We are sharing this research agenda to invite community feedback and foster discussion on the development of advanced AI for African Soil Information Systems.

BEYOND PREDICTION: A RESEARCH AGENDA FOR ADVANCED AI IN AFRICAN SOIL INFORMATION SYSTEMS

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Abstract

Digital soil mapping has produced the first continent-wide baseline estimates of soil properties in Africa, yet existing soil information systems remain fragmented, poorly standardized, and largely confined to static offline spatial prediction. Their ability to capture near-real-time soil conditions or provide timely, field-level decision support is therefore limited. This paper argues that the next step is not simply applying artificial intelligence to improve mapping accuracy, but adopting Advanced AI as the foundation for adaptive Soil Digital Twins that continuously integrate new observations and support evidence-based management. It proposes a ten-pathway research agenda structured around four interconnected pillars: (1) Unlocking legacy archives using Natural Language Processing and Computer Vision to convert unstructured historical records into machine-actionable, AI-ready data; (2) Engineering dynamic systems through Online Learning, Generative AI, and Physics-Informed Neural Networks to continuously assimilate streaming telemetry; (3) Delivering prescriptive intelligence using multi-objective recommendation engines, human-centered Explainable AI (XAI), and Human-in-the-Loop expert validation; and (4) Enforcing sovereign governance via Federated Learning, FAIR and CARE-aligned autonomous stewardship. To operationalize this vision, it calls for a Pan-African AI for Soil Health Consortium to establish sovereign compute hubs, secure sustainable financing, and cultivate a home-grown talent pipeline. This agenda provides a strategic blueprint for transforming fragmented soil observations into a dynamic, trusted public infrastructure that addresses land degradation and food insecurity, while supporting climate resilience and sustainable agriculture across the continent.

Keywords: Artificial Intelligence (AI), Soil Digital Twins, soil information systems (SIS), data sovereignty, Federated Learning, Natural Language Processing (NLP), Explainable AI (XAI), Africa.

INTRODUCTION

Soil information refers to the data and descriptive knowledge used to understand the Earth's upper layer. It includes information on soil composition, profile characteristics, and physical, chemical, and biological properties. At the global level, this information is produced and shared through institutions such as FAO Global Soil Partnership (https://www.fao.org/global-soil-partnership/en/), UNESCO Soil Initiative (https://www.unesco.org/en/soil-initiative), ISRIC – World Soil Information (https://www.isric.org/), EU Mission Soil (https://mission-soil-platform.ec.europa.eu/), Open Land Map-soil Soil Data Base (https://www.soildb.openlandmap.org/), International Union of Soil Sciences (IUSS) (https://www.iuss.org/), and the UK Soil Observatory (https://www.ukso.org/), which provide soil datasets, maps, and related tools for analysis. In practice, soil information often appears as soil maps, classification systems, profile databases, and digital assessments. These resources are central to work on soil health, agricultural planning, and land sustainability. In much of Africa, however, soil information systems remain limited by weak institutional capacity, low technical expertise, poor coordination across countries, and the lack of harmonized methods (Kome et al., 2026). As a result, many countries continue to struggle with access to reliable and usable soil data, even though such data are essential for sustainable agriculture, climate resilience, and ecological restoration.

Over the last two decades, pedometrics has changed substantially. What was once driven mainly by manual mapping and relatively simple geostatistical methods has shifted toward more complex digital and data-intensive approaches (Radocaj et al., 2024; Malone et al., 2023; Heuvelink & Webster, 2022; Ågren et al., 2021; Hengl et al., 2021; Wang et al., 2020; Hu & Chugunova, 2008; Lark et al., 2006; McBratney et al., 2003). Wadoux (2025) reviewed that one of the most important developments in this shift has been the use of Artificial Intelligence (AI) including but not limited to: reasoning and decision-making, as well as machine learning techniques, to account for Digital Soil Mapping (DSM). The European Commission (2019) defined AI as systems that display intelligent behaviour by analyzing their environment and taking actions (with some degree of autonomy) to achieve specific goals. By using machine learning methods, especially Random Forests and Support Vector Machines, researchers have moved beyond conventional polygon maps toward grid-based estimates of soil properties over large areas (Nenkam et al., 2024; Hengl et al., 2015). For Africa, this paradigm shift has been particularly significant. It supported the creation of the first gridded, high-resolution continental soil baselines (Hengl et al., 2021; Miller et al., 2021), opening new possibilities for evidence-based responses to food insecurity and land degradation (Tellen et al., 2025).

Even so, these advances have not yet produced soil information systems in Africa that are truly dynamic, adaptive, or regularly updated. In many countries, soil maps are still treated as finished products. Almost 30% of existing digital soil maps in Africa were based on legacy soil datasets with insufficient spatial coverage, indicating a high need for advanced methodologies (Nenkam et al., 2024). They are characterized by low sampling density, spatial clustering, and point measurement errors. Moreover, they are compiled, modeled, and published, then left unchanged for long periods. Furthermore, empirical evidence demonstrates that many of these static maps remain largely underutilized on the ground, failing to translate into tangible agronomic practices, financial returns, or policy changes because they lack local accuracy and actionable guidance (Bennett et al., 2021; Lobry de Bruyn & Prager, 2024). A large amount of older soil information exists only in paper maps, reports, and poorly organized archives (Kome et al., 2026). This is a serious limitation. Evidence, though anecdotal, suggests that newer streams of data are also being generated through remote sensing, mobile technologies, and low-cost sensors. Unfortunately, most soil information systems globally, and across Africa in particular, rarely bring these two worlds together. With a few exceptions (e.g., Hengl et al., 2026), existing systems also do a poor job of capturing short-term or near-real-time changes in soil condition. Variables such as soil moisture, nutrient status, and soil carbon are often represented through static datasets (Turek et al., 2023; Poggio et al., 2021) rather than continuous monitoring. More importantly, many existing systems are designed mainly to predict soil properties, not to support adaptive decisions as conditions change.

This limitation is evident even in widely used products such as ISRIC SoilGrids (250 m), which provide valuable baseline estimates at standardized depths but remain static representations of average conditions. Recent global advances have begun to address this temporal gap; for example, OpenLandMap-soildb provides 30 m spatiotemporal soil information updated annually from 2000 to 2022+ using spatiotemporal machine learning and harmonized profile data (Hengl et al., 2026). However, while annual retro-prospective mapping represents major progress, existing systems are still not built to ingest live sensor streams or trigger near-real-time field-level decision support. This underscores the need for a conceptual shift from static or annual offline mapping toward intelligent, adaptive soil information systems that can learn, update, and respond continuously.

For Africa, the issue is therefore not simply whether AI can improve spatial prediction. The larger question is whether AI can support a different kind of soil information system altogether. In this paper, we use the term “Advanced AI” to refer to deep learning-based and cognitively oriented methods that can handle more complex tasks than standard predictive modelling alone. These include natural language processing for extracting information from unstructured soil archives, computer vision for digitizing and interpreting legacy soil maps, reinforcement learning for dynamic soil management systems, and AI-driven semantic tools that align local observations with global standards and vocabularies (e.g., GloSIS, WRB) (Palma et al., 2025; Řezník et al., 2022). Thinking about AI in this broader way shifts the goal. The aim is no longer just better maps. It is the development of intelligent, adaptive soil information systems that self improves as new evidence becomes available.

AI in soil science is getting worldwide traction. In Europe, major investments increasingly link soil science with open science, collaborative infrastructure, and advanced digital tools. One important example is the AI4SoilHealth initiative, supported through Horizon Europe and the United Kingdom’s Horizon Europe funding guarantee, in collaboration with the OpenGeoHub Foundation and a wider European consortium. The project is using advanced AI to assess and map soil health across Europe and has contributed to the development of European soil digital twins that can detect degradation trends at 30 m resolution and generate near-real-time warnings (Afshar et al., 2024). This connects directly to the wider EU Soil Mission, which aims to achieve healthy soils by 2030 (European Commission, 2021). Another example comes from Denmark, where the Soil Water Retention Curve (SWRC) project combines physics-based understanding with AI to improve maps of soil water-holding capacity and support irrigation planning and drought risk management (Norouzi et al., 2025). What these examples show is not just technical progress. They show a shift from static soil databases toward integrated systems for monitoring and response.

Similar developments can be seen elsewhere. In Australia, the APSoil/APSIM database has been used to estimate plant available water capacity, characterize soils, and support decision-making for farmers, researchers, and policymakers (Verburg et al., 2020). In the United States, the University of Florida, working with USDA-NIFA, is developing AI-enabled digital infrastructure to speed up the collection, integration, and use of soil health information. This work combines satellite data with computational methods including convolutional neural networks, recurrent neural networks, and few-shot learning to assess and monitor soil health indicators across Florida (University of Florida, n.d.). At the University of Illinois, the AIFARMS research program, supported by the USDA National Institute of Food and Agriculture, has also developed a specific focus on AI applications for soil health in agriculture (AIFARMS, n.d.). By combining machine learning with multiple data sources, these efforts address some of the long-standing limits of conventional soil testing, which is often too infrequent, too localized, and too difficult to scale. Other studies reinforce the same point. Lal (2024), for instance, examined methods for estimating field capacity and wilting point across strategic locations in the United States and showed how better soil-water parameterization can improve irrigation advice, water-use efficiency, and sustainable water management. In China, Xu et al. (2021) developed an artificial neural network, a framework for estimating soil water retention curves in agricultural soils. In Brazil, Tomasella et al. (2000) showed that locally developed pedotransfer functions are often necessary because imported models may not adequately represent regional soil conditions.

In Africa, interest in these approaches is clearly growing, but efforts are still fragmented. A recent example is the World Bank's "Data for Soil Health and Innovation Challenges" project in Kenya, which explicitly promoted AI, machine learning, big data, and generative AI for soil health applications. Its focus included site-specific soil management, soil carbon monitoring and verification, fertilizer optimization, and policy decision support (World Bank, 2025). At the same time, the project also exposed the barriers that continue to slow progress: fragmented and inaccessible datasets, weak data-sharing practices, poor spatial resolution, low adoption of new technologies, limited laboratory infrastructure, and the persistence of unverified tools. These are not minor obstacles. They show that the problem is institutional as much as technical.

There are also promising cases elsewhere in the Global South. Boomitra's soil carbon monitoring initiative combines satellite data, AI, and ground observations to track changes in soil carbon across countries including: Kenya, Mexico, India, and South Africa (Boomitra, 2025). In Nigeria, the International Fertilizer Development Center has supported FarmSpace, a portable, AI-powered soil-testing technology that measures soil nutrients, organic matter, and pH in the field and provides site-specific recommendations to smallholder farmers (FarmSpace Technology, 2023). However, these examples remain isolated. They have not yet developed into a coordinated African agenda comparable to Europe's AI4SoilHealth. Without that kind of shared direction, Africa risks falling further behind while soil monitoring systems in other regions become more automated, more integrated, and more responsive.

This paper responds to that gap. It argues that Africa needs to move from static soil information repositories toward dynamic digital twins of the soil landscape. To support that shift, the paper proposes a ten-pathway research agenda organized around four broad priorities: unlocking and harmonizing data at scale; building dynamic and self-updating soil information systems; producing actionable intelligence for decision-making; and establishing autonomous governance and ethical data stewardship using AI. While individual components of AI (such as machine learning) have been applied to soil mapping, the integration of multi-agent AI systems, the conceptualization of Soil Digital Twins for Africa, and the development of a FAIR-for-AI governance framework constitute a novel and systemic research roadmap that has not been previously articulated. The central argument is simple. Advanced AI should not be treated only as a tool for better mapping. It should be understood as part of the infrastructure needed to turn fragmented and unstandardized soil data, by systematically aligning local observations with global vocabularies and domain ontologies, into shared, usable intelligence for Africa's future.

THE VISION: FROM STATIC MAPS TO NEAR-REAL-TIME SOIL INTELLIGENCE

Africa's shift from a data-poor to a more data-rich environment calls for a goal that goes beyond simply producing more soil maps. The more important task is to build a soil information system that can update, learn, and respond with changing environmental conditions. The vision proposed here is therefore a dynamic African Soil Information System that functions as a high-fidelity digital twin of the continent's soil landscape. This means moving away from the traditional linear model of soil mapping, in which data are collected, processed, and published as static outputs, toward a more continuous system in which soil information is updated in near real time and used directly for decision-making (Figure 1).

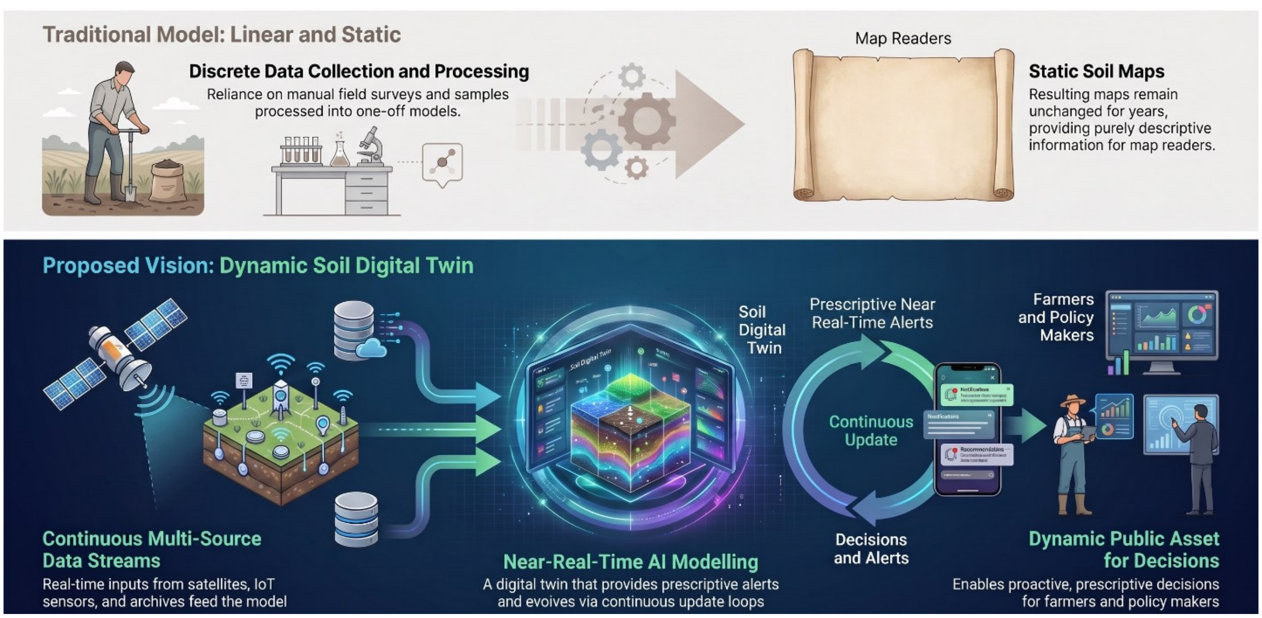

Figure 1. A conceptualized AI-Powered Soil Intelligence System showing a shift from static models, towards dynamic soil digital twins, used directly for decision-making.

Source: Authors' contribution

A Dynamic, Near-Real-Time Digital Twin

At the center of this AI-powered soil intelligence vision is the idea of a Soil Digital Twin: a virtual, high-resolution representation of the physical soil system that is updated continuously. Conventional soil maps are, by nature, static snapshots. In many cases, they remain unchanged for years or even decades, despite the fact that soil conditions are constantly being shaped by land-use change, erosion, and climate-related shocks. The alternative proposed here is to treat soil health not as a fixed condition, but as something that changes over time and can be monitored as it changes. By combining continuous satellite observations, such as Sentinel-1/2 and PlanetScope, with ground-based IoT sensor networks, such a system could detect shifts in soil moisture, nutrient availability, and carbon flux as they occur. It is therefore ideally tailored to support dynamic decision-making frameworks within hydrological digital twins (Brocca et al., 2024). To do this effectively, it would need online learning architectures (supported by human expert knowledge), capable of ingesting new data as they arrive, so that the modelled soil state reflects near real-time conditions rather than relying only on past estimates (Wadoux et al., 2021). A Soil Information System that incorporates AI should not be designed to function independently of human expertise. Instead, the proposed framework adopts a Human-in-the-Loop (HITL) approach in which soil scientists, pedologists, agronomists, and agricultural extension officers remain directly involved in the evaluation of model outputs. Before recommendations are implemented, AI-generated predictions are examined, verified, and, where necessary, adjusted using field observations and expert interpretation. This iterative review process also provides feedback that is used to recalibrate and improve model performance over time. In this way, artificial intelligence serves as a decision-support tool that strengthens, rather than substitutes for, the accumulated experience, contextual understanding, and professional judgment of soil experts and local practitioners (Wadoux et al., 2021).

Continuous Data Fusion: From Archives to Live Feeds

For a digital twin to work, it must be supported by a system that can continuously integrate data from multiple sources (Tsakiridis et al., 2023). This is where an AI-driven processing core becomes important. Most existing soil information systems still operate in a periodic and reactive way, with datasets cleaned, standardized, and updated only after long intervals (Nenkam et al., 2024). Furthermore, a substantial volume of Africa’s soil information remains confined to hardcopy archives or fragmented within legacy data systems (Kome et al., 2026). The vision outlined here is different. It assumes a more active system in which advanced AI, especially natural language processing and computer vision, helps to process information continuously as it becomes available. New field reports, scanned documents, laboratory records, and satellite imagery could be automatically extracted, georeferenced, harmonized, and added to a shared knowledge base (Tellen et al., 2025). In this way, legacy archives and emerging live data streams would no longer remain separate sources of information. Instead, they would become part of one evolving system capable of representing soil dynamics across multiple scales, from historical records to present conditions.

Prescriptive Intelligence and Real-Time Alerts

The real value of such a system lies not only in better data integration but in the ability to turn soil information into actionable intelligence. At present, many systems are designed mainly to describe or predict soil conditions. The broader aim here is to move beyond that, toward a system that can also anticipate likely changes and support timely decisions. In practical terms, this means shifting from questions such as “what is the current soil condition?” to actionable, user-centric queries such as “when should I apply nutrients in my field?” or “what is the current land degradation risk in my field?” For smallholder farmers, this could mean receiving near-real-time alerts through mobile devices, similar to the soil degradation warning systems now being developed in Europe (Afshar et al., 2024). These alerts might warn of localized erosion risks during extreme rainfall events or provide nutrient application advice based on current soil moisture conditions and crop demand (Lobry de Bruyn & Prager, 2024). For policymakers, the same system could provide a live continental dashboard of soil health conditions, making it easier to identify emerging land degradation hotspots or respond quickly to threats to food security. In that sense, the broader significance of the vision is clear: it reduces the delay between observation, interpretation, and action, and positions soil information as an active part of Africa’s agricultural and environmental infrastructure rather than as a static technical resource.

A RESEARCH AGENDA FOR AN AI-POWERED SYSTEM: THE FOUR PILLARS

Making near-real-time soil intelligence possible in Africa will require a research agenda that is both technically strong and institutionally grounded. The challenge is not only to improve models or increase data availability, but also to build systems that can work across fragmented infrastructures, uneven capacities, and different governance contexts by deploying federated learning and open API architectures (CABI & ISRIC, 2024; Yurdem et al., 2024). For that reason, the agenda proposed here is organized around four connected pillars, each addressing a key part of the transition toward an AI-powered soil information system (Figure 2).

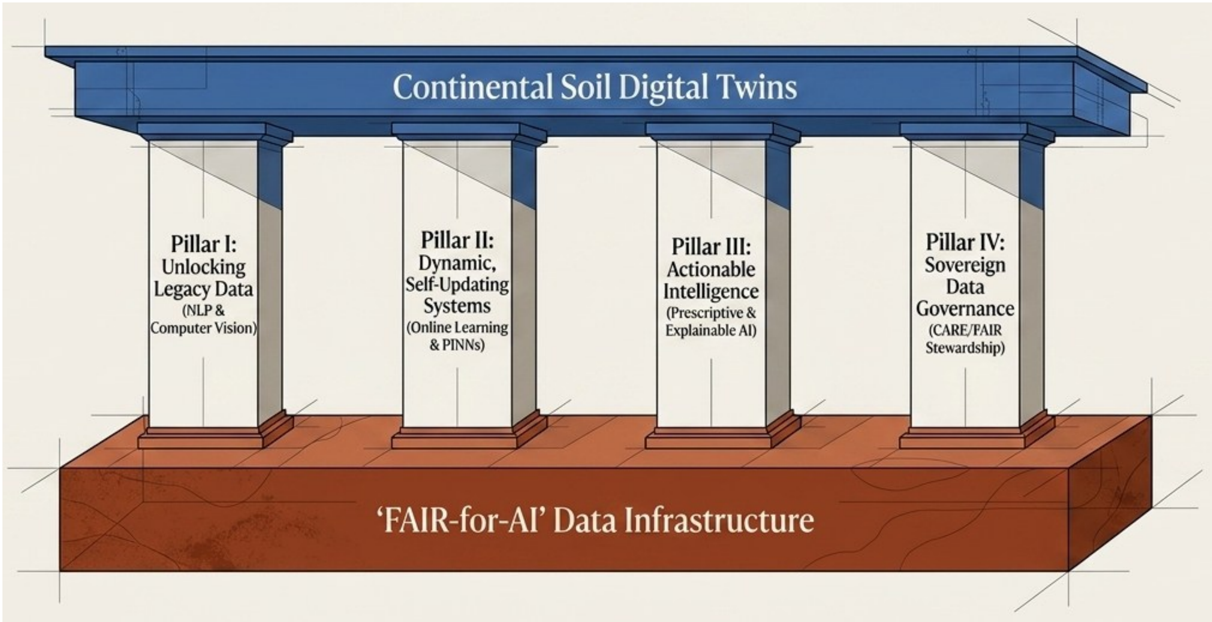

Figure 2. The logical path of the African Soil Information Systems AI Research Agenda. It starts with unlocking fragmented legacy data (Pillar I), then moves on to continuously updating models (Pillar II). From there, it translates those models into actionable decisions (Pillar III) while using AI to establish autonomous governance and ethical data stewardship (Pillar IV) to oversee and sustain the entire intelligence cycle. (NLP = Natural Language Processing, PINNs = Physics Informed Neural Networks)

Pillar I: Unlocking Legacy and Unstructured Data with NLP and Computer Vision

One of the defining features of Africa's soil information landscape is a clear data paradox. There is a major shortage of digital, machine-readable soil data, yet a large amount of valuable historical knowledge already exists in forms that are difficult to use directly (Tellen et al., 2025). Much of this material is scattered across old survey reports, journal articles, laboratory records, and analogue soil maps produced during both the colonial and post-colonial periods. This first pillar therefore focuses on the research needed to recover this information and convert it into usable digital form. The central idea is to use advanced AI, especially natural language processing and computer vision, to transform unstructured and archival material into structured, high-quality soil data, which are continually harmonized using deep learning (Figure 3).

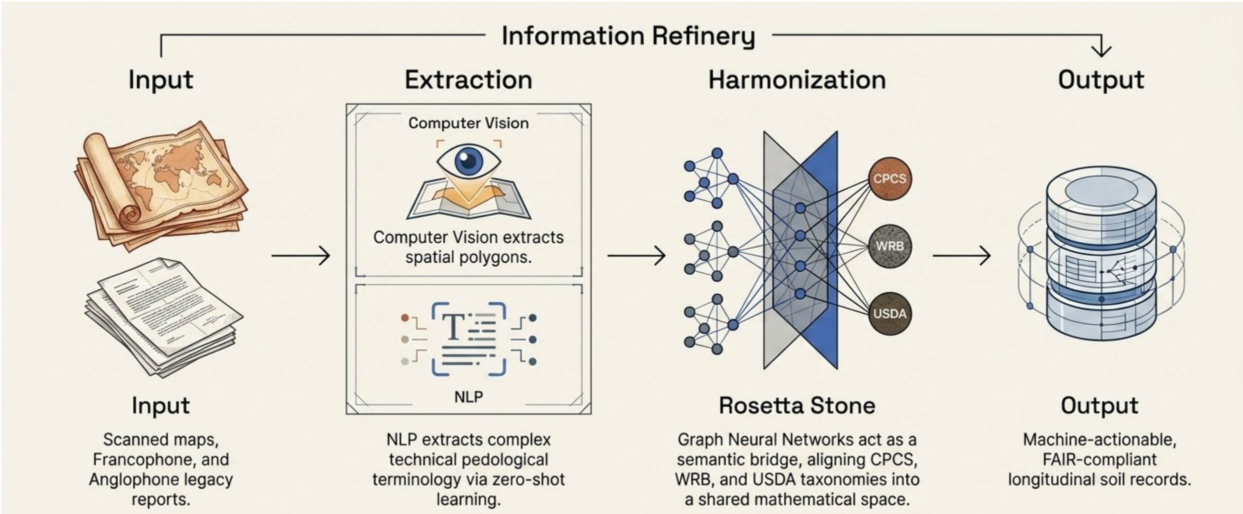

Figure3: An automated refinery to unlock decades of trapped soil knowledge using advanced AI. (NLP = Natural Language Processing, CPCS = Commission de Pédologie et de Cartographie des Sols, WRB = World Reference Base (for Soil Resources), USDA = United States Department of Agriculture, FAIR = Findable, Accessible, Interoperable, Reusable, (standard guiding principles)).

Pathway 1: Natural Language Processing for Textual Data Extraction

At present, many data rescue efforts still depend heavily on manual transcription. That process is slow, costly, and often inconsistent. A major research priority, then, is the development of specialized large language models and named entity recognition pipelines that are tuned specifically to soil science. General-purpose language models are not enough for this task. The models needed here must be able to recognize technical soil terminology, distinguish between related properties such as pH and soil organic carbon, identify specific horizons, and interpret the laboratory methods used to generate the data in the first place. This is especially important because older African soil reports often draw on different analytical procedures depending on the time period, institution, or country. A key research question is therefore how to design zero-shot or few-shot systems that can accurately extract useful soil information from fragmented and heterogeneous reports while requiring only limited human correction (Nenkam et al., 2024).

Pathway 2: Computer Vision for Automated Map Digitization

A second major challenge lies in the large number of historical soil and vegetation maps that still exist only as paper documents or low-quality scans. These materials contain important spatial information, but in their current form they are difficult to integrate into digital systems. The research priority here is to apply computer vision and deep learning methods, including convolutional neural networks, to automate the digitization of these maps. This involves much more than converting paper into image files. It requires methods that can identify and interpret map legends, match historical map features with current geographic references, and extract soil boundaries in forms that can be used analytically. In practical terms, the goal is to move from static images of maps to machine-actionable spatial datasets (Wu et al., 2021).

Pathway 3: Deep Learning for Automated Harmonization and Semantic Interoperability

Recovering historical soil data is only one part of the problem. The larger technical challenge is how to harmonize information that was produced under different classification systems, laboratory methods, and linguistic traditions. In the African context, this often includes bridging the long-standing divide between Francophone and Anglophone soil documentation, as well as aligning systems such as the Commission de Pédologie et de Cartographie des Sols (CPCS), the World Reference Base (WRB), and USDA Soil Taxonomy. This pillar therefore calls for research on AI-driven semantic mapping and knowledge-based integration. Rather than depending entirely on fixed lookup tables created by experts, future work should explore approaches such as graph neural networks that can learn relationships across classification systems and represent them more flexibly. There is also a need for research on latent space representations that allow data generated through different laboratory procedures, such as different phosphorus extraction methods, to be projected into a common mathematical space. This would make it possible to learn more complex transfer relationships across methods than those captured by traditional linear conversion models (Arrouays et al., 2017). The broader aim is to create a continent-wide system of semantic interoperability: in effect, a soil "Rosetta Stone" that allows decades of African soil observations to be integrated into a single, FAIR-compliant longitudinal record.

To handle missing covariates and non-linearities inherent in legacy laboratory data, such as converting between historical soil phosphorus extraction protocols (e.g., Bray-1 versus Olsen) that cannot be accurately reconciled via linear transformation, GNN architectures can be combined with graph-based imputation techniques (You et al., 2020). By modeling soil properties, spatial locations, and laboratory protocols as interconnected nodes in a knowledge graph, latent space embeddings infer missing covariates from contextual neighborhood relationships. This ensures that historical profile datasets with incomplete analytical attributes can still be harmonized and integrated without discarding valuable legacy observations (Jordan-Meille et al., 2012).

Pillar II: AI for Self-Updating, Gap-Filled and Dynamic Soil Information

Most Digital Soil Mapping (DSM) products currently available globally, including across Africa, remain essentially static. They usually represent average soil conditions based on the period when samples were collected, rather than conditions as they change over time. This is a major limitation because soil is not a fixed resource. Properties such as moisture, nutrient availability, and organic carbon can change substantially in response to weather variability, land management, and other environmental pressures (Wadoux et al., 2021, Rudiyanto et al., 2021). The second pillar therefore focuses on the use of advanced AI to build soil information systems that can update themselves continuously and respond more effectively to new data. The emphasis here is on approaches such as online learning and generative modelling, which offer ways to reduce the time gap between observation, analysis, and application (Figure 4).

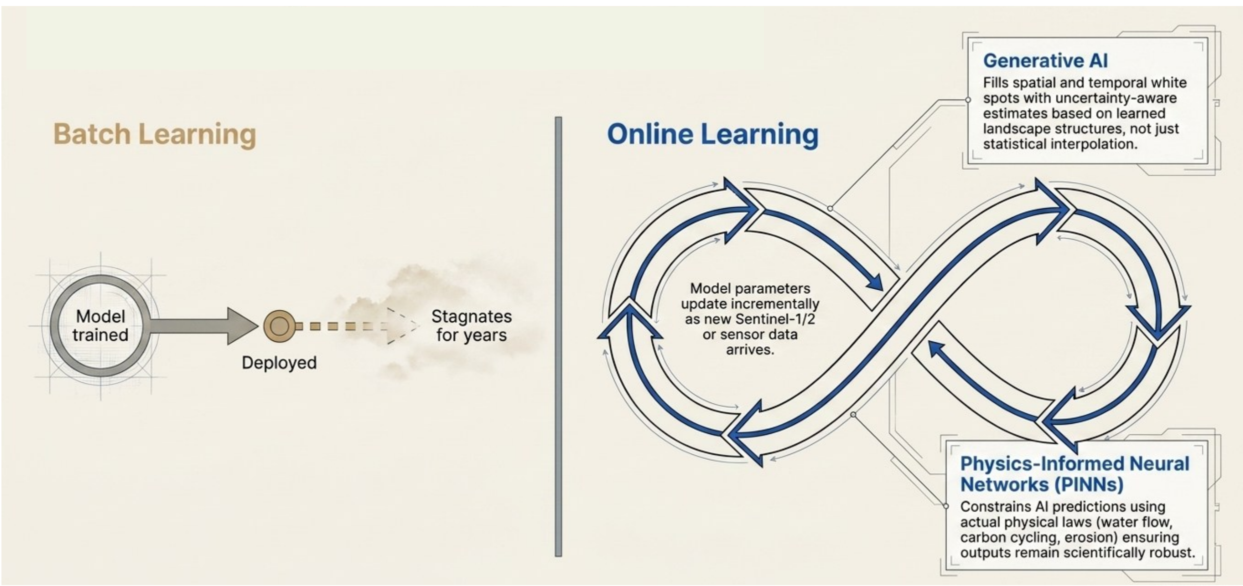

Figure 4. A paradigm shift in African soil informatics: A traditional linear model of soil mapping, which depends on periodic sampling to produce static outputs (Batch learning); and a proposed dynamic architecture that incorporates continuous data feeds and machine learning to allow for a constantly updated Soil Digital Twin, which can generate real-time alerts and provide decision support (Online learning).

Pathway 4: Online Learning and Continuous Data Assimilation

One important research priority is the development of online learning, sometimes referred to as stream learning, for soil information systems. Conventional machine learning usually follows a batch process in which a model is trained, tested, and then deployed, often with long periods before it is updated again. That approach is too slow for monitoring soil conditions that may shift quickly over time. Online learning offers a different model. Instead of waiting for large new datasets to accumulate, the system updates its internal parameters incrementally as new observations become available, whether from farmer-generated soil tests, sensor networks, or satellite imagery. Related to this is the need for research on continuous data assimilation methods, similar to those used in meteorology, where live observations are combined with process-based models to improve current estimates. In the soil context, this raises an important question: how can neural architectures be designed to absorb high-frequency satellite and field data in ways that update soil property maps in near-real time without requiring full retraining each time new information appears? (Afshar et al., 2024; Wu et al., 2021).

A major operational challenge for deploying continuous data assimilation across remote African landscapes is telemetry latency and variable internet connectivity. To make near-real-time updates pragmatically grounded, the research agenda must incorporate Edge AI architectures (O'Grady et al., 2021). By executing lightweight, optimized machine learning models locally on edge devices (such as smartphones, field tablets, or local regional computing nodes), data preprocessing, feature extraction, and immediate inference can occur offline. When network connectivity is restored, compressed model weights and updates are synchronized back to the central cloud system. This decentralized approach minimizes bandwidth dependency, mitigates connectivity bottlenecks, and delivers uninterrupted decision support in remote rural areas.

Pathway 5: Generative AI for Filling Spatial and Temporal Knowledge Gaps

A second challenge is that large parts of Africa still remain poorly covered by both historical and contemporary soil data. In some places, there are major gaps in space, time, or both. This creates what might be called white spots in the soil information landscape where soil information is missing, obsolete, or lacks the details needed for informed land management (Arrouays et al., 2017). The research agenda proposed here includes the use of generative AI, including approaches such as generative adversarial networks and diffusion models, to help address these missing areas. The key point is that these methods would not simply interpolate between known observations in a narrow statistical sense. Rather, they would learn broader soil-landscape relationships from better-sampled regions and use those learned structures to generate plausible estimates for places or periods where direct observations are absent (Yang et al., 2022). This kind of modelling must, however, be handled carefully. A central priority should be the development of uncertainty-aware generative systems that do not present their outputs as direct measurements. Instead, they should communicate ranges of probable soil conditions and make clear where the model is relying on inference rather than observation. That distinction is especially important in data-sparse settings, where scientific credibility depends not only on prediction accuracy but also on transparency about uncertainty (Wadoux et al., 2021).

Pathway 6: Physics-Informed Neural Networks for Process Modelling

A further step in this agenda is to move beyond models based only on statistical association. For this reason, the pillar also highlights the importance of physics-informed neural networks, or PINNs. These models incorporate physical laws directly into the learning process, for example, through equations that describe water flow, carbon cycling, or other soil processes (Liu et al., 2023). However, a critical bottleneck in deploying PINNs for unsaturated flow (e.g., governed by partial differential equations such as the Richards equation) in data-sparse African regions is that essential soil hydraulic parameters (such as the van Genuchten water retention parameters) remain largely unmeasured (Turek et al., 2023; Weber et al., 2024). Enforcing physical constraints without localized hydraulic parameterization risks introducing systematic model bias. This highlights an urgent parallel research priority: developing regional, AI-enhanced hydro-pedotransfer functions capable of estimating soil hydraulic parameters from basic soil physical attributes, thereby providing the necessary empirical foundation to parameterize PINNs effectively across data-sparse landscapes (Xie et al., 2024). In the African context, this is particularly relevant because many important changes in soil condition are driven by processes such as erosion, runoff, and nutrient leaching. A purely data-driven model may detect patterns in these changes, but it may not always represent the underlying mechanisms in a scientifically reliable way. Physics-informed models offer a way to address that problem by constraining predictions to remain consistent with established pedological and geomorphological principles (Trontelj & Chambers, 2021). The longer-term aim is to develop hybrid systems that combine the pattern-recognition strength of deep learning with the scientific robustness of mechanistic process modelling. Such models would provide a more dependable foundation for near-real-time soil health monitoring and for digital twin systems that need to be both adaptive and scientifically grounded.

Pillar III: Delivering Actionable Intelligence with Prescriptive and Explainable AI

The value of a soil information system ultimately depends on whether it can support better decisions. In much of soil science, the main goal has traditionally been prediction: estimating a soil property where no direct measurement exists. That remains important, but prediction alone is not enough for most real-world users. A farmer, extension worker, or policymaker usually needs more than an estimate of current soil conditions. They need guidance on what action to take, when to take it, and why that action makes sense. The third pillar, therefore, focuses on the development of prescriptive intelligence. Its aim is to use AI not only to describe or predict soil conditions, but also to generate practical, context-sensitive recommendations in ways that are transparent, interpretable, and trusted by those who use them.

Pathway 7: Multi-Objective Recommendation Engines for Prescriptive Farming

Moving from “what is happening” to “what should be done” requires a different class of AI tools. One important research direction is the development of prescriptive systems that can evaluate multiple management options and identify those most suited to a given context. Reinforcement learning is especially relevant here because it enables models to simulate a large number of possible actions and their likely consequences within a digital representation of the soil system. In practice, however, these prescriptive systems cannot be built around a single objective such as yield alone. In African farming systems, management decisions involve complex trade-offs between crop productivity, fertilizer efficiency, environmental protection, and long-term soil health. Research is therefore needed on multi-objective recommendation engines capable of weighing these competing priorities simultaneously. A particularly promising avenue lies in multi-agent artificial intelligence architectures, where autonomous, specialized AI agents collaboratively process real-time soil data, run process-based crop-hydrology models, and evaluate socio-economic trade-offs to deliver unified recommendations (Minasny et al., 2026). Such multi-agent frameworks (Figure 5) combine soil information with dynamic external variables, including weather forecasts, crop growth stages, and local market conditions, to optimize outcomes, not only at the field scale, but across wider agricultural landscapes (Lobry de Bruyn & Prager, 2024; Bennett et al., 2021).

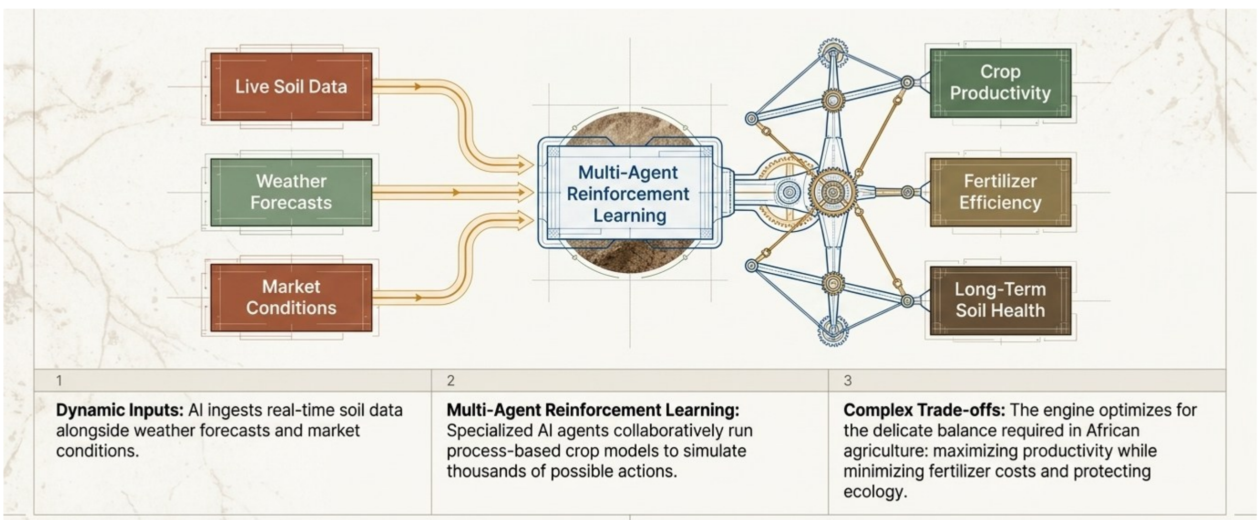

Figure 5. An illustration of the conceptual framework of a multi-objective recommendation engine designed for prescriptive farming. Unlike traditional predictive models, this multi-agent reinforcement learning engine integrates real-time soil data, weather forecasts, and market conditions to effectively balance competing agricultural and environmental goals, such as maximizing crop yield while ensuring the long-term health of the soil.

Pathway 8: Explainable AI and the Foundations of Trust

Even the most technically advanced recommendation system will have limited value if users do not trust it. One of the main barriers to the adoption of AI in agriculture is that many advanced models operate as black boxes (Hassija et al., 2024). They may generate recommendations, but the reasoning behind those recommendations is often difficult for non-specialists to understand. This matters greatly in farming, where suggested actions may involve real financial risk or require users to deviate from established practices. For that reason, explainable AI should be treated as a central part of the research agenda, not as an optional add-on. Methods such as SHAP (Shapley Additive exPlanations) or attention-based interpretation can help reveal which variables are driving a model's outputs (Wadoux et al., 2020), but technical transparency alone is not sufficient. What is needed is a more human-centered form of explainability combined with expert validation workflows, where regional soil specialists verify AI-generated recommendations before they reach farming communities. This multi-layered validation builds institutional trust and ensures advice is grounded in both statistical evidence and agronomic science (Wadoux et al., 2025).

Pathway 9: Large Language Models and Conversational Interfaces for Knowledge Translation

A further challenge is that access to digital soil information is often shaped by literacy, language, and interface design. In many African contexts, highly technical tools remain inaccessible to the people who could benefit most from them (Begho et al., 2025). This creates a need for new forms of knowledge translation that make soil intelligence easier to access and use. One promising direction is the use of Large Language Models (LLMs) as conversational interfaces for soil information systems. Rather than relying on general pre-trained patterns that risk generating unverified answers, Retrieval-Augmented Generation (RAG) tethers the LLM directly to structured soil databases, standardized ontologies (e.g., GloSIS), and verified domain vocabularies (Wang et al., 2024; Liu et al., 2023). This ensures that conversational outputs adhere strictly to scientific standards while translating complex data into local languages and accessible voice prompts for extension workers and farmers.

In practical terms, this could allow a farmer to ask a question about soil moisture, fertilizer timing, or expected rainfall in conversational form and receive an answer that is tied to current field conditions and available data. The broader objective is to make soil information systems less like specialist databases and more like accessible advisory tools that can support everyday agricultural decision-making across diverse user groups.

Pillar IV: Supporting FAIR and Ethical Data Governance with AI

The move toward AI-powered soil intelligence not only creates new technical possibilities. It also raises more demanding questions about how soil data should be managed, shared, protected, and governed (Kikis & Antoniadis, 2026). If the research agenda proposed here is to be sustainable, it must address these wider issues directly rather than treating them as secondary concerns. This is especially important in Africa, where questions of data ownership, control, and equitable use are closely tied to institutional capacity, national sovereignty, and historical patterns of knowledge extraction. The fourth pillar, therefore, focuses on data stewardship. Its aim is to explore how AI can support data governance systems that are both technically effective and ethically grounded, in line with the FAIR principles of findability, accessibility, interoperability, and reusability (Inau et al., 2023), as well as the CARE principles of collective benefit, authority to control, responsibility, and ethics in Indigenous data governance (Carroll et al., 2021). The role of AI in data governance is not merely passive record-keeping, but active, autonomous stewardship (Figure 6). AI agents contribute directly by: (1) automatically scanning and tagging incoming datasets with FAIR-compliant metadata; (2) detecting instrument drift and data anomalies in real-time sensor streams; and (3) enabling federated learning so national institutions can train shared models without surrendering local data control (Jain, 2024; Yurdem et al., 2024). The broader objective is to develop forms of autonomous stewardship that make soil information more usable while also protecting African data interests and supporting responsible scientific collaboration.

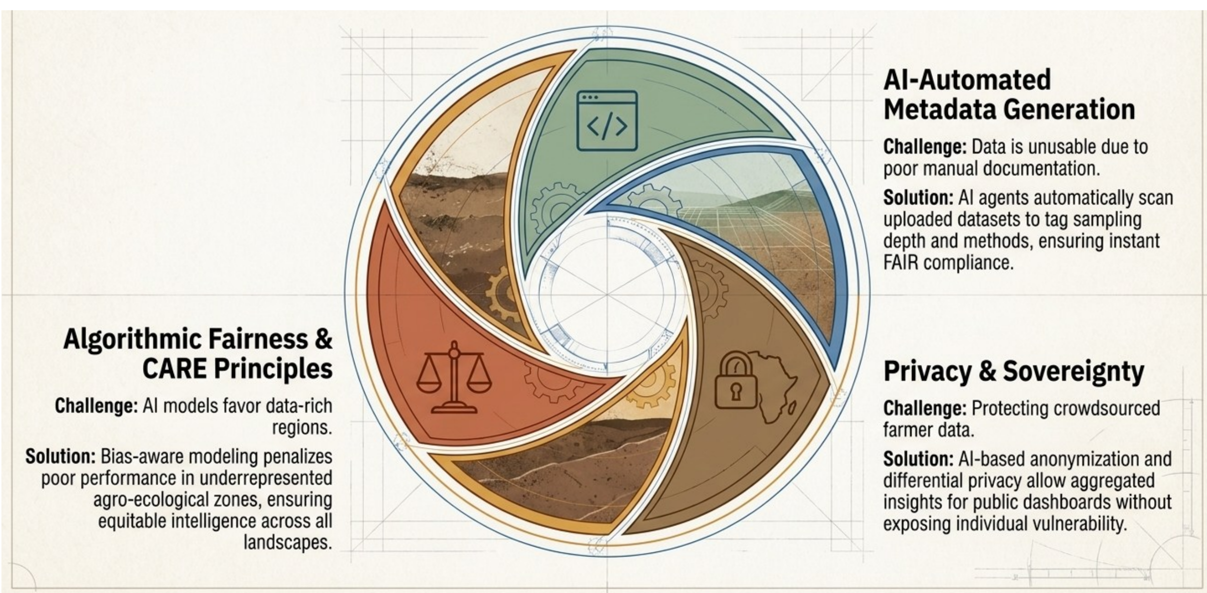

Figure 6. Advanced AI-based autonomous governance, ethics and FAIR data stewardship.

Pathway 10: The Autonomous Governance and Stewardship Framework

The final pathway shifts attention from AI as a tool for prediction and decision support to AI as part of the governance infrastructure of the system itself. In other words, AI should not only help generate soil intelligence; it should also help maintain the quality, accountability, and ethical integrity of the information system on which that intelligence depends (Onyango, 2025). Because these governance challenges are both technical and political, this pathway can be understood through three strategic dimensions.

Dimension 1: AI-Automated Data Stewardship and Metadata Generation

A major obstacle to FAIR data systems is the amount of time and labour required to produce high-quality metadata. In many cases, data become difficult to find, interpret, or reuse not because they are scientifically weak, but because they are poorly documented. One research priority, then, is the development of automated metadata harvesting tools that can assist with this work as new information enters the system. Such tools could scan uploaded datasets and identify key attributes such as sampling depth, location, date, and analytical method, helping ensure that data are properly described from the start. This would make it easier for soil observations to enter the system in a form that is already aligned with FAIR principles. Related to this is the need for AI-based quality control. Real-time data streams, especially those coming from sensors or distributed reporting systems, are vulnerable to errors, inconsistencies, and instrument drift (Jain, 2024). AI-driven anomaly detection could help identify these problems quickly and flag suspicious records before they affect downstream analysis. An important research question here is how far automated agents can support the scientific verification of incoming soil data without slowing down the near-real-time character of the system itself (Wilkinson et al., 2016; Jean-Quartier et al., 2024).

Dimension 2: Privacy-Preserving AI and Data Sovereignty

In the African context, data governance cannot be separated from the question of sovereignty. Soil data are not politically neutral. They relate to land, resources, production systems, and local livelihoods, and for that reason, they must remain subject to meaningful national and community control (Bu et al., 2026). This makes privacy-preserving and sovereignty-aware system design a central research concern. One promising direction is federated learning, which allows models to be trained across multiple decentralized national or institutional nodes without requiring raw data to be transferred to a central server (Yurdem et al., 2024). Under such an approach, the intelligence of the system can improve across countries while the underlying data remain under local control. This offers a possible way of balancing continental-scale analysis with national ownership and security. There is also a need for research on differential privacy and AI-based anonymization methods, especially where soil information systems draw on farmer-generated or crowdsourced data. These techniques could help protect individual privacy while still allowing aggregated information to be used in public dashboards, monitoring platforms, or advisory systems (Yang et al., 2024).

Dimension 3: Ethical AI Frameworks and Bias Mitigation

A further governance issue is that AI systems do not operate neutrally. They can reproduce or even deepen existing inequalities if they are trained on uneven datasets or optimized in ways that favour already well-represented regions (Afreen et al., 2025). In soil science, this could mean that models perform relatively well in data-rich environments but poorly in marginal or under-sampled landscapes. The result would be an intelligence system that appears comprehensive while systematically serving some places better than others. For that reason, this pillar also prioritizes research on algorithmic fairness in soil intelligence. This includes the development of bias-aware modelling strategies that explicitly account for underrepresented agro-ecological zones and penalize models for persistently weak performance in such settings. Ethical governance also extends beyond technical bias to questions of recognition and benefit. Where local communities contribute observations, field knowledge, or other forms of environmental information, the system should be able to acknowledge and credit those contributions (Nguyen, 2026) in ways that are consistent with the CARE principles (Carroll et al., 2022). The wider goal is to ensure that AI-powered soil intelligence is not only accurate and efficient but also inclusive, accountable, and equitable across the range of African countries, landscapes, and farming communities.

A strategy for implementation and a call to action

The four pillars outlined above provide a technical direction for building near-real-time soil intelligence in Africa. But a research agenda, on its own, is not enough. Turning that agenda into a working system will require changes in how African soil science is organized, funded, and governed. AI is not a simple tool that can be added to existing systems without wider reform. Its usefulness depends on the quality of the underlying data, the range of expertise involved, and the strength of the institutions responsible for managing both. For that reason, implementation must be approached strategically. This section outlines the conditions needed to operationalize the agenda and ends with a broader call to action.

The Prerequisite: Accelerating the FAIR-for-AI Transition

The first requirement is data readiness. No advanced AI system can perform well if the data feeding it are incomplete, inconsistent, poorly documented, or difficult to integrate. Earlier work on African soil data has already emphasized the importance of adopting the FAIR principles more broadly (Tellen et al., 2025). However, the requirements of advanced AI go further. What is needed now is not only FAIR data, but data that are genuinely ready for AI use.

This means moving beyond basic digital access toward machine-actionable datasets that are structured, standardized, and rich in context.

For AI systems such as large language models, online learning systems, or reinforcement learning agents, simple availability is not enough. The data must also include the kinds of metadata that allow models to interpret them correctly. Soil observations, therefore, need to be accompanied by detailed information on sampling depth, measurement method, sensor quality, analytical procedures, and provenance (Wilkinson et al., 2016). Building AI-ready repositories of this kind should be treated as a foundational priority. Without this level of preparation, even the most sophisticated models are unlikely to generate reliable insights for African agriculture.

A Multi-Disciplinary Team Science Approach

A second requirement is a shift away from narrow, siloed research structures. The agenda proposed in this paper is too complex to be carried by a single discipline. Developing a near-real-time soil digital twin will require collaboration across several forms of expertise. Soil scientists, pedologists, agronomists and hydrologists are needed to ensure that model outputs remain scientifically credible. AI specialists and data engineers are needed to build and maintain the technical systems behind tools such as NLP pipelines, generative models, and adaptive learning architectures. Social scientists and ethicists are needed to address questions of participation, equity, and responsible data use. Policymakers and extension leaders are needed to define what kinds of intelligence are actually useful in practice and how they should be delivered (Bennett et al., 2021).

This points to the need for a stronger team science model in African soil research. It also suggests that end users should be involved much earlier in system design than is often the case. Farmers and extension agents should not encounter AI tools only at the final stage of deployment. They should be part of the design process from the beginning, so that the resulting systems respond to real needs, fit local decision contexts, and communicate advice in ways that users can understand and apply. Participatory design frameworks are especially important here because technical accuracy alone does not guarantee practical usefulness or social acceptance (Lobry de Bruyn & Prager, 2024).

Call to Action: Towards Sovereign Soil Intelligence as a Public Good

The scale of Africa's soil-related challenges, from land degradation to climate stress and food insecurity, demands a response that goes beyond isolated projects and short funding cycles. What is needed is a coordinated continental effort. For that reason, this paper calls for the establishment of a Pan-African AI for Soil Health Consortium, led through the African Union and coordinated with the African Soil Partnership and the Regional Economic Communities.

The purpose of such a body would be to move beyond the current pattern of fragmented pilots and toward developing a shared, long-term soil intelligence infrastructure for the continent (Figure 5).

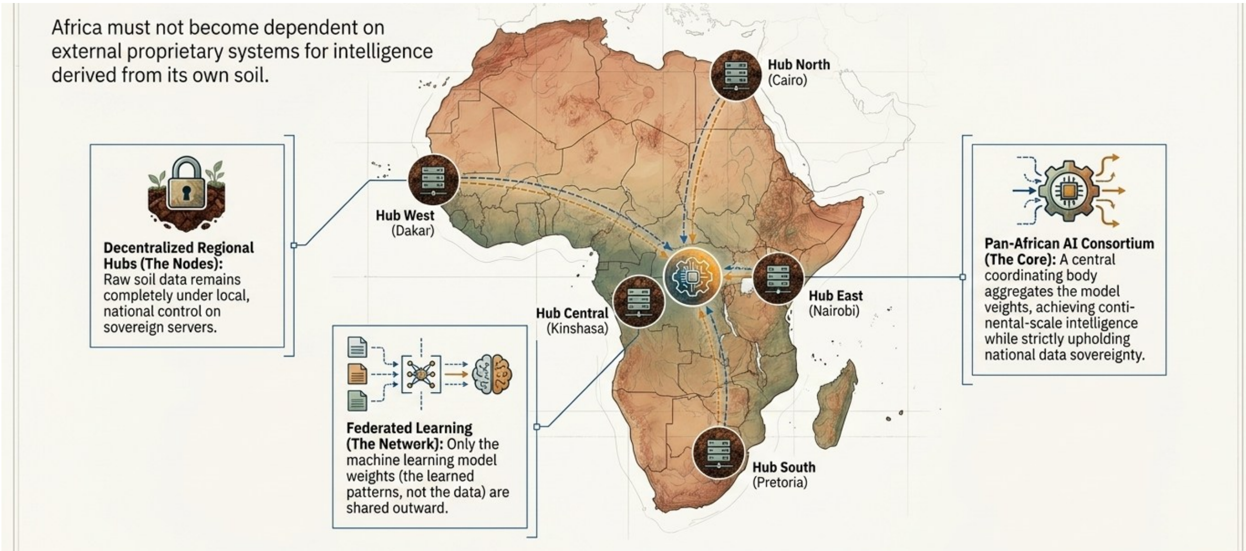

Figure 5. A proposed African vision for federated learning and sovereign computing hubs. The decentralized regional nodes represent the continent's major economic communities (North, South, East, West, and Central). This setup empowers national institutions to maintain local control over their precious raw soil data. At the same time, machine learning model weights are shared with a central Pan-African AI Consortium, striking a balance between harnessing continental intelligence and upholding data sovereignty.

Three strategic priorities should guide this effort:

1. Securing Data and Model Sovereignty

Africa should not become dependent on external proprietary systems for the intelligence derived from its own soil resources. If AI is to play a foundational role in future soil information systems, then the continent needs the capacity to build, host, and govern core parts of that infrastructure itself. This includes open-source tools, local computing capacity, and soil-specific models that can be adapted to national and regional contexts. One practical step would be the creation of continental or regional soil compute hubs that provide national institutions with the computational resources and pre-trained models needed to develop their own digital twins. Maintaining control over this AI processing layer is important not only for technical autonomy, but also for protecting soil intelligence as a strategic public asset rather than allowing it to be externalized through new forms of digital dependency (African Union, 2020).

2. Developing a Home-Grown Talent Pipeline

No long-term system can succeed without people able to build, maintain, interpret, and govern it. The agenda proposed here, therefore, depends on developing a new generation of African soil data scientists with expertise spanning soil science, data science, and AI. This could be supported through a Pan-African Soil Informatics Fellowship, alongside stronger integration of AI-intensive training into agricultural and environmental science programmes at African universities. Capacity development has already been identified as an important priority in earlier work (Kome et al., 2026; Tellen et al., 2025), but the present agenda requires a more specialized focus. The skills needed are not only those of general data management, but also those required to work with adaptive models, digital infrastructure, and the ethical challenges that accompany them.

3. Transitioning to Sustainable, Infrastructure-Based Financing

A final requirement is financial. AI-driven soil intelligence should not be treated as a short-term research add-on or a luxury technology. It needs to be recognized as part of the continent's essential agricultural and environmental infrastructure. That implies a shift away from financing models based mainly on short donor-funded projects and toward more stable support through national budgets, regional cooperation, and long-term climate finance mechanisms, including sources such as the Green Climate Fund. One important task for the African soil science community is therefore to demonstrate the wider value of this investment. If prescriptive soil intelligence can improve input efficiency, reduce land degradation, and strengthen climate resilience, then it should be framed not simply as a scientific tool, but as a public investment with clear economic and social returns (Bennett et al., 2021).

Taken together, these actions would help move African soil science from a history of fragmented observation toward a future of coordinated, actionable intelligence. They would also help ensure that the systems built to manage African soils are shaped by African priorities, hosted within African institutions, and directed toward long-term public benefit.

CONCLUSION

African soil science is at a point where higher-resolution static maps alone will not meet the scale of current land, food, and climate challenges. The next frontier is not simply to produce more soil data, but to build soil information systems that can learn from new evidence, integrate diverse observations, and support decisions as conditions change. Soil digital twins provide a promising framework for this shift by linking legacy soil records, field observations, remote sensing products, and process-based understanding into more adaptive and decision-oriented systems.

Advanced AI can play an important role in this transformation, particularly through natural language processing for extracting knowledge from historical archives, physics-informed modelling for improving prediction under uncertainty, and reinforcement learning for supporting management decisions. Yet the value of these tools will depend on the quality, accessibility, and governance of the data on which they are built. A credible African soil intelligence agenda must therefore combine technical innovation with FAIR-for-AI data systems, African scientific leadership, and strong safeguards for data sovereignty.

Positioning soil information as public infrastructure is essential. Done well, this transition can convert fragmented and poorly standardized soil observations into trusted, actionable intelligence for farmers, land managers, and policymakers, while strengthening Africa’s capacity to respond to land degradation, food insecurity, and climate change.

Statements

Author contributions

VAT: Conceptualization, Validation, Writing – original draft, Writing – review & editing, Visualization, Investigation, Validation.

CK: Conceptualization, Validation, Writing – original draft, Writing – review & editing, Visualization, Investigation, Validation.

LB: Writing – review & editing, Investigation, Validation.

NTN: Writing – review & editing, Investigation, Validation.

KTA: Writing – review & editing, Investigation, Validation.

GAA: Writing – review & editing, Investigation, Validation.

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Conflict of interest

The authors declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Declaration of Generative AI and AI-Assisted Technologies

The authors declare the use of Generative AI and AI-assisted technologies in the preparation of this manuscript. Specifically, Google Gemini was utilized to support conceptual structuring, section-by-section drafting, and organizational refinement. Google

NotebookLM was employed to conceptualize and generate the visual figures based on original author contributions and prompts. Grammarly was used to assist with improving sentence structure, grammar, and overall clarity of the English language.

All AI-generated outputs were thoroughly reviewed, edited, and validated by the authors. The authors performed rigorous checks on all citations and data to ensure scientific accuracy, take full responsibility for the content, originality, interpretation, and integrity of the manuscript, and confirm that no AI tool meets the criteria for authorship.

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