



Emerging paradigm in sensor based pedology: Advances, applications, challenges and future perspectives

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Abstract

Pedology has seen a significant revolution due to the adoption of modern sensors that can provide fast, non-invasive and high resolution measurements of soils. Traditional pedological surveys that rely on field work and laboratory analysis are efficient, yet time consuming, cumbersome and have exhibit low spatial resolution. Modern advancements in sensors that measure optical, geophysical, elemental, moisture and remote sensing characteristics of soils have considerably improved the evaluation of soil's physical, chemical and morphological characteristics. This article provides a detailed overview of emerging sensor-based techniques in pedology including the principles of these techniques, their applications and limitations. The review further examines the roles of digital soil mapping (DSM), proximal soil sensing, Geographic Information Systems (GIS), machine learning and artificial intelligence in enhancing soil property prediction and spatial modelling. This review also highlights the significance of calibration and validation of sensors and ground truthing of observations. It critically analyses the problems associated with the calibration transferability, soil heterogeneity, moisture effects and cost of sensors. Recent advances in sensor fusion, internet of things (IoT)-enabled monitoring, hyperspectral imaging and explainable artificial intelligence are also discussed as promising directions for future soil assessment. Furthermore, major research gaps including the need for standardised calibration protocols, regional soil spectral libraries, affordable sensing technologies and interpretable machine-learning models are identified. Overall, sensor-based pedology complements conventional soil survey methods by providing accurate, efficient and spatially continuous soil information thereby supporting sustainable soil management, precision agriculture, environmental monitoring and evidence-based land-use planning under changing climatic conditions.

Keywords: digital soil mapping; pedology; proximal soil sensing; sensor-based pedology; soil sensors; soil spectroscopy

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1. Introduction

Soil is a dynamic natural body formed through the interaction of climate, organisms, relief (topography), parent material and time which collectively govern the processes of pedogenesis and soil variability (1, 2). Pedogenesis produces soil horizon (a process termed horizonation), defined by the vertical variability in soil characteristics such as texture, structure, colour and chemical composition (3). The knowledge about soil variability at different depths across the landscape is crucial for proper land use, soil management and sustainable agriculture (4). Conventional soil description relies on the visual and tactile observation of soil horizons in the field made by pedologists (5). Although it is informative, soil characterisation based on the field observations is subjective, because it requires high qualifications and experience from a soil scientist. As a result, different soil horizons may be interpreted

subjectively, particularly regarding parameters like soil colour and structure. Recently, modern sensors have enabled rapid, non-invasive and objective analysis of soil properties. Methods of portable X-ray fluorescence (pXRF), visible–near infrared (Vis–NIR) spectroscopy provide information about the elemental composition, minerals and organic matter without any sample pretreatment (6). Pedology is now a predictive and data-driven field that can generate precise soil information at various spatial scales by combining sensing technologies with Geographic Information Systems (GIS), digital soil mapping (DSM), machine learning and artificial intelligence (AI) (7). Sensor-based pedology has become a potent method for enhancing digital soil mapping, sustainable soil resource management and soil characterisation. Unlike previous studies that mostly concentrated on either sensing technology or digital soil mapping alone (8–10), this review takes a pedological approach to comparing different sensing technologies

such as optical, geophysical, elemental, moisture and remote sensing techniques used in soil characterisation. This review brings together recent advancements in sensors, machine learning and digital soil mapping (7), examines calibration and validation methods, analyses the advantages and disadvantages of different sensing technologies and highlights gaps in current research and future prospects. With the help of current developments combined with traditional pedology this review will provide a complete pedological approach to ensure proper soil characterisation and digital soil assessment as well as soil resource management. By providing spatially explicit information on soil texture, organic carbon, moisture, salinity and available nutrients, sensor-based approaches can support crop-suitability assessment, site-specific nutrient and irrigation management and improved understanding of crop growth, yield and soil-health responses.

2. Methodology

A systematic literature search was conducted to identify and syntheses studies related to sensor-based pedology and sensor-assisted soil characterisation. Relevant literature was retrieved from seven electronic databases, namely Scopus, Web of Science, ScienceDirect, SpringerLink, Wiley Online Library, Multidisciplinary Digital Publishing Institute (MDPI) and Google Scholar. The search focused on studies addressing the application of sensor-based approaches for soil characterisation, soil property assessment, pedological interpretation and digital soil mapping. The identification, screening, eligibility assessment and inclusion of studies were conducted following a structured Preferred reporting items for systematic reviews and meta-analyses (PRISMA)-based selection process (Fig. 1).

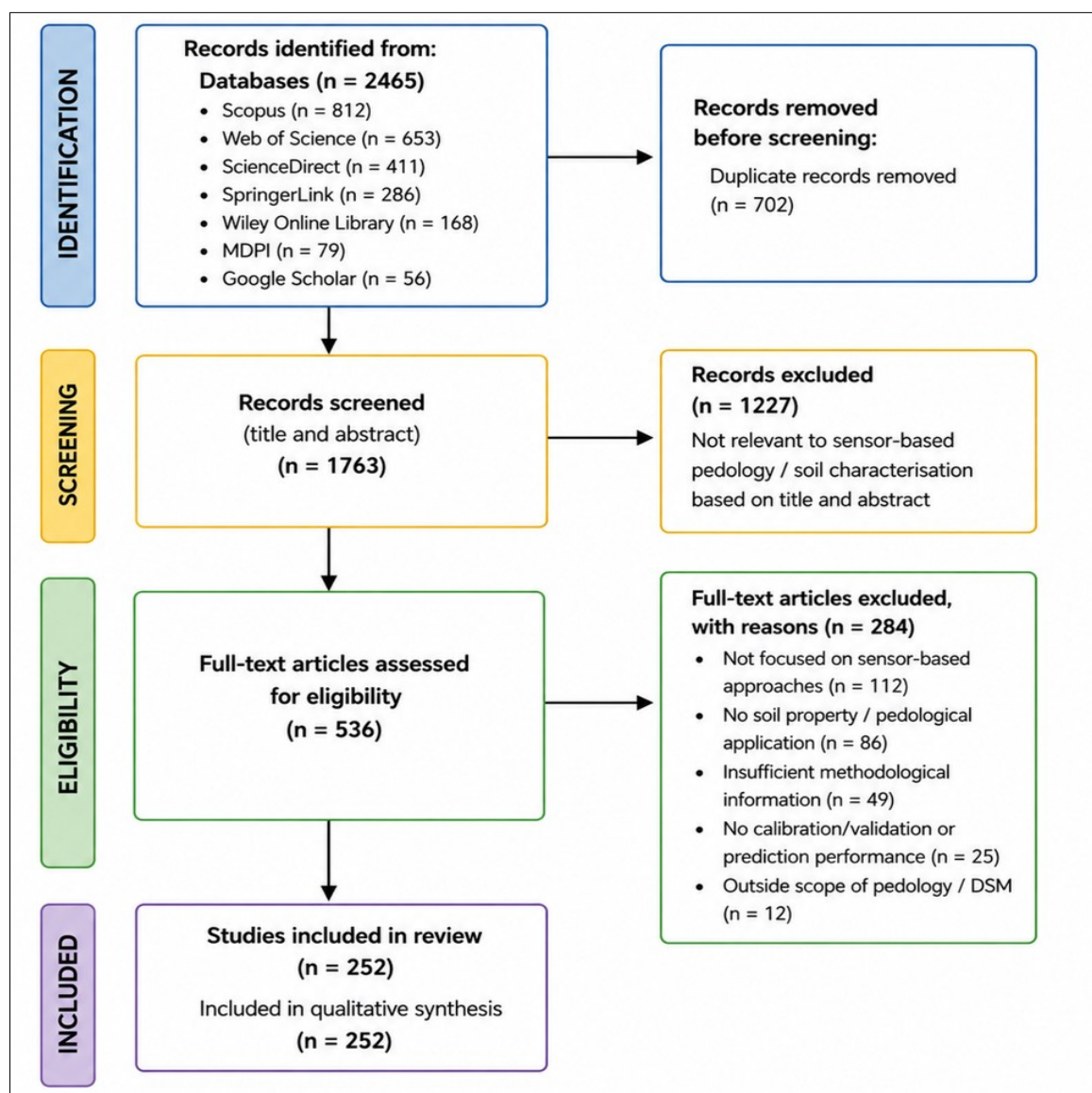


Fig. 1. Preferred reporting items for systematic reviews and meta-analyses (PRISMA) flow diagram showing the identification, screening, eligibility assessment and inclusion of studies in the literature review of sensor-based pedology.

Initially, 2465 records were identified from the selected databases, comprising 812 records from Scopus, 653 from Web of Science, 411 from ScienceDirect, 286 from SpringerLink, 168 from Wiley Online Library, 79 from MDPI and 56 from Google Scholar. After removing 702 duplicate records, a total of 1763 unique records remained for screening. These records were screened based on their titles and abstracts and 1227 records were excluded because they were not relevant to sensor-based pedology or soil characterisation. Subsequently, 536 full-text articles were assessed for eligibility.

During the full-text assessment, 284 articles were excluded for specific reasons. These included studies that were not focused on sensor-based approaches did not address soil properties or pedological applications, lacked sufficient methodological information did not report calibration, validation or prediction performance or were outside the scope of pedology/digital soil mapping. Following this systematic screening and eligibility assessment, 252 studies met the predefined selection criteria and were included in the final review. All 252 eligible studies were considered for the qualitative synthesis of evidence on sensor technologies, soil properties, pedological applications, calibration and validation approaches and emerging developments in sensor-based pedology.

Why sensor-based methods are needed in pedology

Traditional soil profile pits are time-consuming, costly, labour-intensive and destructive making them impractical for large-area soil surveys (11). Ground and proximal sensors enable rapid, non-destructive and continuous acquisition of soil information, facilitating the mapping of soil variability and stratification (12, 13). Profile pits provide only point measurements, while sensors are capable of covering an entire area and measuring differences in soil physical and chemical characteristics (texture, moisture, clay, organic matter, salts, density) related to horizons (14). Such contrasts can indicate potential layer/horizon transitions. Although true horizon classification (A, B, C, etc.) still requires ground-truth data, sensor information can significantly reduce and optimise the number and location of pits needed (15). The physical and chemical properties of the soil may be estimated effectively through techniques such as electromagnetic induction (EMI), electrical resistivity tomography (ERT), pXRF, Vis–NIR spectroscopy and mid-infrared (MIR) spectroscopy (16). Using GIS, Global Navigation Satellite Systems, DSM and machine learning algorithms with these sensors helps us get detailed information about the soil (7). To ensure precise soil characterisation and decision-making, sensor-derived data must be calibrated and validated using traditional pedological observations (17, 18).

Evolution of sensor-based pedology

The evolution of sensor-based pedology from conventional soil survey methods to advanced soil

information systems are illustrated in Fig. 2. Traditionally, pedological studies were based mainly on field observation and laboratory analysis of soil samples. The emergence of DSM incorporated environmental variables and spatial modelling approaches to generate continuous data on soils in the landscape (11). More recently, the integration of proximal and remote sensing technologies with machine learning, AI and real-time monitoring systems has significantly improved soil characterisation, DSM and precision agriculture thereby supporting sustainable soil management and informed decision-making (7, 18). One of the most significant developments in modern pedology has been the advent of DSM, which has transformed conventional soil surveys from point-based observations into predictive, spatially continuous soil information systems. The DSM technology combines soil observation data and environmental factors which include climate, topography, parent material, vegetation and land use through the SCORPAN approach to predict soil properties via the use of statistical and geostatistical models. The DSM is capable of creating high-resolution digital soil maps, but at the same time reducing the sampling effort, cost and surveying time (8). Proximal soil sensing (PSS) and remote sensing technologies are among the revolutions that have taken place in soil profiling to enable fast and non-destructive analysis of soil property characteristics using high spatial resolution. Optical spectroscopic techniques, including Vis–NIR and MIR spectroscopy enable the estimation of soil organic carbon (SOC), texture, clay mineral content, moisture and other soil attributes through spectral reflectance. Geophysical sensors such as EMI, ERT and ground penetrating radar (GPR) are used to obtain vital information related to soil electrical conductivity, soil salinity, soil compaction, stratification and horizons boundaries. Similarly, elemental sensors such as pXRF and laser-induced breakdown spectroscopy (LIBS) can be used to obtain fast elemental composition while satellite imagery, UAVs, light detection and ranging (LiDAR) and hyperspectral sensors can be used for rapid soil mapping in large geographical areas (6, 14). In more recent times, advancements in machine learning, AI and sensor fusion techniques have further increased the efficiency of pedology through sensors. Algorithms including random forest, support vector machine, artificial neural networks and deep learning techniques successfully combine information from several sensors and environmental factors for accurate prediction of soil properties and digital soil maps. Moreover, cloud computing, internet of things (IoT)-enabled soil sensors, real-time monitoring techniques and national soil spectral libraries are being used to carry out continuous soil monitoring and automated analysis of data collected. Such changes have turned pedology into a predictive and data-driven field of study which supports precision agriculture, climate-smart land management, sustainable soil resource management and evidence-based decision making (7, 15).



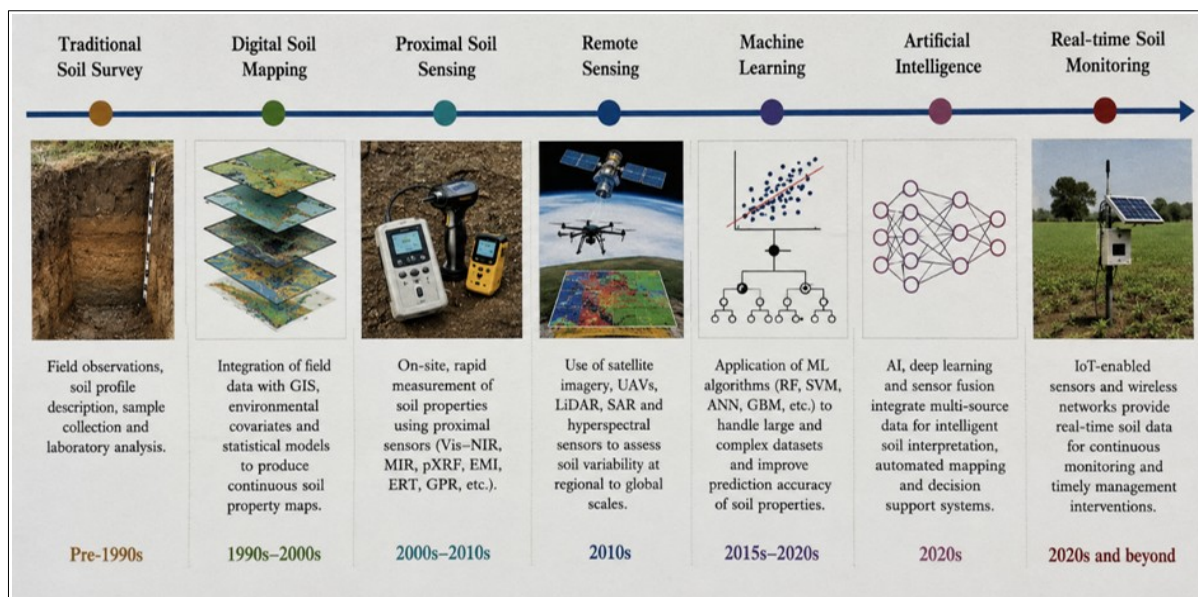


Fig. 2. Evolution of sensor-based pedology.

Types of sensors used in pedology

Sensor technologies used in pedology can be broadly classified into optical, geophysical, elemental, moisture and remote sensing systems (Fig. 3). The major sensor technologies used in sensor-based pedology are compared in Table 1. These sensing technologies enable rapid, non-invasive and high-resolution assessment of soil properties by measuring electromagnetic, electrical, chemical, dielectric and topographic signals (16, 17, 19–21). Compared with laboratory analyses, sensor-based methods enable rapid data acquisition, increased spatial coverage and allow for precision soil mapping and

digital evaluation. The key characteristics, operating principles, applications, advantages and limitations of these sensor technologies are summarised in Table 1. Several technologies may be employed for sensing the soil properties; however, the selection of the most appropriate technology mainly depends on the type of soil property, depth of sensing, scales and objective of the study. A decision framework for selecting appropriate sensing technologies for different pedological applications are presented in Fig. 3. The potential for integrating multiple sensors through DSM and machine learning is illustrated in Fig. 4.

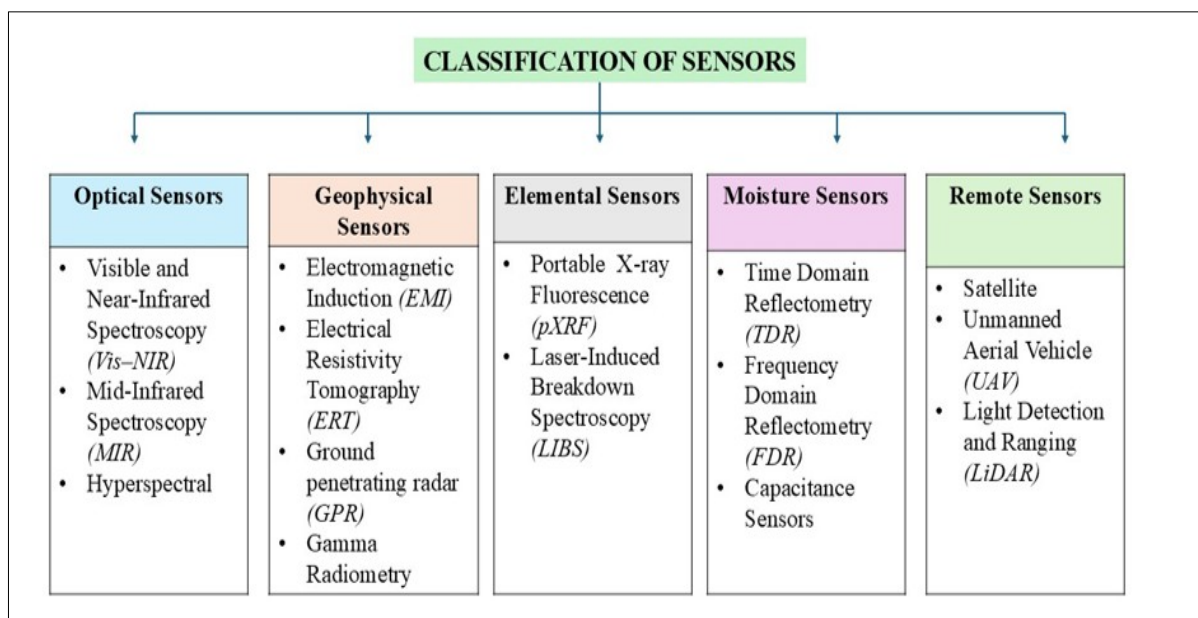
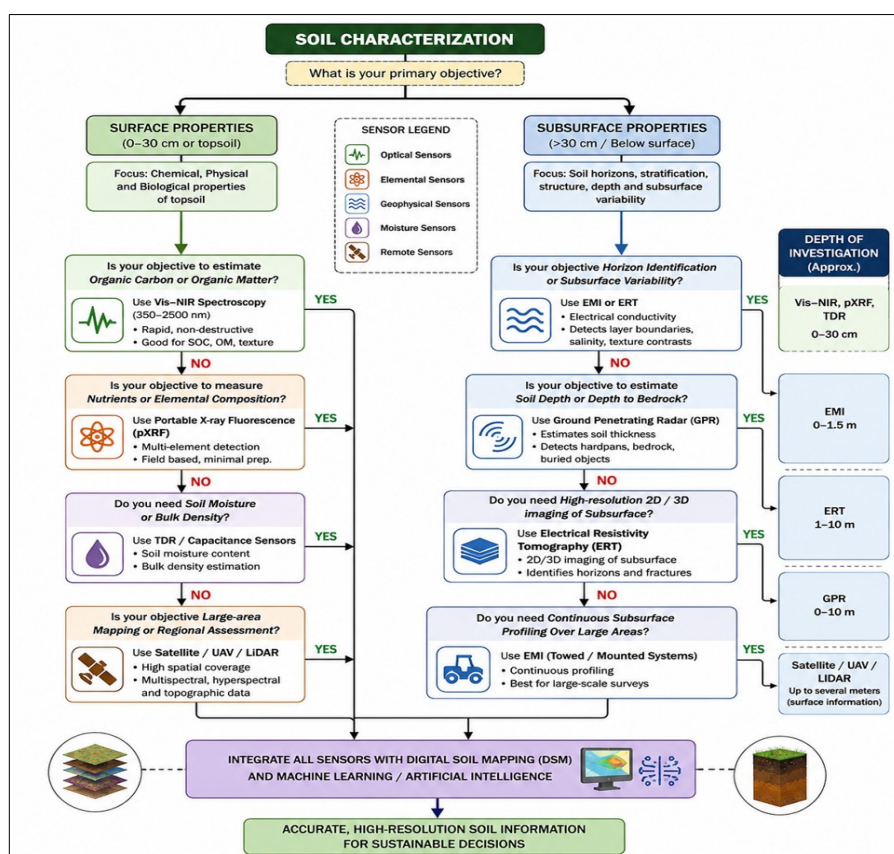


Fig. 3. Classification of sensors used in pedology.

Table 1. Comparison of major sensor types used in soil characterisation, including their principles, measurable soil properties, effective sensing depth, cost, advantages and limitations

Sensors	Principle	Soil properties	Typical sensing depth	Cost	Advantages	Limitations	References
Optical Sensors (Vis–NIR, MIR, Hyperspectral)	Measure reflected or absorbed electromagnetic radiation	Organic carbon, texture, clay minerals, moisture, salinity	Surface (0–5 cm; deeper only with collected samples)	Low -Medium	Rapid, non-destructive, high throughput	Sensitive to soil moisture and surface roughness	(16)
Geophysical Sensors (EMI, ERT, GPR, Gamma Radiometry)	Measure electrical and geophysical properties	Electrical conductivity, salinity, compaction, soil depth	EMI: 0–1.5 m; ERT: up to 20 m; GPR: 1–10 m (soil dependent)	Medium - High	Excellent subsurface characterisation	Requires calibration and skilled interpretation	(17)
Remote Sensors (Satellite, UAV, LiDAR)	Acquire information from airborne or satellite platforms	Soil moisture, landforms, vegetation, erosion	Large-area surface observations	Low -Medium	Large-area and repeated monitoring	Surface conditions and vegetation may influence measurements	(17)
Elemental Sensors (pXRF, LIBS)	Detect elemental composition using X-rays or laser plasma	Major and trace element, contaminants	Surface or laboratory soil samples	Medium - High	Portable, rapid multi-element analysis	Limited detection of light elements	(19, 20)
Moisture Sensors (TDR, FDR, Capacitance)	Measure dielectric properties of soil	Volumetric soil moisture	Point measurements (typically 0–100 cm depending on probe length)	Low -Medium	Continuous and accurate monitoring	Affected by soil texture and salinity	(21)

Vis–NIR: visible–near-infrared; MIR: mid-infrared; EMI: electromagnetic induction; ERT: electrical resistivity tomography; GPR: ground-penetrating radar; UAV: unmanned aerial vehicle; LiDAR: light detection and ranging; pXRF: portable X-ray fluorescence; LIBS: laser-induced breakdown spectroscopy; TDR: time-domain reflectometry; FDR: frequency-domain reflectometry.

**Fig. 4.** Decision framework for selecting appropriate sensors in pedology based on target soil properties, depth of investigation and research objectives.

Conceptual framework

Sensor-based pedology which represents a shift from traditional, labour-intensive soil survey methods to data-driven approaches for analysing soil variability is illustrated in Fig. 5. Conventional techniques using soil pits and laboratory analyses are accurate but limited by time, cost and limited spatial coverage. In contrast, DSM integrates proximal and remote sensing technologies with pedological knowledge, machine learning and

geospatial modelling to provide rapid, non-destructive and spatially continuous prediction of soil properties (7, 11, 22). This framework integrates soil forming factors, sensor observations, ground-truth data and machine learning predictive models to support accurate soil property estimation and DSM (9). Such interactions lead to variations in soil characteristics such as texture, structure and fertility. Traditional surveys provide detailed point observations but have limited spatial continuity.

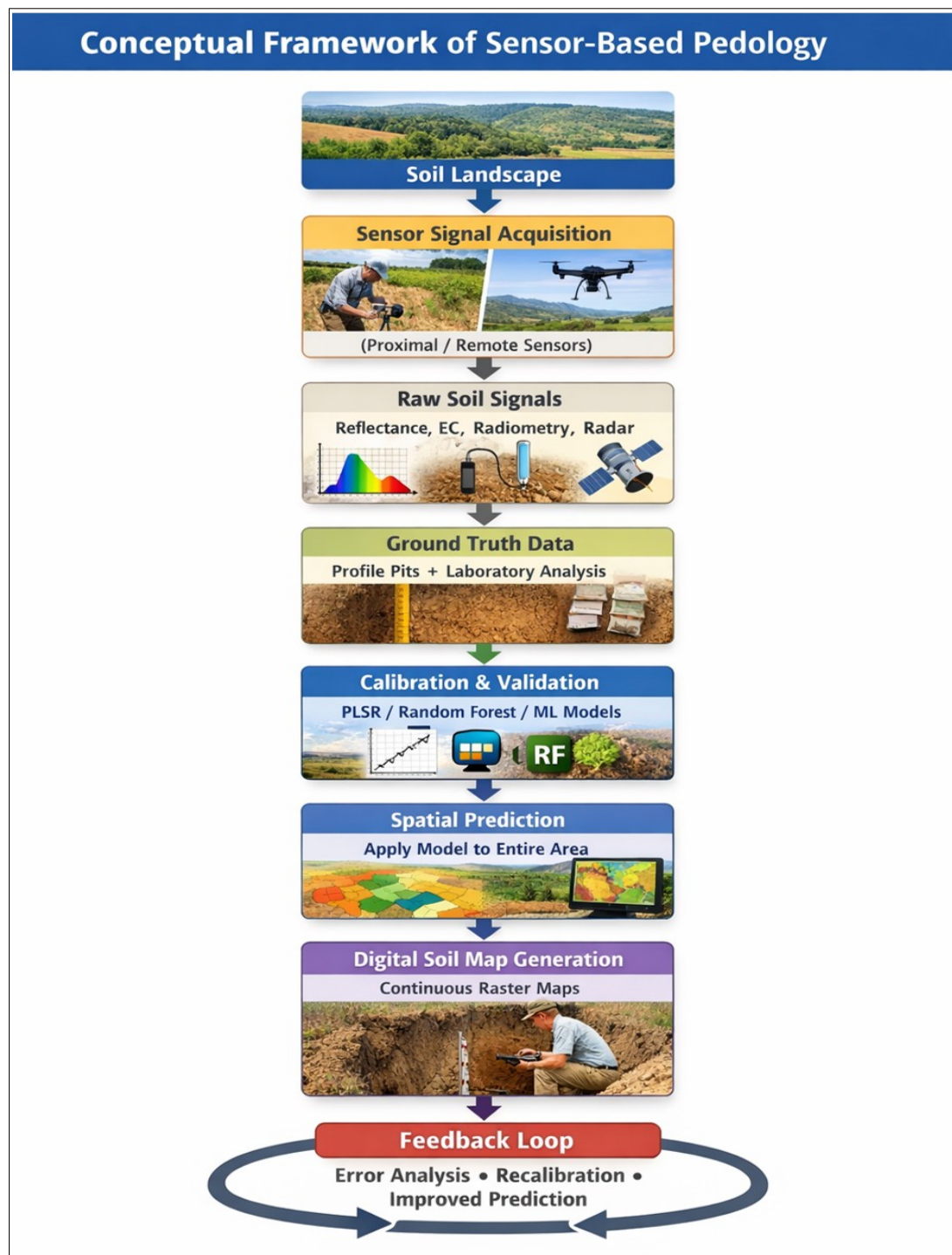


Fig. 5. Sensor-based pedology: From soil sensing to digital soil map.

The DSM takes advantage of the environmental covariates along with models that help predict soil characteristics in different landscapes (11). Signal acquisition by sensors refers to the process of acquiring soil information using proximal and remote sensors. Proximal sensors include electrical conductivity sensors and Vis–NIR spectrometers while remote sensors may be satellites or unmanned aerial vehicles. Sensor signals serve as proxies for soil characteristics including organic carbon, water, salts and minerals (22). Sensor outputs termed raw soil signals (e.g., spectral reflectance, electrical conductivity, gamma radiation, radar backscatter), are indirect and require further interpretation. They reflect soil–energy interactions rather than direct measurements. For example, reflectivity is dependent on organic matter and minerals while conductivity is a measure of salinity and moisture. In such a case, sensors must be calibrated with laboratory reference measurements (23). The ground-truth data are generated from soil samples and laboratory tests, e.g., soil pH and organic carbon contents. Although highly accurate, they have limited spatial coverage, making their integration with sensor data essential for effective soil mapping (11).

The relationship between sensor data and soil properties is modelled using statistical and machine learning techniques such as partial least square regression (PLSR), random forest and support vector machine (SVM) (24). Calibration uses paired sensor-lab data, while validation tests model accuracy. These models handle complex relationships and improve prediction performance (9). After calibration, models are applied across landscapes to generate spatial predictions, forming the basis of DSM. The DSM produces continuous, high-resolution maps of soil properties like organic carbon, moisture and nutrients (11). These digital maps support precision agriculture, land-use planning and environmental monitoring by enabling site-specific management. A feedback loop further refines models over time, improving accuracy and making DSM a dynamic system (9). Integrating sensor data with soil profile information enables robust calibration by linking laboratory measurements with sensor signals, ensuring accurate and scientifically reliable predictions (25). In summary, sensor-based pedology integrated with DSM technique is an innovative approach in which conventional knowledge is combined with current technologies to carry out effective and efficient soil assessment.

Soil properties mapped using sensors

In DSM and proximal soil sensing (PSS) soil properties are generally not measured directly as in conventional soil profile investigations. Instead, sensors detect electromagnetic (spectral reflectance), dielectric (soil moisture response), radiometric (gamma-ray emissions), or mechanical (penetration resistance) signals (26–29). Sensor-based approaches have also been applied for the assessment of important soil chemical properties. Visible and near-infrared spectroscopy can be used to estimate

soil organic carbon content (30) and soil pH (31). Electromagnetic conductivity sensing has been applied for mapping soil salinity and electrical conductivity (32), while Vis–NIR spectroscopy has been used to predict cation exchange capacity (CEC) and pH (33). Spectroscopic approaches have also been applied to estimate available nitrogen, phosphorus and potassium in soils (34). Sensor-based approaches can also be used to characterise soil morphological properties. The ERT and EMI can help identify soil horizon boundaries (35), while EMI and Vis–NIR spectroscopy can support the identification of clay accumulation and Bt (clay-accumulation B) horizons (36). The EMI can also be used to map saline layers at different depths (37), whereas ERT provides information on soil thickness and depth to bedrock (38). These sensor-derived signals are subsequently calibrated using statistical and machine learning approaches such as PLSR and other regression models to estimate with acceptable accuracy soil physical, chemical and morphological properties (Table 2–4). These spatially explicit soil-property predictions can be translated into crop-suitability assessment and site-specific management decisions, including nutrient and irrigation management, thereby supporting improved crop growth, yield and soil-health outcomes. For soil properties that vary continuously with depth, depth-function modelling can represent changes throughout the soil profile rather than restricting predictions to individual sampling depths. Such approaches allow sensor observations and soil-profile data to be modelled as continuous functions of depth, supporting the prediction of soil properties at unsampled depths and improving the representation of vertical soil variability. In addition to conventional accuracy metrics, uncertainty quantification is important for evaluating the reliability of sensor-derived soil-property predictions. Estimating prediction uncertainty can identify areas where model outputs are less reliable and where additional field observations or laboratory measurements may be required. Incorporating uncertainty estimates into DSM can therefore improve the reliability of pedological interpretation and subsequent soil-management decisions.

Pedological interpretation

Sensor-based approaches have significantly improved pedological interpretation, particularly in horizon differentiation and soil boundary delineation. Soil horizons can be identified by evaluating depth-dependent changes in sensor responses which reflect variations in soil properties such as organic matter, clay minerals, iron oxides, moisture content and elemental composition (10). Proximal sensors like Vis–NIR spectroscopy, electrical conductivity (EC), gamma radiometry and pXRF can detect the changes and hence allowing one to identify soil horizons. For example, the A horizon has higher organic matter response, B horizon has higher clay and iron oxide response and C horizon has parent material response. These depth-wise variations allow rapid identification of horizon boundaries, reducing reliance on extensive laboratory analysis (39). At the landscape scale, sensor-



based measurements facilitate soil boundary delineation and soil series discrimination by capturing spatial variability in soil properties. Continuous data obtained from proximal and remote sensing methods provide a significant advantage over traditional point-based observations (40). Integration of sensor data with GIS and DSM techniques enables the identification of homogeneous soil units and improves mapping accuracy. Spatial patterns derived from sensor signals

reflect variations in soil-forming factors, enabling accurate delineation of soil boundaries, discrimination of soil series. The integration of sensor-derived soil information with pedological interpretation can therefore improve the understanding of soil–plant relationships and support crop-suitability assessment, site-specific nutrient and irrigation management and interpretation of spatial differences in crop growth and yield.

Table 2. Physical properties mapped using sensors

Sl. No	Physical property	Sensors used	Principle	Spatial mapping	Accuracy (R^2 ; coefficient of determination)	Major use	References
1	Texture (Sand -Silt - Clay)	Vis–NIR Spectroscopy, EMI, Gamma-ray	Clay minerals show specific spectral absorption (2200 nm)	Field-scale continuous mapping using EMI or on-the-go spectroscopy	Sand: $R^2 = 0.81$ -0.90; Clay: $R^2 = 0.85$ -0.91	Soil classification, hydrological modelling, crop suitability	(26)
2	Bulk Density	Gamma-ray attenuation, Penetrometer, EMI (indirect)	Denser soil attenuates gamma radiation; higher resistance in compact soil	Point-based (penetrometer); interpolated maps	$R^2 > 0.65$	Root restriction detection, compaction assessment	(27)
3	Soil Moisture	TDR, Capacitance sensors, EMI, Microwave sensors	Water has high dielectric constant (~80) compared to soil (~3–7)	High-resolution spatial maps via EMI or remote sensing	$R^2 = 0.54$	Irrigation planning, drought monitoring, hydrology	(28)
4	Compaction	Cone Penetrometer, Mechanical resistance sensor, EMI	Increased penetration resistance in compact layers	Depth-wise profiling; spatial interpolation	$R^2 = 0.86$	Hardpan detection, tillage planning	(29)

Vis–NIR: visible–near-infrared; EMI: electromagnetic induction; TDR: time-domain reflectometry; R^2 : coefficient of determination.

Comparative limitations and sensor selection: The selection of an appropriate sensor should depend on the target soil property, required sampling depth, spatial coverage and available budget. Optical sensors such as Vis–NIR, MIR and hyperspectral systems are suitable for rapid and non-destructive assessment of surface soil properties such as soil organic carbon, texture and mineral composition, but their performance can be affected by soil moisture, surface roughness and calibration requirements. Geophysical sensors such as EMI and ERT are more suitable for assessing subsurface variability, electrical conductivity, salinity, compaction and soil depth, although their responses can be influenced by multiple soil factors and require careful interpretation. Elemental sensors such as pXRF and LIBS are useful for rapid elemental analysis, whereas TDR, FDR and capacitance sensors are particularly suitable for repeated soil-moisture monitoring at specific depths. Remote sensing provides broader spatial coverage and repeated observations but is mainly sensitive to surface conditions and may be influenced by vegetation cover. Therefore, relatively low- to moderate-cost optical and moisture sensors may be preferred for routine surface assessment and monitoring, while EMI and ERT are more appropriate when subsurface information and field-scale spatial variability are required. Combining complementary sensor technologies can provide more comprehensive soil characterization than relying on a single sensor family.

Table 3. Chemical properties mapped using sensors

Sl. No	Chemical property	Sensors used	Principle	Spatial mapping	Accuracy (R^2 ; coefficient of determination)	Major use	References
1	Soil Organic Carbon (SOC)	Vis–NIR Spectroscopy	Organic matter absorbs strongly in Vis–NIR region (400–2500 nm); dark soils show lower reflectance	On-the-go field spectroscopy; interpolated digital maps	$R^2 = 0.740$	Carbon stock estimation, soil quality assessment	(30)
2	Soil pH	Vis–NIR Spectroscopy	Indirect prediction via correlation with clay, OM and mineral composition	Field spectroscopy and geostatistical mapping	$R^2 = 0.81$ –0.85	Fertility management, liming requirement	(31)

3	Electrical Conductivity (EC)	EMI (EM38), Electrical Resistivity	Measures apparent soil conductivity influenced by salts, clay and moisture	Continuous field-scale spatial mapping	$R^2 = 0.88$	Salinity mapping, soil variability analysis	(32)
4	Cation Exchange Capacity (CEC)	Vis–NIR Spectroscopy	Strongly correlated with clay content and SOC; predicted via calibration models	Spectral prediction and kriging	$R^2 = 0.81–0.95$ (calibration)	Fertility evaluation, nutrient retention assessment	(33)
5	Available Nutrients (N, P, K)	Vis–NIR Spectroscopy, Gamma Radiometry (K)	Nutrients predicted indirectly via OM and mineral signals	Site-specific nutrient mapping	Available N: $R^2 = 0.90$; Available P: $R^2 = 0.82$; Available K: $R^2 = 0.94$	Precision nutrient management	(34)

Table 4. Morphological properties mapped using sensors

SI. No	Morphological property	Sensors used	Principle	Spatial mapping	Accuracy/Reliability	Major use	References
1	Hardpan / Compacted Layer	Penetrometer, EMI	Increased penetration resistance and density contrast	Depth-wise profiling; interpolated field maps	Moderate to high reliability; performance depends on depth and soil conditions.	Root restriction detection	(29)
2	Horizon Depth	EMI, Electrical Resistivity (ERT), Vis–NIR	Abrupt changes in EC, clay %, moisture and spectral reflectance indicate horizon boundaries	Transect-based continuous mapping; 2D resistivity sections	Qualitative; accuracy depends on sensor response, soil contrast and calibration	Soil classification, depth to subsoil mapping	(35)
3	Clay Accumulation (Bt Horizon)	EMI, Vis – NIR Spectroscopy	Increased clay shows higher EC and distinct spectral absorption features	Field-scale EC mapping and interpolation	Reliable where clay contrast is strong; performance depends on soil heterogeneity and sensor calibration.	Identification of argillic horizons	(36)
4	Salinity Layers	EMI (EM38), Electrical Resistivity	High salt concentration increases electrical conductivity	Continuous spatial salinity maps	High reliability; apparent electrical conductivity is strongly related to soil salinity.	Mapping saline horizons, reclamation planning	(37)
5	Depth to Bedrock	Electrical Resistivity Tomography (ERT)	Sharp resistivity contrast between soil and rock	2D/3D subsurface imaging	High reliability when a strong resistivity contrast exists between soil and bedrock.	Soil depth classification, land capability assessment	(38)

Validation and ground truth

In sensor-based soil studies, validation and ground-truthing are essential because sensors measure indirect signals rather than actual soil properties. These signals (e.g., spectral reflectance, electrical conductivity) must be calibrated against reference soil data obtained from profile sampling and laboratory analysis to develop reliable prediction models (41). Ground-truth data are typically collected from multiple soil horizons and landscape positions to ensure that the natural variability

of soil properties is adequately represented. Validation of the model is normally done through k-fold cross-validation where data is split into folds; the model is then trained on some and tested on others. Additionally, independent validation is carried out using a separate dataset not involved in model calibration providing a more unbiased evaluation of model performance (42). Several statistical metrics are used to evaluate prediction accuracy. The coefficient of determination (R^2) indicates how well the model explains variability in the observed data, while the root mean square error

(RMSE) quantifies the average prediction error. The residual prediction deviation (RPD), calculated as the ratio of standard deviation to RMSE indicate capability, where higher values indicate better performance. A comparison of prediction accuracies reported in representative sensor-based pedology studies is presented in Table 5.

Limitations of sensor based pedology

Although sensor technologies have significantly advanced soil characterisation, several limitations remain in their application for pedological assessment. Most sensors measure physical characteristics instead of soil characteristics directly; therefore, prediction relies on the calibration process using laboratory data. Prediction efficiency relies highly on the dataset used for calibration. The developed models might not give good predictions in other regions due to differences in soil properties such as texture, composition and organic content in the soils (15). Environmental variables also influence the sensor efficiency in predicting the soil characteristics. Soil moisture affects the spectral reflectance and electrical conductivity resulting in inefficient prediction if calibration is not properly done (13, 14). High spatial variability soils also require extra sampling. ERT, GPR and pXRF are efficient, but they are costly and hence cannot be used in many developing countries. Calibration and regular maintenance are required since sensor efficiency changes with time. Consequently, data obtained from sensors must always be used in conjunction with traditional methods of soil science. Further research

efforts should concentrate on standardisation of calibration procedures, multi-sensor integration and creation of soil spectra libraries.

Emerging trends in sensor-based pedology

The rapid development of sensor technologies, AI, machine learning and geospatial analysis is transforming sensor-based pedology into a more data-driven and spatially explicit discipline. Recent developments are increasingly focused on integrating complementary sensing technologies, improving the interpretation of complex soil datasets and extending soil observations across larger spatial and temporal scales. These emerging approaches have the potential to improve soil characterisation and pedological interpretation, although their maturity and practical applicability vary among technologies.

Multi-sensor integration and sensor fusion

The integration of multiple sensor types, including optical, geophysical, elemental and remote sensing technologies, is an important emerging trend in soil characterisation (43). Different sensors provide complementary information on soil physical, chemical and subsurface characteristics and their integration can provide a more comprehensive representation of soil variability than individual sensors. Multi-sensor approaches can therefore improve the spatial representation of soil properties and support more detailed pedological interpretation. However, differences in measurement principles, spatial resolution, sensing depth and calibration requirements need to be considered when combining datasets (44).

Table 5. Comparison of prediction accuracy reported in representative sensor-based pedology studies

Sensor	Soil property	Region	Validation method	R ² (coefficient of determination)	References
Vis–NIR	SOC	Australia	Cross-validation	0.86	(13)
Vis–NIR	Clay	Sweden	Independent validation	0.81	(14)
EMI	EC	Europe	Independent validation	0.84	(17)
Machine learning + Digital soil mapping (ML+DSM)	Multiple properties	Australia	Cross-validation	0.82–0.93	(18)
Visible Near Infra Red + Machine learning (Vis–NIR + ML)	Soil properties	South Korea	Cross-validation	0.88	(24)
Proximal sensing	Soil health	China	External validation	0.85	(43)
Remote sensing	SOC	Australia	External validation	0.79	(44)

Vis–NIR: visible–near-infrared; SOC: soil organic carbon; EMI: electromagnetic induction; EC: electrical conductivity; ML: machine learning; DSM: digital soil mapping.

Machine learning and explainable artificial intelligence

Machine learning and deep learning approaches, including random forest, SVM, artificial neural networks and convolutional neural networks, are increasingly being applied to interpret sensor data and generate high-resolution soil maps. These methods are particularly useful for modelling complex and nonlinear relationships between sensor observations and soil properties (45). An emerging development is the use of explainable artificial intelligence (XAI), which can improve the interpretability of model predictions by identifying the relative contribution of sensor-derived variables and environmental covariates. This can strengthen the connection between data-driven predictions and pedological interpretation.

Unmanned aerial vehicle, hyperspectral, light detection and ranging and satellite-based soil observation

The UAVs, hyperspectral imaging, LiDAR and high-resolution satellite observations are expanding the spatial and temporal capabilities of sensor-based soil assessment (44, 46). The UAV platforms can provide high-resolution field-scale observations, while hyperspectral sensing provides detailed spectral information that can be related to soil properties (44, 46). The LiDAR contributes high-resolution information on terrain morphology, which can support the interpretation of soil–landscape relationships. High-resolution satellite observations further enable soil variability to be assessed across larger areas (46). The integration of these remotely sensed datasets with proximal sensing and field observations can improve landscape-scale soil mapping, although vegetation cover, surface conditions and the availability of reliable field observations influence their performance (44, 46).

Internet of things, cloud computing and real-time soil monitoring

The integration of IoT sensors, cloud computing and real-time data acquisition is enabling a transition from periodic soil assessment towards continuous soil monitoring. Connected sensors can provide repeated observations of soil moisture, temperature, electrical conductivity and other soil variables, while cloud-based platforms facilitate data storage, processing and integration. Such systems can provide temporally dynamic soil information relevant to precision agriculture, irrigation management and climate-smart land management. However, practical implementation depends on sensor reliability, connectivity, data interoperability, energy requirements and effective management of large volumes of sensor data (6).

Limitations and future directions

Although sensor technologies have made substantial advances, several limitations continue to constrain their wider application in pedology. One of the primary challenges is the transferability of calibration models, whereby prediction models developed for one area may perform poorly in another because of differences in soil

mineralogy, texture, organic matter and climatic conditions (18, 43). The limited availability and geographic representativeness of soil spectral libraries also constrain the broader application of sensor-based prediction models, particularly in tropical and subtropical regions (6). Future research should therefore prioritise the development of regionally representative and interoperable soil spectral libraries covering diverse soil types, depths and environmental conditions. Another important limitation is the need for reliable uncertainty quantification and long-term field validation. Sensor-derived soil predictions should be accompanied by uncertainty estimates to identify areas where predictions are less reliable and where additional field observations are required. Future studies should integrate uncertainty estimation with cross-validation, independent validation datasets, spatial uncertainty mapping and targeted additional sampling to quantify and reduce prediction uncertainty. Long-term field experiments across contrasting soil types and environmental conditions should also be conducted to evaluate sensor stability, model transferability and operational performance over time.

Cost and operational complexity represent additional barriers to the adoption of advanced sensing technologies. Future research should therefore evaluate the cost-effectiveness of different sensor systems by comparing equipment costs, measurement time, maintenance requirements, data-processing demands and the accuracy obtained for specific soil properties. Development of low-cost and portable sensing systems, together with automated calibration procedures, could improve accessibility for soil survey organisations and agricultural practitioners. Standardisation is another important research priority. Future studies should develop standardised protocols for sensor measurement, calibration, validation, data preprocessing and reporting of prediction uncertainty. Open-access soil databases and greater international collaboration and data sharing could further improve the representation of diverse soils in digital soil information systems. The integration of sensor observations with conventional field and laboratory measurements should remain an important component of future soil surveys, particularly where sensor predictions require independent validation and pedological interpretation. Addressing these limitations will improve the reliability, transferability and practical applicability of sensor-based pedology.

3. Conclusion

Sensor-based pedology has emerged as an effective approach for improving soil characterisation by integrating traditional pedological knowledge with advanced sensing technologies and digital analytical tools. Optical, geophysical, elemental, moisture and remote sensing techniques provide rapid, non-destructive and spatially continuous information on soil properties, overcoming several limitations of



conventional soil survey methods. The integration of these technologies with Geographic Information Systems (GIS), digital soil mapping (DSM), machine learning and artificial intelligence (AI) has enhanced the prediction of soil physical, chemical and morphological properties across diverse landscapes. However, sensor-derived information remains dependent on appropriate calibration, validation and expert interpretation because environmental conditions, soil heterogeneity and instrument variability can influence prediction accuracy. Therefore, sensor technologies should complement rather than replace conventional pedological investigations. Continued advances in multi-sensor integration, high-resolution remote sensing, cloud computing and intelligent data analytics, together with standardised calibration procedures, expanded soil spectral libraries and improved model transferability, can strengthen the reliability and broader applicability of digital soil assessment. Overall, integrating modern sensing technologies with conventional pedology provides a robust framework for sustainable soil resource assessment, precision agriculture, environmental monitoring and informed land-use planning, with potential to support improved soil health and long-term agricultural sustainability.

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Authors' contributions

GK wrote the manuscript. PCNM provided guidance in writing and reviewing the manuscript. JP, RV and KP reviewed the manuscript. All authors have read and approved the final manuscript.

Compliance with ethical standards

Conflict of interest

Authors do not have any conflict of interests to declare.

Ethical issues

None

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