lehmann & Kleber, 2015; J. Lehmann et al., 2020). Based on various assessment frameworks (Bridges & Oldeman, 1999; FAO & ITPS, 2015; FAO & United Nations, 2020; Huber et al., 2010), the widely discussed SHIs focus on addressing various soil threats, including soil erosion (from water or wind), loss of organic matter, salinization, acidification, nutrient depletion/excess, pollution, compaction and physical degradation, waterlogging, impaired water regulating, subsidence of organic soils, loss of soil biodiversity, landslides, soil sealing, and desertification (Panagos, Borrelli, et al., 2024). However, the definition and classification of SHIs, as well as approaches for their sampling, measuring and evaluation, remain diverse (European Environment Agency, 2023; Moinet et al., 2023).

In the context of monitoring soil threats and informing policy development, various SHIs have been established to assess soil condition, degradation, resilience, and ecosystem services (see Figure 1). The EU's Soil Mission has identified eight key soil threats: soil pollutants, excess nutrients and salts, soil organic carbon, soil structure, biodiversity, nutrients and pH, vegetation cover, and landscape heterogeneity, as well as the area of forest and wooded lands (European Commission, 2023). Additionally, the EU Soil Monitoring Law highlights 12 critical indicators for monitoring soil health (Directorate General for Environment, 2024). To support these efforts, the EUSO Soil Health Dashboard has been developed, focusing on nine major degradation processes, such as soil erosion, pollution, and nutrient imbalance, loss of soil organic carbon and soil biodiversity, and peatland degradation, using a total of 19 indicators (Panagos, Borrelli, et al., 2024; Panagos, Broothaerts, et al., 2024; Panagos & Montanarella, 2018; Panagos, Montanarella, et al., 2022; Panagos, Vieira, et al., 2024). These integrated frameworks provide a comprehensive approach for assessing and addressing soil health at various levels.

Most of SHIs can be directly obtained from measurable soil properties through field surveys and laboratory experiments (European Environment Agency, 2023). There are also non-soil indicators related to drivers of change in soil health at landscape scales (e.g., vegetation cover and landscape heterogeneity) and can be operationally monitored using remote sensing techniques (spaceborne, airborne, proximal) (Angileri et al., 2023). It is noteworthy that recent advancements in proximal and remote sensing of the land surface and near-surface environmental variables (Manfreda & Ben Dor, 2023; Rodell et al., 2015; Su et al., 2014; J. Wang et al., 2023) have significantly improved the assessment of soil health. For example, Gholami et al. (2024) use precipitation and soil moisture variables as important factors for predicting global land susceptibility to wind erosion. Romero et al. (2024) include climatic factors for deriving the soil health map as a composite index based on soil biodiversity, plant disease control and soil properties. Prăvălie et al. (2024) consider also vegetation parameters (Normalized Difference Vegetation Index—NDVI) and groundwater table, among other factors, for the unified modeling of land multi-degradation pathways in Europe.

However, many indicators represent multiple soil processes, and as a result, SHIs are not always easily distinguishable from one another. 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., 2018), as well as land use and management (as expressed by vegetation cover). Similarly, the evaluation of 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) (Y. Wang et al., 2021; Yu, Fatichi, et al., 2020). 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., 2020, 2023; Panagos et al., 2015; Panagos, Vieira, et al., 2024).

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). Considering the dynamic interactions between soil chemical, physical, and biological properties, the effective determination of threshold values for soil health assessment will require process-based modeling.

Box 2. EU Soil Observatory (EUSO).

Soil science renaissance (SSR), coined by Hartemink and McBratney (2008), refers to the renewed interests to bring soils back onto the global research and policy agendas. Evidence of a continued SSR is the Soil Mission at EU (Panagos, Borrelli, et al., 2024), the NAPESHM in North America (Norris et al., 2020), and the Third National Soil Survey in China (G. L. Zhang et al., 2022). Here, we used the EUSO and its monitoring service as one of the avatars for SSR.

Over the past two decades, the EU has implemented the Soil Thematic Strategy (2006), the Common Agricultural Policy (2013) for agri-environmental protection. Moreover, since 2020, soil health and its protection has been ranked high in the EU Green Deal, EU Soil Biodiversity Strategy 2030, EU Soil Strategy 2030, Zero Pollution Action Plan, the Farm to Fork Strategy, the Carbon Removal Certification framework, and the EU Climate Adaptation Strategy (Panagos, Borrelli, et al., 2024). It reaches its pinnacle with "A Soil Deal for Europe" mission, and the general approach on Soil Monitoring Law being adopted by the EU Council.

To support EU policies, the EUSO aims to be the primary provider of soil reference data and knowledge at the EU level. Its objectives include monitoring soil health, transitioning from soil monitoring to a deeper understanding, supporting soil policy development, engaging with soil research activities, and raising societal awareness about the importance of sustaining healthy soils (Broothaerts et al., 2024; Panagos, Broothaerts, et al., 2024). The monitoring component of EUSO is driven by the LUCAS (Land Use/Cover Area Frame Survey) Soil module, which is the only harmonized and regularly conducted soil survey in the EU, serving as a key reference system for soil monitoring (Panagos, Van Liedekerke, et al., 2022). The LUCAS Soil module (2009–2012 and 2015) includes measurements of 13 physico-chemical properties, along with corresponding visible and near-infrared spectral libraries (Orgiazzi et al., 2018). It was further expanded in the 2018 survey to include soil biodiversity measurements, characterizing taxonomical and functional diversities of soil microbial communities at 1,000 locations, with the number of locations doubled in the 2022 survey (Orgiazzi et al., 2022).

LUCAS Soil is an open-access resource that provides maps of soil properties and derived maps of soil threats (Panagos, Van Liedekerke, et al., 2022), supporting tools like the soil health dashboard (Prăvălie et al., 2024). It is evolving to capture spatiotemporal variations in soil characteristics influenced by land use, land cover changes, and climate change, facilitated by its triennial surveys and the inclusion of a soil biodiversity module. This comprehensive, harmonized, continental-scale soil database, when combined with the LUCAS land cover nomenclature (EUROSTAT, 2018) and other bioclimatic variables, has significantly advanced the trait-based approach to understanding soil health (Dulya et al., 2024; Labouyrie et al., 2023; Smith et al., 2021). This underscores the growing need to explore the mechanistic connections between above- and below-ground ecophysiological processes.

1.1. Soil Microbiome, Soil Structure, and Soil Health

Soil microbial metrics are key indicators of soil health, often involving the measurement of microbial taxa, enzymatic activities, microbial biomass and biodiversity (Anthony et al., 2023; Schloter et al., 2018). However, these metrics can be difficult to interpret due to context-specific biotic and abiotic influences (Fierer, 2017). For instance, enzymatic activity may indicate either nutrient limitation or availability, while microbial biomass alone offers limited insights into soil health (Fierer et al., 2021). Moreover, metrics like fungal-to-bacterial ratios, though widely used, lack conclusive evidence for clear differentiation in nutrient cycling pathways (Philippot et al., 2013). As such, a more targeted approach, tailored to specific management or policy goals, is necessary when evaluating soil health (Jansson et al., 2023).

A trait-based approach offers a promising avenue, as microbial traits reflect variations in soil processes and environmental conditions (Dauphin et al., 2023; Y. Yang, 2021). For example, Tao et al. (2023) finds that microbial carbon use efficiency, while influenced by and interacts with climatic, geographic, soil chemical and vegetation variables, is the major determinant for the preservation of soil organic carbon (SOC). Hawkins et al. (2023) uses satellite-based Net Primary Productivity (NPP) of global vegetation, mycorrhizal vegetation data, and Copernicus Dynamic Land Cover map, to estimate the amount of photosynthate that terrestrial plants allocate to different mycorrhizal types in the soil.

Furthermore, advances in high-throughput molecular technologies and landscape genomics enable detailed analysis of microbial functional traits, which can inform biogeochemical cycling models and soil health management (Crowther et al., 2019; Lahlali et al., 2021). However, achieving broad applicability requires large-scale sequencing and cross-site analyses (Lewin et al., 2022), mirroring the development of global soil spectral libraries for physical, chemical, and biological properties (Orgiazzi et al., 2018; Viscarra Rossel et al., 2016).

Soil microorganisms play a pivotal role in soil formation and soil structure (aggregate) stability, facilitating global elemental cycling through interactions with minerals, water, and plants (Dignac et al., 2017). The weathering of rock minerals creates porosity, allowing autotrophic and heterotrophic microorganisms to colonize, fix carbon, and contribute to organic matter buildup (Banwart et al., 2019). These microorganisms accelerate the dissolution of rock minerals, making nutrients available for plant colonization (Wild et al., 2022). As plants grow, their roots and symbiotic fungi further drive weathering and enhance soil structure by forming aggregates with organic and mineral particles (Giannakis, Nikolaidis, Valstar, & Rowe, 2017). Microorganisms also influence soil structure properties by reorganizing soil particles and pores, affecting water retention and hydraulic conductivity (Cao et al., 2024), which in turn impact ecosystem water, energy, and carbon fluxes (Sullivan et al., 2022). The composition of microbial communities is shaped by environmental factors and plant traits (Sokol et al., 2022), while these microbial communities reciprocally influence nutrient availability and plant growth (Philippot et al., 2024).

Soil structure is essential for driving soil functions by regulating the exchange of water, solutes, energy, and carbon between the atmosphere, biosphere, hydrosphere, and lithosphere (Banwart et al., 2019; Fatichi et al., 2020), and contributes to the reduction of soil degradation processes including soil erosion (Panagos et al., 2015). It creates reactive, porous interfaces that influence microbial interactions, nutrient cycling, and pollutant transformation, acting as a dynamic biogeochemical reactor linking above- and belowground systems (Ebrahimi & Or, 2018; Kravchenko et al., 2019). Soil structure models are based on two perspectives (Vogel et al., 2022): the pore and aggregate approaches. Aggregate-based models focus on the formation, stability, and reformation of aggregates (Segoli et al., 2013; Stamati et al., 2013; Zech et al., 2024), while pore-based models emphasize the interactions among porosity, organic matter, and pore size distribution (König et al., 2023; Meurer, Barron, et al., 2020). Both approaches offer complementary insights into soil functions such as water retention, carbon sequestration, and elemental cycling (Totsche et al., 2024). Advanced models, such as the aggregate-based 1D-ICZ model (Giannakis, Nikolaidis, Valstar, Rowe, et al., 2017) and the pore-based USSF (Jarvis et al., 2024), simulate the dynamic interactions between soil structure and its hydro-biogeochemical consequences across multiple scales, from the microbiome to regional levels (Sullivan et al., 2022; Vereecken et al., 2022). Understanding soil structure's role in soil functions requires integrating key mechanisms and processes within the soil-plant-microbiome continuum to capture the complex interactions governing soil-plant systems (Faucon et al., 2017).

Digital twin technology, initially developed for engineering, and manufacturing industries, is increasingly being applied in Earth system science to create digital replicas of real-world systems, integrating models, data, and artificial intelligence for real-time simulations (Bauer et al., 2024; Bauer, Dueben, et al., 2021). The European Union's Destination Earth (DestinE) program exemplifies this approach by combining Earth system models and Earth Observation data with machine learning to create a high-fidelity digital replica of the planet (Hoffmann et al., 2023). A digital twin's key features include precise digital replicas, real-time data synchronization, lifecycle data management, and model-data fusion for self-evolving simulations that reflect physical reality (Claus et al., 2022; San, 2021; Semeraro et al., 2021; Tao & Qi, 2019). While the use of digital twins in soil research has been limited to small-scale applications (Purcell & Neubauer, 2023; Tsakiridis et al., 2023), the growing availability of soil and plant data (Kattge et al., 2020; Orgiazzi et al., 2018), including multi-omics (Bernatchez et al., 2024), hyperspectral imaging (Chabrillat et al., 2019), and microwave data (Wigneron et al., 2017), positions soil science as a “big data” field (Amelung et al., 2024). Digital twins offer potential for advancing soil structure and soil function models, enabling improved understanding of soil processes and scenario-based assessments of and projections for soil health management under changing environmental conditions (Amelung et al., 2024; Fisher et al., 2018; Purcell et al., 2023; Tsakiridis et al., 2023).

1.2. Structure of This Review

It is critically important for acquiring process-level insights into soil health to grasp the multifaceted functions performed by soils (Baatz et al., 2021; Deckmyn et al., 2020; Vereecken et al., 2016; Vogel et al., 2018). 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 (Amelung et al., 2020; Lal, 2015). Interactions in the soil system, involving soil properties, hydrological processes, soil-plant hydraulic parameters, soil-root interactions, the soil microbiome and land management practices are ever-present (Hartmann & Six, 2023). 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:

1. What are the mechanistic linkages between SHIs and soil functions?
2. How do soil-plant-microbial processes contribute to changes and dynamics in soil properties and subsequent alterations in soil functions?
3. 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. Soil microbiome plays a pivotal role in linking microbial activities at the microscale to larger-scale soil processes at the pedon, field and regional scale, through biochemical and structural alterations to the soil. Therefore, we will review the representation of soil microbiome (Section 2) and soil hydrological processes (Section 3) in the Earth system to comprehend the mechanistic linkages between SHIs and soil functions.

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 modeling. 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 discuss 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, for example, linking soil-plant processes to satellite observables, is poised to stimulate and propel a novel 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 microbiome and landscape genomics (Section 6).

Soil health will be a major theme of the coming decades, and will involve the ever-growing use of Earth Observation data, soil and plant databases, mechanistic and AI-empowered model developments, as well as the digital twin approach. This review aims to set out the opportunities 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. The Soil Microbiome 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 (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 & Chen, 2019), as well as regulating functions related to soil structure (Philippot et al., 2024), soil hydrological processes (Hartmann & Six, 2023), soil erosion (Borrelli et al., 2020) and carbon sequestration (Jansson & Hofmockel, 2020).

In a direct pathway to plants, the functions of three groups of either associative or symbiotic beneficial microorganisms contribute to plant nutrition and health (Coban et al., 2022): plant growth–promoting rhizobacteria (PGPR), symbiotic 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 and enhance plant growth and stress tolerance via a variety of mechanisms, such as nutrient acquisition (including associative N_2 fixation), pathogen suppression and production and modulation of plant hormones (Trivedi et al., 2020). Symbiotic nitrogen-fixing microorganisms (e.g., Rhizobium, Bradyrhizobium and Frankia spp.) form mutualistic relationships with plants, converting atmospheric nitrogen gas into ammonia. This process occurs within specialized symbiotic structures (nodules) of leguminous or actinorhizal plant species and directly supplies nitrogen to the host plant, and subsequently adds biologically available nitrogen to the soil. AMF, in the phylum Glomeromycota, establish a symbiotic relationship with a broad diversity of plant species by penetrating the cortical cells of the roots to enhance access to nutrients and water (Brundrett & Tedersoo, 2018). EMF (in the phylum Ascomycota and Basidiomycota) 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 (termed the community structure) (Bickel & Or, 2020; Sokol et al., 2022). For example, the relative abundances of major bacterial and archeal taxa can vary dramatically depending on the soil environment (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). Such intricate interplays render the direct prediction of soil microbial community structure based on plant species a complex and nontrivial task.

2.1. Characterizing the Soil Microbiome

Currently, 20%–50% of the variation in the mineralization rates of carbon and nitrogen across terrestrial ecosystems can be explained by climate, plant, land use and land cover changes, as well as edaphic factors (Jansson & Hofmockel, 2020; Z. 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 (e.g., nitrogen/carbon fixation, mineralization, decomposition). 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).

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 (e.g., soil microbial biomass) is not enough to comprehend and assess the soil functioning and its health status.

The functional group composition of the soil microbiome offers a more nuanced understanding of soil health compared to microbial biomass alone, which is often treated as a 'black-box' metric lacking specificity on taxa composition. Microbial biomass estimates can vary depending on the methods used and soil properties (Fierer et al., 2021). Partitioning the soil microbiome into broad organismal groups, such as fungi, bacteria, archaea, and protists, enhances our understanding of their differential roles in soil processes. For instance, fungi and bacteria significantly influence carbon and nitrogen mineralization, with fungi dominating in ecosystems with slow-growing plants and bacteria prevailing in fast nutrient-cycling systems like grasslands (Bahram et al., 2018; Coban et al., 2022). The fungal-to-bacterial ratio is often used to indicate soil biogeochemical processes, though its interpretation can be complicated by overlapping niches between these groups (Fierer et al., 2021). Further refining these broad groups into functional guilds, such as AMF and EMF, reveals mechanistic insights into soil functioning. AMF dominate fast nitrogen-cycling ecosystems, while EMF thrive in slow-cycling systems, influencing SOM turnover (Steidinger et al., 2019). Consequently, the AMF:EMF ratio serves as an indicator of elemental cycling rates and soil microbial stability (Frey, 2019; Lu & Hedin, 2019). These functional group analyses are being incorporated into Earth System Models to better represent soil-plant-microbial processes globally (Crowther et al., 2019).

Taxonomic diversity and composition within soil microbial communities provide refined insights into soil functioning by categorizing species into distinct microbial taxa. DNA metabarcoding has transformed the ability to assess microbial taxa abundance, revealing that despite the vast diversity, only a few taxa dominate soil microbial communities (Bahram et al., 2018; Tedersoo et al., 2014). This hyperdominance, similar to patterns in plant communities (McGill et al., 2007), raises questions about whether soil microbial community structures mirror aboveground plant distributions (Fierer et al., 2012). Key edaphic and biotic factors, such as soil pH, C:N ratios, moisture, temperature, texture, climate, and vegetation types, shape the diversity and abundance of microbial taxa (Cameron et al., 2018; Thompson et al., 2024). This relationship helps infer the functional potential of microbial taxa on a broad spatial scale, with studies showing environmental data can predict bacterial distributions globally (Delgado-Baquerizo et al., 2018). However, linking taxonomic diversity to functional biogeography remains challenging, as taxonomic classifications do not always correlate with functional traits, and soil microbial processes involve a complex interplay of active, dormant, and inactive taxa (Blagodatskaya & Kuzyakov, 2013). Additionally, while most DNA sequencing methods measure relative abundance, absolute abundance and functional gene data, which are essential for understanding microbial processes, are harder to obtain, though new approaches are emerging (M. Zhang et al., 2022).

The functional traits of soil organisms, rather than their taxonomic diversity, are key drivers of soil functioning, influencing elemental processing rates and other ecosystem processes (Crowther et al., 2014). These traits encompass structural, morphological, biochemical, and genetic characteristics that shape the performance of individual organisms (Lennon et al., 2012). Advanced molecular techniques, such as metagenomics (genetic composition), metatranscriptomics (active functions), and metaproteomics (protein synthesis and enzyme activity), allow for detailed insights into the functional profiles of entire microbial communities (Bouchez et al., 2016). Measuring these traits facilitates a mechanistic understanding of microbial community assembly, revealing trade-offs between stress tolerance and competitive traits along environmental gradients, with stress tolerance prevailing in colder, drier regions and competitive traits in tropical, moist areas (Fierer, 2017). This understanding, applicable across both fungi and bacteria, helps explain biogeographic patterns in soil functioning, which are shaped by the interactions of climate and soil properties (Maynard et al., 2019). Increasing use of 'omics' technologies offers new opportunities to link genetic and functional diversity with integrated soil functioning, following trait-based frameworks developed in plant ecology (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). In turn, 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 & Six, 2023).

2.2.1. Soil Microorganisms and Physicochemical 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 biosilicification 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, for example, causing reduced hydraulic conductivity and enhanced shear strength (Vaksmaa et al., 2017).

2.2.2. Soil Microorganisms and Soil Aggregates

Soil microorganisms have direct effects on the formation, stabilization, and disintegration of soil aggregates, 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).

EPS play an important role in binding soil particles with carbonates, metal oxides, and organic matter into organo-mineral complexes forming silt-sized aggregates ($<50\ \mu$m) 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 ($>250\ \mu$m) (Costa et al., 2018). It is to acknowledge that microaggregates might form 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). Furthermore, the glomalin-related soil protein, as a component of AMF hyphal walls, contributes significantly to the stabilization of soil aggregates due to its positive correlation with aggregate water stability and its slow turnover rate (Rillig, 2004).

2.2.3. Soil Microorganisms and Soil Hydrological Processes

It is intuitive to reason that the interaction between soil microorganisms and soil processes acts via 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 related pore-size distribution, which can increase the volume of soil micropores, thus directly influencing the water holding capacity of the soil (Rabot et al., 2018). Soil microorganisms and their interactions with plant roots control the stability of soil aggregates (Hartmann & Six, 2023), which has significant effects on soil erodibility (via mechanical soil binding or biochemical effects) (Bezak et al., 2024; Borrelli et al., 2020; Panagos et al., 2015) and will eventually affect soil hydrological processes (Coban et al., 2022; Panagos, Vieira, et al., 2024; Poesen, 2018).

Growing evidence suggests that mycorrhizal fungi can facilitate water movement between plants along their hyphae, and 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 roots 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, which attenuates soil rewetting rates but maintains the continuity of the liquid phase in micropores under extremely dry conditions (Or et al., 2007).

2.3. Soil-Microbiome-Plant Continuum and Trait-Based Approaches

2.3.1. 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 exude organic acids, sugars, and secondary metabolites, serving as signals to attract microbial colonization (J. Xu et al., 2018) onto 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 total carbon allocation to the roots in grasses and cereals (Jones et al., 2009). On the other hand, rhizosphere microbiota are responsible for the plant losing photosynthate via rhizodeposition, imposing a significant cost on plant fitness, because 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 (Klironomos et al., 2011; Neuenkamp et al., 2018; Van Der Heijden et al., 2008; 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).

2.3.2. 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 & 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 (Y. 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 (i.e., 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 data sets. With the current trend of increasing our understanding of the global biogeography of soil communities, geo-referenced, interpolation-based, gridded environmental data sets (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 data sets of below-ground physical, chemical, and biological soil factors are still largely missing, which hinders the application of GEA analyses for evaluating soil health (Dauphin et al., 2023; Lajoie & Kembel, 2019; Leigh et al., 2021).

Making the most of landscape genomics for understanding soil health requires the use of 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 (Y. 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 microbiome on the genetic signature (Lajoie & 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 regional 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 (Brocca et al., 2024; Manfreda & Ben Dor, 2023). 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 retrieval of daily soil moisture at global scales with spatial resolutions ranging from 1 to 25 km (Q. Han et al., 2023; Zeng et al., 2016; L. J. Zhang et al., 2021; Zhuang et al., 2020).

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; J. 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 like those used in the trait-based approaches (such as, PLSR - Partial Least Squares Regression) (Dauphin & 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-plant-microbial 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 & 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 & 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 (DTE) (Hoffmann et al., 2023), promises a substantial amplification of our understanding of this complex continuum (Bauer et al., 2024; Hoffmann et al., 2023; Su, Zeng, et al., 2020; Zeng & Su, 2024).

3. Soil Hydrology and Soil Properties

Quantifying soil hydrological parameters and processes is essential for assessing SHIs (Panagos et al., 2015; Philippot et al., 2024; Prăvălie et al., 2024; Vogel et al., 2018, 2024). On the other hand, as noted in the previous section, soil structure and SOM have a strong influence on soil hydrology, affecting various land surface processes and Earth system components, including vegetation, groundwater, and the atmosphere (Fatichi et al., 2020; Sullivan et al., 2022; Vereecken et al., 2022; Wild et al., 2022).

In this section, we review and discuss soil hydrological processes and their relation to soil health, with a focus on soil structure and its representation in ESMs. We also explore avenues to improve the parameterization of these aspects in ESMs. We consider static basic soil properties such as soil texture and mineralogy, along with the soil structure, which has the strongest influence on soil hydraulic properties (Szabó et al., 2021; Tóth et al., 2017). Secondary, non-static properties, such as water retention characteristics, soil hydraulic and thermal conductivities, are directly influenced by basic (static and dynamic) soil properties. We have deliberately excluded event-driven impacts (e.g., fires, volcanic ash deposition, severe erosion, or aeolian deposition) on soil properties (Doerr & Cerdà, 2005; Furtak & Wolińska, 2023; Lubis et al., 2021; Massman, 2021), as these processes are not yet fully integrated into current-generation land models in ESMs (Fisher & Koven, 2020).

3.1. Soil Hydrological Processes and Soil Health

Soil hydrological processes are governed by the physical, chemical, and biological properties of soils. These properties influence how water flows and is retained in soils, and how it is allocated between storage, evaporation, runoff, lateral flow, deep drainage, percolation, capillary rise or uptake by roots to support transpiration, at any moment in time (Vereecken et al., 2022; Y. Wang et al., 2021; Yu et al., 2016; Yu, Fatichi, et al., 2020). Soil hydrological dynamics are shaped by a combination of soil characteristics such as texture, organic matter content, pH, cation and anion content, structure, and surface condition, as well as vegetation type and climate (Or, 2020; C. Zhang & Lu, 2019). Together, these factors modulate the effects of climate change and soil-land managements on terrestrial ecosystems and control feedback mechanisms within the water, energy, carbon, and nutrient cycles (Fatichi et al., 2020; Stephens et al., 2023; Vereecken et al., 2015). Consequently, soil hydrological processes, together with soil microorganisms, create the links between pore-scale soil properties and broader regional and global climate processes (Figure 1) (Vereecken et al., 2022).

At the pore scale, capillary and molecular forces, such as hydrogen bonding, van der Waals forces, and electromagnetic fields, act on soil water (Luo et al., 2022). These forces influence the storage, flow and transport of water, heat, matter and energy in soil, including the heat of wetting or condensation (Edlefsen & Anderson, 1943). These soil pore-scale processes and properties determine the environmental conditions of microbial habitats (e.g., abiotic characteristics) (Hartmann & Six, 2023), which govern the structure and function of the soil microbiome (e.g., microbial abundances and community composition, and rates of microbial activities) (Fierer, 2017). For example, the spatial organization of soil aggregates can induce sharp gradients in the availability and accessibility of water, oxygen and nutrients for microorganisms (Borer et al., 2018). Such sharp gradients lead to localizations of different microbial communities (e.g., aerobic bacteria colonize larger pores between and within macroaggregates, while anaerobic niches dominate smaller pores within microaggregates) (Z. Li et al., 2024). It has been reported that microbial communities located on the surface of macroaggregates are largely disconnected during

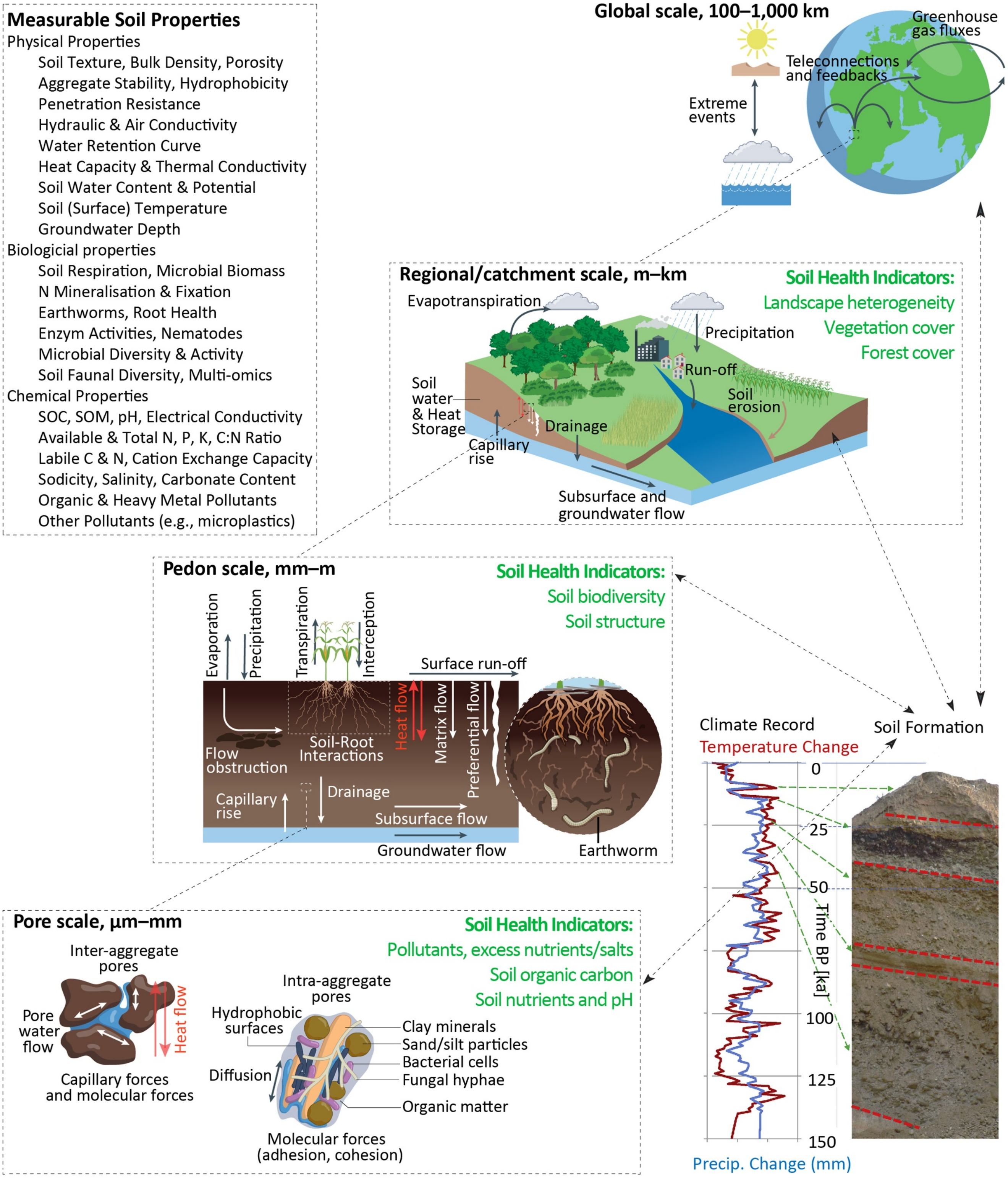

Measurable Soil Properties
Physical Properties
Soil Texture, Bulk Density, Porosity
Aggregate Stability, Hydrophobicity
Penetration Resistance
Hydraulic & Air Conductivity
Water Retention Curve
Heat Capacity & Thermal Conductivity
Soil Water Content & Potential
Soil (Surface) Temperature
Groundwater Depth
Biologicial properties
Soil Respiration, Microbial Biomass
N Mineralisation & Fixation
Earthworms, Root Health
Enzym Activities, Nematodes
Microbial Diversity & Activity
Soil Faunal Diversity, Multi-omics
Chemical Properties
SOC, SOM, pH, Electrical Conductivity
Available & Total N, P, K, C:N Ratio
Labile C & N, Cation Exchange Capacity
Sodicity, Salinity, Carbonate Content
Organic & Heavy Metal Pollutants
Other Pollutants (e.g., microplastics)
Global scale, 100–1,000 km
Greenhouse gas fluxes
Teleconnections and feedbacks
Extreme events
Regional/catchment scale, m–km
Soil Health Indicators:
Landscape heterogeneity
Vegetation cover
Forest cover
Evapotranspiration
Precipitation
Run-off
Soil erosion
Soil water & Heat Storage
Drainage
Capillary rise
Subsurface and groundwater flow
Pedon scale, mm–m
Soil Health Indicators:
Soil biodiversity
Soil structure
Evaporation
Precipitation
Transpiration
Interception
Surface run-off
Heat flow
Matrix flow
Preferential flow
Flow obstruction
Soil-Root Interactions
Capillary rise
Drainage
Subsurface flow
Groundwater flow
Earthworm
Climate Record
Temperature Change
Soil Formation
0
25
50
Time BP [ka]
100
125
150
Precip. Change (mm)
Pore scale, µm–mm
Soil Health Indicators:
Pollutants, excess nutrients/salts
Soil organic carbon
Soil nutrients and pH
Inter-aggregate pores
Pore water flow
Heat flow
Capillary forces and molecular forces
Intra-aggregate pores
Hydrophobic surfaces
Diffusion
Clay minerals
Sand/silt particles
Bacterial cells
Fungal hyphae
Organic matter
Molecular forces (adhesion, cohesion)

Figure 1.

soil drying while again becoming interconnected during (re)wetting events (Wilpiszeski et al., 2019). This highlights the importance of soil hydrological processes for the assessment of soil health.

At the soil profile scale, soil hydrological processes involve infiltration, runoff, internal and deep drainage, evapotranspiration, soil water storage, and capillary rise, including 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 catchment to regional scale, water flow within and over the surface of the soil is routed across the landscape. At the global scale, large-scale atmospheric processes, such as atmospheric blocking and large convective rainfall events, can cause droughts and floods, which interact with soil physical and biological 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). For example, soil moisture content will affect atmospheric boundary layer growth and hence affect the occurrence of cloud-forming processes. 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, soil functioning, and soil development. Changes to the soil system can occur at an accelerated rate due to human activity and climate change. For example, the projected more vigorous hydrological cycle under global warming (i.e., more intensive precipitation combined with increased runoff) is expected to increase the water-driven soil erosion 30%–60% globally (Borrelli et al., 2020), depending on soil properties (e.g., texture, organic content, permeability, structure and stone cover), land use/land cover management, and soil conservation practices (Borrelli et al., 2023). Therefore, accurately representing soil hydrological processes and properties in ESMs is crucial, as the pace of soil hydrological changes (e.g., acceleration of surface runoff due to climate change) can serve as a key indicator of soil health and sustainability (K. Yang et al., 2011).

3.2. Soil Structure and Soil Hydro-Biogeochemical Processes

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., 2018). Over time, macropores form between macroaggregates and peds, often induced by shrinkage and swelling of active clays (such as montmorillonite) in clay-rich soils due to soil drying-wetting, or due to freeze-thaw cycles. Additionally, soil structure formation in many terrestrial ecosystems is driven by root systems and burrowing soil fauna, which create biopores (Robinson et al., 2019). At the scale of the soil-plant system, a healthy soil structure can be conceptualized as an efficient "biogeochemical reactor" that facilitates the abiotic and biotic processes mentioned above. It establishes a mechanistic link between the aboveground vegetation and belowground soils, via connecting soil to microorganisms, plants and to the atmosphere, as well as to groundwater (Ebrahimi & Or, 2018; Kravchenko 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 SOM 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 (Wild et al., 2022). For instance, pore clogging can reduce soil hydraulic conductivity and decrease water infiltration and subsequent internal drainage, 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 the soil microbial community (Bickel & Or, 2020).

Figure 1. Soil properties, microbiome, soil hydrological processes at pore-scale, to pedon, regional (weather), and global (climate) scales (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)) relates, 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 exchanges 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), mainly based on the review by Bünemann et al. (2018). The eight soil health indicators adopted by European Commission's Soil Mission (European Commission, 2023) are listed with the diagrams representing the scales at which these indicators are measurable.

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 plow 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). 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 & 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).

The soil structure-facilitated processes range from long-term regolith transformation, to seasonal shifts in vegetation inputs of organic matter, and diurnal variations in water, heat and gas flows and solute transport (Wild et al., 2022). 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). Capturing these slow, ongoing soil-forming processes 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). These temporal 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 modeling (Rahmati et al., 2023). Simulating the Earth System at the kilometer 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.

3.3. Modeling Hydro-Biogeochemical Consequences of Soil Structure

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), the 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). The continuous and dynamic reorganization of soil aggregates between disintegration and assemblage has important implications for the turnover of POM. 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, Chenu, et al. (2020). These models focus on the dynamic interactions among SOM 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, POM, pores, and the characteristics of biogeochemical interfaces (such as topography and heterogeneity) across various scales (Totsche et al., 2024). Improving our understanding of the intricate links between soil structure and soil function requires high-fidelity simulation of soil structural changes and their effects on the exchanges within the SPAC, across various spatial scales and complexities.

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, Nikolaidis, Valstar, Rowe, et al., 2017). 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, Nikolaidis, Valstar, &

Rowe, 2017). 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, Chenu, et al. (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, and how these influence crop production and organic matter cycling at the soil profile scale (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, SOM turnover, and soil hydraulic properties (Jarvis et al., 2024).

These advanced soil function models demonstrate that the understanding of the linkage between soil structure and soil functions can only be achieved through modeling 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.

3.4. Soil Property Maps for ESMs

Basic soil property maps serve as essential inputs for pedotransfer functions (PTFs) to estimate soil hydraulic and thermal characteristics in ESMs. A key consideration is how these soil property maps are initially generated. Soil mapping approaches can generally be categorized into two main types:

1. The traditional (or conventional) soil survey-based mapping. This approach relies on the identification of map units, which are derived from the delineation of soil boundaries based on either remote sensing imageries or field observations with a conceptual model about the relationships between soil attributes and visual features of landscape. Next, field observations are made to describe the representative soil profiles within each map unit. The produced soil map (representing a discrete spatial model) is presented as polygons that reflect distinct soil types across the landscape. This method forms the basis for many national and regional soil maps (Kempen et al., 2012). An example is the harmonized soil databases for Europe, such as the European Soil Database v2.0 (Panagos, Van Liedekerke, et al., 2022);
2. Digital soil mapping (DSM). This method is defined as "the creation and population of spatial soil information systems by numerical models inferring the spatial and temporal variations of soil types and soil properties from soil observation and knowledge and from related environmental variables" (Lagacherie & McBratney, 2006). DSM has three main components (Minasny & McBratney, 2016): (a) input from legacy soil observations (from fields and laboratories) and soil maps, or information from newly acquired soil samples, obtained using statistical sampling techniques; (b) the development of mathematical or statistical models (continuous spatial model) for spatial and non-spatial soil inference, identifying relationships between soil properties and soil covariates or environmental factors such as *s*oil, *c*limate, *o*rganisms, *r*elief, *p*arent materials, *a*ge and spatial positio*n* (*scorpan*) (Chen et al., 2022; McBratney et al., 2003; G. L. Zhang et al., 2017); (c) the output as a continuous spatial soil information system that can be readily updated when new information becomes available (Helfenstein et al., 2024; Hengl et al., 2017; Liakos & Panagos, 2022; Poggio et al., 2021).

Soil maps derived from the discrete spatial model-based approaches cannot be directly applied in ESMs due to several limitations (Dai, Shangguan, et al., 2019; Schoorl & 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.

DSM combines geostatistical methods with regression-based or machine learning-based models (and their ensemble) to generate high-resolution soil property maps by leveraging a wealth of auxiliary data and soil profile databases at regional and national levels (Minasny & McBratney, 2016), such as SoilGrids250 m (Hengl et al., 2017) and euptfv2 (Szabó et al., 2021). This approach explains variations in soil properties across different soil types, linking them to soil formation covariates (*scorpan*), in line with the Catena concept (Jenny & Amundson, 1994; Pennock & Veldkamp, 2006; Schoorl & Veldkamp, 2016).

Although DSM addresses the limitations of the discrete spatial model-based approach, both methods face uncertainties due to the use of different analytical methods for the same soil property across various soil profile databases (Dai, Shangguan, et al., 2019). Additionally, since most legacy soil profile data were not collected with the probability sampling method (Batjes et al., 2020), the spatial uncertainty estimates of the resulting soil property maps are not significantly robust (Bregt, 1992; Stoorvogel et al., 2017). It is to note that the LUCAS soil module (Orgiazzi et al., 2018), as the reference system for soil monitoring in EU, is currently collecting temporal variation of soil characteristics with a stratified sampling method within the EUSO framework (Panagos, Broothaerts, et al., 2024). The EUSO's approach will contribute significantly to EU Soil Monitoring Law (for the need of monitoring soil taking into account both spatial and temporal aspects), to the development of transient PTFs, and to produce soil maps with spatial uncertainty information. For example, the LUCAS database has been used to map topsoil physical and chemical properties at the European scale, with associated uncertainties and errors quantified (Ballabio et al., 2016, 2019).

Despite the abovementioned advancement, 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 data set with 196,498 geo-referenced profiles collected between 1920 and 2020 (Batjes et al., 2020). The data set 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).

3.5. Challenges in Representing Soil Properties in ESMs

Current ESMs rely on static data such as soil texture to derive soil hydrothermal parameters using PTFs (Weber et al., 2024). These parameters feed into the mathematical functions that model soil hydraulic (and thermal) functions, including the water retention and hydraulic conductivity curves, within soil hydrological sub-models (Van Looy et al., 2017). 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 soil hydraulic functions (Fatichi et al., 2020). This limitation arises from a lack of understanding regarding the turnover timescales of aggregates and macropores, as a function of natural and management processes (Vereecken et al., 2022). A recent study (M. Zhao et al., 2022) found that the absence of soil structure representation in ESMs (used for CMIP6, the Coupled Model Intercomparison Project Phase 6) 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 climate of the Earth.

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). 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, Xin, et al., 2019; 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; Weber et al., 2024):

1. Different measurement methods and instruments used to assess basic and hydraulic soil properties can introduce systematic biases (Vereecken et al., 2010);
2. There are significant data gaps in the development of multiscale PTFs, ranging from soil profile to global scale, especially for soils formed under natural vegetation in varying climatic conditions (Vereecken et al., 2022). 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);

3. 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). However, soil management practices (and history) can induce structural alterations to the soil and its hydraulic and thermal properties. The transient PTFs are needed to account for such temporal effects;
4. 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 (P. Lehmann et al., 2021);
5. 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);
6. Many LSMs consider deep vadose zones and even the depth to bedrock (DTB) while applying the same soil hydraulic and thermal parameterization as used for the top 1–2 m layers throughout the entire soil profile (Condon et al., 2021). Deep sediments are fundamentally different from the soil layer close to the surface, since they have not undergone pedogenic processes and not influenced by the vegetation-induced pore-space-forming processes. However, very few observational data have been collected to characterize hydrothermal properties of deep vadose zones (Marthews et al., 2014);

Vereecken et al. (2022) advocated for closer collaboration between soil hydrology scientists and global land surface and climate modelers to enhance the representation of soil hydrological processes in PTF-aided LSMs. Two potential pathways forward were proposed: (a) 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 & Mohanty, 2011); (b) 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 in PTF predictive ability. It is recommended to use ensemble PTFs that combine multiple PTF sets (Dai, Xin, et al., 2019; He et al., 2020). Furthermore, a roadmap for the future development of PTFs has been presented by the International Soil Modeling Consortium (ISMC) PTF Working Group (Weber et al., 2024). Among other issues, they address the fundamental concern on the scale mismatch between PTF derivation (based on laboratory measurements) and its applications (at the field to regional scales), and suggest evaluating PTFs functionally by using ecosystem-scale observations of water, energy, carbon fluxes to tackle such scale discrepancy.

In addition to soil properties extending 1–2 m below the surface, ESMs also require information on soil properties down to the DTB (Shangguan et al., 2017). However, due to a lack of reliable data, creating an accurate global DTB map, along with corresponding soil property maps below the 1–2 m depth, remains challenging. While applying DTB data to define the lower boundary in ESM configurations 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 100 m) 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).

3.6. Ways Forward

There are various other soil properties that are not yet fully represented in ESMs. For example, the presence of gravel significantly impacts soil hydrothermal properties (You et al., 2022; H. Zhao et al., 2018), yet there is a lack of PTFs to account for the effects of gravel on a global scale. Additionally, there are no global sequences of maps of temporally variable soil chemical and physical properties, which would recognize that soils evolve and change over time (Pennock & Veldkamp, 2006; Schoorl & 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 modeling, such as with the LAPSUS model (Landscape Process Modeling at Multi-dimensions and Scales) (Schoorl & Veldkamp, 2016; Schoorl et al., 2000, 2014).

Given these complexities, integrating ESMs with soil-landscape models is essential for simulating soil formation processes, including the roles of the soil microbiome and soil aggregation as discussed earlier. This coupling will allow ESMs to account for temporal changes in soil properties, leading to more precise and nuanced predictions of the fluxes and state variables of the Earth system (Dai, Shangguan, et al., 2019; Pelletier et al., 2015). There are recent progresses in mapping temporally variable soil properties (Weber et al., 2024) to inform ESMs: for example, Jha et al. (2023) used soil structure dynamics to couple organic carbon dynamics with hydraulic properties.

As mentioned in Section 3.4 and 3.5, among others, the main challenge of representing soil properties in ESMs is the data scarcity. To address this data constrain, 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 DA approach for updating soil maps aligns closely with the Digital Twin methodology (Bauer, Dueben, et al., 2021; Bauer, Stevens, & Hazeleger, 2021; European Commission, 2021), which can simulate and analyze 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 & Gomez, 2018; Viscarra Rossel et al., 2022). With the increasing availability of remote sensing products and other big data in Earth system science (X. 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 soil health, soil monitoring must accurately measure inputs and outputs to soils, as well as 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 (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 Environment 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 by 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 the effects of 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): (a) the monitoring and recording of 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; (b) Earth Observation of the soil-plant system and the land cover manifestations linked to land-use practices; (c) 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 toward 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." 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 & 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.

Soil and land management practices influence soil health, and the direction and extent of this impact can be assessed through field surveys, soil mapping, physically-based modeling, and crucially by remote sensing-based monitoring of the abovementioned tegon-pedon pair. Although remote sensing has been recognized as an

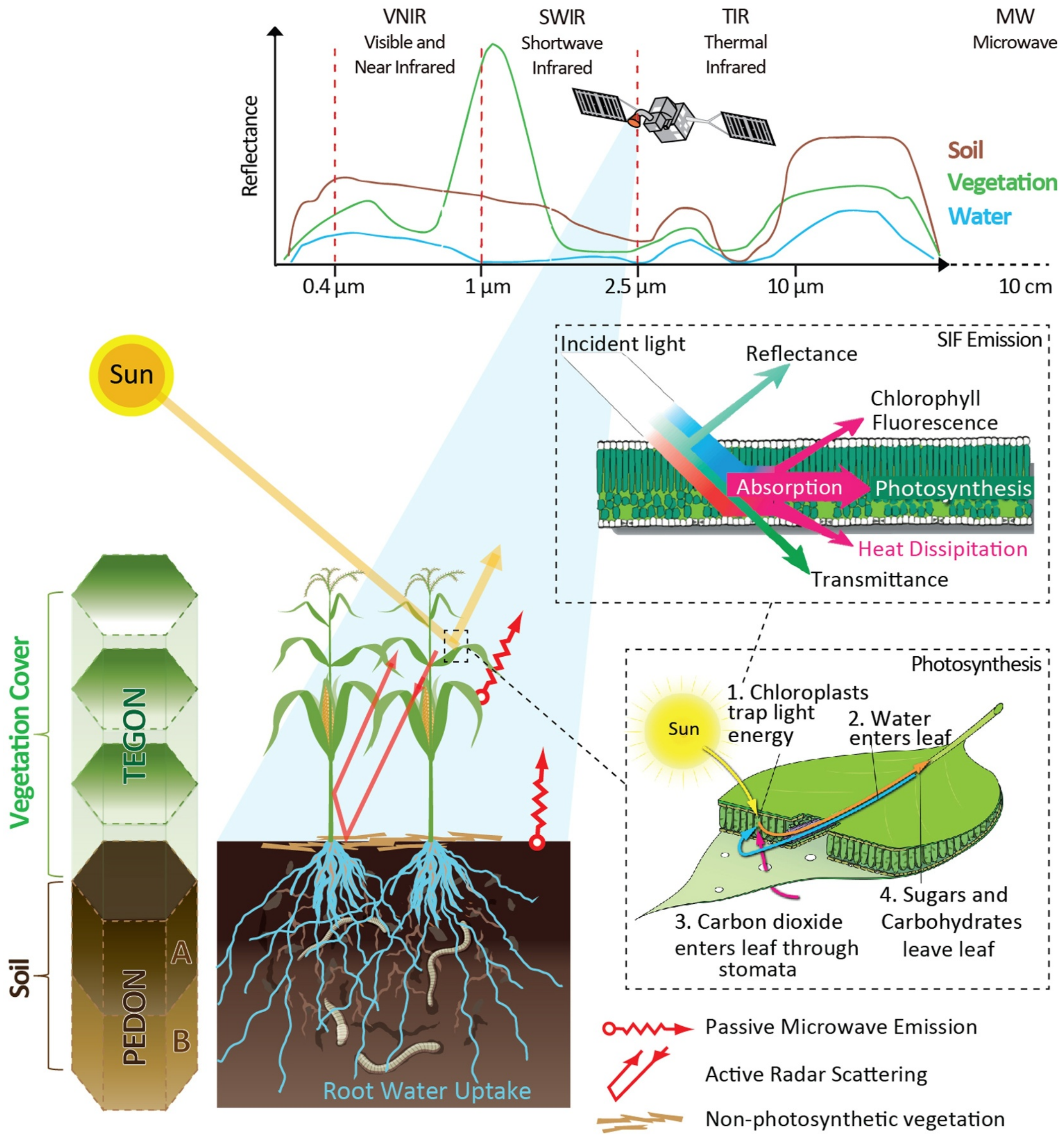


Figure 2. The “Tegon-Pedon” pair as the three-dimensional elementary unit of the soil-plant-atmosphere continuum (SPAC), whose biophysical characteristics can be observed with remote sensing across the VNIR-SWIR-TIR-MW domains of the electromagnetic spectrum (VNIR—Visible and Near Infrared [0.4–1.0 µm], 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 by 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 emit absorbed light energy at longer wavelength as chlorophyll fluorescence (i.e., solar-induced chlorophyll fluorescence, solar-induced fluorescence (SIF), in natural environment). 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. Recent progress in drone technology can provide high spectral separation and temporal resolution of relatively large areas, such as agricultural fields. These are pivotal advances in the context of high-resolution soil health monitoring (Manfreda & Ben Dor, 2023).

innovative technique for soil health monitoring, few review articles and reports elaborate how to apply remote sensing technique for monitoring soil health, for example, 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 modeling. The connection between SHIs and soil functions, considering the synergy between soil biological and physico-chemical properties, as well as soil management practices (and histories), requires the combined use of process-based models, Earth Observation (EO) data, DA and physics-informed machine learning, which has been coined as the digital twin approach (Bauer, Dueben, et al., 2021; Bauer, Stevens, & Hazeleger, 2021; Zeng & 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 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 SOC, particle size distribution (PSD, e.g., sand-clay-silt fractions), 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 and photosynthetic vegetation. Non-photosynthetic vegetation (NPV) refers to plant materials that are incapable of performing photosynthesis, such as crop residues, straw/balk mulch, wood chips, dead plant material (e.g., litter, stumps), and senesced vegetation (Verrelst et al., 2023). 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, radiation that reaches a satellite can be affected by atmospheric conditions, such as gases, clouds, aerosols as well as viewing geometry (Chabrillat et al., 2019).

Despite challenges, due to their cost-effectiveness (e.g., costing one-tenth of a chemical analysis) and high reliability (repeatable and reproducible results), soil spectroscopy methods for estimating soil properties have improved significantly over the years (Viscarra Rossel & Bouma, 2016; Viscarra Rossel et al., 2022). This progress has led to the on-going development of standards and protocols for soil spectroscopy (Ben-Dor et al., 2024). Many soil spectral libraries (SSL), such as the LUCAS SSL and the world soil SSL (Leenen et al., 2022; Viscarra Rossel et al., 2016), taking advantage of LUCAS Soil and other databases (Orgiazzi et al., 2018), have been established to advance remote sensing-assisted soil monitoring.

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 have been developed with disturbed soil samples from the field, that is, with a non-intact soil surface. However, based on the innovative "field-lab" apparatus developed by Ben-Dor et al. (2017), SSL for the soil surface can be established based on in-situ measurements with undisturbed soil surface. Common metadata on soil attributes in SSLs include textural composition (clay, silt, and sand content), organic matter, calcium-carbonate, iron oxides, hygroscopic moisture content, and specific surface area (as in the LUCAS SSL and global SSL) (D'Andrimont et al., 2020; Ben Dor et al., 2022; Orgiazzi et al., 2018). SSLs provide a foundation for developing proxy models for quantifying, classifying, mapping, and monitoring soil properties from remote sensing. 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 surface 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, thereby defining 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 and separate assessment of these properties challenging. However, a thorough understanding of the radiative transfer process within the soil-plant system and their interactions with soil state variables and properties can help resolve specific spectral signals (Ben-Dor et al., 2019; Chabrillat et al., 2019) (Figure 2). For example, advancements in radiative transfer modeling (RTM) have improved the quantification of NPV cover and biomass in croplands and grasslands by better simulating the interactions between radiation and NPV (Verrelst et al., 2023).

Recent advancements in field-based soil measurements under laboratory conditions, for example, 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 physico-chemical properties with spectral measurements (Francos et al., 2021; Su, Zeng, et al., 2020). 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 PTFs for deriving soil hydraulic parameters (Romano et al., 2023; Su, Zeng, et al., 2020), although note the issues with PTFs as pointed out in Section 3.5.

4.4. Soil Sensors in Space

The concept of Image Spectroscopy (IS, also termed as hyperspectral imaging), which involves creating a 'spectral cube' composed of numerous spectral bands, has been employed to obtain spectral views of soils. This technique allows for extracting information representing the spectral features of the soil for each pixel in a spectral image.

New orbiting sensors such as PRISMA (PRecursore IperSpettrale della Missione Applicativa) (Cogliati et al., 2021) and EnMAP (Environmental Mapping and Analysis Program) (Chabrillat et al., 2020), 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 (Chabrillat et al., 2019). Upcoming missions from the Copernicus Programme, such as LSTM (Land Surface Temperature Monitoring Mission) (Koetz et al., 2018) and CHIME (Copernicus Hyperspectral Imaging Mission for the Environment) (Rast et al., 2021), 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 Surface Biology and Geology (SBG) hyperspectral sensor. The SBG aims to acquire global spectroscopic (hyperspectral) imagery across visible to shortwave infrared (VSWIR; 380–2,500 nm) and multispectral mid-wave 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). There are also sensors deployed on the International Space Station (ISS). For example, HISUI (Hyperspectral Imager Suite) has 185 spectral bands between 0.4 and 2.5 μm with spectral resolution of 10 nm for VNIR and 12.5 nm for SWIR (Matsunaga et al., 2020). The EMIT (Earth Surface Mineral Dust Source Investigation) mission has a spectral coverage between 0.41–2.45 μm and a spectral sampling ≤10 nm, and aims to determine the mineral composition and abundance of arid lands (Green et al., 2023).

This expanding availability of high signal-to-noise ratio spaceborne spectral data is anticipated to support global monitoring of soils, provided that the STF (i.e., a regression function between spectral signal and observable soil properties) is known, soils are well-exposed (i.e., bare soil pixels), and local SSLs are available (Chabrillat et al., 2019). 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–1 mm of the soil body in the VNIR-TIR domains (Ben-Dor et al., 2019; Dupiau et al., 2022).

Developing pixel-unmixing solutions at high spectral and spatial resolutions is key to deriving pure soil pixels, when there is a mixed cover of photosynthetic and NPV (Verrelst et al., 2023). Gallo et al. (2018) and Rogge et al. (2018), in separate studies, successfully resolved the contributions of vegetation cover (photosynthetic vegetation) and litter cover (NPV) on the soil spectrum by utilizing temporal satellite imageries of an area and "summarizing" the exposed pixel of bare soil. They assumed that in a dynamically managed 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 "pure" soil image.

Though optical remote sensing cannot penetrate the soil surface, spectral images combined with in-situ 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) evaluated the reclamation quality in post-mining regions using spectrally measured leaf properties such as chlorophylls a and b, carotenoids, and relative water content. Belgiu et al. (2023) successfully retrieved pre-harvest nutrient concentrations in crop grains using PRISMA and Sentinel-2 spectral imagery. However, nutrient accumulation in grains is governed by several processes, including soil uptake, internal transport, storage, and remobilization from vegetative tissues during senescence. These processes can be effectively modeled through a soil-plant digital twin, which can be applied for retrieving soil nutrient content and other SHIs. Such mechanistic understanding of soil-plant interactions enhances the potential of vegetation remote sensing as a tool for inferring soil properties. 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. Such an 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. The next section will expand on the Vegetation-as-a-Soil-Sensor (VaaSS) approach, as this is a promising avenue in the context of representing dynamic soil properties in ESMs.

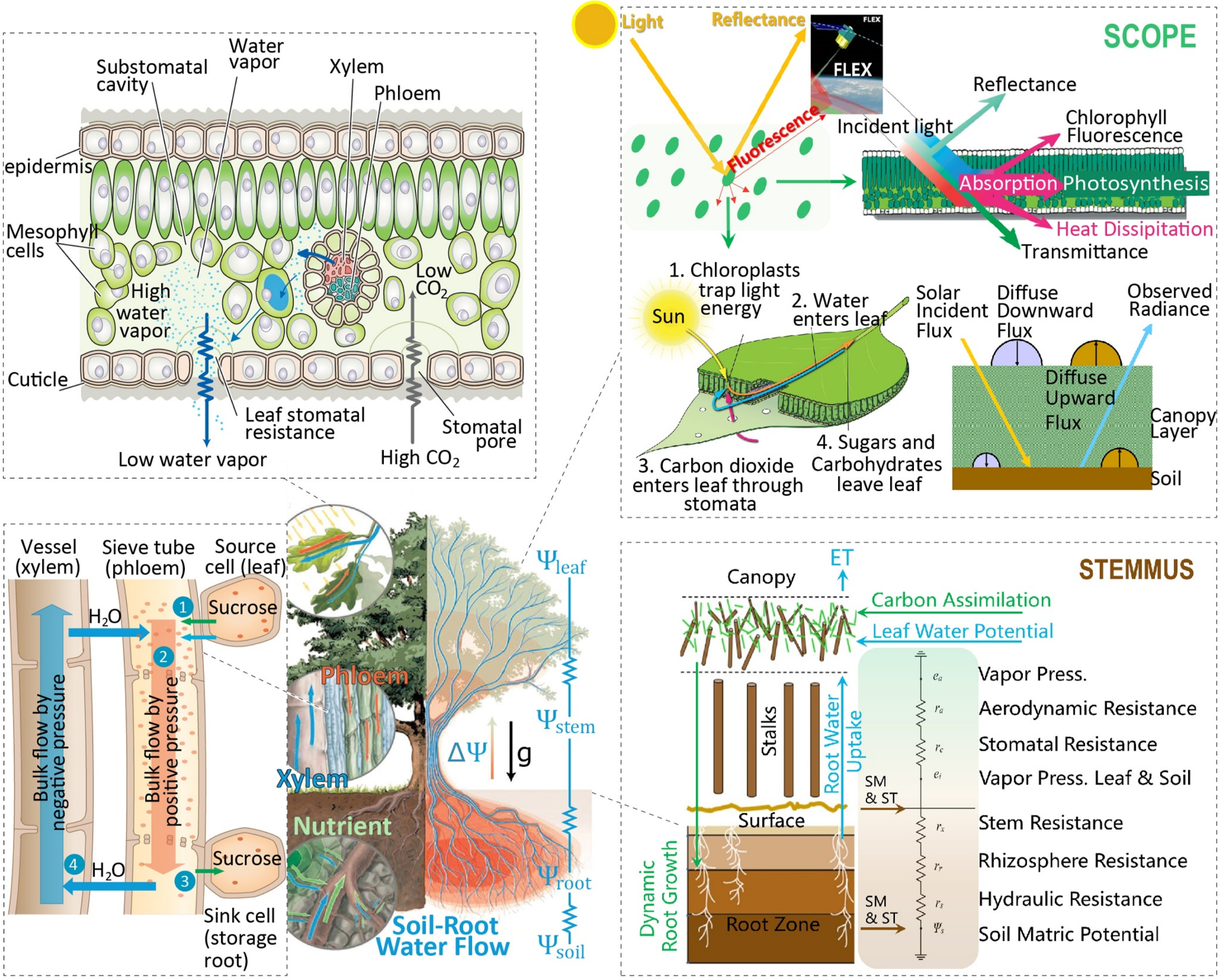
5. Vegetation-As-A-Soil-Sensor (VaaSS)

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 NDVI. However, VIs often confront 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 yield NDVI values that cause bare soil to be incorrectly classified as vegetation.

Analyses of VI data products are mostly focusing on structural properties such as Leaf Area Index, and to a lesser extent, on vegetation functioning (e.g., greenness parameters are used to estimate Fraction of Absorbed Photosynthetically Active Radiation, fAPAR, and Gross Primary Production, GPP) (Pierrat et al., 2022). The recent advancements in satellite remote sensing of solar-induced fluorescence (SIF), such as the Fluorescence Explorer (FLEX) mission, offer new opportunities for assessing vegetation functioning and utilizing 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., 2019). 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), 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; Y. Wang et al., 2021).



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 pressure gradient between 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. Illustration of 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 solar-induced fluorescence 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.

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 VaaSS 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 (L. J. 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 (Q. 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 LSMs via data assimilation techniques, can be used to estimate soil hydraulic parameters (Pinnington et al., 2021; Santanello et al., 2007) and soil texture (H. Zhao et al., 2023). However, both SSM and RZSM data are derived from satellite products using retrieval algorithms that simplify radiative transfer processes and depend on ancillary data sets (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 (de Rosnay et al., 2020; X. Han et al., 2014) or discrete emission-scattering model (H. Zhao et al., 2021), have been developed to directly assimilate brightness temperature to retrieve soil properties (H. 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., 2020). 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, Piles, et al., 2017). 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 (X. Xu et al., 2021).

5.3. Satellite Observables for Soil-Plant Hydraulics

Currently, there is a growing trend toward incorporating soil-plant hydraulics into ESMs. 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 & 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 "$E - \Psi_{\text{leaf}} - \Psi_{\text{soil}}$" 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 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).

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 hydrothermal properties, SOC content, and soil texture (Y. Wang et al., 2021; H. Zhao et al., 2023). It is important to note that remote sensing-based estimates of Ψ_{leaf} and Ψ_{soil} are currently limited by the scarcity of in-situ measurements across diverse global biomes. Hence, we strongly encourage wider research in this area.

5.4. 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 soil management (e.g., tillage practices) can be gleaned from VWC's sensitivity to the amount of aboveground biomass (T. 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 allows us to link 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 (Y. Wang et al., 2021). Therefore, sub-daily monitoring of SPHVs holds promise as an early warning system for drought risks.

By monitoring the soil-plant system SPHVs with 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.

5.5. 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 Ψ_{leaf} and SIF, both influenced by root zone soil moisture via the water stress factor (WSF). This is evident from the fact that the variation of Ψ_{leaf} is regulated by WSF (Figure 4a). SIF is also regulated by WSF, and in the STEMMUS-SCOPE model this is reflected by the fact the WSF affects the maximum carboxylation rate and the maximum electron transport rate, which determines the SIF yield (Y. Wang et al., 2021). Considering that both SIF and Ψ_{leaf} are regulated by WSF, Figure 4c demonstrates that the SIF-Ψ_{leaf}

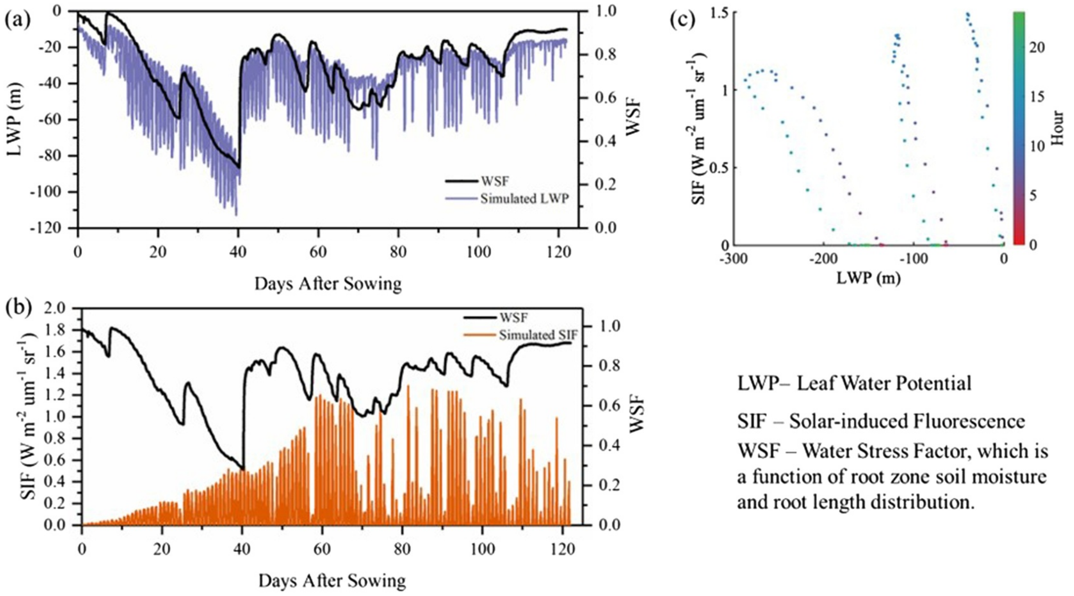


Figure 4. (a) The sub-daily (half-hourly) variations in leaf water potential (Ψ_{leaf}) and water stress factor (WSF), illustrating the coordinated variation between leaf water potential and WSF, which is a function of root zone soil moisture and root length distribution. WSF = 1 means there is no stress, while WSF = 0 means there is no plant-available water available for uptake by roots; (b) solar-induced fluorescence (SIF). (c) The SIF-LWP relationship under stressed and non-stressed conditions. Under stressed conditions (LWP from ca. −150 to −300 m), SIF has a negative linear relationship with LWP. This linear relationship provides an opportunity to derive LWP from SIF remote sensing data.

relationship is negative and linear under water-stressed conditions, with a sub-daily hysteresis loop (Y. Wang et al., 2021). This 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 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., 2019; 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 VaaSS methodologies. 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, temporal and spectral resolution technology could be used to detect VWC, and other related variables in the SPAC.

Existing and planned passive microwave radiometers (e.g., AMSR-E, SMAP, SMOS, CIMR, and AMSR-3) as well as active scatterometers (e.g., ASCAT) 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. Other active microwave sensors (e.g., ROSE-L), however, provide high spatial resolution (<1 km) synthetic aperture radar measurements on a weekly basis (Bueso et al., 2023; Frappart et al., 2020; 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, Yu, et al., 2017). 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 as for 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 (H. Zhao et al., 2022) (Figures 2 and 3).

6. Toward a Soil-Plant Digital Twin

6.1. 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, Stevens, & Hazeleger, 2021). A digital twin is essentially a digital replica 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 & Qi, 2019). One notable application of the 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 ESMs and EO data with DA techniques, in conjunction with artificial intelligence (e.g., physics-informed machine learning and deep learning) (Bauer et al., 2024).

The concept of DTE is rapidly evolving, revolutionizing Earth system science through its multifaceted approach and advanced digital technologies (Bauer, Dueben, et al., 2021). Its importance is increasingly acknowledged for its ability to agilely and accurately forecast extreme climate events and predict environmental impacts (Bauer, Stevens, & Hazeleger, 2021; Bi et al., 2023). At the core of DTE 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 first-principle physics-based models and EO via data assimilation (X. 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 DTE approach can be generalized to build DTE components, including DTE-Climate (Bauer, Stevens, & Hazeleger, 2021), 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 & Su, 2024), or a digital twin of the soil-microbiome-plant continuum.

The integration of digital twin technology in soil monitoring has been limited, and primarily conducted at small scales (Tsakiridis et al., 2023). However, the rapid expansion of observation data on soil-plant systems, including spectro-microscopy with tomography and multi-omics (Amelung et al., 2024), hyperspectral imaging of soil's and plant'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-plant data. This wealth of soil-plant data has established the arena of soil and plant sciences 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 the further development of soil-plant (hydraulic) models, as well as soil structure and soil function models by integrating dynamic structural components into the soil-plant modeling (Fisher & Koven, 2020; Sullivan et al., 2022). By combining algorithms grounded in physical, chemical, biological, and ecological principles with big soil-plant data, we can improve our understanding of the soil-plant system, and 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.

6.2. Soil Microbial Processes Within a Digital Twin Framework

Recent years have witnessed significant strides in the integration of diverse processes into ESMs (Blyth et al., 2021). These advancements span various domains, including biogeochemical cycles (Fisher & Koven, 2020; Yu, Fatichi, et al., 2020), plant hydraulics (Kennedy et al., 2019; Sabot et al., 2020; Y. Wang et al., 2021), coupled moisture and heat transfer (Garcia Gonzalez et al., 2012; Yu, Zeng, & Su, 2020; Zeng et al., 2011), freeze-thaw dynamics (Yu et al., 2018), groundwater flow (Condon et al., 2021) and beyond.

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).

For example, 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 & Kembel, 2019). Together with these traits and multi-omics data, microbial models that consider 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).

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 POM (Hartmann & 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 in-situ/laboratory measurements, remote sensing observations and data assimilation techniques, microbial processes are then deemed embedded within a digital twin framework. With the increasing availability of novel and high-quality geo-referenced environmental data from satellites (X. Li et al., 2023; Vance et al., 2024), integrated ecosystem and critical zone observatories (Ohnemus et al., 2024; Pastorello et al., 2020), as well as soil (Orgiazzi et al., 2018) and plant databases (Kattge et al., 2020), and the Earth BioGenome projects (Blaxter et al., 2022; Lewin et al., 2022), we are now presented with a unique opportunity to realize such a digital twin.

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. 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, Dueben, et al., 2021). 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 & 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 process-based soil-plant model, multi- and hyperspectral, VNIR-SWIR-TIR-MW data from satellite sensors, drone surveys, and in situ measurements, as well as the application of machine learning algorithms (Su, Zeng, et al., 2020).

The fundamental characteristics of a soil-plant digital twin include (Tsakiridis et al., 2023; Zeng & Su, 2024): (a) a highly precise and high-fidelity digital replica of the physical soil-plant system; (b) near-real-time accurate measurements and model predictions; (c) lifecycle data management for both measurements and model simulation results; (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; (e) the possibility for interrogation of what-if questions and scenario analyses; and (f) computational science and AI-empowered modeling 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; Eyring et al., 2024).

A soil-plant digital twin, fully equipped with soil-microbiome-plant continuum processes, 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). However, by mathematically modeling soil-microbiome-plant continuum 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 (Lv et al., 2023; Su, Wen, et al., 2020; H. Zhao et al., 2021, 2022).

The integration of the soil-microbiome-plant continuum processes with radiative transfer processes connects the digital model of the soil-plant system to satellite observations. This linkage between physical soil-microbiome-plant 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. While traditional point-based sampling methods are essential and indispensable, they are not cost-effective for large-scale quantification of SHIs. The envisioned soil-plant digital twin enhances existing soil and plant databases by integrating multi-scale observations, ranging from point measurements to air- and space-borne sensor footprints, offering an innovative approach for monitoring and predicting SHIs with comprehensive spatial and temporal coverage (Abdulraheem et al., 2023; Zeng & Su, 2024).

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 (in the form of 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). It is evident that continuous interactions occur among soil properties, soil-forming processes, and land management. Therefore, monitoring soil health extends beyond soil alone and must include the soil-plant system, as soil acts as the interface between the atmosphere, biosphere, geosphere, and hydrosphere.

7.1.1. Soil-Microbiome-Plant Continuum and Trait-Based Approaches

Diverse plant traits in mixed vegetation can shape the abundance and structure of belowground soil microbial 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). These interlinkages 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). It is, therefore, expected that soil microorganisms' community structure and dynamics can be inferred from measurable environmental characteristics at landscape scales (i.e., landscape genomics) (Dauphin et al., 2023; Y. 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. Nevertheless, achieving this goal requires sequencing, cataloging, and characterizing soil microbial genomes worldwide. Additionally, comprehensive, cross-site analysis of environmental impacts on microbial functional traits and the influence of microbes on biogeochemical processes is necessary.

7.1.2. Soil Hydrological Processes

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. Although state-of-the-art field and laboratory methods are available to measure these soil properties at specific locations, extending these measurements to a global scale remains challenging. Notably, advancements in DSM have revolutionized the production of global soil property maps (Arrouays et al., 2020). These innovations promote more time-efficient and cost-effective soil sampling strategies and analysis methods, enabling more accurate spatiotemporal characterization of soil properties and soil health (Panagos, Broothaerts, et al., 2024). Additionally, the growing availability of remote sensing products for soil co-variate factors further enhances this capability (G. L. Zhang et al., 2017).

In recent decades, pedotransfer functions 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; Weber et al., 2024) that are 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 and soil management effects over time, including the occurrence of dual or multimodal pore systems (P. Lehmann et al., 2021). This underscores the need for stronger collaborations between soil scientists, and global land surface, carbon and climate modelers to enhance the physical realism of PTFs used in LSMs.

7.1.3. Soil Remote Sensing

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. 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 (Lajoie & Kembel, 2019). 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 (Zeng & Su, 2024).

7.1.4. Vegetation-As-A-Soil Sensor (VaaSS)

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 (Drusch et al., 2017). 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; Y. Wang et al., 2021), particularly when considering the hydraulic connections across the SPAC continuum.

Remote sensing of soil-plant hydraulics involves satellite observables across the electromagnetic spectrum (Figure 2), capturing root zone soil moisture, surface soil moisture, vegetation optical depth, VWC, 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 VWC 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 VWC and leaf water potential are integrated with a process-based soil-plant model that explicitly accounts for plant hydraulics.

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 SHIs, including metrics related to soil organic carbon content, soil structure, soil biodiversity, landscape heterogeneity, and forest and woodland area (Panagos, Montanarella, et al., 2022).

7.1.5. Soil-Plant Digital Twin

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, Stevens, & Hazeleger, 2021). 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 carbon content stocks (Gaudaré et al., 2023). Additionally, via integrating soil-microbiome-plant continuum processes with radiative transfer processes, 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. Where Is It Going?

7.2.1. Soil (and Plant) Spectral Libraries

The use of soil spectroscopy to predict soil properties—such as SOC, nitrogen, clay content, mineral composition, and water retention—is rapidly expanding (Ben-Dor et al., 2019). This growth is reflected in several global efforts to develop standardized soil spectral libraries (SSLs), such as the Global SSL by Viscarra-Rossel et al. (2016), the Global Soil Laboratory Network initiative on soil spectroscopy (GLOSOLAN-Spec) (Benedetti and van Egmond, 2021), and the IEEE AS P4005 working group aimed at defining soil spectroscopy standards and protocols (Ben-Dor et al., 2024). Additionally, the Open SSL, created by the Soil Spectroscopy for Global Good

(SS4GG) (Safanelli et al., 2024), has contributed significantly to these advancements. The LUCAS SSL also plays a key role in supporting these global initiatives (Jones et al., 2020). Despite the proven success of spectral measurements in characterizing soil properties, the potential to develop corresponding plant spectral libraries has largely been overlooked by the soil research community.

Plant spectroscopy can estimate various traits across spectral domains (Hank et al., 2019; Jacquemound & Ustin, 2019; Verrelst et al., 2023). In the VIS spectral region, it captures biochemical leaf traits, such as photosynthetic pigments like chlorophyll and carotenoids. In the NIR region, it provides insights into ecophysiological processes (e.g., light use efficiency) and structural information (e.g., biomass, leaf orientation, plant density). The SWIR region can detect NPV traits of senescent materials, such as cellulose, lignin, and proteins, while VWC is assessed between the NIR and SWIR domains. The plant spectra reflect plant vigor, which is highly sensitive to root-zone soil conditions (Philippot et al., 2024). This means that any changes in soil conditions, such as fluctuations in nutrient inputs or contamination, are manifested in the plant's biochemical, biophysical, and structural traits, which, in turn, alter the reflectance spectra.

For example, Belgiu et al. (2023) successfully estimated nutrient concentrations in crop grains before harvest using PRISMA and Sentinel-2 spectral imagery. However, nutrient accumulation in grains is governed by multiple processes and factors, including soil nutrient uptake, soil water status, internal plant transport, storage, and remobilization from vegetative tissues during senescence. A forward model that mechanistically links these soil-plant interactions with reflectance spectra could enhance the application of vegetation remote sensing to infer soil physicochemical and biological properties. The recent proliferation of hyperspectral sensors in space (Section 4.4) offers new opportunities for advancing soil health monitoring by incorporating plant spectral data into future soil surveys. This potential is enhanced by the development of the Open Plant Spectral library - Ecological Spectral Information System (Wagner et al., 2018) and the development of SpecNet (Spectral Network), which connects optical measurements with flux sampling worldwide (Gamon & Rahman, 2012).

7.2.2. Embracing the Digital Twin Approach

The future of soil health monitoring is shifting toward a more holistic and integrative approach, encompassing not only soil properties but also the interactions and feedbacks within the soil-microbiome-plant continuum. Advancements in molecular technologies (multi-omics) (Bernatchez et al., 2024) and trait-based approaches are revolutionizing our ability to understand soil health by providing insights into microbial functional traits and soil-plant interactions (Labouyrie et al., 2023; Lausch et al., 2016). The development of landscape genomics (Dauphin et al., 2023) allows us to infer microbial community dynamics from environmental characteristics, offering an opportunity to bridge the gap between laboratory-based microbial studies and real-world landscape-scale processes (Martin & van der Heijden, 2024). However, to fully harness these advancements, there is a need for global cataloging of microbial genomes (Blaxter et al., 2022; Lewin et al., 2022), as well as cross-site analyses that can link microbial functional traits to biogeochemical processes, enabling more precise management of soil health.

Furthermore, to advance our understanding of soil-plant hydraulics and its interactions with microbial processes, and other above- and below-ground ecophysiological dynamics, it is crucial to bridge the gap between soil and plant databases. For example, existing SSLs and soil databases should actively integrate global plant databases, such as the TRY plant trait database (Kattge et al., 2020), and new initiatives like the PSInet soil-plant water potential network (Novick et al., 2022). By connecting these resources, we can develop a more comprehensive framework for understanding soil-plant-microbe interactions, leading to more accurate and comprehensive understanding of soil health.

The expanding variety of data sources, ranging from in-situ measurements to remote sensing and modeling, provides extensive insights into characterizing the soil-microbiome-plant continuum. The comprehensive understanding of soil health requires integrating these diverse data streams. This can only be achieved by combining space-based observations with complementary ground-based and airborne measurements, whether through dedicated campaigns (Orgiazzi et al., 2018) or long-term networks (Ohnemus et al., 2024; Pastorello et al., 2020), and leveraging process-based models, including AI/ML approaches and digital twins, to handle increasing data volumes and finer spatiotemporal and spectral resolutions (Eyring et al., 2024). Notably, process-based modeling is crucial for understanding soil health, as it allows us to infer "unobservable" soil properties from EO through physically consistent frameworks like soil-plant digital twins (Zeng & Su, 2024).

Leveraging the soil-plant digital twin throughout the "measure-understand-predict-decide-act cycle" is essential for transforming data and knowledge into actionable information for various stakeholders, such as policymakers, farmers, land managers, non-profit organizations, and agribusinesses. To achieve this, modern, agile, and powerful open infrastructures, grounded in the FAIR principles (Findability, Accessibility, Interoperability, and Reusability) alongside Open Science and Open Innovation (European Space Agency, 2024), as well as the AI-empowered hybrid approach (physics-informed ML) for faster and accurate modeling (Eyring et al., 2024), serve as critical enablers (Liakos & Panagos, 2022).

Appendix A

Table A1
List of Abbreviations Used in the Paper, Along With Their Explanations and Full Spellings.

Abbreviations	Explanations and full spellings
1D-ICZ	The one-dimensional Integrated Critical Zone model
AggModel	A simulation model connecting soil aggregate dynamics with SOM dynamics
AMF	Arbuscular mycorrhizal fungi
BODIUM	A soil model simulating soil function dynamics under agricultural management
BRNS	Biogeochemical Reaction Network Simulator
C:N	Carbon versus nutrient ratio
CAM	Cellular Automaton Model
CAP	Common Agriculture Policy
CAST	Coupled Carbon, Aggregation and Structure Turnover model
CbM	Checks by monitoring
CHIME	Copernicus Hyperspectral Imaging Mission for the Environment
CMIP6	Coupled Model Intercomparison Project Phase 6
DA	Data Assimilation
DEM	Digital Elevation Model
DestinE	Destination Earth
DNA	Deoxyribonucleic acid
DSM	Digital Soil Mapping
DTB	Depth to bedrock
DTE	Digital Twin Earth
EC	European Commission
EMF	Ectomycorrhizal fungi
EMIT	Earth Surface Mineral Dust Source Investigation
EnMAP	Environmental Mapping and Analysis Program
EO	Earth Observation
EPS	Extracellular polymeric substances
ESA	European Space Agency
ESM	Earth System Model
EU	European Union
EUSO	EU Soil Observatory
F:B	Fungi versus bacteria ratio
FAO	Food and Agriculture Organization of the United Nations (FAO)
fAPAR	Fraction of Absorbed Photosynthetically Active Radiation

Table A1
Continued

Abbreviations	Explanations and full spellings
FLEX	Fluorescence Explorer
GEA	Genotype-environment associations
GPP	Gross Primary Production
HISUI	Hyperspectral Imager Suite
HYDRUS-1D	It is a public domain software, simulating water flow, solute and heat transport in one-dimension
IS	Image Spectroscopy
ISMC	International Soil Modeling Consortium
ISS	International Space Station
ITPS	The Intergovernmental Technical Panel on Soils
LAI	Leaf Area Index
LAPSUS	Landscape Process Modeling at Multi-dimensions and Scales
LSM	Land Surface Model
LSTM	Land Surface Temperature Monitoring Mission
LUCAS	Land Use/Cover Area Frame Survey
LWP	Leaf Water Potential
MICP	Microbially induced carbonate precipitation
MW	Microwave
MWIR	Mid-wave and thermal infrared
NAPESHM	North American Project to Evaluate Soil Health Measurements
NDVI	Normalized Difference Vegetation Index
NDVI	Normalized Difference Vegetation Index
NPV	Non-Photosynthetic Vegetation
PGPR	Plant growth–promoting rhizobacteria
pH	Potential of hydrogen, a logarithmic scale used to specify the acidity
POM	Particulate organic matter
PRISMA	PRecursore IperSpettrale della Missione Applicativa
PROSUM	PROductivity and SUccession Model
PSD	Particle Size Distribution
PTFs	Pedotransfer functions (PTFs)
REWT	Root Exudation in Watershed-Scale Transport
RTM	Radiative Transfer Modeling
RZSM	Root Zone Soil Moisture
SAFE	An integrated process-oriented forest model for long-term sustainability assessments
SAR	Synthetic Aperture Radar
SBG	Surface Biology and Geology
SCOPE	Soil Canopy Observation of Photosynthesis and Energy fluxes
SHI	Soil Health Indicators
SIF	Solar-induced chlorophyll fluorescence
SoilGen	It is a (1-D) simulation model for the study of pedogenesis
SOM	Soil organic matter
SPAC	Soil plant atmosphere continuum

Table A1
Continued

Abbreviations	Explanations and full spellings
SPHVs	Soil-Plant Hydraulics Variables
SSL	Soil Spectral Libraries
SSM	Surface Soil Moisture
STEMMUS	Simultaneous Transfer of Energy, Momentum, and Mass in Unsaturated Soil
STF	Spectral Transfer Functions
SWIR	Short Wave Infrared
TIR	Thermal Infrared
USDA-NRCS	U.S. Department of Agriculture Natural Resource Conservation Service
USSF	Uppsala model of Soil Structure and Function
VaaSS	Vegetation as a soil sensor
VI	Vegetation Indices
VNIR	Visible and Near Infrared
VOD	Vegetation Optical Depth
VSWIR	Visible to Shortwave Infrared
VWC	Vegetation Water Content
WoSIS	World Soil Information Service
WSF	Water Stress Factor

Data Availability Statement

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

Acknowledgments
This research has been funded by the Dutch Research Council (NWO) KIC, WUNDER project (Grant KICH1.LWV02.20.004); the Netherlands eScience Center, EcoExtreML project (Grant 27020G07); the ESA-MOST Dragon V & VI program (project 58516, Climate-PAN-TPE, project 95357, DTE-Climate).

References

Abdulraheem, M. I., Zhang, W., Li, S., Moshayedi, A. J., Farooque, A. A., & Hu, J. (2023). Advancement of remote sensing for soil measurements and applications: A comprehensive review. *Sustainability*, *15*(21), 15444. https://doi.org/10.3390/su152115444

Adewopo, J. B., VanZomeren, C., Bhomia, R. K., Almaraz, M., Bacon, A. R., Eggleston, E., et al. (2014). Top-ranked priority research questions for soil science in the 21st century. *Soil Science Society of America Journal*, *78*(2), 337–347. https://doi.org/10.2136/sssaj2013.07.0291

Adhikari, K., & Hartemink, A. E. (2016). Linking soils to ecosystem services—A global review. *Geoderma*, *262*, 101–111. https://doi.org/10.1016/j.geoderma.2015.08.009

Amelung, W., Bossio, D., de Vries, W., Kögel-Knabner, I., Lehmann, J., Amundson, R., et al. (2020). Towards a global-scale soil climate mitigation strategy. *Nature Communications*, *11*(1), 1–10. https://doi.org/10.1038/s41467-020-18887-7

Amelung, W., Tang, N., Siebers, N., Aehnelt, M., Eusterhues, K., Felde, V. J. M. N. L., et al. (2024). Architecture of soil microaggregates: Advanced methodologies to explore properties and functions. *Journal of Plant Nutrition and Soil Science*, *187*(1), 17–50. https://doi.org/10.1002/JPLN.202300149

Anderson, E. N. (2005). Collapse: How societies choose to fail or succeed. *Journal of Ethnobiology*, *25*(1), 143–145. https://doi.org/10.2993/0278-0771(2005)25[143:br]2.0.co;2

Angileri, V., Devos, W., Erdogan, H., Milenov, P., Puerta Pinero, C., Rembowski, M., et al. (2023). *Geodata and technologies for a greener agriculture in Europe*. Publications Office of the European Union.

Angst, G., Mueller, K. E., Nierop, K. G. J., & Simpson, M. J. (2021). Plant- or microbial-derived? A review on the molecular composition of stabilized soil organic matter. *Soil Biology and Biochemistry*, *156*, 108189. https://doi.org/10.1016/j.soilbio.2021.108189

Anthony, M. A., Bender, S. F., & van der Heijden, M. G. A. (2023). Enumerating soil biodiversity. *Proceedings of the National Academy of Sciences of the United States of America*, *120*(33), e2304663120. https://doi.org/10.1073/PNAS.2304663120/SUPPL_FILE/PNAS.2304663120.SAPP.PDF

Arrouays, D., McBratney, A., Bouma, J., Libohova, Z., Richer-de-Forges, A. C., Morgan, C. L. S., et al. (2020). Impressions of digital soil maps: The good, the not so good, and making them ever better. *Geoderma Regional*, *20*, e00255. https://doi.org/10.1016/J.GEODRS.2020.E00255

Aziz, I., Mahmood, T., & Islam, K. R. (2013). Effect of long term no-till and conventional tillage practices on soil quality. *Soil and Tillage Research*, *131*, 28–35. https://doi.org/10.1016/j.still.2013.03.002

Baatz, R., Hendricks Franssen, H. J., Euskirchen, E., Sihi, D., Dietze, M., Ciavatta, S., et al. (2021). Reanalysis in Earth system science: Toward terrestrial ecosystem reanalysis. *Reviews of Geophysics*, *59*(3), e2020RG000715. https://doi.org/10.1029/2020RG000715

Babaeian, E., Homaee, M., Montzka, C., Vereecken, H., & Norouzi, A. A. (2015). Towards retrieving soil hydraulic properties by hyperspectral remote sensing. *Vadose Zone Journal*, *14*(3), 1–17. https://doi.org/10.2136/vzj2014.07.0080

Babaeian, E., Homaee, M., Montzka, C., Vereecken, H., Norouzi, A. A., & van Genuchten, M. T. (2016). Soil moisture prediction of bare soil profiles using diffuse spectral reflectance information and vadose zone flow modeling. *Remote Sensing of Environment*, *187*, 218–229. https://doi.org/10.1016/j.rse.2016.10.029

Bahram, M., Hildebrand, F., Forslund, S. K., Anderson, J. L., Soudzilovskaia, N. A., Bodegom, P. M., et al. (2018). Structure and function of the global topsoil microbiome. *Nature*, *560*(7717), 233–237. https://doi.org/10.1038/s41586-018-0386-6

Ballabio, C., Lugato, E., Fernández-Ugalde, O., Orgiazzi, A., Jones, A., Borrelli, P., et al. (2019). Mapping LUCAS topsoil chemical properties at European scale using Gaussian process regression. *Geoderma*, *355*, 113912. https://doi.org/10.1016/j.geoderma.2019.113912

Ballabio, C., Panagos, P., & Montanarella, L. (2016). Mapping topsoil physical properties at European scale using the LUCAS database. *Geoderma*, *261*, 110–123. https://doi.org/10.1016/j.geoderma.2015.07.006

Banerjee, S., & van der Heijden, M. G. A. (2023). Soil microbiomes and one health. *Nature Reviews Microbiology*, *21*(1), 6–20. https://doi.org/10.1038/s41579-022-00779-w

Banwart, S. A., Nikolaidis, N. P., Zhu, Y. G., Peacock, C. L., & Sparks, D. L. (2019). Soil functions: Connecting Earth's critical zone. *Annual Review of Earth and Planetary Sciences*, *47*(1), 333–359. https://doi.org/10.1146/annurev-earth-063016-020544

Bardgett, R. D., & Van Der Putten, W. H. (2014). Belowground biodiversity and ecosystem functioning. *Nature*, *515*(7528), 505–511. https://doi.org/10.1038/nature13855

Basile-Doelsch, I., Balesdent, J., & Pellerin, S. (2020). Reviews and syntheses: The mechanisms underlying carbon storage in soil. *Biogeosciences*, *17*(21), 5223–5242. https://doi.org/10.5194/bg-17-5223-2020

Batjes, N. H., Ribeiro, E., & Van Oostrum, A. (2020). Standardised soil profile data to support global mapping and modelling (WoSIS snapshot 2019). *Earth System Science Data*, *12*(1), 299–320. https://doi.org/10.5194/essd-12-299-2020

Bauer, P., Dueben, P. D., Hoefler, T., Quintino, T., Schulthess, T. C., & Wedi, N. P. (2021). The digital revolution of Earth-system science. *Nature Computational Science*, *1*(2), 104–113. https://doi.org/10.1038/s43588-021-00023-0

Bauer, P., Hoefler, T., Stevens, B., & Hazeleger, W. (2024). Digital twins of Earth and the computing challenge of human interaction. *Nature Computational Science*, *4*(3), 154–157. https://doi.org/10.1038/s43588-024-00599-3

Bauer, P., Stevens, B., & Hazeleger, W. (2021). A digital twin of Earth for the green transition. *Nature Climate Change*, *11*(2), 80–83. https://doi.org/10.1038/s41558-021-00986-y

Belgiu, M., Marshall, M., Boschetti, M., Pepe, M., Stein, A., & Nelson, A. (2023). PRISMA and Sentinel-2 spectral response to the nutrient composition of grains. *Remote Sensing of Environment*, *292*, 113567. https://doi.org/10.1016/j.rse.2023.113567

Ben-Dor, E., & Banin, A. (1995). Quantitative analysis of convolved thematic mapper spectra of soils in the visible near-infrared and shortwave-infrared spectral regions (0.4–2.5 μm). *International Journal of Remote Sensing*, *16*(18), 3509–3528. https://doi.org/10.1080/01431169508954643

Ben-Dor, E., Chabrillat, S., & Demattê, J. A. M. (2019). Characterization of soil properties using reflectance spectroscopy. In P. S. Thenkabail, J. G. Lyon, & A. Huete (Eds.), *Fundamentals, sensor systems, spectral libraries, and data mining for vegetation* (pp. 187–247). CRC Press.

Ben-Dor, E., Chabrillat, S., Demattê, J. A. M., Taylor, G. R., Hill, J., Whiting, M. L., & Sommer, S. (2009). Using imaging spectroscopy to study soil properties. *Remote Sensing of Environment*, *113*(SUPPL. 1), S38–S55. https://doi.org/10.1016/j.rse.2008.09.019

Ben-Dor, E., Chabrillat, S., & Karyotis, K. (2024). *P4005 - Standards and protocols for soil spectroscopy - Home*. IEEE Standards Association. Retrieved from https://sagroups.ieee.org/4005/

Ben Dor, E., Francos, N., Ogen, Y., & Banin, A. (2022). Aggregate size distribution of arid and semiarid laboratory soils (<2 mm) as predicted by VIS-NIR-SWIR spectroscopy. *Geoderma*, *416*, 115819. https://doi.org/10.1016/j.geoderma.2022.115819

Ben-Dor, E., Granot, A., & Notesco, G. (2017). A simple apparatus to measure soil spectral information in the field under stable conditions. *Geoderma*, *306*, 73–80. https://doi.org/10.1016/j.geoderma.2017.06.025

Ben-Dor, E., Granot, A., Wallach, R., Francos, N., Heller Pearlstein, D., Efrati, B., et al. (2023). Exploitation of the SoilPRO® (SP) apparatus to measure soil surface reflectance in the field: Five case studies. *Geoderma*, *438*, 116636. https://doi.org/10.1016/j.geoderma.2023.116636

Benedetti, F., & van Egmond, F. (2021). *Global soil spectroscopy assessment. Spectral soil data – Needs and capacities*. FAO. Retrieved from http://www.fao.org/documents/card/en/c/cb6265en

Bernatchez, L., Ferchaud, A. L., Berger, C. S., Venney, C. J., & Xuereb, A. (2024). Genomics for monitoring and understanding species responses to global climate change. *Nature Reviews Genetics*, *25*(3), 165–183. https://doi.org/10.1038/s41576-023-00657-y

Bezak, N., Borrelli, P., Mikoš, M., Jemec Auflič, M., & Panagos, P. (2024). Towards multi-model soil erosion modelling: An evaluation of the erosion potential method (EPM) for global soil erosion assessments. *Catena*, *234*, 107596. https://doi.org/10.1016/J.CATENA.2023.107596

Bi, K., Xie, L., Zhang, H., Chen, X., Gu, X., & Tian, Q. (2023). Accurate medium-range global weather forecasting with 3D neural networks. *Nature*, *619*(7970), 533–538. https://doi.org/10.1038/s41586-023-06185-3

Bickel, S., & Or, D. (2020). Soil bacterial diversity mediated by microscale aqueous-phase processes across biomes. *Nature Communications*, *11*(1), 1–9. https://doi.org/10.1038/s41467-019-13966-w

Bitterlich, M., Franken, P., & Graefe, J. (2018). Arbuscular mycorrhiza improves substrate hydraulic conductivity in the plant available moisture range under root growth exclusion. *Frontiers in Plant Science*, *9*, 301. https://doi.org/10.3389/fpls.2018.00301

Blagodatskaya, E., & Kuzyakov, Y. (2013). Active microorganisms in soil: Critical review of estimation criteria and approaches. *Soil Biology and Biochemistry*, *67*, 192–211. https://doi.org/10.1016/j.soilbio.2013.08.024

Blaxter, M., Mieszkowska, N., Di Palma, F., Holland, P., Durbin, R., Richards, T., et al. (2022). Sequence locally, think globally: The Darwin Tree of Life Project. *Proceedings of the National Academy of Sciences*, *119*(4), e2115642118. https://doi.org/10.1073/pnas.2115642118

Blyth, E. M., Arora, V. K., Clark, D. B., Dadson, S. J., De Kauwe, M. G., Lawrence, D. M., et al. (2021). Advances in land surface modelling. *Current Climate Change Reports*, *7*(2), 45–71. https://doi.org/10.1007/s40641-021-00171-5

Bonetti, S., Wei, Z., & Or, D. (2021). A framework for quantifying hydrologic effects of soil structure across scales. *Communications Earth & Environment*, *2*(1), 1–10. https://doi.org/10.1038/s43247-021-00180-0

Borer, B., Tecon, R., & Or, D. (2018). Spatial organization of bacterial populations in response to oxygen and carbon counter-gradients in pore networks. *Nature Communications*, *9*(1), 1–11. https://doi.org/10.1038/s41467-018-03187-y

Borrelli, P., Panagos, P., Alewell, C., Ballabio, C., de Oliveira Fagundes, H., Haregeweyn, N., et al. (2023). Policy implications of multiple concurrent soil erosion processes in European farmland. *Nature Sustainability*, *6*(1), 103–112. https://doi.org/10.1038/s41893-022-00988-4

Borrelli, P., Robinson, D. A., Panagos, P., Lugato, E., Yang, J. E., Alewell, C., et al. (2020). Land use and climate change impacts on global soil erosion by water (2015–2070). *Proceedings of the National Academy of Sciences of the United States of America*, *117*(36), 21994–22001. https://doi.org/10.1073/pnas.2001403117

Bouchez, T., Blieux, A. L., Dequiedt, S., Domaizon, I., Dufresne, A., Ferreira, S., et al. (2016). Molecular microbiology methods for environmental diagnosis. *Environmental Chemistry Letters*, *14*(4), 423–441. https://doi.org/10.1007/s10311-016-0581-3

Bregt, A. K. (1992). Processing of soil survey data (p. 167).

Bridges, E. M., & Oldeman, L. R. (1999). Global assessment of human-induced soil degradation. *Arid Soil Research and Rehabilitation*, *13*(4), 319–325. https://doi.org/10.1080/089030699263212

Brocca, L., Barbetta, S., Camici, S., Ciabatta, L., Dari, J., Filippucci, P., et al. (2024). A digital twin of the terrestrial water cycle: A glimpse into the future through high-resolution Earth observations. *Frontiers in Science*, *1*, 1190191. https://doi.org/10.3389/fsci.2023.1190191

Broothaerts, N., Navarro, A., Ballabio, C., Belitrandi, C., Medici, D., Rosa, D., et al. (2024). *EUSO annual bulletin 2023*. JRC Publications Repository.

Brundrett, M. C., & Tedersoo, L. (2018). Evolutionary history of mycorrhizal symbioses and global host plant diversity. *New Phytologist*, *220*(4), 1108–1115. https://doi.org/10.1111/nph.14976

Bueso, D., Piles, M., Ciais, P., Wigneron, J. P., Moreno-Martínez, Á., & Camps-Valls, G. (2023). Soil and vegetation water content identify the main terrestrial ecosystem changes. *National Science Review*, *10*(5), nwad026. https://doi.org/10.1093/nsr/nwad026

Buitink, J., Swank, A. M., Van Der Ploeg, M., Smith, N. E., Benninga, H. J. F., Van Der Bolt, F., et al. (2020). Anatomy of the 2018 agricultural drought in The Netherlands using in situ soil moisture and satellite vegetation indices. *Hydrology and Earth System Sciences*, *24*(12), 6021–6031. https://doi.org/10.5194/hess-24-6021-2020

Bünemann, E. K., Bongiorno, G., Bai, Z., Creamer, R. E., De Deyn, G., de Goede, R., et al. (2018). Soil quality – A critical review. *Soil Biology and Biochemistry*, *120*, 105–125. https://doi.org/10.1016/j.soilbio.2018.01.030

Busch, F. A., Holloway-Phillips, M., Stuart-Williams, H., & Farquhar, G. D. (2020). Revisiting carbon isotope discrimination in C_3 plants shows respiration rules when photosynthesis is low. *Nature Plants*, *6*(3), 245–258. https://doi.org/10.1038/s41477-020-0606-6

Calabrese, S., Chakrawal, A., Manzoni, S., & Van Cappellen, P. (2021). Energetic scaling in microbial growth. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(47), 1–8. https://doi.org/10.1073/pnas.2107668118

Cameron, E. K., Martins, I. S., Lavelle, P., Mathieu, J., Tedersoo, L., Gottschall, F., et al. (2018). Global gaps in soil biodiversity data. *Nature Ecology & Evolution*, *2*(7), 1042–1043. https://doi.org/10.1038/s41559-018-0573-8

Cao, T., Luo, Y., Shi, M., Tian, X., & Kuzyakov, Y. (2024). Microbial interactions for nutrient acquisition in soil: Miners, scavengers, and carriers. *Soil Biology and Biochemistry*, *188*, 109215. https://doi.org/10.1016/j.soilbio.2023.109215

Carminati, A., & Javaux, M. (2020). Soil rather than xylem vulnerability controls stomatal response to drought. *Trends in Plant Science*, *25*(9), 868–880. https://doi.org/10.1016/j.tplants.2020.04.003

Carranza, C. D. U., Van Der Ploeg, M. J., & Torfs, P. J. J. F. (2018). Using lagged dependence to identify (de)coupled surface and subsurface soil moisture values. *Hydrology and Earth System Sciences*, *22*(4), 2255–2267. https://doi.org/10.5194/hess-22-2255-2018

Cawse-Nicholson, K., Townsend, P. A., Schimel, D., Assiri, A. M., Blake, P. L., Buongiorno, M. F., et al. (2021). NASA's Surface Biology and Geology Designated Observable: A perspective on surface imaging algorithms. *Remote Sensing of Environment*, *257*, 112349. https://doi.org/10.1016/j.rse.2021.112349

Chabrillat, S., Ben-Dor, E., Cierniewski, J., Gomez, C., Schmid, T., & van Wesemael, B. (2019). Imaging spectroscopy for soil mapping and monitoring. *Surveys in Geophysics*, *40*(3), 361–399. https://doi.org/10.1007/s10712-019-09524-0

Chabrillat, S., Guanter, L., Segl, K., Foerster, S., Fischer, S., Rossner, G., et al. (2020). The EnMAP German Spaceborne Imaging Spectroscopy Mission: Update and highlights of recent preparatory activities. *International Geoscience and Remote Sensing Symposium*, *1*, 3278–3281. https://doi.org/10.1109/IGARSS39084.2020.9324006

Chen, S., Arrouays, D., Leatitia Mulder, V., Poggio, L., Minasny, B., Roudier, P., et al. (2022). Digital mapping of GlobalSoilMap soil properties at a broad scale: A review. *Geoderma*, *409*, 115567. https://doi.org/10.1016/j.geoderma.2021.115567

Claus, M., Gundlach, S., Hasselbring, W., Jung, R., Rath, W., & Schnoor, H. (2022). Modularizing Earth system models for interactive simulation. *Informatik-Spektrum*, *45*(5), 300–303. https://doi.org/10.1007/s00287-022-01490-z

Coban, O., de Deyn, G. B., & van der Ploeg, M. (2022). Soil microbiota as game-changers in restoration of degraded lands. *Science*, *375*(6584), abe0725. https://doi.org/10.1126/science.abe0725

Cogliati, S., Sarti, F., Chiarantini, L., Cosi, M., Lorusso, R., Lopinto, E., et al. (2021). The PRISMA imaging spectroscopy mission: Overview and first performance analysis. *Remote Sensing of Environment*, *262*, 112499. https://doi.org/10.1016/j.rse.2021.112499

Colliander, A., Jackson, T. J., Bindlish, R., Chan, S., Das, N., Kim, S. B., et al. (2017). Validation of SMAP surface soil moisture products with core validation sites. *Remote Sensing of Environment*, *191*, 215–231. https://doi.org/10.1016/j.rse.2017.01.021

Colliander, A., Reichle, R. H., Crow, W. T., Cosh, M. H., Chen, F., Chan, S., et al. (2022). Validation of soil moisture data products from the NASA SMAP mission. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *15*, 364–392. https://doi.org/10.1109/JSTARS.2021.3124743

Condon, L. E., Kollet, S., Bierkens, M. F. P., Fogg, G. E., Maxwell, R. M., Hill, M. C., et al. (2021). Global groundwater modeling and monitoring: Opportunities and challenges. *Water Resources Research*, *57*(12), e2020WR029500. https://doi.org/10.1029/2020WR029500

Conesa, M. R., Conejero, W., Vera, J., & Ruiz-Sánchez, M. C. (2023). Assessment of trunk microtensiometer as a novel biosensor to continuously monitor plant water status in nectarine trees. *Frontiers in Plant Science*, *14*, 1–16. https://doi.org/10.3389/fpls.2023.1123045

Costa, O. Y. A., Raaijmakers, J. M., & Kuramae, E. E. (2018). Microbial extracellular polymeric substances: Ecological function and impact on soil aggregation. *Frontiers in Microbiology*, *9*, 1636. https://doi.org/10.3389/fmicb.2018.01636

Coyne, M. S., Pena-Yewtukhiw, E. M., Grove, J. H., Sant'Anna, A. C., & Mata-Padrino, D. (2022). Soil health – It's not all biology. *Soil Security*, *6*, 100051. https://doi.org/10.1016/j.soisec.2022.100051

Crowther, T. W., Maynard, D. S., Crowther, T. R., Peccia, J., Smith, J. R., & Bradford, M. A. (2014). Untangling the fungal niche: The trait-based approach. *Frontiers in Microbiology*, *5*, 100607. https://doi.org/10.3389/fmicb.2014.00579

Crowther, T. W., van den Hoogen, J., Wan, J., Mayes, M. A., Keiser, A. D., Mo, L., et al. (2019). The global soil community and its influence on biogeochemistry. *Science*, *365*(6455), eaav0550. https://doi.org/10.1126/science.aav0550

Dai, Y., Shangguan, W., Wei, N., Xin, Q., Yuan, H., Zhang, S., et al. (2019). A review of the global soil property maps for Earth system models. *Soil*, *5*(2), 137–158. https://doi.org/10.5194/soil-5-137-2019

Dai, Y., Xin, Q., Wei, N., Zhang, Y., Shangguan, W., Yuan, H., et al. (2019). A global high-resolution data set of soil hydraulic and thermal properties for land surface modeling. *Journal of Advances in Modeling Earth Systems*, *11*(9), 2996–3023. https://doi.org/10.1029/2019MS001784

Damm, A., Paul-Limoges, E., Haghighi, E., Simmer, C., Morsdorf, F., Schneider, F. D., et al. (2018). Remote sensing of plant-water relations: An overview and future perspectives. *Journal of Plant Physiology*, *227*, 3–19. https://doi.org/10.1016/j.jplph.2018.04.012

D'Andrimont, R., Yordanov, M., Martinez-Sanchez, L., Eiselt, B., Palmieri, A., Dominici, P., et al. (2020). Harmonised LUCAS in-situ land cover and use database for field surveys from 2006 to 2018 in the European Union. *Scientific Data*, *7*(1), 352. https://doi.org/10.1038/s41597-020-00675-z

Dauphin, B., & Peter, M. (2023). Advancing research on ectomycorrhizal fungal adaptation with landscape genomics. *Trends in Microbiology*, *31*(5), 439–443. https://doi.org/10.1016/j.tim.2023.02.002

Dauphin, B., Rellstab, C., Wüest, R. O., Karger, D. N., Holderegger, R., Gugerli, F., & Manel, S. (2023). Re-thinking the environment in landscape genomics. *Trends in Ecology & Evolution*, *38*(3), 261–274. https://doi.org/10.1016/j.tree.2022.10.010

Deckmyn, G., Flores, O., Mayer, M., Domene, X., Schnepf, A., Kuka, K., et al. (2020). KEYLINK: Towards a more integrative soil representation for inclusion in ecosystem scale models. I. Review and model concept. *PeerJ*, *8*, e9750. https://doi.org/10.7717/peerj.9750

de Graaf, I. E. M., van Beek, R. L. P. H., Gleeson, T., Moosdorf, N., Schmitz, O., Sutanudjaja, E. H., & Bierkens, M. F. P. (2017). A global-scale two-layer transient groundwater model: Development and application to groundwater depletion. *Advances in Water Resources*, *102*, 53–67. https://doi.org/10.1016/j.advwatres.2017.01.011

Delgado-Baquerizo, M., Oliverio, A. M., Brewer, T. E., Benavent-González, A., Eldridge, D. J., Bardgett, R. D., et al. (2018). A global atlas of the dominant bacteria found in soil. *Science*, *359*(6373), 320–325. https://doi.org/10.1126/science.aap9516

de Rosnay, P., Muñoz-Sabater, J., Albergel, C., Isaksen, L., English, S., Drusch, M., & Wigneron, J. P. (2020). SMOS brightness temperature forward modelling and long-term monitoring at ECMWF. *Remote Sensing of Environment*, *237*, 111424. https://doi.org/10.1016/j.rse.2019.111424

Devos, W., & Milenov, P. (2013). Introducing the TEGON as the elementary physical land cover feature. In *2013 2nd International Conference on Agro-Geoinformatics: Information for Sustainable Agriculture, Agro-Geoinformatics 2013* (pp. 562–567).

Devos, W., Sima, A., & Milenov, P. (2021). Conceptual basis of checks by monitoring.

Dignac, M. F., Derrien, D., Barré, P., Barot, S., Cécillon, L., Chenu, C., et al. (2017). Increasing soil carbon storage: Mechanisms, effects of agricultural practices and proxies. A review. *Agronomy for Sustainable Development*, *37*(2), 14. https://doi.org/10.1007/s13593-017-0421-2

Directorate General for Environment. (2024). Proposal for a Directive of the European Parliament and of the Council on Soil Monitoring and Resilience (Soil Monitoring Law).

Doerr, S. H., & Cerdà, A. (2005). Fire effects on soil system functioning: New insights and future challenges. *International Journal of Wildland Fire*, *14*(4), 339–342. https://doi.org/10.1071/WF05094

Doran, J. W. (2002). Soil health and global sustainability: Translating science into practice. *Agricultural Ecosystems & Environment*, *88*(2), 119–127. https://doi.org/10.1016/S0167-8809(01)00246-8

Dorigo, W., Himmelbauer, I., Aberer, D., Schremmer, L., Petrakovic, I., Zappa, L., et al. (2021). The International Soil Moisture Network: Serving Earth system science for over a decade. *Hydrology and Earth System Sciences*, *25*(11), 5749–5804. https://doi.org/10.5194/HESS-25-5749-2021

Drusch, M., Moreno, J., Del Bello, U., Franco, R., Goulas, Y., Huth, A., et al. (2017). The FLuorescence EXplorer Mission Concept—ESA's Earth Explorer 8. *IEEE Transactions on Geoscience and Remote Sensing*, *55*(3), 1273–1284. https://doi.org/10.1109/TGRS.2016.2621820

Du, L., Zeng, Y., Ma, L., Qiao, C., Wu, H., Su, Z., & Bao, G. (2021). Effects of anthropogenic revegetation on the water and carbon cycles of a desert steppe ecosystem. *Agricultural and Forest Meteorology*, *300*, 108339. https://doi.org/10.1016/j.agrformet.2021.108339

Dulya, O., Mikryukov, V., Shchepkin, D. V., Pent, M., Tamm, H., Guazzini, M., et al. (2024). A trait-based ecological perspective on the soil microbial antibiotic-related genetic machinery. *Environmental International*, *190*, 108917. https://doi.org/10.1016/J.ENVINT.2024.108917

Dupiau, A., Jacquemoud, S., Briottet, X., Fabre, S., Viallefont-Robinet, F., Philpot, W., et al. (2022). MARMIT-2: An improved version of the MARMIT model to predict soil reflectance as a function of surface water content in the solar domain. *Remote Sensing of Environment*, *272*, 112951. https://doi.org/10.1016/j.rse.2022.112951

Durner, W. (1994). Hydraulic conductivity estimation for soils with heterogeneous pore structure. *Water Resources Research*, *30*(2), 211–223. https://doi.org/10.1029/93WR02676

Ebrahimi, A., & Or, D. (2018). On upscaling of soil microbial processes and biogeochemical fluxes from aggregates to landscapes. *Journal of Geophysical Research: Biogeosciences*, *123*(5), 1526–1547. https://doi.org/10.1029/2017JG004347

Edlefsen, N. E., & Anderson, A. B. C. (1943). Thermodynamics of soil moisture. *Hilgardia*, *15*(2), 31–298. https://doi.org/10.3733/hilg.v15n02p031

European Commission. (2021). Destination Earth|Shaping Europe's digital future. Retrieved from https://digital-strategy.ec.europa.eu/en/policies/destination-earth

European Commission. (2022). Common Agricultural Policy for 2023-2027: 28 CAP Strategic Plans at a Glance, *Agriculture and Rural Development* (pp. 5–8). Retrieved from https://agriculture.ec.europa.eu/system/files/2022-12/csp-at-a-glance-eu-countries_en.pdf

European Commission. (2023). EU Mission: A Soil Deal for Europe. Retrieved from https://research-and-innovation.ec.europa.eu/funding/funding-opportunities/funding-programmes-and-open-calls/horizon-europe/eu-missions-horizon-europe/soil-deal-europe_en

European Environment Agency. (2023). *Soil Monitoring in Europe, indicators and thresholds for soil health assessments*. Publications Office of the European Union.

European Space Agency. (2024). ESA Earth Observation Science Strategy: Earth Science in Action for Tomorrow's World. Retrieved from https://esamultimedia.esa.int/docs/EarthObservation/ESA_Earth_Observation_Science_Strategy_issued_Sept_2024.pdf

EUROSTAT. (2018). LUCAS 2018 (Land Use/Cover Area Frame Survey), Technical reference document C3 Classification (Land cover & Land use). Retrieved from https://ec.europa.eu/eurostat/documents/205002/%0A8072634/LUCAS2018-C3-Classification.pdf

Evans, S. E., Allison, S. D., Hawkes, C. V., Kellogg, W., & Evans, C. E. (2022). Microbes, memory and moisture: Predicting microbial moisture responses and their impact on carbon cycling. *Functional Ecology*, *36*(6), 1430–1441. https://doi.org/10.1111/1365-2435.14034

Eyring, V., Gentine, P., Camps-Valls, G., Lawrence, D. M., & Reichstein, M. (2024). AI-empowered next-generation multiscale climate modelling for mitigation and adaptation. *Nature Geoscience*, *17*(10), 1–9. https://doi.org/10.1038/s41561-024-01527-w

FAO. (2022). *The State of the World's Land and Water Resources for Food and Agriculture 2021 – Systems at breaking point*. FAO.

FAO, & ITPS. (2015). Status of the World's Soil Resources – Technical Summary. Retrieved from http://www.fao.org/3/i5126e/i5126e.pdf

FAO, & United Nations. (2020). System of Environmental-Economic Accounting for Agriculture, Forestry and Fisheries (SEEA AFF).

Fatichi, S., Or, D., Walko, R., Vereecken, H., Young, M. H., Ghezzehei, T. A., et al. (2020). Soil structure is an important omission in Earth System Models. *Nature Communications*, *11*(1), 1–11. https://doi.org/10.1038/s41467-020-14411-z

Faucon, M. P., Houben, D., & Lambers, H. (2017). Plant functional traits: Soil and ecosystem services. *Trends in Plant Science*, *22*(5), 385–394. https://doi.org/10.1016/j.tplants.2017.01.005

Fierer, N. (2017). Embracing the unknown: Disentangling the complexities of the soil microbiome. *Nature Reviews Microbiology*, *15*(10), 579–590. https://doi.org/10.1038/nrmicro.2017.87

Fierer, N., Leff, J. W., Adams, B. J., Nielsen, U. N., Bates, S. T., Lauber, C. L., et al. (2012). Cross-biome metagenomic analyses of soil microbial communities and their functional attributes. *Proceedings of the National Academy of Sciences of the United States of America*, *109*(52), 21390–21395. https://doi.org/10.1073/pnas.1215210110

Fierer, N., Wood, S. A., & Bueno de Mesquita, C. P. (2021). How microbes can, and cannot, be used to assess soil health. *Soil Biology and Biochemistry*, *153*, 108111. https://doi.org/10.1016/j.soilbio.2020.108111

Fisher, R. A., & Koven, C. D. (2020). Perspectives on the future of land surface models and the challenges of representing complex terrestrial systems. *Journal of Advances in Modeling Earth Systems*, *12*(4), e2018MS001453. https://doi.org/10.1029/2018MS001453

Fisher, R. A., Koven, C. D., Anderegg, W. R. L., Christoffersen, B. O., Dietze, M. C., Farrior, C. E., et al. (2018). Vegetation demographics in Earth System Models: A review of progress and priorities. *Global Change Biology*, *24*(1), 35–54. https://doi.org/10.1111/gcb.13910

Fongaro, C. T., Demattê, J. A. M., Rizzo, R., Safanelli, J. L., Mendes, W. D. S., Dotto, A. C., et al. (2018). Improvement of clay and sand quantification based on a novel approach with a focus on multispectral satellite images. *Remote Sensing*, *10*(10), 1555. https://doi.org/10.3390/rs10101555

Francos, N., Chabrillat, S., Tziolas, N., Milewski, R., Brell, M., Samarinas, N., et al. (2023). Estimation of water-infiltration rate in Mediterranean sandy soils using airborne hyperspectral sensors. *Catena*, *233*, 107476. https://doi.org/10.1016/j.catena.2023.107476

Francos, N., Romano, N., Nasta, P., Zeng, Y., Szabó, B., Manfreda, S., et al. (2021). Mapping water infiltration rate using ground and UAV hyperspectral data: A case study of Alento, Italy. *Remote Sensing*, *13*(13), 2606. https://doi.org/10.3390/rs13132606

Frappart, F., Wigneron, J. P., Li, X., Liu, X., Al-Yaari, A., Fan, L., et al. (2020). Global monitoring of the vegetation dynamics from the vegetation optical depth (VOD): A review. *Remote Sensing*, *12*(18), 2915. https://doi.org/10.3390/RS12182915

Frey, S. D. (2019). Mycorrhizal fungi as mediators of soil organic matter dynamics. *Annual Review of Ecology, Evolution, and Systematics*, *50*(1), 237–259. https://doi.org/10.1146/annurev-ecolsys-110617-062331

Furtak, K., & Wolińska, A. (2023). The impact of extreme weather events as a consequence of climate change on soil moisture and on the quality of the soil environment and agriculture – A review. *Catena*, *231*, 107378. https://doi.org/10.1016/j.catena.2023.107378

Gallo, B. C., Demattê, J. A. M., Rizzo, R., Safanelli, J. L., Mendes, W. D. S., Lepsch, I. F., et al. (2018). Multi-temporal satellite images on topsoil attribute quantification and the relationship with soil classes and geology. *Remote Sensing*, *10*(10), 1571. https://doi.org/10.3390/rs10101571

Gamon, J. A., & Rahman, A. (2012). SpecNet (Spectral Network) linking optical measurements with flux sampling around the world. Retrieved from https://specnet.info/wp-content/uploads/2020/08/NCEAS_Proposal_full.pdf

Gao, B.-C., & Goetz, A. F. H. (1990). Column atmospheric water vapor and vegetation liquid water retrievals from airborne imaging spectrometer data. *Journal of Geophysical Research*, *95*(D4), 3549–3564. https://doi.org/10.1029/jd095id04p03549

Garcia Gonzalez, R., Verhoef, A., Vidale, P. L., & Braud, I. (2012). Incorporation of water vapor transfer in the JULES land surface model: Implications for key soil variables and land surface fluxes. *Water Resources Research*, *48*(5), W05538. https://doi.org/10.1029/2011WR011811

Gaudaré, U., Kuhnert, M., Smith, P., Martin, M., Barbieri, P., Pellerin, S., & Nesme, T. (2023). Soil organic carbon stocks potentially at risk of decline with organic farming expansion. *Nature Climate Change*, *13*(7), 719–725. https://doi.org/10.1038/s41558-023-01721-5

Gholami, H., Mohammadifar, A., Song, Y., Li, Y., Rahmani, P., Kaskaoutis, D. G., et al. (2024). An assessment of global land susceptibility to wind erosion based on deep-active learning modelling and interpretation techniques. *Scientific Reports*, *14*(1), 1–16. https://doi.org/10.1038/s41598-024-70125-y

Giannakis, G. V., Nikolaidis, N. P., Valstar, J., & Rowe, E. C. (2017). *Integrated Critical Zone Model (1D-ICZ): A tool for dynamic simulation of soil functions and soil structure* (1st ed.). Elsevier Inc.

Giannakis, G. V., Nikolaidis, N. P., Valstar, J., Rowe, E. C., Moirogiorgou, K., Kotronakis, M., et al. (2017). Integrated Critical Zone Model (1D-ICZ): A tool for dynamic simulation of soil functions and soil structure. *Advances in Agronomy*, *142*, 277–314. https://doi.org/10.1016/bs.agron.2016.10.009

Giauque, H., Connor, E. W., & Hawkes, C. V. (2019). Endophyte traits relevant to stress tolerance, resource use and habitat of origin predict effects on host plants. *New Phytologist*, *221*(4), 2239–2249. https://doi.org/10.1111/nph.15504

Green, R. O., Mahowald, N., Thompson, D. R., Ung, C., Brodrick, P., Pollock, R., et al. (2023). Performance and early results from the Earth Surface Mineral Dust Source Investigation (EMIT) imaging spectroscopy mission. In *IEEE Aerospace Conference Proceedings, 2023-March*. https://doi.org/10.1109/AERO55745.2023.10115851

Gregorich, L. J., & Acton, D. F. (2012). The health of our soils: Toward sustainable agriculture in Canada. https://doi.org/10.5962/bhl.title.58906

Gregory, P. J. (2022). RUSSELL REVIEW: Are plant roots only "in" soil or are they "of" it? Roots, soil formation, and function. *European Journal of Soil Science*, *73*(1), e13219. https://doi.org/10.1111/ejss.13219

Greiner, L., Keller, A., Grêt-Regamey, A., & Papritz, A. (2017). Soil function assessment: Review of methods for quantifying the contributions of soils to ecosystem services. *Land Use Policy*, *69*, 224–237. https://doi.org/10.1016/j.landusepol.2017.06.025

Haberern, J. (1992). A soil health index. *Journal of Soil and Water Conservation*, *47*(1), 6.

Han, Q., Zeng, Y., Zhang, L., Wang, C., Prikaziuk, E., Niu, Z., & Su, B. (2023). Global long-term daily 1 km surface soil moisture dataset with physics-informed machine learning. *Scientific Data*, *10*(1), 1–12. https://doi.org/10.1038/s41597-023-02011-7

Han, X., Franssen, H. J. H., Montzka, C., & Vereecken, H. (2014). Soil moisture and soil properties estimation in the Community Land Model with synthetic brightness temperature observations. *Water Resources Research*, *50*(7), 6081–6105. https://doi.org/10.1002/2013WR014586

Hank, T. B., Berger, K., Bach, H., Clevers, J. G. P. W., Gitelson, A., Zarco-Tejada, P., & Mauser, W. (2019). *Spaceborne imaging spectroscopy for sustainable agriculture: Contributions and challenges*. Springer.

Hartemink, A. E., & McBratney, A. (2008). A soil science renaissance. *Geoderma*, *148*(2), 123–129. https://doi.org/10.1016/j.geoderma.2008.10.006

Hartmann, M., & Six, J. (2023). Soil structure and microbiome functions in agroecosystems. *Nature Reviews Earth & Environment*, *4*(1), 4–18. https://doi.org/10.1038/s43017-022-00366-w

Hawkins, H. J., Cargill, R. I. M., Van Nuland, M. E., Hagen, S. C., Field, K. J., Sheldrake, M., et al. (2023). Mycorrhizal mycelium as a global carbon pool. *Current Biology*, *33*(11), R560–R573. https://doi.org/10.1016/j.cub.2023.02.027

He, H., He, D., Jin, J., Smits, K. M., Dyck, M., Wu, Q., et al. (2020). Room for improvement: A review and evaluation of 24 soil thermal conductivity parameterization schemes commonly used in land-surface, hydrological, and soil-vegetation-atmosphere transfer models. *Earth-Science Reviews*, *211*, 103419. https://doi.org/10.1016/j.earscirev.2020.103419

Helfenstein, A., Mulder, V. L., Hack-Ten Broeke, M. J. D., van Doorn, M., Teuling, K., Walvoort, D. J. J., & Heuvelink, G. B. M. (2024). BIS-4D: Mapping soil properties and their uncertainties at 25 m resolution in The Netherlands. *Earth System Science Data*, *16*(6), 2941–2970. https://doi.org/10.5194/ESSD-16-2941-2024

Hengl, T., De Jesus, J. M., Heuvelink, G. B. M., Gonzalez, M. R., Kilibarda, M., Blagotić, A., et al. (2017). SoilGrids250m: Global gridded soil information based on machine learning. *PLoS One*, *12*(2), e0169748. https://doi.org/10.1371/journal.pone.0169748

Heuvelink, G. B. M., Schoorl, J. M., Veldkamp, A., & Pennock, D. J. (2006). Space-time Kalman filtering of soil redistribution. *Geoderma*, *133*(1–2), 124–137. https://doi.org/10.1016/j.geoderma.2006.03.041

Hoffmann, J., Bauer, P., Sandu, I., Wedi, N., Geenen, T., & Thiemert, D. (2023). Destination Earth – A digital twin in support of climate services. *Climate Services*, *30*, 100394. https://doi.org/10.1016/j.cliser.2023.100394

Hu, L., Robert, C. A. M., Cadot, S., Zhang, X., Ye, M., Li, B., et al. (2018). Root exudate metabolites drive plant-soil feedbacks on growth and defense by shaping the rhizosphere microbiota. *Nature Communications*, *9*(1), 1–13. https://doi.org/10.1038/s41467-018-05122-7

Huber, S., Prokop, G., Arrouays, D., Banko, G., Bispo, A., Jones, R. J. A., et al. (2010). Environmental assessment of soil for monitoring Volume I: Indicators & criteria (Report No. 339). https://doi.org/10.2788/93515

Huet, S., Romdhane, S., Breuil, M. C., Bru, D., Mounier, A., Spor, A., & Philippot, L. (2023). Experimental community coalescence sheds light on microbial interactions in soil and restores impaired functions. *Microbiome*, *11*(1), 1–17. https://doi.org/10.1186/s40168-023-01480-7

Huscroft, J., Gleeson, T., Hartmann, J., & Börker, J. (2018). Compiling and mapping global permeability of the unconsolidated and consolidated Earth: Global hydrogeology maps 2.0 (GLHYMPS 2.0). *Geophysical Research Letters*, *45*(4), 1897–1904. https://doi.org/10.1002/2017GL075860

Jacquemound, S., & Ustin, S. (2019). *Leaf optical properties* (1st ed.). Cambridge University Press.

Jain, P., Liu, W., Zhu, S., Chang, C. Y. Y., Melkonian, J., Rockwell, F. E., et al. (2021). A minimally disruptive method for measuring water potential in planta using hydrogel nanoreporters. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(23), e2008276118. https://doi.org/10.1073/pnas.2008276118

Jana, R. B., & Mohanty, B. P. (2011). Enhancing PTFs with remotely sensed data for multi-scale soil water retention estimation. *Journal of Hydrology*, *399*(3–4), 201–211. https://doi.org/10.1016/j.jhydrol.2010.12.043

Jansson, J. K., & Hofmockel, K. S. (2020). Soil microbiomes and climate change. *Nature Reviews Microbiology*, *18*(1), 35–46. https://doi.org/10.1038/s41579-019-0265-7

Jansson, J. K., McClure, R., & Egbert, R. G. (2023). Soil microbiome engineering for sustainability in a changing environment. *Nature Biotechnology*, *41*(12), 1716–1728. https://doi.org/10.1038/s41587-023-01932-3

Jarvis, N., Coucheney, E., Lewan, E., Klöffel, T., Meurer, K. H. E., Keller, T., & Larsbo, M. (2024). Interactions between soil structure dynamics, hydrological processes, and organic matter cycling: A new soil-crop model. *European Journal of Soil Science*, *75*(2), e13455. https://doi.org/10.1111/EJSS.13455

Jenny, H., & Amundson, R. (1994). *Factors of soil formation: System of quantitative pedology*. Dover Publications. Retrieved from https://books.google.com/books/about/Factors_of_Soil_Formation.html?id=orjZZS3H-hAC

Jha, A., Bonetti, S., Smith, A. P., Souza, R., & Calabrese, S. (2023). Linking soil structure, hydraulic properties, and organic carbon dynamics: A holistic framework to study the impact of climate change and land management. *Journal of Geophysical Research: Biogeosciences*, *128*(7), e2023JG007389. https://doi.org/10.1029/2023JG007389

Jiang, F., Bennett, J. A., Crawford, K. M., Heinze, J., Pu, X., Luo, A., & Wang, Z. (2024). Global patterns and drivers of plant–soil microbe interactions. *Ecology Letters*, *27*(1), 1–12. https://doi.org/10.1111/ele.14364

Jones, A., Fernandez-Ugalde, O., & Scarpa, S. (2020). *LUCAS 2015 topsoil survey: Presentation of dataset and results* JRC121325. Publications Office of the European Union.

Jones, D. L., Nguyen, C., & Finlay, R. D. (2009). Carbon flow in the rhizosphere: Carbon trading at the soil-root interface. *Plant and Soil*, *321*(1–2), 5–33. https://doi.org/10.1007/s11104-009-9925-0

Jongmans, A. G., Van Breemen, N., Lundström, U., Van Hees, P. A. W., Finlay, R. D., Srinivasan, M., et al. (1997). Rock-eating fungi. *Nature*, *389*(6652), 682–683. https://doi.org/10.1038/39493

Joshi, J., Stocker, B. D., Hofhansl, F., Zhou, S., Dieckmann, U., & Prentice, I. C. (2022). Towards a unified theory of plant photosynthesis and hydraulics. *Nature Plants*, *8*(11), 1304–1316. https://doi.org/10.1038/s41477-022-01244-5

Kakouridis, A., Hagen, J. A., Kan, M. P., Mambelli, S., Feldman, L. J., Herman, D. J., et al. (2022). Routes to roots: Direct evidence of water transport by arbuscular mycorrhizal fungi to host plants. *New Phytologist*, *236*(1), 210–221. https://doi.org/10.1111/nph.18281

Kattge, J., Bönisch, G., Díaz, S., Lavorel, S., Prentice, I. C., Leadley, P., et al. (2020). TRY plant trait database – Enhanced coverage and open access. *Global Change Biology*, *26*(1), 119–188. https://doi.org/10.1111/gcb.14904

Keesstra, S. D., Bouma, J., Wallinga, J., Tittonell, P., Smith, P., Cerdà, A., et al. (2016). The significance of soils and soil science towards realization of the United Nations sustainable development goals. *Soil*, *2*(2), 111–128. https://doi.org/10.5194/SOIL-2-111-2016

Kempen, B., Brus, D. J., Stoorvogel, J. J., Heuvelink, G. B. M., & de Vries, F. (2012). Efficiency comparison of conventional and digital soil mapping for updating soil maps. *Soil Science Society of America Journal*, *76*(6), 2097–2115. https://doi.org/10.2136/sssaj2011.0424

Kennedy, D., Swenson, S., Oleson, K. W., Lawrence, D. M., Fisher, R., Lola da Costa, A. C., & Gentine, P. (2019). Implementing plant hydraulics in the community land model, version 5. *Journal of Advances in Modeling Earth Systems*, *11*(2), 485–513. https://doi.org/10.1029/2018MS001500

Klironomos, J., Zobel, M., Tibbett, M., Stock, W. D., Rillig, M. C., Parrent, J. L., et al. (2011). Forces that structure plant communities: Quantifying the importance of the mycorrhizal symbiosis. *New Phytologist*, *189*(2), 366–370. https://doi.org/10.1111/J.1469-8137.2010.03550.X

Koetz, B., Bastiaanssen, W., Berger, M., Defourney, P., Bello, U. D., Drusch, M., et al. (2018). High spatio-temporal resolution land surface temperature mission - A Copernicus candidate mission in support of agricultural monitoring. In *International Geoscience and Remote Sensing Symposium, 2018-July* (pp. 8160–8162). https://doi.org/10.1109/IGARSS.2018.8517433

König, S., Weller, U., Betancur-Corredor, B., Lang, B., Reitz, T., Wiesmeier, M., et al. (2023). BODIUM—A systemic approach to model the dynamics of soil functions. *European Journal of Soil Science*, *74*(5), e13411. https://doi.org/10.1111/ejss.13411

Konings, A. G., Piles, M., Das, N., & Entekhabi, D. (2017). L-band vegetation optical depth and effective scattering albedo estimation from SMAP. *Remote Sensing of Environment*, *198*, 460–470. https://doi.org/10.1016/j.rse.2017.06.037

Konings, A. G., Rao, K., & Steele-Dunne, S. C. (2019). Macro to micro: Microwave remote sensing of plant water content for physiology and ecology. *New Phytologist*, *223*(3), 1166–1172. https://doi.org/10.1111/nph.15808

Konings, A. G., Saatchi, S. S., Frankenberg, C., Keller, M., Leshyk, V., Anderegg, W. R. L., et al. (2021). Detecting forest response to droughts with global observations of vegetation water content. *Global Change Biology*, *27*(23), 6005–6024. https://doi.org/10.1111/gcb.15872

Konings, A. G., Yu, Y., Xu, L., Yang, Y., Schimel, D. S., & Saatchi, S. S. (2017). Active microwave observations of diurnal and seasonal variations of canopy water content across the humid African tropical forests. *Geophysical Research Letters*, *44*(5), 2290–2299. https://doi.org/10.1002/2016GL072388

Kravchenko, A., Otten, W., Garnier, P., Pot, V., & Baveye, P. C. (2019). Soil aggregates as biogeochemical reactors: Not a way forward in the research on soil–atmosphere exchange of greenhouse gases. *Global Change Biology*, *25*(7), 2205–2208. https://doi.org/10.1111/GCB.14640

Labouyrie, M., Ballabio, C., Romero, F., Panagos, P., Jones, A., Schmid, M. W., et al. (2023). Patterns in soil microbial diversity across Europe. *Nature Communications*, *14*(1), 3311. https://doi.org/10.1038/s41467-023-37937-4

Lagacherie, P., & Gomez, C. (2018). Vis-NIR-SWIR remote sensing products as new soil data for digital soil mapping. In *Advances in Soil Science* (pp. 415–437). https://doi.org/10.1007/978-3-319-63439-5_13

Lagacherie, P., & McBratney, A. B. (2006). Spatial soil information systems and spatial soil inference systems: Perspectives for digital soil mapping. *Developments in Soil Science*, *31*, 3–22. https://doi.org/10.1016/S0166-2481(06)31001-X

Lahlali, R., Ibrahim, D. S. S., Belabess, Z., Roni, M. Z. K., Radouane, N., Vicente, C. S. L., et al. (2021). High-throughput molecular technologies for unraveling the mystery of soil microbial community: Challenges and future prospects. *Heliyon*, *7*(10), e042. https://doi.org/10.1016/j.heliyon.2021.e08142

Laishram, J., Saxena, K. G., Maikhuri, R. K., & Rao, K. S. (2015). Soil quality and soil health: A review. *International Journal of Ecology and Environmental Sciences*, *38*, 19–37.

Lajoie, G., & Kembel, S. W. (2019). Making the most of trait-based approaches for microbial ecology. *Trends in Microbiology*, *27*(10), 814–823. https://doi.org/10.1016/j.tim.2019.06.003

Lakso, A. N., Santiago, M., & Stroock, A. D. (2022). Monitoring stem water potential with an embedded microtensiometer to inform irrigation scheduling in fruit crops. *Horticulturae*, *8*(12), 1207. https://doi.org/10.3390/horticulturae8121207

Lal, R. (2015). A system approach to conservation agriculture. *Journal of Soil and Water Conservation*, *70*(4), 82A–88A. https://doi.org/10.2489/jswc.70.4.82A

Lal, R., Bouma, J., Brevik, E., Dawson, L., Field, D. J., Glaser, B., et al. (2021). Soils and sustainable development goals of the United Nations: An International Union of Soil Sciences perspective. *Geoderma Regional*, *25*, e00398. https://doi.org/10.1016/J.GEODRS.2021.E00398

Lausch, A., Bannehr, L., Beckmann, M., Boehm, C., Feilhauer, H., Hacker, J. M., et al. (2016). Linking Earth observation and taxonomic, structural, and functional biodiversity: Local to ecosystem perspectives. *Ecological Indicators*, *70*, 317–339. https://doi.org/10.1016/j.ecolind.2016.06.022

Leenen, M., Pätzold, S., Tóth, G., & Welp, G. (2022). A LUCAS-based mid-infrared soil spectral library: Its usefulness for soil survey and precision agriculture. *Journal of Plant Nutrition and Soil Science*, *185*(3), 370–383. https://doi.org/10.1002/JPLN.202100031

Lehmann, J., Bossio, D. A., Kögel-Knabner, I., & Rillig, M. C. (2020). The concept and future prospects of soil health. *Nature Reviews Earth & Environment*, *1*(10), 544–553. https://doi.org/10.1038/s43017-020-0080-8

Lehmann, J., & Kleber, M. (2015). The contentious nature of soil organic matter. *Nature*, *528*(7580), 60–68. https://doi.org/10.1038/nature16069

Lehmann, P., Leshchinsky, B., Gupta, S., Mirus, B. B., Bickel, S., Lu, N., & Or, D. (2021). Clays are not created equal: How clay mineral type affects soil parameterization. *Geophysical Research Letters*, *48*(20), e2021GL095311. https://doi.org/10.1029/2021GL095311

Leigh, D. M., van Rees, C. B., Millette, K. L., Breed, M. F., Schmidt, C., Bertola, L. D., et al. (2021). Opportunities and challenges of macrogenetic studies. *Nature Reviews Genetics*, *22*(12), 791–807. https://doi.org/10.1038/s41576

Lennon, J. T., Aanderud, Z. T., Lehmkuhl, B. K., & Schoolmaster, D. R. (2012). Mapping the niche space of soil microorganisms using taxonomy and traits. *Ecology*, *93*(8), 1867–1879. https://doi.org/10.1890/11-1745.1

Levy, A., Salas Gonzalez, I., Mittelviefhaus, M., Clingenpeel, S., Herrera Paredes, S., Miao, J., et al. (2018). Genomic features of bacterial adaptation to plants. *Nature Genetics*, *50*(1), 138–150. https://doi.org/10.1038/s41588-017-0012-9

Lewin, H. A., Richards, S., Aiden, E. L., Allende, M. L., Archibald, J. M., Bálint, M., et al. (2022). The Earth BioGenome Project 2020: Starting the clock. *Proceedings of the National Academy of Sciences of the United States of America*, *119*(4), e2115635118. https://doi.org/10.1073/pnas.2115635118

Li, X., Feng, M., Ran, Y., Su, Y., Liu, F., Huang, C., et al. (2023). Big data in Earth system science and progress towards a digital twin. *Nature Reviews Earth & Environment*, *4*(5), 319–332. https://doi.org/10.1038/s43017-023-00409-w

Li, Y., Zhang, X. X., Mao, R. L., Yang, J., Miao, C. Y., Li, Z., & Qiu, Y. X. (2017). Ten years of landscape genomics: Challenges and opportunities. *Frontiers in Plant Science*, *8*, 287667. https://doi.org/10.3389/fpls.2017.02136

Li, Z., Kravchenko, A. N., Cupples, A., Guber, A. K., Kuzyakov, Y., Robertson, G. P., & Blagodatskaya, E. (2024). Composition and metabolism of microbial communities in soil pores. *Nature Communications*, *15*(1), 1–16. https://doi.org/10.1038/s41467-024-47755-x

Li, Z., Tian, D., Wang, B., Wang, J., Wang, S., Chen, H. Y. H., et al. (2019). Microbes drive global soil nitrogen mineralization and availability. *Global Change Biology*, *25*(3), 1078–1088. https://doi.org/10.1111/gcb.14557

Liakos, L., & Panagos, P. (2022). Challenges in the geo-processing of big soil spatial data. *Land*, *11*(12), 2287. https://doi.org/10.3390/land11122287

Little, A. E. F., Robinson, C. J., Peterson, S. B., Raffa, K. F., & Handelsman, J. (2008). Rules of engagement: Interspecies interactions that regulate microbial communities. *Annual Review of Microbiology*, *62*(1), 375–401. https://doi.org/10.1146/annurev.micro.030608.101423

Lu, M., & Hedin, L. O. (2019). Global plant–symbiont organization and emergence of biogeochemical cycles resolved by evolution-based trait modelling. *Nature Ecology & Evolution*, *3*(2), 239–250. https://doi.org/10.1038/s41559-018-0759-0

Lubis, R. L., Juniarti, R., Rajmi, S. L., Armer, A. N., Hidayat, F. R., Zulhakim, H., et al. (2021). Chemical properties of volcanic soil after 10 years of the eruption of Mt. Sinabung (North Sumatera, Indonesia). *IOP Conference Series: Earth and Environmental Science*, *757*(1), 012043. https://doi.org/10.1088/1755-1315/757/1/012043

Luo, S., Lu, N., Zhang, C., & Likos, W. (2022). Soil water potential: A historical perspective and recent breakthroughs. *Vadose Zone Journal*, *21*(4), 1–39. https://doi.org/10.1002/vzj2.20203

Lv, S. N., Simmer, C., Zeng, Y. J., Su, Z. B., & Wen, J. (2023). Impact of profile-averaged soil ice fraction on passive microwave brightness temperature diurnal amplitude variations (DAV) at L-band. *Cold Regions Science and Technology*, *205*, 103674. https://doi.org/10.1016/j.coldregions.2022.103674

Ma, H., Mo, L., Crowther, T. W., Maynard, D. S., van den Hoogen, J., Stocker, B. D., et al. (2021). The global distribution and environmental drivers of aboveground versus belowground plant biomass. *Nature Ecology & Evolution*, *5*(8), 1110–1122. https://doi.org/10.1038/s41559-021-01485-1

Maharjan, B., Das, S., & Acharya, B. S. (2020). Soil health gap: A concept to establish a benchmark for soil health management. *Global Ecology and Conservation*, *23*, e01116. https://doi.org/10.1016/j.gecco.2020.e01116

Manfreda, S., & Ben Dor, E. (2023). *Unmanned aerial systems for monitoring soil, vegetation, and riverine environments*. Elsevier.

Manzoni, S., & Porporato, A. (2009). Soil carbon and nitrogen mineralization: Theory and models across scales. *Soil Biology and Biochemistry*, *41*(7), 1355–1379. https://doi.org/10.1016/j.soilbio.2009.02.031

Marthews, T. R., Quesada, C. A., Galbraith, D. R., Malhi, Y., Mullins, C. E., Hodnett, M. G., & Dharssi, I. (2014). High-resolution hydraulic parameter maps for surface soils in tropical South America. *Geoscientific Model Development*, *7*(3), 711–723. https://doi.org/10.5194/gmd-7-711-2014

Martin, F., Kohler, A., Murat, C., Veneault-Fourrey, C., & Hibbett, D. S. (2016). Unearthing the roots of ectomycorrhizal symbioses. *Nature Reviews Microbiology*, *14*(12), 760–773. https://doi.org/10.1038/nrmicro.2016.149

Martin, F. M., & van der Heijden, M. G. A. (2024). The mycorrhizal symbiosis: Research frontiers in genomics, ecology, and agricultural application. *New Phytologist*, *242*(4), 1486–1506. https://doi.org/10.1111/nph.19541

Massman, W. J. (2021). The challenges of an in situ validation of a nonequilibrium model of soil heat and moisture dynamics during fires. *Hydrology and Earth System Sciences*, *25*(2), 685–709. https://doi.org/10.5194/hess-25-685-2021

Matsunaga, T., Iwasaki, A., Tachikawa, T., Tanii, J., Kashimura, O., Mouri, K., et al. (2020). Hyperspectral imager suite (HISUI): Its launch and current status. *International Geoscience and Remote Sensing Symposium*, 3272–3273. https://doi.org/10.1109/IGARSS39084.2020.9323376

Mausel, P. W. (1971). Soil quality in Illinois—An example of a soils geography resource analysis. *Professional Geographer*, *23*(2), 127–136. https://doi.org/10.1111/j.0033-0124.1971.00127.x

Maynard, D. S., Bradford, M. A., Covey, K. R., Lindner, D., Glaeser, J., Talbert, D. A., et al. (2019). Consistent trade-offs in fungal trait expression across broad spatial scales. *Nature Microbiology*, *4*(5), 846–853. https://doi.org/10.1038/s41564-019-0361-5

McBratney, A. B., Mendonça Santos, M. L., & Minasny, B. (2003). On digital soil mapping. *Geoderma*, *117*(1–2), 3–52. https://doi.org/10.1016/S0016-7061(03)00223-4

McGill, B. J., Etienne, R. S., Gray, J. S., Alonso, D., Anderson, M. J., Benecha, H. K., et al. (2007). Species abundance distributions: Moving beyond single prediction theories to integration within an ecological framework. *Ecology Letters*, *10*(10), 995–1015. https://doi.org/10.1111/j.1461-0248.2007.01094.x

Meurer, K., Barron, J., Chenu, C., Coucheney, E., Fielding, M., Hallett, P., et al. (2020). A framework for modelling soil structure dynamics induced by biological activity. *Global Change Biology*, *26*(10), 5382–5403. https://doi.org/10.1111/GCB.15289

Meurer, K. H. E., Chenu, C., Coucheney, E., Herrmann, A. M., Keller, T., Kätterer, T., et al. (2020). Modelling dynamic interactions between soil structure and the storage and turnover of soil organic matter. *Biogeosciences*, *17*(20), 5025–5042. https://doi.org/10.5194/bg-17-5025-2020

Minasny, B., Malone, B. P., McBratney, A. B., Angers, D. A., Arrouays, D., Chambers, A., et al. (2017). Soil carbon 4 per mille. *Geoderma*, *292*, 59–86. https://doi.org/10.1016/j.geoderma.2017.01.002

Minasny, B., & McBratney, A. B. (2016). Digital soil mapping: A brief history and some lessons. *Geoderma*, *264*, 301–311. https://doi.org/10.1016/J.GEODERMA.2015.07.017

Mohammed, G. H., Colombo, R., Middleton, E. M., Rascher, U., van der Tol, C., Nedbal, L., et al. (2019). Remote sensing of solar-induced chlorophyll fluorescence (SIF) in vegetation: 50 years of progress. *Remote Sensing of Environment*, *231*, 111180. https://doi.org/10.1016/j.rse.2019.04.030

Moinet, G. Y. K., Hijbeek, R., van Vuuren, D. P., & Giller, K. E. (2023). Carbon for soils, not soils for carbon. *Global Change Biology*, *29*(9), 2384–2398. https://doi.org/10.1111/gcb.16570

Mondal, S., & Chakraborty, D. (2022). Global meta-analysis suggests that no-tillage favourably changes soil structure and porosity. *Geoderma*, *405*, 115443. https://doi.org/10.1016/j.geoderma.2021.115443

Montzka, C., Herbst, M., Weihermüller, L., Verhoef, A., & Vereecken, H. (2017). A global data set of soil hydraulic properties and sub-grid variability of soil water retention and hydraulic conductivity curves. *Earth System Science Data*, *9*(2), 529–543. https://doi.org/10.5194/essd-9-529-2017

Neuenkamp, L., Moora, M., Öpik, M., Davison, J., Gerz, M., Männistö, M., et al. (2018). The role of plant mycorrhizal type and status in modulating the relationship between plant and arbuscular mycorrhizal fungal communities. *New Phytologist*, *220*(4), 1236–1247. https://doi.org/10.1111/NPH.14995

Nocita, M., Stevens, A., van Wesemael, B., Aitkenhead, M., Bachmann, M., Barthès, B., et al. (2015). Soil spectroscopy: An alternative to wet chemistry for soil monitoring. *Advances in Agronomy*, *132*, 139–159. https://doi.org/10.1016/bs.agron.2015.02.002

Norris, C. E., Bean, G. M., Cappellazzi, S. B., Cope, M., Greub, K. L. H., Liptzin, D., et al. (2020). Introducing the North American project to evaluate soil health measurements. *Agronomy Journal*, *112*(4), 3195–3215. https://doi.org/10.1002/agj2.20234

Novick, K. A., Ficklin, D. L., Baldocchi, D., Davis, K. J., Ghezzehei, T. A., Konings, A. G., et al. (2022). Confronting the water potential information gap. *Nature Geoscience*, *15*(3), 158–164. https://doi.org/10.1038/s41561-022-00909-2

O'Brien, S. L., Gibbons, S. M., Owens, S. M., Hampton-Marcell, J., Johnston, E. R., Jastrow, J. D., et al. (2016). Spatial scale drives patterns in soil bacterial diversity. *Environmental Microbiology*, *18*(6), 2039–2051. https://doi.org/10.1111/1462-2920.13231

Ohnemus, T., Zacharias, S., Dirnböck, T., Bäck, J., Brack, W., Forsius, M., et al. (2024). The eLTER research infrastructure: Current design and coverage of environmental and socio-ecological gradients. *Environmental Sustainability Indicators*, *23*, 100456. https://doi.org/10.1016/J.INDIC.2024.100456

Or, D. (2020). The tyranny of small scales—On representing soil processes in global land surface models. *Water Resources Research*, *56*(6), e2019WR024846. https://doi.org/10.1029/2019WR024846

Or, D., Keller, T., & Schlesinger, W. H. (2021). Natural and managed soil structure: On the fragile scaffolding for soil functioning. *Soil & Tillage Research*, *208*, 104912. https://doi.org/10.1016/j.still.2020.104912

Or, D., Phutane, S., & Dechesne, A. (2007). Extracellular polymeric substances affecting pore-scale hydrologic conditions for bacterial activity in unsaturated soils. *Vadose Zone Journal*, *6*(2), 298–305. https://doi.org/10.2136/vzj2006.0080

Orgiazzi, A., Ballabio, C., Panagos, P., Jones, A., & Fernández-Ugalde, O. (2018). LUCAS Soil, the largest expandable soil dataset for Europe: A review. *European Journal of Soil Science*, *69*(1), 140–153. https://doi.org/10.1111/ejss.12499

Orgiazzi, A., Panagos, P., Fernández-Ugalde, O., Wojda, P., Labouyrie, M., Ballabio, C., et al. (2022). LUCAS Soil Biodiversity and LUCAS Soil Pesticides, new tools for research and policy development. *European Journal of Soil Science*, *73*(5), e13299. https://doi.org/10.1111/EJSS.13299

Ottoni, M. V., Ottoni Filho, T. B., Schaap, M. G., Lopes-Assad, M. L. R. C., & Rotunno Filho, O. C. (2018). Hydrophysical database for Brazilian soils (HYBRAS) and pedotransfer functions for water retention. *Vadose Zone Journal*, *17*(1), 1–17. https://doi.org/10.2136/vzj2017.05.0095

Panagos, P., Borrelli, P., Jones, A., & Robinson, D. A. (2024). A 1 billion euro mission: A soil deal for Europe. *European Journal of Soil Science*, *75*(1), e13466. https://doi.org/10.1111/EJSS.13466

Panagos, P., Borrelli, P., Poesen, J., Ballabio, C., Lugato, E., Meusburger, K., et al. (2015). The new assessment of soil loss by water erosion in Europe. *Environmental Science & Policy*, *54*, 438–447. https://doi.org/10.1016/J.ENVSCI.2015.08.012

Panagos, P., Broothaerts, N., Ballabio, C., Orgiazzi, A., De Rosa, D., Borrelli, P., et al. (2024). How the EU Soil Observatory is providing solid science for healthy soils. *European Journal of Soil Science*, *75*(3), e13507. https://doi.org/10.1111/EJSS.13507

Panagos, P., & Montanarella, L. (2018). Soil Thematic Strategy: An important contribution to policy support, research, data development and raising the awareness. *Current Opinion in Environmental Science & Health*, *5*, 38–41. https://doi.org/10.1016/j.coesh.2018.04.008

Panagos, P., Montanarella, L., Barbero, M., Schneegans, A., Aguglia, L., & Jones, A. (2022). Soil priorities in the European Union. *Geoderma Regional*, *29*, e00510. https://doi.org/10.1016/j.geodrs.2022.e00510

Panagos, P., Van Liedekerke, M., Borrelli, P., Köninger, J., Ballabio, C., Orgiazzi, A., et al. (2022). European Soil Data Centre 2.0: Soil data and knowledge in support of the EU policies. *European Journal of Soil Science*, *73*(6), 1–18. https://doi.org/10.1111/ejss.13315

Panagos, P., Vieira, D., Eekhout, J. P. C., Biddoccu, M., Cerdà, A., Evans, D. L., et al. (2024). How the EU Soil Observatory contributes to a stronger soil erosion community. *Environmental Research*, *248*, 118319. https://doi.org/10.1016/J.ENVRES.2024.118319

Paruta, A., Ciraolo, G., Capodici, F., Manfreda, S., Sasso, S. F. D., Zhuang, R., et al. (2021). A geostatistical approach to map near-surface soil moisture through hyperspatial resolution thermal inertia. *IEEE Transactions on Geoscience and Remote Sensing*, *59*(6), 5352–5369. https://doi.org/10.1109/TGRS.2020.3019200

Pastorello, G., Trotta, C., Canfora, E., Chu, H., Christianson, D., Cheah, Y. W., et al. (2020). The FLUXNET2015 dataset and the ONEFlux processing pipeline for eddy covariance data. *Scientific Data*, *7*(1), 1–27. https://doi.org/10.1038/s41597-020-0534-3

Paz-Kagan, T., Zaady, E., Salbach, C., Schmidt, A., Lausch, A., Zacharias, S., et al. (2015). Mapping the spectral soil quality index (SSQI) using airborne imaging spectroscopy. *Remote Sensing*, *7*(11), 15748–15781. https://doi.org/10.3390/rs71115748

Pelletier, J. D., Brad Murray, A., Pierce, J. L., Bierman, P. R., Breshears, D. D., Crosby, B. T., et al. (2015). Forecasting the response of Earth's surface to future climatic and land use changes: A review of methods and research needs. *Earth's Future*, *3*(7), 220–251. https://doi.org/10.1002/2014EF000290

Pennock, D. J., & Veldkamp, A. (2006). Advances in landscape-scale soil research. *Geoderma*, *133*(1–2), 1–5. https://doi.org/10.1016/j.geoderma.2006.03.032

Philippot, L., Chenu, C., Kappler, A., Rillig, M. C., & Fierer, N. (2024). The interplay between microbial communities and soil properties. *Nature Reviews Microbiology*, *22*(4), 226–239. https://doi.org/10.1038/s41579-023-00980-5

Philippot, L., Raaijmakers, J. M., Lemanceau, P., & Van Der Putten, W. H. (2013). Going back to the roots: The microbial ecology of the rhizosphere. *Nature Reviews Microbiology*, *11*(11), 789–799. https://doi.org/10.1038/nrmicro3109

Pierrat, Z., Magney, T., Parazoo, N. C., Grossmann, K., Bowling, D. R., Seibt, U., et al. (2022). Diurnal and seasonal dynamics of solar-induced chlorophyll fluorescence, vegetation indices, and gross primary productivity in the boreal forest. *Journal of Geophysical Research: Biogeosciences*, *127*(2), e2021JG006588. https://doi.org/10.1029/2021JG006588

Pinnington, E., Amezcua, J., Cooper, E., Dadson, S., Ellis, R., Peng, J., et al. (2021). Improving soil moisture prediction of a high-resolution land surface model by parameterising pedotransfer functions through assimilation of SMAP satellite data. *Hydrology and Earth System Sciences*, *25*(3), 1617–1641. https://doi.org/10.5194/hess-25-1617-2021

Poesen, J. (2018). Soil erosion in the Anthropocene: Research needs. *Earth Surface Processes and Landforms*, *43*(1), 64–84. https://doi.org/10.1002/ESP.4250

Poggio, L., De Sousa, L. M., Batjes, N. H., Heuvelink, G. B. M., Kempen, B., Ribeiro, E., & Rossiter, D. (2021). SoilGrids 2.0: Producing soil information for the globe with quantified spatial uncertainty. *Soil*, *7*(1), 217–240. https://doi.org/10.5194/soil-7-217-2021

Porcar-Castell, A., Malenovský, Z., Magney, T., Van Wittenberghe, S., Fernández-Marín, B., Maignan, F., et al. (2021). Chlorophyll a fluorescence illuminates a path connecting plant molecular biology to Earth-system science. *Nature Plants*, *7*(8), 998–1009. https://doi.org/10.1038/s41477-021-00980-4

Prăvălie, R., Borrelli, P., Panagos, P., Ballabio, C., Lugato, E., Chappell, A., et al. (2024). A unifying modelling of multiple land degradation pathways in Europe. *Nature Communications*, *15*(1), 1–13. https://doi.org/10.1038/s41467-024-48252-x

Purcell, W., & Neubauer, T. (2023). Digital twins in agriculture: A state-of-the-art review. *Smart Agriculture Technology*, *3*, 100094. https://doi.org/10.1016/j.atech.2022.100094

Purcell, W., Neubauer, T., & Mallinger, K. (2023). Digital twins in agriculture: Challenges and opportunities for environmental sustainability. *Current Opinion in Environmental Sustainability*, *61*, 101252. https://doi.org/10.1016/j.cosust.2022.101252

Querejeta, J. I. (2017). Soil water retention and availability as influenced by mycorrhizal symbiosis: Consequences for individual plants, communities, and ecosystems. In *Mycorrhizal Mediation of Soil Fertility, Structure, and Carbon Storage* (pp. 299–317). Elsevier. https://doi.org/10.1016/B978-0-12-804312-7.00017-6

Rabot, E., Wiesmeier, M., Schlüter, S., & Vogel, H. J. (2018). Soil structure as an indicator of soil functions: A review. *Geoderma*, *314*, 122–137. https://doi.org/10.1016/j.geoderma.2017.11.009

Rahmati, M., Or, D., Amelung, W., Bauke, S. L., Bol, R., Hendricks Franssen, H. J., et al. (2023). Soil is a living archive of the Earth system. *Nature Reviews Earth & Environment*, *4*(7), 421–423. https://doi.org/10.1038/s43017-023-00454-5

Rast, M., Nieke, J., Adams, J., Isola, C., & Gascon, F. (2021). Copernicus hyperspectral imaging mission for the environment (CHIME). In *International Geoscience and Remote Sensing Symposium (IGARSS)* (pp. 108–111). https://doi.org/10.1109/IGARSS47720.2021.9553319

Reed, D. C., Algar, C. K., Huber, J. A., & Dick, G. J. (2014). Gene-centric approach to integrating environmental genomics and biogeochemical models. *Proceedings of the National Academy of Sciences*, *111*(5), 1879–1884. https://doi.org/10.1073/pnas.1313713111

Reichle, R. H., De Lannoy, G. J. M., Liu, Q., Ardizzone, J. V., Colliander, A., Conaty, A., et al. (2017). Assessment of the SMAP Level-4 surface and root-zone soil moisture product using in situ measurements. *Journal of Hydrometeorology*, *18*(10), 2621–2645. https://doi.org/10.1175/JHM-D-17-0063.1

Rillig, M. C. (2004). Arbuscular mycorrhizae, glomalin, and soil aggregation. *Canadian Journal of Soil Science*, *84*(4), 355–363. https://doi.org/10.4141/S04-003

Rillig, M. C., van der Heijden, M. G. A., Berdugo, M., Liu, Y. R., Riedo, J., Sanz-Lazaro, C., et al. (2023). Increasing the number of stressors reduces soil ecosystem services worldwide. *Nature Climate Change*, *13*(5), 478–483. https://doi.org/10.1038/s41558-023-01627-2

Robichaud, P. R., Lewis, S. A., Laes, D. Y. M., Hudak, A. T., Kokaly, R. F., & Zamudio, J. A. (2007). Postfire soil burn severity mapping with hyperspectral image unmixing. *Remote Sensing of Environment*, *108*(4), 467–480. https://doi.org/10.1016/j.rse.2006.11.027

Robinson, D. A., Hopmans, J. W., Filipovic, V., van der Ploeg, M., Lebron, I., Jones, S. B., et al. (2019). Global environmental changes impact soil hydraulic functions through biophysical feedbacks. *Global Change Biology*, *25*(6), 1895–1904. https://doi.org/10.1111/gcb.14626

Rodell, M., Beaudoing, H. K., L'Ecuyer, T. S., Olson, W. S., Famiglietti, J. S., Houser, P. R., et al. (2015). The observed state of the water cycle in the early twenty-first century. *Journal of Climate*, *28*(21), 8289–8318. https://doi.org/10.1175/JCLI-D-14-00555.1

Rogge, D., Bauer, A., Zeidler, J., Mueller, A., Esch, T., & Heiden, U. (2018). Building an exposed soil composite processor (SCMaP) for mapping spatial and temporal characteristics of soils with Landsat imagery (1984–2014). *Remote Sensing of Environment*, *205*, 1–17. https://doi.org/10.1016/j.rse.2017.11.004

Romano, N., Szabó, B., Belmonte, A., Castrignanò, A., Dor, E. B., Francos, N., & Nasta, P. (2023). Mapping soil properties for unmanned aerial system–based environmental monitoring. In *Unmanned Aerial Systems for Monitoring Soil, Vegetation, and Riverine Environments* (pp. 155–178). Elsevier. https://doi.org/10.1016/B978-0-323-85283-8.00010-2

Romero, F., Labouyrie, M., Orgiazzi, A., Ballabio, C., Panagos, P., Jones, A., et al. (2024). Soil health is associated with higher primary productivity across Europe. *Nature Ecology & Evolution*, *8*(10), 1847–1855. https://doi.org/10.1038/s41559-024-02511-8

Romero-Ruiz, A., Linde, N., Keller, T., & Or, D. (2018). A review of geophysical methods for soil structure characterization. *Reviews of Geophysics*, *56*(4), 672–697. https://doi.org/10.1029/2018RG000611

Sabot, M. E. B., De Kauwe, M. G., Pitman, A. J., Medlyn, B. E., Verhoef, A., Ukkola, A. M., & Abramowitz, G. (2020). Plant profit maximization improves predictions of European forest responses to drought. *New Phytologist*, *226*(6), 1638–1655. https://doi.org/10.1111/nph.16376

Safanelli, J. L., Hengl, T., Parente, L., Minarik, R., Bloom, D. E., Todd-Brown, K., et al. (2024). Open Soil Spectral Library (OSSL): Building reproducible soil calibration models through open development and community engagement. *BioRxiv*. https://doi.org/10.1101/2023.12.16.572011

San, O. (2021). The digital twin revolution. *Nature Computational Science*, *1*(5), 307–308. https://doi.org/10.1038/s43588-021-00077-0

Santanello, J. A., Peters-Lidard, C. D., Garcia, M. E., Mocko, D. M., Tischler, M. A., Moran, M. S., & Thoma, D. P. (2007). Using remotely-sensed estimates of soil moisture to infer soil texture and hydraulic properties across a semi-arid watershed. *Remote Sensing of Environment*, *110*(1), 79–97. https://doi.org/10.1016/j.rse.2007.02.007

Schloter, M., Nannipieri, P., Sørensen, S. J., & van Elsas, J. D. (2018). Microbial indicators for soil quality. *Biology and Fertility of Soils*, *54*(1), 1–10. https://doi.org/10.1007/s00374-017-1248-3

Schoorl, J. M., Sonneveld, M. P. W., & Veldkamp, A. (2000). Three-dimensional landscape process modelling: The effect of DEM resolution. *Earth Surface Processes and Landforms*, *25*(9), 1025–1034. https://doi.org/10.1002/1096-9837(200008)25:9<1025::AID-ESP116>3.0.CO;2-Z

Schoorl, J. M., Temme, A. J. A. M., & Veldkamp, T. (2014). Modelling centennial sediment waves in an eroding landscape—Catchment complexity. *Earth Surface Processes and Landforms*, *39*(11), 1526–1537. https://doi.org/10.1002/esp.3605

Schoorl, J. M., & Veldkamp, A. (2016). Multiscale soil-landscape process modeling. In S. Grunwald (Ed.), *Environmental soil-landscape modeling: Geographic information technologies and pedometrics* (pp. 417–435). CRC Press (Taylor & Francis).

Segoli, M., De Gryze, S., Dou, F., Lee, J., Post, W. M., Denef, K., & Six, J. (2013). AggModel: A soil organic matter model with measurable pools for use in incubation studies. *Ecological Modelling*, *263*, 1–9. https://doi.org/10.1016/j.ecolmodel.2013.04.010

Semeraro, C., Lezoche, M., Panetto, H., & Dassisti, M. (2021). Digital twin paradigm: A systematic literature review. *Computers in Industry*, *130*, 103469. https://doi.org/10.1016/j.compind.2021.103469

Shangguan, W., Hengl, T., Mendes de Jesus, J., Yuan, H., & Dai, Y. (2017). Mapping the global depth to bedrock for land surface modeling. *Journal of Advances in Modeling Earth Systems*, *9*(1), 65–88. https://doi.org/10.1002/2016MS000686

Silvero, N. E. Q., Demattê, J. A. M., Amorim, M. T. A., dos Santos, N. V., Rizzo, R., Safanelli, J. L., et al. (2021). Soil variability and quantification based on Sentinel-2 and Landsat-8 bare soil images: A comparison. *Remote Sensing of Environment*, *252*, 112117. https://doi.org/10.1016/j.rse.2020.112117

Six, J., Elliott, E. T., & Paustian, K. (2000). Soil macroaggregate turnover and microaggregate formation: A mechanism for C sequestration under no-tillage agriculture. *Soil Biology and Biochemistry*, *32*(14), 2099–2103. https://doi.org/10.1016/S0038-0717(00)00179-6

Smith, L. C., Orgiazzi, A., Eisenhauer, N., Cesarz, S., Lochner, A., Jones, A., et al. (2021). Large-scale drivers of relationships between soil microbial properties and organic carbon across Europe. *Global Ecology and Biogeography*, *30*(10), 2070–2083. https://doi.org/10.1111/geb.13371

Sokol, N. W., Slessarev, E., Marschmann, G. L., Nicolas, A., Blazewicz, S. J., Brodie, E. L., et al. (2022). Life and death in the soil microbiome: How ecological processes influence biogeochemistry. *Nature Reviews Microbiology*, *20*(7), 415–430. https://doi.org/10.1038/s41579-022-00695-z

Sommer, M., Jochheim, H., Höhn, A., Breuer, J., Zagorski, Z., Busse, J., et al. (2013). Si cycling in a forest biogeosystem—The importance of transient state biogenic Si pools. *Biogeosciences*, *10*(7), 4991–5007. https://doi.org/10.5194/bg-10-4991-2013

Sonneveld, M. P. W., Bouma, J., & Veldkamp, A. (2002). Refining soil survey information for a Dutch soil series using land use history. *Soil Use and Management*, *18*(3), 157–163. https://doi.org/10.1111/j.1475-2743.2002.tb00235.x

Stamati, F. E., Nikolaidis, N. P., Banwart, S., & Blum, W. E. H. (2013). A coupled carbon, aggregation, and structure turnover (CAST) model for topsoils. *Geoderma*, *211–212*(1), 51–64. https://doi.org/10.1016/j.geoderma.2013.06.014

Steidinger, B. S., Crowther, T. W., Liang, J., Van Nuland, M. E., Werner, G. D. A., Reich, P. B., et al. (2019). Climatic controls of decomposition drive the global biogeography of forest-tree symbioses. *Nature*, *569*(7756), 404–408. https://doi.org/10.1038/s41586-019-1128-0

Stephens, G., Polcher, J., Zeng, X., van Oevelen, P., Poveda, G., Bosilovich, M., et al. (2023). The first 30 years of GEWEX. *Bulletin of the American Meteorological Society*, *104*(1), E126–E157. https://doi.org/10.1175/BAMS-D-22-0061.1

Stoorvogel, J. J., Bakkenes, M., Temme, A. J. A. M., Batjes, N. H., & ten Brink, B. J. E. (2017). S-World: A global soil map for environmental modelling. *Land Degradation & Development*, *28*(1), 22–33. https://doi.org/10.1002/ldr.2656

Su, Z., De Rosnay, P., Wen, J., Wang, L., & Zeng, Y. (2013). Evaluation of ECMWF's soil moisture analyses using observations on the Tibetan Plateau. *Journal of Geophysical Research: Atmospheres*, *118*(11), 5304–5318. https://doi.org/10.1002/jgrd.50468

Su, Z., Fernández-Prieto, D., Timmermans, J., Chen, X., Hungershoefer, K., Roebeling, R., et al. (2014). First results of the Earth observation water cycle multi-mission observation strategy (WACMOS). *International Journal of Applied Earth Observation and Geoinformation*, *26*, 270–285. https://doi.org/10.1016/j.jag.2013.08.002

Su, Z., Timmermans, W., Zeng, Y., Schulz, J., John, V. O., Roebeling, R. A., et al. (2018). An overview of European efforts in generating climate data records. *Bulletin of the American Meteorological Society*, *99*(2), 349–359. https://doi.org/10.1175/BAMS-D-16-0074.1

Su, Z., Wen, J., Zeng, Y., Zhao, H., Lv, S., van der Velde, R., et al. (2020). Multiyear in-situ L-band microwave radiometry of land surface processes on the Tibetan Plateau. *Scientific Data*, *7*(1), 317. https://doi.org/10.1038/s41597-020-00657-1

Su, Z., Zeng, Y., Romano, N., Manfreda, S., Francés, F., Ben Dor, E., et al. (2020). An integrative information aqueduct to close the gaps between satellite observation of the water cycle and local sustainable management of water resources. *Water*, *12*(5), 1495. https://doi.org/10.3390/w12051495

Sullivan, P. L., Billings, S. A., Hirmas, D., Li, L., Zhang, X., Ziegler, S., et al. (2022). Embracing the dynamic nature of soil structure: A paradigm illuminating the role of life in critical zones of the Anthropocene. *Earth-Science Reviews*, *225*, 103873. https://doi.org/10.1016/j.earscirev.2021.103873

Sun, Y., Gu, L., Wen, J., van der Tol, C., Porcar-Castell, A., Joiner, J., et al. (2023). From remotely sensed solar-induced chlorophyll fluorescence to ecosystem structure, function, and service: Part I—Harnessing theory. *Global Change Biology*, *29*(11), 2926–2952. https://doi.org/10.1111/gcb.16634

Szabó, B., Weynants, M., & Weber, T. K. D. (2021). Updated European hydraulic pedotransfer functions with communicated uncertainties in the predicted variables (EUPTFV2). *Geoscientific Model Development*, *14*(1), 151–175. https://doi.org/10.5194/gmd-14-151-2021

Tao, F., Huang, Y., Hungate, B. A., Manzoni, S., Frey, S. D., Schmidt, M. W. I., et al. (2023). Microbial carbon use efficiency promotes global soil carbon storage. *Nature*, *618*(7967), 981–985. https://doi.org/10.1038/s41586-023-06042-3

Tao, F., & Qi, Q. (2019). Make more digital twins. *Nature*, *573*(7775), 490–491. https://doi.org/10.1038/d41586-019-02849-1

Taylor, C. M. (2015). Detecting soil moisture impacts on convective initiation in Europe. *Geophysical Research Letters*, *42*(11), 4631–4638. https://doi.org/10.1002/2015GL064030

Tedersoo, L., Bahram, M., Põlme, S., Kõljalg, U., Yorou, N. S., Wijesundera, R., et al. (2014). Global diversity and geography of soil fungi. *Science*, *346*(6213), 1256688. https://doi.org/10.1126/science.1256688

Teng, Y., & Chen, W. (2019). Soil microbiomes—A promising strategy for contaminated soil remediation: A review. *Pedosphere*, *29*(3), 283–297. https://doi.org/10.1016/S1002-0160(18)60061-X

Thompson, D. R., Green, R. O., Bradley, C., Brodrick, P. G., Mahowald, N., Dor, E. B., et al. (2024). On-orbit calibration and performance of the EMIT imaging spectrometer. *Remote Sensing of Environment*, *303*, 113986. https://doi.org/10.1016/j.rse.2023.113986

Tian, F., Wigneron, J. P., Ciais, P., Chave, J., Ogée, J., Peñuelas, J., et al. (2018). Coupling of ecosystem-scale plant water storage and leaf phenology observed by satellite. *Nature Ecology & Evolution*, *2*(9), 1428–1435. https://doi.org/10.1038/s41559-018-0630-3

Tóth, B., Weynants, M., Pásztor, L., & Hengl, T. (2017). 3D soil hydraulic database of Europe at 250 m resolution. *Hydrological Processes*, *31*(14), 2662–2666. https://doi.org/10.1002/HYP.11203

Totsche, K. U., Amelung, W., Gerzabek, M. H., Guggenberger, G., Klumpp, E., Knief, C., et al. (2018). Microaggregates in soils. *Journal of Plant Nutrition and Soil Science*, *181*(1), 104–136. https://doi.org/10.1002/jpln.201600451

Totsche, K. U., Ray, N., & Kögel-Knabner, I. (2024). Structure–function co-evolution during pedogenesis—Microaggregate development and turnover in soils. *Journal of Plant Nutrition and Soil Science*, *187*(1), 5–16. https://doi.org/10.1002/jpln.202400012

Trivedi, P., Leach, J. E., Tringe, S. G., Sa, T., & Singh, B. K. (2020). Plant–microbiome interactions: From community assembly to plant health. *Nature Reviews Microbiology*, *18*(11), 607–621. https://doi.org/10.1038/s41579-020-0412-1

Tsakiridis, N. L., Samarinas, N., Kalopesa, E., & Zalidis, G. C. (2023). Cognitive soil digital twin for monitoring the soil ecosystem: A conceptual framework. *Soil Systems*, *7*(4), 88. https://doi.org/10.3390/soilsystems7040088

Vahedifard, F., Goodman, C. C., Paul, V., & AghaKouchak, A. (2024). Amplifying feedback loop between drought, soil desiccation cracking, and greenhouse gas emissions. *Environmental Research Letters*, *19*(3), 031005. https://doi.org/10.1088/1748-9326/AD2C23

Vaksmaa, A., van Alen, T. A., Ettwig, K. F., Lupotto, E., Valè, G., Jetten, M. S. M., & Lüke, C. (2017). Stratification of diversity and activity of methanogenic and methanotrophic microorganisms in a nitrogen-fertilized Italian paddy soil. *Frontiers in Microbiology*, *8*, 297368. https://doi.org/10.3389/fmicb.2017.02127

van den Hoogen, J., Geisen, S., Routh, D., Ferris, H., Traunspurger, W., Wardle, D. A., et al. (2019). Soil nematode abundance and functional group composition at a global scale. *Nature*, *572*(7768), 194–198. https://doi.org/10.1038/s41586-019-1418-6

van der Tol, C., Rossini, M., Cogliati, S., Verhoef, W., Colombo, R., Rascher, U., & Mohammed, G. (2016). A model and measurement comparison of diurnal cycles of sun-induced chlorophyll fluorescence of crops. *Remote Sensing of Environment*, *186*, 663–677. https://doi.org/10.1016/j.rse.2016.09.021

Vance, T. C., Huang, T., & Butler, K. A. (2024). Big data in Earth science: Emerging practice and promise. *Science*, *383*(6688). https://doi.org/10.1126/science.adh9607

Van Der Heijden, M. G. A., Bardgett, R. D., & Van Straalen, N. M. (2008). The unseen majority: Soil microbes as drivers of plant diversity and productivity in terrestrial ecosystems. *Ecology Letters*, *11*(3), 296–310. https://doi.org/10.1111/J.1461-0248.2007.01139.X

Van der Putten, W. H., Bardgett, R. D., Bever, J. D., Bezemer, T. M., Casper, B. B., Fukami, T., et al. (2013). Plant-soil feedbacks: The past, the present, and future challenges. *Journal of Ecology*, *101*(2), 265–276. https://doi.org/10.1111/1365-2745.12054

Van Looy, K., Bouma, J., Herbst, M., Koestel, J., Minasny, B., Mishra, U., et al. (2017). Pedotransfer functions in Earth system science: Challenges and perspectives. *Geoderma*, *287*(4), 1–13. https://doi.org/10.1016/j.geoderma.2017.01.017

Veldkamp, A., Baartman, J. E. M., Coulthard, T. J., Maddy, D., Schoorl, J. M., Storms, J. E. A., et al. (2017). Two decades of numerical modelling to understand long term fluvial archives: Advances and future perspectives. *Quaternary Science Reviews*, *166*, 177–187. https://doi.org/10.1016/j.quascirev.2016.10.002

Vereecken, H. (2023). On the hydrology of soils in the Earth system. *EGU23*. https://doi.org/10.5194/EGUSPHERE-EGU23-1156

Vereecken, H., Amelung, W., Bauke, S. L., Bogena, H., Brüggemann, N., Montzka, C., et al. (2022). Soil hydrology in the Earth system. *Nature Reviews Earth & Environment*, *3*(9), 573–587. https://doi.org/10.1038/s43017-022-00324-6

Vereecken, H., Huisman, J. A., Hendricks Franssen, H. J., Brüggemann, N., Bogena, H. R., Kollet, S., et al. (2015). Soil hydrology: Recent methodological advances, challenges, and perspectives. *Water Resources Research*, *51*(4), 2616–2633. https://doi.org/10.1002/2014WR016852

Vereecken, H., Schnepf, A., Hopmans, J. W., Javaux, M., Or, D., Roose, T., et al. (2016). Modeling soil processes: Review, key challenges, and new perspectives. *Vadose Zone Journal*, *15*(5), 1–57. https://doi.org/10.2136/vzj2015.09.0131

Vereecken, H., Weihermüller, L., Assouline, S., Šimůnek, J., Verhoef, A., Herbst, M., et al. (2019). Infiltration from the pedon to global grid scales: An overview and outlook for land surface modeling. *Vadose Zone Journal*, *18*(1), 1–53. https://doi.org/10.2136/vzj2018.10.0191

Vereecken, H., Weynants, M., Javaux, M., Pachepsky, Y., Schaap, M. G., & van Genuchten, M. T. (2010). Using Pedotransfer Functions to estimate the van Genuchten–Mualem soil hydraulic properties: A review. *Vadose Zone Journal*, *9*(4), 795–820. https://doi.org/10.2136/vzj2010.0045

Verhoef, W., Jia, L., Xiao, Q., & Su, Z. (2007). Unified optical-thermal four-stream radiative transfer theory for homogeneous vegetation canopies. *IEEE Transactions on Geoscience and Remote Sensing*, *45*(6), 1808–1822. https://doi.org/10.1109/TGRS.2007.895844

Verrelst, J., Halabuk, A., Atzberger, C., Hank, T., Steinhauser, S., & Berger, K. (2023). A comprehensive survey on quantifying non-photosynthetic vegetation cover and biomass from imaging spectroscopy. *Ecological Indicators*, *155*, 110911. https://doi.org/10.1016/J.ECOLIND.2023.110911

Viscarra Rossel, R. A., Behrens, T., Ben-Dor, E., Brown, D. J., Demattê, J. A. M., Shepherd, K. D., et al. (2016). A global spectral library to characterize the world's soil. *Earth-Science Reviews*, *155*, 198–230. https://doi.org/10.1016/j.earscirev.2016.01.012

Viscarra Rossel, R. A., Behrens, T., Ben-Dor, E., Chabrillat, S., Demattê, J. A. M., Ge, Y., et al. (2022). Diffuse reflectance spectroscopy for estimating soil properties: A technology for the 21st century. *European Journal of Soil Science*, *73*(4), e13271. https://doi.org/10.1111/ejss.13271

Viscarra Rossel, R. A., & Bouma, J. (2016). Soil sensing: A new paradigm for agriculture. *Agricultural Systems*, *148*, 71–74. https://doi.org/10.1016/j.agsy.2016.07.001

Vogel, H. J., Amelung, W., Baum, C., Bonkowski, M., Blagodatsky, S., Grosch, R., et al. (2024). How to adequately represent biological processes in modeling multifunctionality of arable soils. *Biology and Fertility of Soils*, *60*(3), 263–306. https://doi.org/10.1007/S00374-024-01802-3

Vogel, H. J., Balseiro-Romero, M., Kravchenko, A., Otten, W., Pot, V., Schlüter, S., et al. (2022). A holistic perspective on soil architecture is needed as a key to soil functions. *European Journal of Soil Science*, *73*(1). https://doi.org/10.1111/EJSS.13152

Vogel, H. J., Bartke, S., Daedlow, K., Helming, K., Kögel-Knabner, I., Lang, B., et al. (2018). A systemic approach for modeling soil functions. *Soil*, *4*(1), 83–92. https://doi.org/10.5194/soil-4-83-2018

Vogel, H. J., Eberhardt, E., Franko, U., Lang, B., Ließ, M., Weller, U., et al. (2019). Quantitative evaluation of soil functions: Potential and state. *Frontiers in Environmental Science*, *7*, 463905. https://doi.org/10.3389/fenvs.2019.00164

Wagner, E. P., Merz, J., & Townsend, P. A. (2018). Ecological spectral information system: An open spectral library. In *AGU Fall Meeting Abstracts* (pp. B41L–2878). Retrieved from https://ui.adsabs.harvard.edu/abs/2018AGUFM.B41L2878W/abstract

Wang, J., Zhen, J., Hu, W., Chen, S., Lizaga, I., Zeraatpisheh, M., & Yang, X. (2023). Remote sensing of soil degradation: Progress and perspective. *International Soil and Water Conservation Research*, *11*(3), 429–454. https://doi.org/10.1016/j.iswcr.2023.03.002

Wang, Y., Zeng, Y., Yu, L., Yang, P., Van Der Tol, C., Yu, Q., et al. (2021). Integrated modeling of canopy photosynthesis, fluorescence, and the transfer of energy, mass, and momentum in the soil-plant-atmosphere continuum (STEMMUS-SCOPE v1.0.0). *Geoscientific Model Development*, *14*(3), 1379–1407. https://doi.org/10.5194/gmd-14-1379-2021

Wardle, D. A., Bardgett, R. D., Klironomos, J. N., Setälä, H., Van Der Putten, W. H., & Wall, D. H. (2004). Ecological linkages between aboveground and belowground biota. *Science*, *304*(5677), 1629–1633. https://doi.org/10.1126/SCIENCE.1094875

Weber, T. K. D., Weihermüller, L., Nemes, A., Bechtold, M., Degré, A., Diamantopoulos, E., et al. (2024). Hydro-pedotransfer functions: A roadmap for future development. *Hydrology and Earth System Sciences*, *28*(14), 3391–3433. https://doi.org/10.5194/hess-28-3391-2024

Weihermüller, L., Lehmann, P., Herbst, M., Rahmati, M., Verhoef, A., Or, D., et al. (2021). Choice of pedotransfer functions matters when simulating soil water balance fluxes. *Journal of Advances in Modeling Earth Systems*, *13*(3), e2020MS002404. https://doi.org/10.1029/2020MS002404

Weksler, S., Rozenstein, O., Haish, N., Moshelion, M., Walach, R., & Ben-Dor, E. (2020). A hyperspectral-physiological phenomics system: Measuring diurnal transpiration rates and diurnal reflectance. *Remote Sensing*, *12*(9), 1493. https://doi.org/10.3390/RS12091493

Wieder, W. R., Allison, S. D., Davidson, E. A., Georgiou, K., Hararuk, O., He, Y., et al. (2015). Explicitly representing soil microbial processes in Earth system models. *Global Biogeochemical Cycles*, *29*(10), 1782–1800. https://doi.org/10.1002/2015GB005188

Wieder, W. R., Bonan, G. B., & Allison, S. D. (2013). Global soil carbon projections are improved by modelling microbial processes. *Nature Climate Change*, *3*(10), 909–912. https://doi.org/10.1038/nclimate1951

Wielemaker, W. G., De Bruin, S., Epema, G. F., & Veldkamp, A. (2001). Significance and application of the multi-hierarchical landsystem in soil mapping. *Catena*, *43*(1), 15–34. https://doi.org/10.1016/S0341-8162(00)00121-1

Wigneron, J. P., Jackson, T. J., O'Neill, P., De Lannoy, G., de Rosnay, P., Walker, J. P., et al. (2017). Modelling the passive microwave signature from land surfaces: A review of recent results and application to the L-band SMOS & SMAP soil moisture retrieval algorithms. *Remote Sensing of Environment*, *192*, 238–262. https://doi.org/10.1016/j.rse.2017.01.024

Wigneron, J. P., Li, X., Frappart, F., Fan, L., Al-Yaari, A., De Lannoy, G., et al. (2021). SMOS-IC data record of soil moisture and L-VOD: Historical development, applications and perspectives. *Remote Sensing of Environment*, *254*, 112238. https://doi.org/10.1016/j.rse.2020.112238

Wild, B., Gerrits, R., & Bonneville, S. (2022). The contribution of living organisms to rock weathering in the critical zone. *npj Materials Degradation*, *6*(1), 98. https://doi.org/10.1038/s41529-022-00312-7

Wilpiszeski, R. L., Aufrecht, J. A., Retterer, S. T., Sullivan, M. B., Graham, D. E., Pierce, E. M., et al. (2019). Soil aggregate microbial communities: Towards understanding microbiome interactions at biologically relevant scales. *Applied and Environmental Microbiology*, *85*(14), e00324-19. https://doi.org/10.1128/AEM.00324-19

Xu, J., Zhang, Y., Zhang, P., Trivedi, P., Riera, N., Wang, Y., et al. (2018). The structure and function of the global citrus rhizosphere microbiome. *Nature Communications*, *9*(1), 1–10. https://doi.org/10.1038/s41467-018-07343-2

Xu, X., Konings, A. G., Longo, M., Feldman, A., Xu, L., Saatchi, S., et al. (2021). Leaf surface water, not plant water stress, drives diurnal variation in tropical forest canopy water content. *New Phytologist*, *231*(1), 122–136. https://doi.org/10.1111/nph.17254

Yang, K., Ye, B., Zhou, D., Wu, B., Foken, T., Qin, J., & Zhou, Z. (2011). Response of hydrological cycle to recent climate changes in the Tibetan Plateau. *Climatic Change*, *109*(3–4), 517–534. https://doi.org/10.1007/s10584-011-0099-4

Yang, Y. (2021). Emerging patterns of microbial functional traits. *Trends in Microbiology*, *29*(10), 874–882. https://doi.org/10.1016/j.tim.2021.04.004

Yin, X., Busch, F. A., Struik, P. C., & Sharkey, T. D. (2021). Evolution of a biochemical model of steady-state photosynthesis. *Plant, Cell & Environment*, *44*(9), 2811–2837. https://doi.org/10.1111/pce.14070

You, H., Lyu, S., Zhang, S., Xu, Y., Ma, C., Tao, X., et al. (2022). Application and evaluation of the gravel parameterization scheme in the WRF-CLM4 model. *Journal of Advances in Modeling Earth Systems*, *14*(12), e2022MS003241. https://doi.org/10.1029/2022MS003241

Yu, L., Fatichi, S., Zeng, Y., & Su, Z. (2020). The role of vadose zone physics in the ecohydrological response of a Tibetan meadow to freeze-thaw cycles. *The Cryosphere*, *14*(12), 4653–4673. https://doi.org/10.5194/tc-14-4653-2020

Yu, L., Zeng, Y., & Su, Z. (2020). Understanding the mass, momentum, and energy transfer in the frozen soil with three levels of model complexities. *Hydrology and Earth System Sciences*, *24*(10), 4813–4830. https://doi.org/10.5194/hess-24-4813-2020

Yu, L., Zeng, Y., Su, Z., Cai, H., & Zheng, Z. (2016). The effect of different evapotranspiration methods on portraying soil water dynamics and ET partitioning in a semi-arid environment in Northwest China. *Hydrology and Earth System Sciences*, *20*(3), 975–990. https://doi.org/10.5194/hess-20-975-2016

Yu, L., Zeng, Y., Wen, J., & Su, Z. (2018). Liquid-vapor-air flow in the frozen soil. *Journal of Geophysical Research: Atmospheres*, *123*(14), 7393–7415. https://doi.org/10.1029/2018JD028502

Zech, S., Prechtel, A., & Ray, N. (2024). Coupling scales in process-based soil organic carbon modeling including dynamic aggregation. *Journal of Plant Nutrition and Soil Science*, *187*(1), 130–142. https://doi.org/10.1002/JPLN.202300080

Zech, S., Schweizer, S. A., Bucka, F. B., Ray, N., Kögel-Knabner, I., & Prechtel, A. (2022). Explicit spatial modeling at the pore scale unravels the interplay of soil organic carbon storage and structure dynamics. *Global Change Biology*, *28*(15), 4589–4604. https://doi.org/10.1111/gcb.16230

Zeng, Y., Hao, D., Huete, A., Dechant, B., Berry, J., Chen, J. M., et al. (2022). Optical vegetation indices for monitoring terrestrial ecosystems globally. *Nature Reviews Earth & Environment*, *3*(7), 477–493. https://doi.org/10.1038/s43017-022-00298-5

Zeng, Y., & Su, Z. (2024). Digital twin approach for the soil-plant-atmosphere continuum: Think big, model small. *Frontiers in Science*, *2*, 1376950. https://doi.org/10.3389/fsci.2024.1376950

Zeng, Y., Su, Z., Barmpadimos, I., Perrels, A., Poli, P., Boersma, K. F., et al. (2019). Towards a traceable climate service: Assessment of quality and usability of essential climate variables. *Remote Sensing*, *11*(10), 1186. https://doi.org/10.3390/rs11101186

Zeng, Y., Su, Z., Calvet, J. C., Manninen, T., Swinnen, E., Schulz, J., et al. (2015). Analysis of current validation practices in Europe for space-based climate data records of essential climate variables. *International Journal of Applied Earth Observation and Geoinformation*, *42*, 150–161. https://doi.org/10.1016/j.jag.2015.06.006

Zeng, Y., Su, Z., Van Der Velde, R., Wang, L., Xu, K., Wang, X., & Wen, J. (2016). Blending satellite observed, model simulated, and in situ measured soil moisture over the Tibetan Plateau. *Remote Sensing*, *8*(3), 268. https://doi.org/10.3390/rs8030268

Zeng, Y., Su, Z., Wan, L., & Wen, J. (2011). Numerical analysis of air-water-heat flow in unsaturated soil: Is it necessary to consider airflow in land surface models? *Journal of Geophysical Research*, *116*(20), 20107. https://doi.org/10.1029/2011JD015835

Zhang, C., & Lu, N. (2019). Unitary definition of matric suction. *Journal of Geotechnical and Geoenvironmental Engineering*, *145*(2), 02818004. https://doi.org/10.1061/(asce)gt.1943-5606.0002004

Zhang, G. L., Liu, F., & Song, X. D. (2017). Recent progress and future prospects of digital soil mapping: A review. *Journal of Integrative Agriculture*, *16*(12), 2871–2885. https://doi.org/10.1016/S2095-3119(17)61762-3

Zhang, G. L., Wu, H., Shi, Z., Yan, X., & Shen, R. (2022). Priorities of soil research and soil management in China in the coming decade. *Geoderma Regional*, *29*, e00537. https://doi.org/10.1016/J.GEODRS.2022.E00537

Zhang, L. J., Zeng, Y. J., Zhuang, R. D., Szabó, B., Manfreda, S., Han, Q. Q., et al. (2021). In situ observation-constrained global surface soil moisture using random forest model. *Remote Sensing*, *13*(23), 4893. https://doi.org/10.3390/rs13234893

Zhang, M., Zhang, L., Huang, S., Li, W., Zhou, W., Philippot, L., & Ai, C. (2022). Assessment of spike-AMP and qPCR-AMP in soil microbiota quantitative research. *Soil Biology and Biochemistry*, *166*, 108570. https://doi.org/10.1016/J.SOILBIO.2022.108570

Zhang, T., Niinemets, Ü., Sheffield, J., & Lichstein, J. W. (2018). Shifts in tree functional composition amplify the response of forest biomass to climate. *Nature*, *556*(7699), 99–102. https://doi.org/10.1038/nature26152

Zhao, H., Zeng, Y., Han, X., & Su, Z. (2023). Retrieving soil physical properties by assimilating SMAP brightness temperature observations into the Community Land Model. *Sensors*, *23*(5), 2620. in Review. https://doi.org/10.3390/s23052620

Zhao, H., Zeng, Y., Hofste, J. G., Duan, T., Wen, J., & Su, Z. (2022). Modelling of multi-frequency microwave backscatter and emission of land surface by a community land active passive microwave radiative transfer modelling platform (CLAP). *Hydrology and Earth System Sciences Discussions*. https://doi.org/10.5194/hess-2022-333

Zhao, H., Zeng, Y., Lv, S., & Su, Z. (2018). Analysis of soil hydraulic and thermal properties for land surface modeling over the Tibetan Plateau. *Earth System Science Data*, *10*(2), 1031–1061. https://doi.org/10.5194/essd-10-1031-2018

Zhao, H., Zeng, Y., Wen, J., Wang, X., Wang, Z., Meng, X., & Su, Z. (2021). An air-to-soil transition model for discrete scattering-emission modelling at L-band. *Journal of Remote Sensing*, *2021*, 3962350. https://doi.org/10.34133/2021/3962350

Zhao, M., Geruo, A., Liu, Y., & Konings, A. G. (2022). Evapotranspiration frequently increases during droughts. *Nature Climate Change*, *12*(11), 1024–1030. https://doi.org/10.1038/s41558-022-01505-3

Zhuang, R., Zeng, Y., Manfreda, S., & Su, Z. (2020). Quantifying long-term land surface and root zone soil moisture over Tibetan plateau. *Remote Sensing*, *12*(3), 509. https://doi.org/10.3390/rs12030509

Zuzana, L., Lukáš, B., Lucie, K., Kopačková, V., Markéta, P., Jan, M., et al. (2013). Detection of multiple stresses in Scots pine growing at post-mining sites using visible to near-infrared spectroscopy. *Environmental Science: Processes & Impacts*, *15*(11), 2004–2015. https://doi.org/10.1039/c3em00388d