Environmental Science & Technology

pubs.acs.org/est

Critical Review

A Critical Review for Real-Time Continuous Soil Monitoring: Advantages, Challenges, and Perspectives

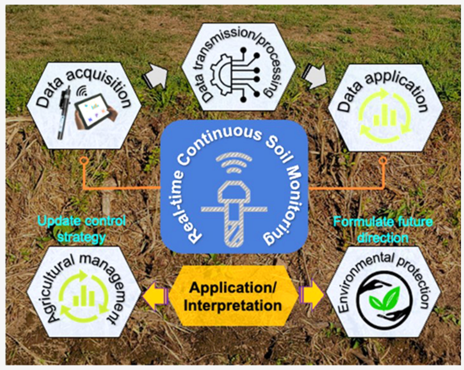
Yingzheng Fan, Xingyu Wang, Thomas Funk, Ishrat Rashid, Brianna Herman, Nefeli Bompoti, MD Shaad Mahmud, Maria Chrysochoou, Meijian Yang, Timothy M. Vadas, Yu Lei, and Baikun Li*

Cite This: https://doi.org/10.1021/acs.est.2c03562

Read Online

ACCESS | Metrics & More | Article Recommendations | Supporting Information

ABSTRACT: Most soil quality measurements have been limited to laboratory-based methods that suffer from time delay, high cost, intensive labor requirement, discrete data collection, and tedious sample pretreatment. Real-time continuous soil monitoring (RTCSM) possesses a great potential to revolutionize field measurements by providing first-hand information for continuously tracking variations of heterogeneous soil parameters and diverse pollutants in a timely manner and thus enable constant updates essential for system control and decision-making. Through a systematic literature search and comprehensive analysis of state-of-the-art RTCSM technologies, extensive discussion of their vital hurdles, and sharing of our future perspectives, this critical review bridges the knowledge gap of spatiotemporal uninterrupted soil monitoring and soil management execution. First, the barriers for reliable RTCSM data acquisition are elucidated by examining typical soil monitoring techniques (e.g., electrochemical and spectroscopic sensors). Next, the prevailing challenges of the RTCSM sensor network, data transmission, data processing, and personalized data management are comprehensively discussed. Furthermore, this review explores RTCSM data application for updating diverse strategies including high-fidelity soil process models, control methodologies, digital soil mapping, soil degradation, food security, and climate change mitigation. Finally, the significance of RTCSM implementation in agricultural and environmental fields is underscored through illuminating future directions and perspectives in this systematic review.



KEYWORDS: *real-time continuous soil monitoring, soil data acquisition, soil data application, agricultural and environmental practices*

1. INTRODUCTION

Through complex interactions with air, water, nutrients, and organisms, soil plays a vital role on the earth which includes storing water and nutrients, sustaining food security, contributing to biodiversity, supplying antibiotics used to fight diseases, improving resilience to floods and droughts, and protecting the planet from climate change.[1] The United States Environmental Protection Agency (U.S. EPA) has prioritized the promotion of soil health with respect to nutrient cycling, water infiltration, bioremediation, contamination removal, and carbon sequestration.[2] The Food and Agriculture Organization (FAO) also underscores the significance of soil health to maintain a diverse community of soil organisms, to control plant disease, insect and weed pests, and ultimately to improve crop production.[3] Nevertheless, soil health has been jeopardized globally by numerous pollution sources including industrial chemicals, domestic and municipal wastes, agrochemicals, pharmaceuticals, pathogens, and petroleum-derived products.[4] These pollutants are released to the environment either accidentally (e.g., oil spills and/or leaching from landfills[5]) or intentionally (e.g., the use of fertilizers and pesticides,[6] irrigation with untreated wastewater,[7] and land application of biosolids[8]). In the past decade, emerging contaminants (ECs) such as pharmaceuticals, endocrine disruptors, hormones, and microplastics have drawn high concern in terms of soil usage and food safety.[9−12] Given the significance of sustaining soil health and fertility and minimizing soil contamination, continuous monitoring and expeditious assessment of soil quality, soil nutrient/contaminant dynamics, and soil mechanics become essential.

Traditional soil measurement techniques are primarily laboratory-based analysis such as ion chromatography (IC), inductively coupled plasma-optical emission spectrometry/mass spectrometry (ICP-OES/MS), gas chromatography−mass spectrometry (GC-MS), and chemiluminescence.[13,14] Although these methods have high accuracy and low detection limit, the time and effort associated with the sampling, transfer, pretreatment, and analysis processes are enormous. Furthermore, these methods are unable to obtain soil data in a real-

Received: May 17, 2022
Revised: August 6, 2022
Accepted: September 9, 2022

time, continuous, and in situ mode, resulting in information deficiency hindering decision-making for precaution, prevention, and management. Despite the era of "Big Data" renders a unique opportunity to improve the efficiency of soil surface analysis,[15] obtaining a large amount of soil data is still dependent upon satellites,[16] manned aircrafts, and unmanned aerial vehicles (UAVs),[17,18] which are unable to obtain profiling data along soil depth or subdivide fields into small areas or points and thus suffer from low-resolution data sets.[19] Meanwhile, soil complexities including soil texture (e.g., sand, silt, and clay) and soil properties (e.g., soil porosity, density, pH, inorganic/organic matters, and water tension) interfere with soil monitoring and impair monitoring accuracy, thus posing challenges for soil data acquisition, data collection, data processing, and data interpretation.[20,21] Last two decades have seen 4021 publications on the soil monitoring using sensors (Figure 1), covering broad areas ranging from soil data/information, soil environmental management, erosion control, to soil organic management and constitutive management.[22−25] However, these studies barely considered the chain and irreversible effects that transient soil pollution (e.g., heavy metals discharge, pesticides spray, excess fertilization, and acid rain) can cause. Such neglect stems from the lack of reliable, swift, and continuous assessment tools and devices, as corroborated by 558 publications about real-time monitoring, among which only 67 publications relate to the topic of continuous soil measurement using real-time monitoring devices (Figure 1). Such lack of knowledge creates an outstanding gap between the perception of spatiotemporal variation of soil quality and execution of soil management and control and fails to provide continual information essential for formulating up-to-date decisions.[26,27]

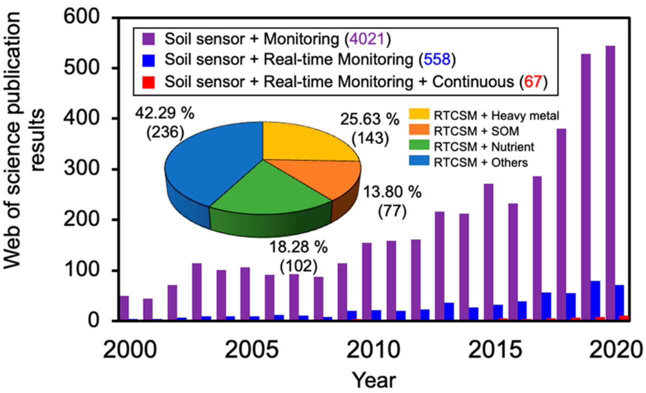


Figure 1. Number of publications in soil monitoring based on Web of Science with the keywords "soil sensor", "monitoring", and "real-time monitoring" and "continuous". The inset shows the subtopic results from 2000 to 2020 with the keywords specified (details of the literature search are described in Text S1).

Hence, this review seeks to bridge this gap by considering the importance of real-time continuous soil monitoring (RTCSM) methodology, which is defined as uninterruptedly monitoring soil physicochemical parameters (e.g., soil moisture and nutrient), soil biochemical parameters (e.g., microbes and enzymes) and soil contaminants (e.g., heavy metal and ECs) and continuously obtaining the measured data in a real-time in situ mode. A panoramic vision of RTCSM application is demonstrated based on the close-loop interactions among these parameters and contaminants in the soil environment (Figure 2a). For example, soil organic carbon (SOC) contributes to nutrient retention and turnover and affects contaminant degradation and climatic conditions including temperature, CO_2, and soil aeration (oxygen level) (Figure 2a).[28−30] Soil nitrogen can be converted to N_2, N_2O, and NH_3 through denitrification and ammonification, playing a vital role in soil fertility and climate change.[31−34] The phosphorus cycle via mineralization, adsorption, desorption, and dissolution in the soil pool directly affects its transformation into forms that plants can absorb.[35−37] Recalcitrant ECs deposited to soil particles can migrate through soil unsaturated zones to groundwater, and have adverse effects on human health and aquatic ecosystems.[9,38,39] In contrast, some of soil physical parameters (e.g., soil temperature, texture, porosity, and density) are not necessary to be timely and continuously captured and belong to the non-RTCSM category, since these parameters normally stabilize in a reasonable range without drastic fluctuation, and will not cause instantaneous or chain effects to the soil environment (Figure 2a). To elucidate such complex interactions and sustain soil development, it is vital to identify soil information with high need of RTCSM, develop reliable and durable RTCSM techniques, acquire various types of continuous sensor data through wireless network, integrate these RTCSM data with non-RTCSM data for data processing and interpretation, and eventually execute efficient control methodologies (Figure 2a).

This critical review focuses on advancing the understanding of RTCSM at scientific level toward the panoramic and profiling-based soil information analysis and bridging the gap between time-delayed detection and real-time continuous self-parameter tuning for uncertainty variates in agricultural and environmental practices (Figure 2b). Specifically, we first evaluate the challenges and bottlenecks of state-of-the-art RTCSM sensing technologies to promote accurate real-time continuous and personalized data acquisition. We then compare existing approaches of RTCSM data collection and data processing and elaborate the urgent need of reliable wireless soil network (WSN) and machine learning (ML) algorithms. Subsequently, we explore data application with soil process modeling, system control, and soil digital mapping as distinct examples. In addition, we illustrate RTCSM technologies for diverse environmental and agricultural applications to transfer real-time soil data from scientific discoveries to real-world practices (Figure 2b). Finally, we lay out strategic outlook for future directions of RTCSM and highlight its potential in four key domains of environmental and agricultural fields including soil sensors, soil data, soil environment, and soil knowledge advancement.

2. CURRENT STATUS AND MAJOR CHALLENGES OF RTCSM DATA ACQUISITION

Data acquisition is the first step for RTCSM, in which electrochemistry and spectroscopy are two main techniques applied to monitor and examine spatial and temporal variability of a broad spectrum of soil constituents (e.g., minerals, soil organic matters (SOM), gas, and water), soil contaminants (e.g., nutrients and heavy metals), and soil properties (e.g., pH and moisture). Both methods possess unique characteristics including nondestructive measurement, rapid response, high sensitivity and selectivity. Nevertheless, both techniques suffer from severe bottlenecks toward RTCSM. Specifically, electrochemical sensors require frequent calibration due to the interference coming from complicated soil chemical and

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

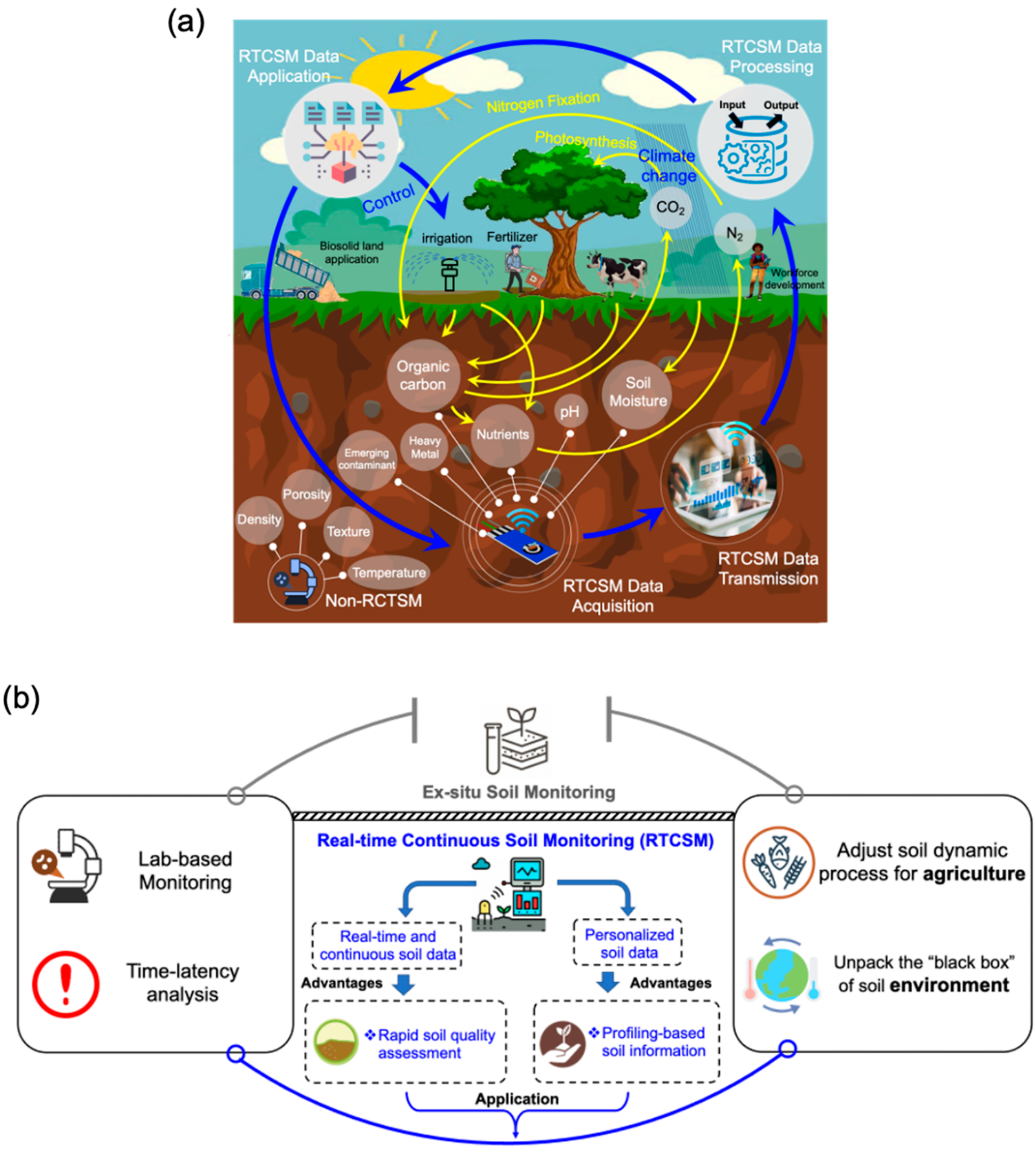


Figure 2. (a) Comprehensive scope of RTCSM in the soil environment. (b) Scientific value of RTCSM to bridge the current knowledge gap.

biological contents (e.g., microbes, protons, and inorganic/organic compounds) and varying soil environment, while the design of spectroscopic sensors neglects the interferences caused by the external soil environmental factors (e.g., soil texture, bulk density, and soil moisture) and the reflectance of electromagnetic energy, which diminish the amplitude of scanning reflectance from soil surface. In this section, we methodically discuss state-of-the-art soil sensing technologies and their specific barriers as the RTCSM devices from the perspective of internal sensor technical principles and external soil environment influences.

2.1. Major Challenge of Electrochemical Technique as RTCSM Sensors. *2.1.1. Potentiometric Sensors.* Potentiometric sensors can selectively detect the target ions and convert the ion activity into an electrical potential based on the Nernstian equation.[40−42]

$$\text{EMF (electrical potential)} = E^0 \text{ (standard potential)} + \frac{2.303RT}{z_1F}\log a_1 \text{ (primary ion activity)}$$

As a point-based soil sensing technique, potentiometric sensors are not affected by external physical factors (e.g., soil porosity and soil texture) and have gained high attention for real-time and continuous soil monitoring (Table 1). Nevertheless, potentiometric sensors still encounter several key barriers as the RTCSM devices (Figure 3). First, potentiometric sensors must contact water solution as the medium for the target analyte (ion), which results in the inability to monitor ions absorbed by soils.[42] Some potentiometric sensors (e.g., poly(3-octylthiophene) and molybdenum disulfide (POT-MoS_2) soil sensor and SiO_2/Si diaphragm sensor) suffer from severe reading decline (>50%) when the volumetric soil water content (%) drops below 15%.[43,44] Second, pH and temperature can deviate the Nernst slopes of potentiometric sensors, and thus impair the sensor sensitivity (mV/dec). For example,

Table 1. Major Characteristics of Current Soil Sensing Techniques

detection method	detection technique	type of analyte	specific analyte	calibration/materials[a]	spectral wavelength/detection range	main challenges as RTCSM	ref
electrochemical techniques	potentiometry	general soil parameter	pH moisture	polyaniline	0−100%	soil pH, soil temperature, soil particle fouling	96,97
		macronutrient	N; P; K	molybdenum; thread-based; cobalt-based	1−1500 ppm		44,98,99
		heavy metal	Pb^{2+}; Cu^{2+}	biofilm-populated	10−100 ppm		100,101
	voltammetry	general soil parameter	pH	screen-printed electrode	3.5−9	soil moisture, soil particle fouling	102
		macronutrient	N; K	Nafion-modified; silver particle−polymethacrylic acid-based	1−1250 ppm		50,103
		heavy metal	Pb^{2+}, Cd^{2+}	Fe_3O_4/multiwalled carbon nanotube/laser scribed graphene composites	100−2000 ppm		104,105
	conductometry	general soil parameter	pH; moisture	polyaniline/SU-8	2−10, 0−100%	soil particle fouling	54,106
		macronutrient	N; K	GO-PEDOT-NFs; zeolite-modified	0.44−442 ppm		55,107
		heavy metal	Hg^{2+}	planar thin-film interdigitated electrodes	2−250 ppm		108
spectroscopic techniques	IR	general soil parameter	moisture; SOM, pH	LR; PLS, SVM	350−2500 nm	soil texture; soil surface roughness, soil water content	109−111
		macronutrient	N; P; K	LR; PLS, ANN	1100−2498 nm		112,113
		ECs	PCBs; PAHs	LR, PLS; RF	305−2500 nm		114,115
		heavy metal	As, Cu, Pb, Cr, Zn, Cd	ANN, RF; PLS	350−2500 nm		116,117
	Raman	general soil parameter	SOM	PLS	180−3200 cm^{-1}	soil water content (%), soil texture	118
		macronutrient	N; P; K	LR; PLS, SVM	400−1800 cm^{-1}		119,120
		ECs	PCBs; PAHs	LR; PLS, SVM	400−1800 cm^{-1}		121,122
	LIF	general soil parameter	moisture; SOM, pH	LR; PLS	500−850 nm	soil density, soil hydraulic conductivity	91,123
		macronutrient	N; P; K	LR, PLS; Lasso; GPR	335 nm		124,125
		ECs	PAHs	LR; PLS	266 nm		126

[a]LR, linear regression; PLS, partial lease squares; ANN, artificial neural network; RF, random forest; Lasso, least absolute shrinkage and selection operator regression; GPR, Gaussian process regression; SVM, support vector machine.

copper-based potentiometric sensors exhibited a variation of 22 and 34% at pH values of 5 and 4.65, respectively.[45] The measurement error for 50 mg N/L using NH_4^+ ion selective electrodes (ISE) was 16.20% at the temperatures of 4 and 36 °C when the NH_4^+ content was calculated based on the calibration curve obtained at 20 °C.[46] Third, the fouling on the sensor surface caused by the attachment of inorganic/organic compounds and microbes in soil eventually diminishes the sensor durability, since the attachment forms an ion resistive layer on the sensor surface, inhibits the ion transport process, and deteriorates soil sensor's response and accuracy.[47,48] Fourth, current soil potentiometric sensors have been developed mainly for soil nutrient monitoring, such as poly(3-octylthiophene) potentiometric sensor for nitrate,[44] cobalt potentiometric sensor for phosphate,[49] and Nafion-modified potentiometric sensor for potassium,[50] but are scarce for monitoring ECs (e.g., per- and polyfluoroalkyl substances (PFAS)) and SOM (Table S1). The possible reason is that the detection limit (normally, 1 g/kg) of potentiometric sensors cannot meet the ultralow concentration requirement (<50 mg/kg) of ECs in soil, since lipophilic components (e.g., ionophores in ISEs) continuously leach from the sensor polymer matrix over time and lower the sensors' accuracy and sensitivity.[40,51] Until now, the only method reported for SOM monitoring is to convert the carbon compounds in soil to CO_2 and then the resulting CO_2 concentration is measured using potentiometry,[52] meaning that SOM cannot be real-time continuously monitored using the potentiometric method, and the conversion process inevitably causes large concentration deviations (>30%) for the measured results. Given these barriers, potentiometric sensors are still in the early development stage and have not become a mature in-field monitoring device (Table S1).

2.1.2. Voltammetric and Conductometric Sensors. The mechanism of voltammetry is to analyze the soil chemical reaction on the electrode by recording the current over the potential applied, while the mechanism of conductometry is to measure the electric response (e.g., impedance) by applying a small amplitude AC (alternating current) in a wide range of frequencies.[53,54] Despite both techniques have been used to measure soil extraction solutions (e.g., 21.039 μA/ppm for Nafion-modified voltammetric sensor[50] and 52 μS/pH for polyaniline conductometric sensor[55]), they suffer from poor repeatability caused by the unpredictable redox reactions of the voltammetric sensor components and the interferences from soil chemical properties (e.g., soil salinity and SOC). For example, graphene foam−titanium voltammetric sensors are incapable of continuous measurement and require frequent replacement of the sensor components in the probe.[56] The double layer capacity of conductometric sensors and the electrode polarization disturb the sensing reaction, resulting in their ineffectiveness in distinguishing between signals and noise

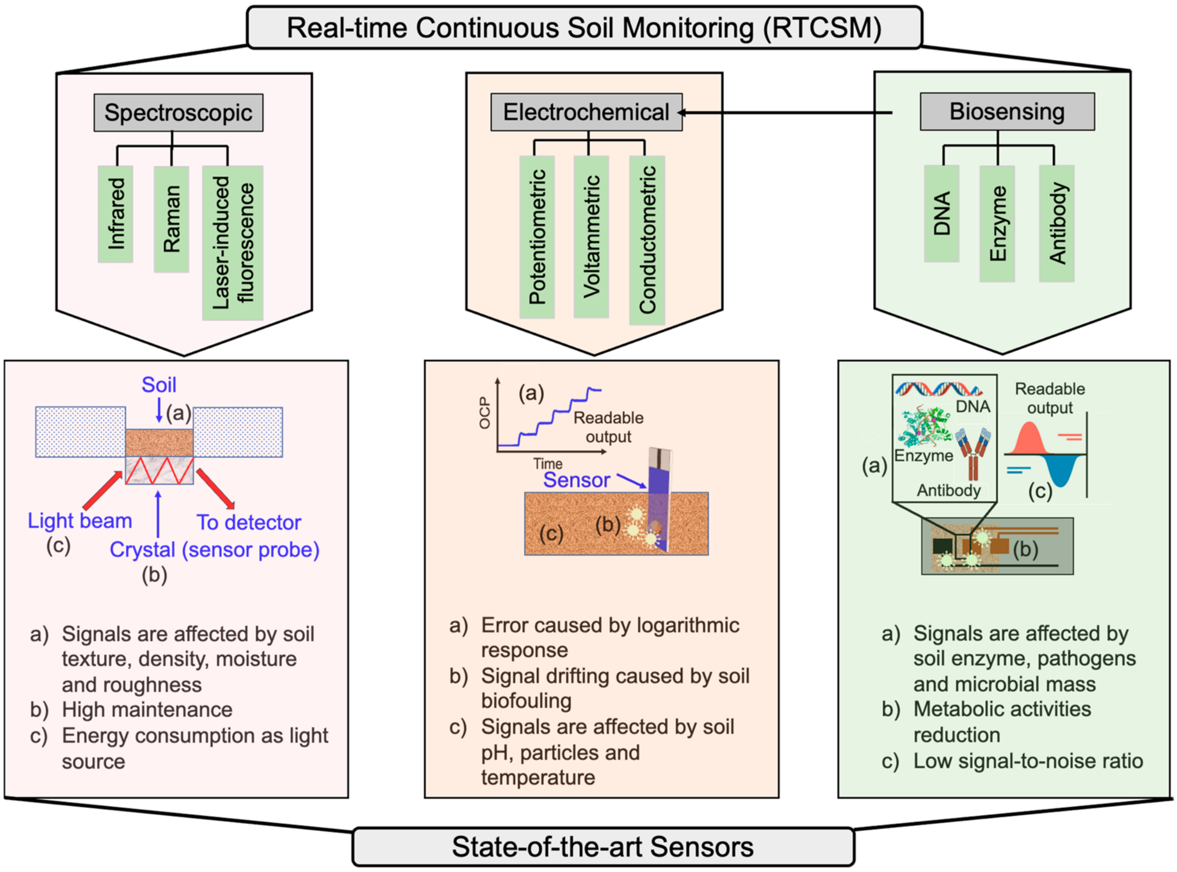


Figure 3. Classification of soil sensors for real-time continuous soil monitoring (RTCSM) and major challenges of state-of-the-art sensing technologies for RTCSM.

(>2%).[54] Some novel materials (e.g., novel Nylon-6,6-modified graphite HB pencil electrode,[57] gadolinium niobate nanoparticles,[58] and zeolite[59]) have been developed to enhance the repeatability (RSD < 5%) of voltammetric and conductometric sensors. However, biofouling and unpredictable fluctuations in pH, temperature, and pressure undermine the interpretation of sensor signals collected in the soil field (Table 1).[54] For example, as the dynamic parameter in soil environment, temperature is related to the enthalpy change of the voltametric voltage sweeping process, which can cause the deviation of voltammetric signals in field tests. Furthermore, in situ voltammetric and conductometric sensors exposed to soil particles suffer from biofouling as a result of the adhesion of organic/inorganic compounds and/or soil particles, and thus vitiates the sensitivity and response and shortens the lifespan to a few hours or couple days.[60,61] As yet these challenges have not been solved to make these types of sensors as an efficient and reliable in-field RTCSM device, and voltammetric and conductometric sensors possess high accuracy (R^2 > 0.9) only in lab environment (Table S1).

2.1.3. Biosensors. Electrochemical biosensors contain biological recognition elements (e.g., microorganisms and enzymes) that specifically reacts with the target of interest, and then converts such changes into electrical signals (e.g., current, voltage, and resistance).[62] Biosensors can achieve low detection limits (<0.05 mg/L) for contaminants (e.g., trichloroethylene) due to the selective binding of the targets (Table 1).[63] Various electrochemical biosensors (e.g., immunosensors and DNA sensors) have been developed to monitor toxins (e.g., cyanobacteria and photosynthetic microalgae) and organic pollutants (e.g., per- and polyfluoroalkyl substances (PFAS) and polycyclic aromatic hydrocarbons (PAHs)) in aquatic environments.[64−66] Nevertheless, application of electrochemical biosensors in the soil environment is utterly challenging due to its poor sensitivity (<10 mV/dec) ascribed to the unstable biorecognition elements on the surface of biosensors.[67,68] For example, soil enzyme and microbial biomass can attach to the surface of biosensors, thus causing inconsistent binding for the target analyte, and ultimately result in unstable biorecognition (Figure 3).[69] One potential application of electrochemical biosensors in the soil environment is to detect agrochemicals, such as pesticides, herbicides and fertilizers. Specifically, biosensors have been used for the determination of organophosphate and carbamate pesticides based on the inhibition of cholinesterase activity.[70] However, the analyte needs certain incubation period (e.g., minutes to hours) to inhibit the activity of the immobilized enzyme, resulting in steadily declining signals over time (e.g., hours).[71] Although the detection of carbamate pesticides demonstrated a good stability by the enzymatic reactions of acetylcholinesterase (AChE),[72] the weak signals (SNR (signal-to-noise) < 3) inhibited the capability of such biosensors to determine low analyte concentrations (<0.05 mg/L) in soil. Thereby, additional effort should be made to develop highly sensitive devices with high SNR ratios (>5) to enhance the accuracy of agrochemical detections.

2.2. Major Challenges of Spectroscopic Techniques as RTCSM Sensors. Spectroscopy is another promising technique for the continuous soil monitoring due to their fast, environmental-friendly, nondestructive, and repeatable

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

properties.[73−76] Infrared (IR) spectroscopic technique has been used as the real-time continuous and spatiotemporal measurement tool for soil quality/health monitoring.[77−79] Given the impact of different vibrational energies from the spectra, the IR spectroscopy is sensitive to varying soil parameters (e.g., pH, soil moisture, SOM) and environmental conditions (Figure 3).[80,81] Although acquiring the spectroscopic data (wavelengths) is a feasible and rapid procedure, many external soil environmental factors (e.g., soil texture, soil surface roughness, and atmosphere condition) have been found to interfere with soil surface measurements in the scanning area (Table 1).[82,83] Specifically, large particles reflect less energy because of larger void spaces between particles and cause additional scattering and absorption of light.[84] The energy reflected from the soil surface declines with soil roughness, due to the light diffusion on rough soil surface.[85] The fluctuation of the local atmosphere (e.g., water vapor and CO_2) can cause the deviation of the actual sample spectrum within the time lapse of scanning.[86] Soil moisture can also interfere soil parameter measurements, and the effect of soil moisture on SOC measurements has been investigated.[87,88] To overcome this challenge, a normalized index based on soil-moisture has been developed, which is a new criterion for quick assessment of surface soil moisture from reflectance data in the solar spectral range (250−2500 nm).[89]

In terms of other spectroscopic techniques (e.g., Raman and laser-induced fluorescence (LIF)), their application for RTCSM remains limited, as well.[90−93] For example, the LIF fluorescence intensity is affected by numerous factors such as photophysical properties of analytes, soil density, and soil hydraulic conductivity (Figure 3).[91] Soil particles may impede the adsorption of the analyte onto the Raman sensor substrate, which requires surface functionalization of the substrate.[94] Once the calibration curve matrix (intensity−concentration) is obtained for each soil type, these spectroscopic techniques can be applied over a wide range of soil types using multivariate statistical models (e.g., partial least-squares regression (PLSR), principal component regression (PCR), artificial neural network (ANN), Text S2).[95] In addition to the modification of these data analysis algorithms/models in current lab studies, future work could focus on the development of precisely normalized Raman and LIF calibration functions and methods for in-field soil samples with different physical compositions and moisture contents (Table S1).

3. CURRENT STATE AND CHALLENGES OF RTCSM DATA TRANSMISSION, DATA PROCESSING, AND DATA MANAGEMENT

Data, defined as a systematic record corresponding to a specific quantity, plays the most important role to bridge the facilities in a soil sensor network and provides high-fidelity snapshot illustrating soil conditions. Properly collected and managed data are necessary for modern soil networks. Spatiotemporally, due to site-specific unevenly distributed physical patterns and chemical dynamic fluctuations, especially in the areas with human interventions, drastic variation poses an urgent need for continuous monitoring and accurate depiction of the soil quality. The data of all the sensors being discussed in section 2 can be collected and stored digitally as exact values (quantitative) or indicators (qualitative) and then preprocessed to ensure compatible formats with proper labels for categorization. Specifically, electrochemical sensors convert the electrochemical responsive information to electric signals, while spectroscopic sensors are both qualitative and quantitative that record the frequency values and determine the relationship between peak intensity and concentration.

Typically, a wireless sensor network (WSN) consists of various simple nodes which operate with exhaustible batteries.[127] Manual replacement or recharging these batteries is not an easy or desirable task. Hence, energy utilization by various hardware subsystems of individual nodes directly affects the scope and usefulness of the entire network. The characteristics of WSNs bring immense challenges, such as the ultra large number of sensor nodes, dense deployment, changing topology structure, and the limited resources including power, computation, storage, and communication capability.[128] All these require the applications and protocols running on WSN to be not only energy-efficient, scalable, and robust, but also "adapt" to the changing environment or context, and application scope or focus among others, and demonstrate intelligent behaviors.[129] In this section, we discuss the current state and challenge of RTCSM from the perspectives of sensor network, data transmission, data processing, and personalized data management.

3.1. Computing at the Edge. For large-scale RTCSM networks, wireless nodes are required to upload enormous volumes of data to the cloud, which has been proved as the bottleneck of the whole procedure,[130] since it incurs a long wait time and the execution depends on the Internet connectivity, making the applications unfeasible once the device is online. Another critical challenge in large-scale outdoor WSN deployments is the energy consumption, especially as more of outdoor sensor nodes are operated by battery power.[131] This myriad of information requires efficient methods of classification and analysis, where deep learning (DL) is a promising technique for large-scale data analytics.[132] Traditional computing architecture relies on cloud computing to provide the computational power.[133] However, the cost of data transportation sometimes can be unacceptable, especially for latency-sensitive applications. To address these challenges, a low-power and slimmer version of a machine learning (ML) model can be applied for optimizing data compression and transmission technique.[134]

In recent years, the emergence of edge computing in various fields has presented great potential in reducing latency and saving cost and power.[135] It would be advantageous if more complex analysis could be performed on these devices. The emergence of DL methodologies capable of extracting features of data and augmenting the data processing capabilities in real-time continuous monitoring has enhanced the possibility of performing more complex data analysis on-site without transferring data. Unlike the cloud computing architecture, edge computing enables data processing at the edge of the network. On one hand, data computing is brought closer to the data source, which greatly facilitates the development of delay-sensitive applications.[136] On the other hand, the network traffic is largely reduced since the local processing avoids much data transmission, which remarkably saves the cost.[136] As a result, AI-enabled edge devices are getting popular. Even with minimal capability, this local processing can help a great deal to reduce data transmission costs by sending only the data that requires further processing.[137] Adding intelligence to edge devices makes them self-contained and allows them to make intelligent decisions based on the data they collect. Slimmer version ML algorithms (i.e., TfLite, TinyML) has been used in edge devices for diverse applications such as smart irrigation of

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

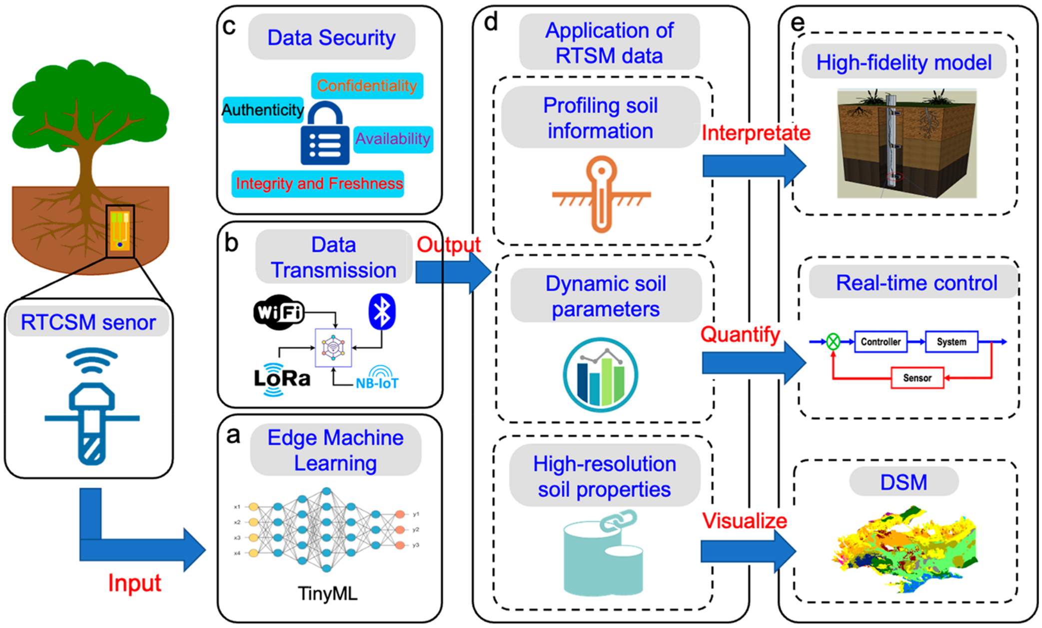


Figure 4. Significance of RTCSM for (a) edge machine learning, (b) data transmission and (c) data security, (d) soil process modeling, real-time control strategy, and digital soil mapping, and (e) their respective correlation. Modified with permission from ref 209 (copyright 2019 Elsevier B.V.) and ref 210 (copyright 2019 Elsevier B.V.).

Table 2. Comparisons of Data Processing Algorithms for Different Types of Soil Data

soil data targeted	methods[a]	input	output	best performance	ref
soil moisture estimation	SVM, ANN	spaceborne remote sensing data	estimated soil moisture	RMSE = 0.02	155
	SVM, ANN	air temperature, relative humidity, average solar radiation, soil temperature		RMSE = 4.05	166
				MAE = 0.0365	
	DBN, MLP	evapotranspiration, leaf area index, meteorological information, land surface temperature		RMSE = 0.0315	167
drought prediction	SVR, grought Index	area index, intensity index, ridge position index, western ridge point index, northern boundary position index	standardized precipitation evapotranspiration index	RMSE = 0.344	168
	DT, RF	automatic synoptic observation system data, drought indicator, remote sensing data	drought accuracy	accuracy rate = 0.65	169
water depth	LSTM	irrigation volume, rainfall volume, evaporation volume, temperature	water table depth	RMSE = (0.07, 0.184)	170
soil organic carbon	MARS, ANN, SVM, PLSR, RF	spectral measurements, total carbon, total nitrogen, pH	soil organic carbon	RMSE = 0.62	171
soil mapping workflow	k-NN, SVM, RF	soil texture, horizon, depth, mottle depth, soil moisture, landform	soil mapping covariates	accuracy rate = 0.66	172
soil erosion and remediation	DT	geological formation, soil type, annual precipitation, elevation, inclination, vegetation	soil erosion prediction	fitted probability = (50.3, 100)	173
	RF	topographic wetness index, stream power index, transport capacity index, slope, curvature, relief elevation, land use	erosion process class	percent correct = (39.22, 67.98)	174
soil contaminants	MPL, ANN, M5P, LR	moisture, organic carbon, total carbon, total nitrogen, total phosphorus, available phosphorus, loss on ignition	PAH bioavailability	RMSE = 0.974	175
	RF, ERF, SVM, MLP	high-resolution aerial imaging of arsenic-contaminated agricultural field	soil risk level	accurate rate = (0.76−0.87)	176

[a]DT, decision tree; k-NN, k-nearest neighbor; PLSR, partial least-square regression; DBN, deep brief network; MLP, multilayer perception; SVM, support vector machine; ANN, artificial neural network; RF, random forest; ERF, extreme random forest; LSTM, long−short-term memory; M5P, M5model tree; LR, linear regression.

agricultural systems and detection of soil contaminations (Figure 4a).[138] Specifically, water surveillance (e.g., soil moisture, drought, water depth) in RTCSM has widely adopted ML algorithms (e.g., support vector machine, random forest, artificial neural network) for estimation and prediction of agricultural productions (Table 2).[139] Some well-developed ML algorithms have even been used to evaluate SOC, benefiting the soil mapping.[140] Moreover, due to the powerful prediction ability, ML was also applied to the prediction and decision-making about soil erosion and pollution control (Table 2).[141] Running live data points into a ML algorithm deployed on edge devices has immense potential, but it is still in its infancy. Because RTCSM in a large area requires the deployment of numerous sensor nodes and synchronization of ML and hardware, edge computing is critical to expand soil data transmission and analysis with low cost and high efficiency (Figure 4a).

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

3.2. Data Transmission and Processing. *3.2.1. Wireless Sensor Network (WSN) Types and Challenges.* Real-time continuous soil data collection is fundamental to converting invisible soil conditions into specific numerical values for further analysis and visualization. Spatially distributed smart sensor nodes in a WSN can achieve reliable data transmission within the network, as well as autonomous dissemination of data preprocessing and calibration according to auxiliary parameters in the environment (Figure 4b).[142] To combat the energy consumption and augment the data collection/storage efficiency, Zigbee-based WSN equipped with general packet radio service (GPRS) and web service technology powered by solar battery have been developed to monitor the temperature and humidity in the soil environment, which achieved pure solar-powered sensor nodes with a resolution of 0.1 °C and a response time of less than 3s.[143] Recently, a sophisticated hardware-constrained WSN with high flexibility for data personalization has pushed the WSN development into a new stage, which focuses on the networking techniques and information processing tools for dynamic environments and energy-efficient networks. This new WSN pattern shifts the emphasis from “data” itself to “human” attached to data, which decentralizes traditional big data (Petabytes) into personalized nodes (Gigabytes) that is easy to customize with low power consumption and protect data privacy.[144] Under the new WSN architecture, selection of communication protocols should be entirely incorporated with land coverage and soil condition so as to optimize data collection. In addition, in-field distributed WSN has been developed in small urban farms to control of irrigation systems using Bluetooth radio communication, through which soil moisture and relative humidity data are transmitted to the on-site base station.[145] Recently, large-scale WSNs have been implemented by using high-density WiFi-based WSN capable of collecting and storing data of soil, plants and atmosphere in a cloud server with a 15 min measurement frequency and 30 min cloud communication frequency.[146] Other emerging technologies relevant to RTCSM scenarios are low-power wide area networks (LPWANs), specially designed for low-cost, low-power and small data rate transferability among a large number of wireless devices distributed over large areas. Two of the subcategories of LPWANs are, LoRa that is proprietary to Semtech Corporation and LoRaWAN that is open network architecture maintained by LoRa Alliance.[147,148] Many countries including Netherlands, Belgium, France, Germany, Italy, and Switzerland have started implementing LoRaWAN for precision agriculture.[149] LoRaWAN can achieve up to 9.3 miles with clear line-of-sight (suburban areas) and 1.2−3 miles in urban areas. However, one key disadvantage of LoRaWAN networks is a low data rate, which prevents to for wireless multimedia sensor network to be used in real-time.[150]

A newest addition to the LPWANs is narrowband IoT (NBIoT), also known as LTE Cat NB to connect multiple wireless sensor devices using existing cellular networks. NBIoT offers a low-power technology that transmits small amount of data in an efficient, secure, and reliable manner. However, NBIoT adoption in the USA is lagging (only T-Mobile offers NBIoT connectivity), while its adoption in the Europe has accelerated and paved the way for more edge devices like sensors, trackers, and consumer electronics.[151]

3.2.2. Data Preprocessing for ML. As a three-phase junction for solid, liquid, and gas, soil comprises the exterior environment with dynamic substance distributions and heterogeneous physiochemical properties. Statistically, signals from the ambient generate much lower minimum mean square error (MMSE) to ensure fidelity of data interpretation.[152] Unlike conventional data processing algorithms using the empirical coefficients (e.g., dispersion coefficient, degradation constant, and Darcy velocity) and creating bias, ML algorithms can be trained effectively with data acquired from multiple sources (e.g., soil sensors, historical weather data, statistical agricultural data, and literature) to improve single performance by reconstructing the signals and further optimize soil parameters under synergetic effect of both exterior and interior soil environments.[153] Commonly used ML algorithms such as linear regression and logistic regression can enhance the fidelity of the original data (e.g., crop growth status) by integrating core optimization methods into the image-based remote sensing data, but the performance of these algorithms severely compromises when the dimension of data grows larger in time and space domain.[154,155] In a recent study, the capability of seven ML models using soil mapping technique was compared in terms of predicting soil quality, where random forest (RF) exhibited the best result within 10 replicates of 5-fold cross-validation.[156] By summarizing and classifying more than 100 variants of ML algorithms with real-time continuous soil data, an inclusive study demonstrated that the utilization of ML models such as support vector machine (SVM) and multivariate adaptive regression spline (MARS) give way to methods like RF and deep neural network (DNN) (Table 2).[157] This result reveals the ongoing efforts to solve two obstacles of ML methods, poor interpretability and rigid physiochemical model structures. The popularity of RF represents the direction of interpretable ML, which could ensure the extraction of related soil information captured by the calibrated ML models. DNN may shed light into the areas where conventional ML algorithms poorly performed due to fixed model structure.[140] Developed under universal approximation theory (UAT), DNN integrates all relevant soil dynamics with periodicity from continuous soil data and enables precise prediction. In addition, UAT also secures ML to discriminate the data during the training and testing processes, so that any soil parameters/contaminants under whichever circumstances can be predicted by ML in an undifferentiated way, which enables flexible personalized data set in line with different environment/agricultural requirements.[158,159]

3.3. Sensor and Data Security of RTCSM. The networks of RTCSM focus on sensing and transmitting the continuous soil data to the back-end (e.g., local server or host) for further processing and analysis. However, security is considered the major challenge in the deployment of RTCSM networks due to the publicity of wireless communication channels (Figure 4c).[160] The network must be secured to avoid any intruder attacking the transmission of continuous data. Wireless soil sensor networks must fulfill the requirements for providing a secure communication. For example, the general requirements such as confidentiality, availability, integrity, freshness authenticity, nonrepudiation, forward secrecy, and backward secrecy must be supplied. Confidentiality is the fundamental security service to keep the privacy of the transmitted data from sensor nodes.[161] Data confidentiality achieved through encrypting certain sections of the data by sending node and decrypt it at the receiving node. The application layer determines the type of information to be encrypted. Authenticity verifies the all the nodes, even a message comes

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

from a true sender (Figure 4c). It is crucial for a receiving node to conduct a proper authentication that the data are coming from a verified node.[162] Integrity should be provided, since an attacker can modify/change the original message and may change the message according to their needs and transmit the new message to receiving node.[163] Availability means that all the soil sensor network services are available all the time even in the case of ongoing attack such as Denial of Service (Figure 4c).[164] Data freshness should be placed so that each message transmitted to the nodes is new and fresh, which ensures that the old data cannot be transmitted by any node.[165]

4. CURRENT STATE AND CHALLENGES OF RTCSM DATA APPLICATION IN SOIL-RELATED FIELDS

After soil sensor data collection, processing and management, RTCSM data can be applied to implement various soil-related functions. In this section, we use soil process modeling, system control, and digital soil mapping (DSM) as three distinct examples of RTCSM data application. Major progress has been made toward soil mass transport and fate modeling, including watershed-scale models, single phase flow models and poly scale scape models, which effectively explicate complex soil dynamics.[177,178] Detailed soil information from these models can be organized, harmonized, and visualized by DSM. Furthermore, current environmental and agricultural control strategies highly rely on the data-based controller (e.g., proportional integral derivative (PID) controller and supervisory control and data acquisition (SCADA) controller) to provide optimal management strategies.[179,180] However, owing to the lack of continuous soil physical/chemical/biological information, these models and control strategies remain disjointed between soil abiotic and biotic processes.[178] Thereby, various types of RTCSM are expected to provide comprehensive, first-hand, continuous and high-resolution soil data sets, decode the "black box" of heterogeneous soil environment, and ensure self-parameter tuning for efficient environmental and agricultural practices.

4.1. High-Fidelity Modeling of Soil Process Using RTCSM. Modeling of fate and transport of soil contaminants is vital for quantifying and predicting soil dynamics and process.[177,178,181,182] Currently, typical soil physical models mainly use the Richards equation and convection−dispersion equations to describe water and solute flow and transport through soils.[183] Modeling of soil biodegradation is often driven by soil pore water composition, weathering, and microbiological and chemical processes (e.g., oxidation of pyrite in clay barriers).[184] Through combining with the analytical computation and numerical algorithms, these models greatly enhance our understanding of the soil complexity from the pore scale to the global scale. Nevertheless, the quantitative description of soil abiotic/biotic processes and their correlation with natural and human variables are still inadequate. For example, the variations of soil microbiomes with soil carbon and nitrogen pools remain unclear, and differences in microbial responses with soil locations cannot be recognized nor predicted in many soil-based models.[185]

Detailed information acquired using RTCSM could advance soil process modeling by continuous characterization, which will alleviate the time consumption and improve the accuracy for the calibration, parametrization, and validation of soil dynamic process models. For example, common soil moisture redistribution models combine the Darcy equation with the continuity equation including a sink term for soil water extraction by roots,[186] which require the soil volumetric water content data set for high precision. Potentiometric sensing data can continuously present soil information across the soil depth to update the coefficients of the Darcy equation so as to adjust the dynamic accuracy of these models (Figure 4d,e).[44] In addition, heterogeneous soil environment could be deciphered by RTCSM data, which will enable analyzing microbial processes.[187] The CENTURY/DAYCENT models have been extensively used for ecological and biogeochemical communities,[188] but they cannot be incorporated into soil processes due to the lack of profiling-based soil information and governing equations. Such information deficiency can be solved by deploying in situ electrochemical sensors along the soil depth, through which vegetation canopy, soil water budgets and physiological control of evapotranspiration can be explicitly determined to improve water budget estimation along groundwater rather than just limited to the top soil layer (15 cm).[189] The unique profiling ability of in situ RTCSM is expected to provide more frequent and representative groundwater data, accelerate the understanding of groundwater characteristics, and renovate groundwater modeling (e.g., Gray Markov model) that has solely relied on sparse groundwater well observation (e.g., once per week or month) to obtain historical data.[190]

4.2. Real-Time Control for Environmental and Agricultural Soil Management. A variety of advanced controllers (e.g., PID and SCADA) have been operated based on feedback schemes in soil-related fields.[191−193] For example, irrigation controllers normalize the desired moisture level in the agricultural soil by controlling the water flow of irrigation pumps according to soil moisture sensor readings.[194] In addition, the beta-Poisson model has been developed to assess the pathogen survival after the biosolid land application, determine the risk of emerging pathogens, and formulate effective solutions to mitigate the threat of pathogen transmission in the soil.[195] These control schemes highly rely on the historical database (e.g., local weather data), which suffer from tremendous difficulty when facing with unexpected and sudden dynamic changes such as storm, gas tank spill, and/or pesticide spray. For example, the energy saving can reach up to 87% under normal condition by using a PID controller for soil-air heat exchanger, but this performance plummets to less than 20% under the transient shocks of soil temperature and moisture in the field.[196]

RTCSM can provide continuous and high-resolution soil data sets and enable real-time self-parameter tuning for controllers (Figure 4d,e). For example, in a fuzzy rule-based agricultural control system, conductometric-based RTCSM data provide real-time conductivity and pH values to compare with the preset values,[54,106] and thus equipping the control systems with predictive parameters (e.g., pressure gauge and pressure regulator), self-controlling ability, rapid stabilization time (within 3 min), and a high degree of precision (within ± 0.15 mS/cm).[197] In terms of environmental controllers, the newest SWAT (Soil and Water Assessment Tool) model is interfaced into the process of soil runoff and sediment yield by supplementing real-time continuous biological information (e.g., total pathogens and total enzymes) so as to effectively control soil erosion and prevent the formation or advance of gullies.[198]

4.3. Evidence-Based Digital Soil Mapping for Soil Environment. DSM is an effective implement to organize, harmonize, and visualize the detailed soil information, and

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

defines soil differences over an area of interest based on a set of soil-environmental relationships. DSM has been applied to diminish the uncertainty of soil biodiversity and quantify the relationships between soil properties and ecosystems.[199,200] One of the most well-documented frameworks for DSM is the *scorpan-SSPFe* framework[201] that is established based on a spatial soil prediction function employing "scorpan" factors (stands for soil, climate, organisms, relief, parent material, age and n for space) with autocorrelated error (SSPFe).[199] However, with sparse and interrupted data sets and uncertain accuracy of legacy data,[202,203] the major knowledge gap of DSM comes from the uncertainty of the covariates' evaluation and the sparsity of data sets.[204] For instance, Kenya's DSM excludes the usage on small farm operations that lack continuous soil data and covariates.[205]

RTCSM is expected to generate and deliver long-term continuous and in situ soil data on each customized location, which will enable the correction of inconsistent and inaccurate covariates in small farm operation areas (Figure 4d,e). Introducing robust RTCSM data sets of soil properties to the current DSM projects like *GlobalSoilMap* allows the inclusion of additional soil properties and consequently expands the usage of DSM.[206,207] Moreover, prediction models ranging from geostatistical methods, geographically weighted regressions, tree models, neural networks to 3D DSM could also be improved by using RTCSM data (e.g., soil nutrient data from potentiometric sensors and toxin data from biosensors).[208] These improved models possess the capability to optimize the sample numbers and sampling locations and enhance the uncertainty prediction. For example, high-accuracy Ecuador DSM successfully generated spatial indicators of land degradation (e.g., salinity and erosion) through linking 13,696 soil profiles and reduced land degradation from 40 to 25% at the national scale.[208] Thereby, RTCSM is capable of facilitating the evidence-based soil environmental management for end-users by incorporating soil mapping, soil function analysis, and social covariates with continuous soil information.

5. CRITICAL NEEDS AND PROSPECTS OF RTCSM FOR KEY ENVIRONMENTAL AND AGRICULTURAL PRACTICES

After elaborating each component involved in RTCSM including data acquisition, data transmission, data processing, data management, and data application, we will explicate the profound role of RTCSM in environmental and agricultural domains by highlighting several key practices. Traditional ex situ soil measurement approaches (e.g., ion chromatography, gas chromatography−mass spectrometry) suffer from an inherent time lag and inefficient information between soil status change and subsequent intervention.[211,212] Conversely, RTCSM can embark a revolution for soil monitoring in various soil-related practices, improve data transparency across academic, industrial, and agricultural communities, and thus create an inclusive database to foster swift and competent decision-making.

5.1. Assessment and Remediation of Contaminated Sites. Assessment and remediation of contaminated sites are conducted following a tiered approach involving preliminary desktop study, comprehensive site investigation, evaluation, and implementation.[213] According to the EPA's data quality objectives process, contaminant site assessment is currently performed through sample collection and analysis of the constituents of concern by certified laboratories following quality assurance and quality control protocols.[214] However, for soil destruction caused by human activities (e.g., deforestation, intensive cultivation, and construction work),[215] execution of remediation solution might be delayed if contaminated sites are not assessed in a timely manner. RTCSM possess a reliable ability for real-time assessment of diverse soil contaminants by capturing the transient variations promptly and accurately, through which the impacts caused by soil destruction can be attenuated. For example, the amount of SOM in the soil surface layer drops through water erosion,[216] which would cause flooding and lower the soil capability of sustaining crops. LIF-based SOM sensors can provide adequate SOM data within several minutes to build the updated SOM dynamic profiles,[91] so that quantitative soil microbes can be instantly introduced into the soil to prevent the loss of SOM. Likewise, IR-based devices present continuous data for managing the dosage of rhamnolipid to degrade more than 85% petroleum spill.[217,218] Through the application of RTCSM, contaminant site assessment can be considerably accelerated, and thus advance the effectiveness of remediation strategies.

5.2. Agricultural Activities and Food Security. Intensification of agricultural practice and overuse of synthetic fertilizers and pesticides are the main reasons causing soil health deterioration.[219,220] Closing the yield gaps has been intended as the appropriate solutions to sustain food security.[221] The major challenge here lies in the lack of a thorough understanding of the impacts of agricultural activities on soil health and food security. RTCSM can address this challenge through low-cost long-term continuous data acquisition. For example, continuous monitoring (27 days) of soil nutrients (e.g., nitrogen and phosphorus) using low-cost (<\$10 each piece) miniature poly(3-octylthiophene) potentiometric sensors provides a panoramic view of nutrient dynamics under diverse agricultural activities and presents a spatiotemporal data set applicable for fertilization visualization and control.[44] Biofunctionalized nanoparticle-integrated sensing data have been found to prevent staple calorie crops from being infected by providing high-resolution information for emerging fungi and oomycete pathogen control strategies.[222] Mm-sized discs etching soil moisture sensors (MSMS: <\$2 each piece) mounted on a hollow rod were deployed along soil depth (1 m) to continuously profile soil moisture over 18 months.[210] With the ability of collecting these continuous data sets over months or even years, the control models (e.g., SWAT (soil−water model[223]), STICS (soil−plant model[224])) can be updated for agricultural practices including irrigation, fertilization, planting, soil health managements, and pathogen control to sustain food security.

5.3. Climate Change Mitigation. Concerns over global warming and carbon emissions have sparked intensive interests in developing novel technologies of carbon sequestration to reduce its serial effects including polar ice melting, sea level rising, and extreme weather.[225,226] Current carbon sequestration approaches can be divided into two categories: direct carbon capture (a process of removing CO_2 from flue gases and storing it for extended periods to prevent emission) and indirect carbon capture (natural processes of up-taking CO_2 by living organisms).[225] Additionally, soil microbiomes play a key role in climate feedback, including production and/or consumption of greenhouse gases (GHG: CO_2, CH_4, N_2O, and water vapor),[185] since soil microorganisms can mineralize

SOC and contribute to GHG emissions. Nevertheless, whether soil is a source or sink of GHG under different climate scenarios remains unpredictable due to incapability of accurate and continuous monitoring of variation of soil carbon and nitrogen pools as well as soil microbial responses.[227] RTCSM using in situ IR spectroscopic sensors could render continuous, accurate, inexpensive and nondestructive measurements of SOC stocks. For example, through IR spectroscopy, a high-quality 3D data set of CO_2 at the soil depth of 0−5 cm is obtained to estimate the amount of carbon released to the air near the soil surface.[228] According to these comprehensive data, appropriate carbon sequestration control strategies (e.g., bioenergy carbon capture and storage (CCS),[229] carbon pyrolysis to biochar[230]) can be determined and updated to attain a high carbon fixing rate. Although CCS holds a great promise to store CO_2 before it is released into the atmosphere, limited knowledge is available regarding geohydrological processes of CO_2 migration and CO_2 fate in surface water and groundwater.[231] RTCSM could combat this knowledge gap and bolster the evaluation of CCS location and/or storage rate by real-time continuous tracking CO_2 spread in the subsurface environment. Based on these continuous data, an appropriate amount of biochar could be applied into soil under anaerobic condition to sequester 5.5−9.5 GtC/year (Gigatonnes of carbon per year) for long time period (e.g., years), resulting in the soil property improvement, biomass waste management, and climate change mitigation.[226]

5.4. Workforce Development and Citizen Science. Adoption and utilization of soil sensing technologies by general end-users with minimal training incurs high requirements for usability of soil sensors and accessibility of soil data.[232] Factors such as end-users' education background, age, field size, location, and specialization significantly affect the degree of precision agriculture adoption and have therefore to be considered when designing a deployment strategy and training program.[19,233] Widespread usage of complex methods (e.g., radars and radiometers onboard satellites) that involves costly and bulky equipment cannot be realistically consummated at the citizen scientist level, since it requires the involvement of experts such as agricultural consultants and field officers to conduct data collection, data analyses, and data interpretation.[234] RTCSM using low-cost and easy-to-deploy electrochemical sensors possesses the ability to provide vast amounts of data to end-users ranging from farmers to contaminated field operators through energy-efficient soil sensor networks and straightforward data access, ensuring the transparency of the monitoring process.[235] This spawns a great opportunity to improve equitable systems across the academic, industrial, agricultural communities, and policy makers. For example, a network of soil moisture has been developed on 19 sites in Switzerland, in which nearly a thousand low-cost in situ sensors were deployed to collect continuous data recorded using a Campbell Scientific CR1000 wireless data logger over a 13 month period with temperature ranging from −15 to 50 °C.[236] This process allows data sharing in a trade-off between farmers and national databases that keeps farmers informed with soil health at relevant scales and puts them in control of monitoring their own soils, supporting the movement toward farmer-led and data-driven decision-making.[237,238] Therefore, citizen science action is critical to become a part of future decisions in order to improve end-users' access to independent environmental advisory services, and thus providing practical advice to improve soil health, crop productivity and contaminant mitigation.

6. FUTURE PERSPECTIVE OF RTCSM TECHNOLOGY

RTCSM system possesses immense potential of bringing a new-round revolution for environmental protection and agricultural management. Sensor−data−environment−energy−human nexus becomes indispensable toward establishing a sophisticated and efficient RTCSM framework. In this section, we recommend four intertwined domains for future RTCSM studies.

6.1. Soil Sensor/Sensor Network. The foundation for future RTCSM studies is to enhance the performance of soil sensors and sensor networks. In terms of sensors, sensor lifespan and long-term accuracy should be improved through developing innovative sensor materials. Novel antifouling protection materials, such as polyvinylidene fluoride[239] and zwitterionic copolymer[240] have been printed (e.g., electrospray[241]) onto the sensor surface to eliminate the interference of external soil environment, strengthen electron transfer between soil and sensor matrix, and ultimately enhance the sensor accuracy, stability, and durability. In terms of sensor networks, sensor array consisting of multiple pieces of low-cost miniature sensors connected with Internet of Things (IoT) can be deployed to collect and exchange multiple types of sensor data, boost sensor-to-sensor communication, and make optimal decisions but with less human interaction.[242] For example, smart water management platform (SWAMP) is an IoT-based irrigation project designed to automatically manage water reserves, distribution, and consumption, and avoid over-irrigation/under-irrigation, which has improved energy-efficient water management by 30%.[243]

6.2. Sensor Data Processing/Control. The complexity of soil processes should be modulated, incorporated, and integrated for next generation of soil data processing algorithms in order to elevate the data correction capability for RTCSM. Moreover, ex situ non-RTCSM data (e.g., soil density and soil porosity) can provide a precise calibration benchmark for validation of RTCSM, and thus elevating the dimension of data. Recent ML-based mobile application using Appery.io. has incorporated input parameters (e.g., location, soil type, and soil pH) that farmers need for growing crops, and thereby allowing them to access the relevant farmland information and enabling timely guidance and service.[244]

6.3. Critical Zone/Soil Environment as a Whole. Omnidirectional deployment of RTCSM (e.g., in situ sensor arrays targeting SOM and ECs) and modulation of non-RTCSM (e.g., ex situ measurement using consolidometer and density gauge set) possess an unprecedented monitoring capability for diverse soil-related elements closely linked between organisms, air, water, and subsurface ecosystems. Activities (e.g., excess fertilization and pesticide overuse) resulting in breaking these links can be detected in a real-time continuous manner to minimize deterioration of soil environment. For example, SOC is associated with nutrient retention and turnover, soil contaminant degradation, and climatic change.[28] Once in situ IR spectroscopic sensing data reveal the abnormal concentration of SOC, control strategies (e.g., bioenergy carbon capture, carbon pyrolysis) can be promptly executed to adjust the SOC content on the given site and sustain the critical parameters (e.g., nutrient, CO_2, and O_2) in a reasonable range.[245]

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

6.4. Soil Knowledge Advancement. Rapid development of RTCSM offers exceptional opportunities for end-users (e.g., middle/high school students, householders, and underrepresented farmers) to advance their soil knowledge ranging from land use and energy-saving irrigation to ecosystem service and soil management. In opposition, the feedback of these end-users will advance the future design and deployment of RTCSM systems. For example, individualized data (e.g., soil moisture and nutrient) attained by RTCSM coupled with local weather information (e.g., temperature and precipitation) can be used as the inputs for farmers to promptly implement effective actions and receive real-time feedback on the impact of their actions.[246,247] Eventually, end-users' personalized requirements will be integrated into the hardware and software design of RTCSM systems with distinct features of easy-to-install, customized dashboards, graphic visualization, and automatic issue diagnosis that can further advance data accessibility and transparency and promote soil knowledge among broad communities.

ASSOCIATED CONTENT

Supporting Information

The Supporting Information is available free of charge at https://pubs.acs.org/doi/10.1021/acs.est.2c03562.

> Details of systematic literature search displayed in Figure 1; comparison of various data analysis models for spectroscopic techniques; development and implementation status of current soil sensing techniques (PDF)

AUTHOR INFORMATION

Corresponding Author

Baikun Li − *Department of Civil and Environmental Engineering and Center for Environmental Science and Engineering, University of Connecticut, Storrs, Connecticut 06269, United States;* orcid.org/0000-0002-5623-5912; Phone: 860-486-2339; Email: baikun.li@uconn.edu

Authors

Yingzheng Fan − *Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut 06269, United States*

Xingyu Wang − *Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut 06269, United States*

Thomas Funk − *Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut 06269, United States*

Ishrat Rashid − *Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut 06269, United States*

Brianna Herman − *Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut 06269, United States*

Nefeli Bompoti − *Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut 06269, United States;* orcid.org/0000-0003-2799-188X

MD Shaad Mahmud − *Department of Electrical and Computer Engineering, University of New Hampshire, Durham, New Hampshire 03824, United States*

Maria Chrysochoou − *Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut 06269, United States*

Meijian Yang − *Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut 06269, United States*

Timothy M. Vadas − *Department of Civil and Environmental Engineering, University of Connecticut, Storrs, Connecticut 06269, United States*

Yu Lei − *Department of Chemical and Biomolecular Engineering, University of Connecticut, Storrs, Connecticut 06269, United States;* orcid.org/0000-0002-0184-0373

Complete contact information is available at: https://pubs.acs.org/10.1021/acs.est.2c03562

Notes

The authors declare no competing financial interest.

ACKNOWLEDGMENTS

This study was supported by National Science Foundation (NSF) Environmental Engineering Program GOALI Project (Grant No. 1706343), NSF Signal in the soil (SitS) Projects (Grant Nos. 1935599 and 1935578), NSF Smart and Connected Communities (SCC) project (Grant No. ECCS-2018492), U.S.−Egypt Science and Technology Joint Fund (Grant No. 2000009132), and Connecticut SPARK Program. X.W. was partially supported by School of Engineering GE Fellowship at University of Connecticut.

REFERENCES

(1) Bünemann, E. K.; Bongiorno, G.; Bai, Z.; Creamer, R. E.; De Deyn, G.; de Goede, R.; Fleskens, L.; Geissen, V.; Kuyper, T. W.; Mäder, P.; Pulleman, M.; Sukkel, W.; van Groenigen, J. W.; Brussaard, L. Soil Quality − A Critical Review. *Soil Biology and Biochemistry*; Elsevier Ltd., 2018; pp 105−125.

(2) FRRCC Report to the Administrator. *EPA's Potential Role in Supporting Soil Health*, 2015, 1−9; https://www.epa.gov/sites/default/files/2017-01/documents/frrcc_report_to_the_administrator.2016_002.pdf.

(3) *Save and grow: A policymaker's guide to the sustainable intensification of smallholder crop production*; Bristol Food Network Website; https://www.bristolfoodnetwork.org/blog/save-and-grow-a-policymaker%E2%80%99s-guide-to-the-sustainable-intensification-of-smallholder-crop-production/ (accessed 2022-09-15).

(4) Lehmann, J.; Bossio, D. A.; Kögel-Knabner, I.; Rillig, M. C. The Concept and Future Prospects of Soil Health. *Nat. Rev. Earth Environ.* **2020**, *1* (10), 544−553.

(5) Dumitran, C.; Onutu, I. Environmental Risk Analysis for Crude Oil Soil Pollution. *Carpathian J. Earth Environ. Sci.* **2010**, *5*, 83−92.

(6) Prashar, P.; Shah, S. Impact of Fertilizers and Pesticides on Soil Microflora in Agriculture. In *Sustainable Agriculture Reviews*; Lichtfouse, E., Ed.; Springer International Publishing: Cham, Switzerland, 2016; Vol. 19, pp 331−361.

(7) Dalkmann, P.; Siebe, C.; Amelung, W.; Schloter, M.; Siemens, J. Does Long-Term Irrigation with Untreated Wastewater Accelerate the Dissipation of Pharmaceuticals in Soil? *Environ. Sci. Technol.* **2014**, *48* (9), 4963−4970.

(8) Sepulvado, J. G.; Blaine, A. C.; Hundal, L. S.; Higgins, C. P. Occurrence and Fate of Perfluorochemicals in Soil Following the Land Application of Municipal Biosolids. *Environ. Sci. Technol.* **2011**, *45* (19), 8106−8112.

(9) Mohapatra, D. P.; Cledón, M.; Brar, S. K.; Surampalli, R. Y. Application of Wastewater and Biosolids in Soil: Occurrence and Fate of Emerging Contaminants. *Water. Air. Soil Pollut.* **2016**, *227* (3), 77.

(10) Gworek, B.; Kijeńska, M.; Wrzosek, J.; Graniewska, M. Pharmaceuticals in the Soil and Plant Environment: A Review. *Water. Air. Soil Pollut.* **2021**, *232* (4), 145.

(11) Guo, J.-J.; Huang, X.-P.; Xiang, L.; Wang, Y.-Z.; Li, Y.-W.; Li, H.; Cai, Q.-Y.; Mo, C.-H.; Wong, M.-H. Source, Migration and Toxicology of Microplastics in Soil. *Environ. Int.* **2020**, *137*, 105263.
(12) Xu, B.; Liu, F.; Cryder, Z.; Huang, D.; Lu, Z.; He, Y.; Wang, H.; Lu, Z.; Brookes, P. C.; Tang, C.; Gan, J.; Xu, J. Microplastics in the Soil Environment: Occurrence, Risks, Interactions and Fate − A Review. *Crit. Rev. Environ. Sci. Technol.* **2020**, *50* (21), 2175−2222.
(13) Nocita, M.; Stevens, A.; van Wesemael, B.; Aitkenhead, M.; Bachmann, M.; Barthes, B.; Ben Dor, E.; Brown, D. J.; Clairotte, M.; Csorba, A.; Dardenne, P.; Dematte, J. A.M.; Genot, V.; Guerrero, C.; Knadel, M.; Montanarella, L.; Noon, C.; Ramirez-Lopez, L.; Robertson, J.; Sakai, H.; Soriano-Disla, J. M.; Shepherd, K. D.; Stenberg, B.; Towett, E. K.; Vargas, R.; Wetterlind, J. Soil Spectroscopy: An Alternative to Wet Chemistry for Soil Monitoring. *Adv. Agron.* **2015**, *132*, 139−159.
(14) Laskar, S.; Mukherjee, S. Optical Sensing Methods for Assessment of Soil Macro-Nutrients and Other Properties for Application in Precision Agriculture: A Review. *ADBU-J. Eng. Technol. AJET.* **2016**, *4* (1), 206.
(15) Vidana Gamage, D. N.; Biswas, A.; Strachan, I. B. Field Water Balance Closure with Actively Heated Fiber-Optics and Point-Based Soil Water Sensors. *Water* **2019**, *11* (1), 135.
(16) Wagner, W.; Naeimi, V.; Scipal, K.; de Jeu, R.; Martínez-Fernández, J. Soil Moisture from Operational Meteorological Satellites. *Hydrogeol. J.* **2007**, *15* (1), 121−131.
(17) Dai, E.; Venkitasubramony, A.; Gasiewski, A.; Stachura, M.; Elston, J. High Spatial Soil Moisture Mapping Using Small Unmanned Aerial System. *IEEE Xplore* **2018**, 6496−6499.
(18) D'Oleire-Oltmanns, S.; Marzolff, I.; Peter, K. D.; Ries, J. B. Unmanned Aerial Vehicle (UAV) for Monitoring Soil Erosion in Morocco. *Remote Sens.* **2012**, *4* (11), 3390−3416.
(19) Lindblom, J.; Lundström, C.; Ljung, M.; Jonsson, A. Promoting Sustainable Intensification in Precision Agriculture: Review of Decision Support Systems Development and Strategies. *Precis. Agric.* **2017**, *18* (3), 309−331.
(20) Phillips, J. D. Soil Complexity and Pedogenesis. *Soil Sci.* **2017**, *182* (4), 117−127.
(21) Rinot, O.; Levy, G. J.; Steinberger, Y.; Svoray, T.; Eshel, G. Soil Health Assessment: A Critical Review of Current Methodologies and a Proposed New Approach. *Sci. Total Environ.* **2019**, *648*, 1484−1491.
(22) Barré, P.; Durand, H.; Chenu, C.; Meunier, P.; Montagne, D.; Castel, G.; Billiou, D.; Soucémarianadin, L.; Cécillon, L. Geological Control of Soil Organic Carbon and Nitrogen Stocks at the Landscape Scale. *Geoderma* **2017**, *285*, 50−56.
(23) Uchida, S.; Soga, K.; Yamamoto, K. Critical State Soil Constitutive Model for Methane Hydrate Soil. *J. Geophys. Res. Solid Earth* **2012**, DOI: 10.1029/2011JB008661.
(24) Ali, Md. A.; Dong, L.; Dhau, J.; Khosla, A.; Kaushik, A. Perspective—Electrochemical Sensors for Soil Quality Assessment. *J. Electrochem. Soc.* **2020**, *167* (3), 037550.
(25) Evett, S. R.; Schwartz, R. C.; Casanova, J. J.; Heng, L. K. Soil Water Sensing for Water Balance, ET and WUE. *Agric. Water Manag.* **2012**, *104*, 1−9.
(26) Ayangbenro, A. S.; Babalola, O. O. A New Strategy for Heavy Metal Polluted Environments: A Review of Microbial Biosorbents. *Int. J. Environ. Res. Public. Health* **2017**, *14* (1), 94.
(27) Devi, G.; Sowmiya, N.; Yasoda, K.; Muthulakshmi, K.; Balasubramanian, K. Review on Application of Drones for Crop Health Monitoring and Spraying Pesticides and Fertilizer. *J. Crit. Rev.* **2020**, *7*, 2020.
(28) Wiesmeier, M.; Urbanski, L.; Hobley, E.; Lang, B.; von Lützow, M.; Marin-Spiotta, E.; van Wesemael, B.; Rabot, E.; Ließ, M.; Garcia-Franco, N.; Wollschläger, U.; Vogel, H.-J.; Kögel-Knabner, I. Soil Organic Carbon Storage as a Key Function of Soils - A Review of Drivers and Indicators at Various Scales. *Geoderma* **2019**, *333*, 149−162.
(29) Yost, J. L.; Hartemink, A. E. Chapter Four - Soil Organic Carbon in Sandy Soils: A Review. In *Advances in Agronomy*; Sparks, D. L., Ed.; Academic Press, 2019; Vol. *158*, pp 217−310.
(30) Hoyle, F. C.; Baldock, J. A.; Murphy, D. V. Soil Organic Carbon − Role in Rainfed Farming Systems. In *Rainfed Farming Systems*; Tow, P., Cooper, I., Partridge, I., Birch, C., Eds.; Springer: Dordrecht, The Netherlands, 2011; pp 339−361.
(31) Clough, T. J.; Condron, L. M.; Kammann, C.; Müller, C. A Review of Biochar and Soil Nitrogen Dynamics. *Agronomy* **2013**, *3* (2), 275−293.
(32) Chen, B.; Liu, E.; Tian, Q.; Yan, C.; Zhang, Y. Soil Nitrogen Dynamics and Crop Residues. A Review. *Agron. Sustain. Dev.* **2014**, *34* (2), 429−442.
(33) Mooshammer, M.; Wanek, W.; Hämmerle, I.; Fuchslueger, L.; Hofhansl, F.; Knoltsch, A.; Schnecker, J.; Takriti, M.; Watzka, M.; Wild, B.; Keiblinger, K. M.; Zechmeister-Boltenstern, S.; Richter, A. Adjustment of Microbial Nitrogen Use Efficiency to Carbon:Nitrogen Imbalances Regulates Soil Nitrogen Cycling. *Nat. Commun.* **2014**, *5* (1), 3694.
(34) Fowler, D.; Coyle, M.; Skiba, U.; Sutton, M. A.; Cape, J. N.; Reis, S.; Sheppard, L. J.; Jenkins, A.; Grizzetti, B.; Galloway, J. N.; Vitousek, P.; Leach, A.; Bouwman, A. F.; Butterbach-Bahl, K.; Dentener, F.; Stevenson, D.; Amann, M.; Voss, M. The Global Nitrogen Cycle in the Twenty-First Century. *Philos. Trans. R. Soc. B Biol. Sci.* **2013**, *368* (1621), 20130164.
(35) Hallama, M.; Pekrun, C.; Lambers, H.; Kandeler, E. Hidden Miners − the Roles of Cover Crops and Soil Microorganisms in Phosphorus Cycling through Agroecosystems. *Plant Soil.* **2019**, *434* (1), 7−45.
(36) Turner, B. L.; Lambers, H.; Condron, L. M.; Cramer, M. D.; Leake, J. R.; Richardson, A. E.; Smith, S. E. Soil Microbial Biomass and the Fate of Phosphorus during Long-Term Ecosystem Development. *Plant Soil.* **2013**, *367* (1), 225−234.
(37) Li, F.; Liang, X.; Niyungeko, C.; Sun, T.; Liu, F.; Arai, Y. Chapter Two - Effects of Biochar Amendments on Soil Phosphorus Transformation in Agricultural Soils. In *Advances in Agronomy*; Sparks, D. L., Ed.; Academic Press, 2019; Vol. *158*, pp 131−172.
(38) Gomes, A. R.; Justino, C.; Rocha-Santos, T.; Freitas, A. C.; Duarte, A. C.; Pereira, R. Review of the Ecotoxicological Effects of Emerging Contaminants to Soil Biota. *J. Environ. Sci. Health Part A* **2017**, *52* (10), 992−1007.
(39) Naidu, R.; Arias Espana, V. A.; Liu, Y.; Jit, J. Emerging Contaminants in the Environment: Risk-Based Analysis for Better Management. *Chemosphere.* **2016**, *154*, 350−357.
(40) Zdrachek, E.; Bakker, E. Potentiometric Sensing. *Anal. Chem.* **2021**, *93* (1), 72−102.
(41) Fan, Y.; Huang, Y.; Linthicum, W.; Liu, F.; Beringhs, A. O.; Dang, Y.; Xu, Z.; Chang, S.-Y.; Ling, J.; Huey, B. D.; Suib, S. L.; Ma, A. W. K.; Gao, P.-X.; Lu, X.; Lei, Y.; Shaw, M. T.; Li, B. Toward Long-Term Accurate and Continuous Monitoring of Nitrate in Wastewater Using Poly (Tetrafluoroethylene)(PTFE)−Solid-State Ion-Selective Electrodes (S-ISEs). *ACS Sens.* **2020**, *5* (10), 3182−3193.
(42) Fan, Y.; Wang, X.; Qian, X.; Dixit, A.; Herman, B.; Lei, Y.; McCutcheon, J.; Li, B. Enhancing the Understanding of Soil Nitrogen Fate Using a 3D-Electrospray Sensor Roll Casted with a Thin-Layer Hydrogel. *Environ. Sci. Technol.* **2022**, *56* (8), 4905−4914.
(43) Chen, Y.; Tian, Y.; Wang, X.; Dong, L. Miniaturized Soil Sensor for Continuous, in-Situ Monitoring of Soil Water Potential. *IEEE Xplore* **2019**, 2025−2028.
(44) Ali, M. A.; Wang, X.; Chen, Y.; Jiao, Y.; Mahal, N. K.; Moru, S.; Castellano, M. J.; Schnable, J. C.; Schnable, P. S.; Dong, L. Continuous Monitoring of Soil Nitrate Using a Miniature Sensor with Poly(3-Octyl-Thiophene) and Molybdenum Disulfide Nanocomposite. *ACS Appl. Mater. Interfaces* **2019**, *11* (32), 29195−29206.
(45) Kang, W.; Pei, X.; Rusinek, C. A.; Bange, A.; Haynes, E. N.; Heineman, W. R.; Papautsky, I. Determination of Lead with a Copper-Based Electrochemical Sensor. *Anal. Chem.* **2017**, *89* (6), 3345−3352.
(46) Huang, Y.; Wang, T.; Xu, Z.; Hughes, E.; Qian, F.; Lee, M.; Fan, Y.; Lei, Y.; Brückner, C.; Li, B. Real-Time in Situ Monitoring of Nitrogen Dynamics in Wastewater Treatment Processes Using

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

Wireless, Solid-State, and Ion-Selective Membrane Sensors. *Environ. Sci. Technol.* **2019**, *53* (6), 3140−3148.

(47) Toure, Y.; Mabon, N.; Sindic, M. Soil Model Systems Used to Assess Fouling, Soil Adherence and Surface Cleanability in the Laboratory: A Review. *Biotechnol Agron Soc. Env.* **2013**, *17* (3), 527−539.

(48) Weltin, A.; Ganatra, D.; König, K.; Joseph, K.; Hofmann, U. G.; Urban, G. A.; Kieninger, J. New Life for Old Wires: Electrochemical Sensor Method for Neural Implants. *J. Neural Eng.* **2020**, *17* (1), 016007.

(49) Zeitoun, R.; Biswas, A. Potentiometric Determination of Phosphate Using Cobalt: A Review. *J. Electrochem. Soc.* **2020**, *167* (12), 127507.

(50) Bhandari, S.; Singh, U.; Kumbhat, S. Nafion-Modified Carbon Based Sensor for Soil Potassium Detection. *Electroanalysis* **2019**, *31* (5), 813−819.

(51) Zdrachek, E.; Bakker, E. Potentiometric Sensing. *Anal. Chem.* **2019**, *91* (1), 2−26.

(52) Bow, Y.; Hairul, H.; Hajar, I. The Application of Potentiometric Methods in Determination Total Organic Carbon Content of Soil. *Int. J. Adv. Sci. Eng. Inf. Technol.* **2014**, *4*, 249.

(53) Pei, X.; Kang, W.; Yue, W.; Bange, A.; Heineman, W. R.; Papautsky, I. Disposable Copper-Based Electrochemical Sensor for Anodic Stripping Voltammetry. *Anal. Chem* **2014**, *86* (10), 4893−4900.

(54) Patil, S.; Ghadi, H.; Ramgir, N.; Adhikari, A.; Rao, V. R. Monitoring Soil PH Variation Using Polyaniline/SU-8 Composite Film Based Conductometric Microsensor. *Sens. Actuators B Chem.* **2019**, *286*, 583−590.

(55) Ali, M. A.; Jiang, H.; Mahal, N. K.; Weber, R. J.; Kumar, R.; Castellano, M. J.; Dong, L. Microfluidic Impedimetric Sensor for Soil Nitrate Detection Using Graphene Oxide and Conductive Nanofibers Enabled Sensing Interface. *Sens. Actuators B Chem.* **2017**, *239*, 1289−1299.

(56) Ali, Md. A.; Mondal, K.; Wang, Y.; Jiang, H.; Mahal, N. K.; Castellano, M. J.; Sharma, A.; Dong, L. In Situ Integration of Graphene Foam−Titanium Nitride Based Bio-Scaffolds and Microfluidic Structures for Soil Nutrient Sensors. *Lab. Chip* **2017**, *17* (2), 274−285.

(57) Thanalechumi, P.; Yusoff, A. R. M.; Yusop, Z. Novel Electrochemical Sensor Based on Nylon 6, 6-Modified Graphite HB Pencil Electrode for Chlorothalonil Determination by Differential Pulse Cathodic Stripping Voltammetry. *Water. Air. Soil Pollut.* **2020**, *231* (5), 189.

(58) Gopi, P. K.; Mutharani, B.; Chen, S.-M.; Chen, T.-W.; Eldesoky, G. E.; Ali, M. A.; Wabaidur, S. M.; Shaik, F.; Tzu, C. Y. Electrochemical Sensing Base for Hazardous Herbicide Aclonifen Using Gadolinium Niobate (GdNbO4) Nanoparticles-Actual River Water and Soil Sample Analysis. *Ecotoxicol. Environ. Saf.* **2021**, *207*, 111285.

(59) Saiapina, O. Y.; Dzyadevych, S. V.; Walcarius, A.; Jaffrezic-Renault, N. A Novel Highly Sensitive Zeolite-Based Conductometric Microsensor for Ammonium Determination. *Anal. Lett.* **2012**, *45* (11), 1467−1484.

(60) Jiang, C.; He, Y.; Liu, Y. Recent Advances in Sensors for Electrochemical Analysis of Nitrate in Food and Environmental Matrices. *Analyst.* **2020**, *145* (16), 5400−5413.

(61) Mc Eleney, C.; Alves, S.; Mc Crudden, D. Novel Determination of Cd and Zn in Soil Extract by Sequential Application of Bismuth and Gallium Thin Films at a Modified Screen-Printed Carbon Electrode. *Anal. Chim. Acta* **2020**, *1137*, 94−102.

(62) Ispas, C. R.; Crivat, G.; Andreescu, S. Review: Recent Developments in Enzyme-Based Biosensors for Biomedical Analysis. *Anal. Lett.* **2012**, *45* (2−3), 168−186.

(63) Chee, G. J. A Novel Whole-Cell Biosensor for the Determination of Trichloroethylene. *Sens. Actuators B Chem.* **2016**, *237*, 836−840.

(64) Vogiazi, V.; de la Cruz, A.; Mishra, S.; Shanov, V.; Heineman, W. R.; Dionysiou, D. D. A Comprehensive Review: Development of Electrochemical Biosensors for Detection of Cyanotoxins in Freshwater. *ACS Sens.* **2019**, *4* (5), 1151−1173.

(65) Li, X.; Kaattari, S. L.; Vogelbein, M. A.; Vadas, G. G.; Unger, M. A. A Highly Sensitive Monoclonal Antibody Based Biosensor for Quantifying 3−5 Ring Polycyclic Aromatic Hydrocarbons (PAHs) in Aqueous Environmental Samples. *Sens. Bio-Sens. Res.* **2016**, *7*, 115−120.

(66) Cennamo, N.; Zeni, L.; Tortora, P.; Regonesi, M. E.; Giusti, A.; Staiano, M.; D'Auria, S.; Varriale, A. A High Sensitivity Biosensor to Detect the Presence of Perfluorinated Compounds in Environment. *Talanta* **2018**, *178*, 955−961.

(67) Cioffi, A.; Mancini, M.; Gioia, V.; Cinti, S. Office Paper-Based Electrochemical Strips for Organophosphorus Pesticide Monitoring in Agricultural Soil. *Environ. Sci. Technol.* **2021**, *55* (13), 8859−8865.

(68) Martinazzo, J.; Muenchen, D.; de Cezaro, A.; Nava, A.; Rigo, A.; Manzoli, A.; Leite, F.; Steffens, C.; Steffens, J. Pesticide Detection in Soil Using Biosensors and Nanobiosensors. *Biointerface Res. Appl. Chem.* **2018**, *6*, 1659−1675.

(69) Morales, M. A.; Halpern, J. M. Guide to Selecting a Biorecognition Element for Biosensors. *Bioconjugate Chem.* **2018**, *29* (10), 3231−3239.

(70) Zamora-Sequeira, R.; Starbird-Pérez, R.; Rojas-Carillo, O.; Vargas-Villalobos, S. What Are the Main Sensor Methods for Quantifying Pesticides in Agricultural Activities? A Review. *Molecules* **2019**, *24* (14), 2659.

(71) Das, J.; Sarkar, P. Enzymatic Electrochemical Biosensor for Urea with a Polyaniline Grafted Conducting Hydrogel Composite Modified Electrode. *RSC Adv.* **2016**, *6* (95), 92520−92533.

(72) Montes, R.; Céspedes, F.; Gabriel, D.; Baeza, M. Electrochemical Biosensor Based on Optimized Biocomposite for Organophosphorus and Carbamates Pesticides Detection. *J. Nanomater.* **2018**, *2018*, 1−13.

(73) Nocita, M.; Stevens, A.; van Wesemael, B.; Aitkenhead, M.; Bachmann, M.; Barthès, B.; Ben Dor, E.; Brown, D. J.; Clairotte, M.; Csorba, A.; Dardenne, P.; Demattê, J. A. M.; Genot, V.; Guerrero, C.; Knadel, M.; Montanarella, L.; Noon, C.; Ramirez-Lopez, L.; Robertson, J.; Sakai, H.; Soriano-Disla, J. M.; Shepherd, K. D.; Stenberg, B.; Towett, E. K.; Vargas, R.; Wetterlind, J. Chapter Four - Soil Spectroscopy: An Alternative to Wet Chemistry for Soil Monitoring. In *Advances in Agronomy*; Sparks, D. L., Ed.; Academic Press, 2015; Vol. *132*, pp 139−159.

(74) Villas-Boas, P. R.; Romano, R. A.; de Menezes Franco, M. A.; Ferreira, E. C.; Ferreira, E. J.; Crestana, S.; Milori, D. M. B. P. Laser-Induced Breakdown Spectroscopy to Determine Soil Texture: A Fast Analytical Technique. *Geoderma* **2016**, *263*, 195−202.

(75) Theurer, L. S.; Maiwald, M.; Sumpf, B. Shifted Excitation Raman Difference Spectroscopy: A Promising Tool for the Investigation of Soil. *Eur. J. Soil Sci.* **2021**, *72* (1), 120−124.

(76) Demattê, J. A. M.; Dotto, A. C.; Bedin, L. G.; Sayão, V. M.; Souza, A. B. e. Soil Analytical Quality Control by Traditional and Spectroscopy Techniques: Constructing the Future of a Hybrid Laboratory for Low Environmental Impact. *Geoderma* **2019**, *337*, 111−121.

(77) Ge, Y.; Morgan, C. L. S.; Wijewardane, N. K. Visible and Near-Infrared Reflectance Spectroscopy Analysis of Soils. *Soil Sci. Soc. Am. J.* **2020**, *84* (5), 1495−1502.

(78) Horta, A.; Malone, B.; Stockmann, U.; Minasny, B.; Bishop, T. F. A.; McBratney, A. B.; Pallasser, R.; Pozza, L. Potential of Integrated Field Spectroscopy and Spatial Analysis for Enhanced Assessment of Soil Contamination: A Prospective Review. *Geoderma* **2015**, *241*−*242*, 180−209.

(79) Pasquini, C. Near Infrared Spectroscopy: A Mature Analytical Technique with New Perspectives − A Review. *Anal. Chim. Acta* **2018**, *1026*, 8−36.

(80) Ben-Dor, E.; Chabrillat, S.; Demattê, J. A. M. Characterization of Soil Properties Using Reflectance Spectroscopy. *Fundamentals, Sensor Systems, Spectral Libraries, and Data Mining for Vegetation*; CRC Press, 2018; pp 184−247.

(81) Wenjun, J.; Zhou, S.; Jingyi, H.; Shuo, L. In Situ Measurement of Some Soil Properties in Paddy Soil Using Visible and Near-Infrared Spectroscopy. *PLoS One* **2014**, *9* (8), e105708.

(82) Reda, R.; Saffaj, T.; Itqiq, S. E.; Bouzida, I.; Saidi, O.; Yaakoubi, K.; Lakssir, B.; El Mernissi, N.; El Hadrami, E. M. Predicting Soil Phosphorus and Studying the Effect of Texture on the Prediction Accuracy Using Machine Learning Combined with Near-Infrared Spectroscopy. *Spectrochim. Acta. A. Mol. Biomol. Spectrosc.* **2020**, *242*, 118736.

(83) Stenberg, B.; Viscarra Rossel, R. A.; Mouazen, A. M.; Wetterlind, J. Chapter Five - Visible and Near Infrared Spectroscopy in Soil Science. In *Advances in Agronomy*; Sparks, D. L., Ed.; Academic Press, 2010; Vol. *107*, pp 163−215.

(84) Udvardi, B.; Kovács, I. J.; Fancsik, T.; Kónya, P.; Bátori, M.; Stercel, F.; Falus, G.; Szalai, Z. Effects of Particle Size on the Attenuated Total Reflection Spectrum of Minerals. *Appl. Spectrosc.* **2017**, *71* (6), 1157−1168.

(85) Rodionov, A.; Pätzold, S.; Welp, G.; Pallares, R. C.; Damerow, L.; Amelung, W. Sensing of Soil Organic Carbon Using Visible and Near-Infrared Spectroscopy at Variable Moisture and Surface Roughness. *Soil Sci. Soc. Am. J.* **2014**, *78* (3), 949−957.

(86) Zhang, X.; He, A.; Guo, R.; Zhao, Y.; Yang, L.; Morita, S.; Xu, Y.; Noda, I.; Ozaki, Y. A New Approach to Removing Interference of Moisture from FTIR Spectrum. *Spectrochim. Acta. A. Mol. Biomol. Spectrosc.* **2022**, *265*, 120373.

(87) Nocita, M.; Stevens, A.; Noon, C.; van Wesemael, B. Prediction of Soil Organic Carbon for Different Levels of Soil Moisture Using Vis-NIR Spectroscopy. *Geoderma* **2013**, *199*, 37−42.

(88) Jiang, Q.; Chen, Y.; Guo, L.; Fei, T.; Qi, K. Estimating Soil Organic Carbon of Cropland Soil at Different Levels of Soil Moisture Using VIS-NIR Spectroscopy. *Remote Sens.* **2016**, *8* (9), 755.

(89) Haubrock, S.-N.; Chabrillat, S.; Lemmnitz, C.; Kaufmann, H. Surface Soil Moisture Quantification Models from Reflectance Data under Field Conditions. *Int. J. Remote Sens.* **2008**, *29* (1), 3−29.

(90) Li, D.-W.; Zhai, W.-L.; Li, Y.-T.; Long, Y.-T. Recent Progress in Surface Enhanced Raman Spectroscopy for the Detection of Environmental Pollutants. *Microchim. Acta* **2014**, *181* (1), 23−43.

(91) Tadini, A. M.; Xavier, A. A. P.; Milori, D. M. B. P.; Oliveira, P. P. A.; Pezzopane, J. R.; Bernardi, A. C. C.; Martin-Neto, L. Evaluation of Soil Organic Matter from Integrated Production Systems Using Laser-Induced Fluorescence Spectroscopy. *Soil Tillage Res.* **2021**, *211*, 105001.

(92) Villas-Boas, P. R.; Franco, M. A.; Martin-Neto, L.; Gollany, H. T.; Milori, D. M. B. P. Applications of Laser-Induced Breakdown Spectroscopy for Soil Characterization, Part II: Review of Elemental Analysis and Soil Classification. *Eur. J. Soil Sci.* **2020**, *71* (5), 805−818.

(93) Schlack, T. R.; Beal, S. A.; Corriveau, E. J.; Clausen, J. L. Detection Limits of Trinitrotoluene and Ammonium Nitrate in Soil by Raman Spectroscopy. *ACS Omega* **2021**, *6* (25), 16316−16323.

(94) Kammrath, B. W.; Koutrakos, A.; Castillo, J.; Langley, C.; Huck-Jones, D. Morphologically-Directed Raman Spectroscopy for Forensic Soil Analysis. *Forensic Sci. Int.* **2018**, *285*, e25−e33.

(95) Nie, P.; Dong, T.; Xiao, S.; Lin, L.; He, Y.; Qu, F. Quantitative Determination of Thiabendazole in Soil Extracts by Surface-Enhanced Raman Spectroscopy. *Molecules* **2018**, *23* (8), 1949.

(96) Gaikwad, P.; Devendrachari, M. C.; Thimmappa, R.; Paswan, B.; Raja Kottaichamy, A.; Makri Nimbegondi Kotresh, H.; Thotiyl, M. O. Galvanic Cell Type Sensor for Soil Moisture Analysis. *Anal. Chem.* **2015**, *87* (14), 7439−7445.

(97) Choi, W.-H.; Shann, J. R.; Papautsky, I. Multi-Analyte Needle-Type Sensor for Measurement of PH, Phosphate, and Redox Potential in Soil. *IEEE Sensors* **2010**, 931−935.

(98) Mousavi, M. P. S.; Ainla, A.; Tan, E. K. W.; K. Abd El-Rahman, M.; Yoshida, Y.; Yuan, L.; Sigurslid, H. H.; Arkan, N.; Yip, M. C.; Abrahamsson, C. K.; Homer-Vanniasinkam, S.; Whitesides, G. M. Ion Sensing with Thread-Based Potentiometric Electrodes. *Lab. Chip* **2018**, *18* (15), 2279−2290.

(99) Zeitoun, R.; Biswas, A. Electrochemical Mechanisms in Potentiometric Phosphate Sensing Using Pure Cobalt, Molybdenum and Their Alloy for Environmental Applications. *Electroanalysis* **2021**, *33* (2), 421−430.

(100) Ding, R.; Cheong, Y. H.; Ahamed, A.; Lisak, G. Heavy Metals Detection with Paper-Based Electrochemical Sensors. *Anal. Chem.* **2021**, *93* (4), 1880−1888.

(101) Wilson, D.; Gutiérrez, J. M.; Alegret, S.; del Valle, M. Simultaneous Determination of Zn(II), Cu(II), Cd(II) and Pb(II) in Soil Samples Employing an Array of Potentiometric Sensors and an Artificial Neural Network Model. *Electroanalysis* **2012**, *24* (12), 2249−2256.

(102) Singh, M.; Patkar, R.; Vinchurkar, M.; Baghini, M. S. Voltammetry Based Handheld Measurement System for Soil PH. *J. Electroanal. Chem.* **2021**, *885*, 115086.

(103) Leonardi, S. G.; Donato, N.; Bonavita, A.; Neri, G.; Bonyani, M.; Mirzaei, A. Ag-Doped Nanostructured Materials for Electrochemical Sensors. *IEEE Xplore* **2015**, 1−4.

(104) Xu, Z.; Fan, X.; Ma, Q.; Tang, B.; Lu, Z.; Zhang, J.; Mo, G.; Ye, J.; Ye, J. A Sensitive Electrochemical Sensor for Simultaneous Voltammetric Sensing of Cadmium and Lead Based on Fe3O4/Multiwalled Carbon Nanotube/Laser Scribed Graphene Composites Functionalized with Chitosan Modified Electrode. *Mater. Chem. Phys.* **2019**, *238*, 121877.

(105) Zhao, G.; Si, Y.; Wang, H.; Liu, G. A Portable Electrochemical Detection System Based on Graphene/Ionic Liquid Modified Screen-Printed Electrode for the Detection of Cadmium in Soil by Square Wave Anodic Stripping Voltammetry. *Int. J. Electrochem. Sci.* **2016**, *11* (1), 54−64.

(106) Smagin, A. V.; Sadovnikova, N. B.; Kirichenko, A. V.; Egorov, Yu. V.; Vityazev, V. G.; Bashina, A. S. Dependence of the Osmotic Pressure and Electrical Conductivity of Soil Solutions on the Soil Water Content. *Eurasian Soil Sci.* **2018**, *51* (12), 1462−1473.

(107) Day, C.; Søpstad, S.; Ma, H.; Jiang, C.; Nathan, A.; Elliott, S. R.; Karet Frankl, F. E.; Hutter, T. Impedance-Based Sensor for Potassium Ions. *Anal. Chim. Acta* **2018**, *1034*, 39−45.

(108) Soldatkin, O. O.; Kucherenko, I. S.; Pyeshkova, V. M.; Kukla, A. L.; Jaffrezic-Renault, N.; El'skaya, A. V.; Dzyadevych, S. V.; Soldatkin, A. P. Novel Conductometric Biosensor Based on Three-Enzyme System for Selective Determination of Heavy Metal Ions. *Bioelectrochemistry* **2012**, *83*, 25−30.

(109) Yin, Z.; Lei, T.; Yan, Q.; Chen, Z.; Dong, Y. A Near-Infrared Reflectance Sensor for Soil Surface Moisture Measurement. *Comput. Electron. Agric.* **2013**, *99*, 101−107.

(110) Kuang, B.; Tekin, Y.; Mouazen, A. M. Comparison between Artificial Neural Network and Partial Least Squares for On-Line Visible and near Infrared Spectroscopy Measurement of Soil Organic Carbon, PH and Clay Content. *Soil Tillage Res.* **2015**, *146*, 243−252.

(111) Nawar, S.; Buddenbaum, H.; Hill, J. Estimation of Soil Salinity Using Three Quantitative Methods Based on Visible and Near-Infrared Reflectance Spectroscopy: A Case Study from Egypt. *Arab. J. Geosci.* **2015**, *8* (7), 5127−5140.

(112) Shao, Y.; He, Y. Nitrogen, Phosphorus, and Potassium Prediction in Soils, Using Infrared Spectroscopy. *Soil Res.* **2011**, *49* (2), 166−172.

(113) Zhou, P.; Zhang, Y.; Yang, W.; Li, M.; Liu, Z.; Liu, X. Development and Performance Test of an In-Situ Soil Total Nitrogen-Soil Moisture Detector Based on near-Infrared Spectroscopy. *Comput. Electron. Agric.* **2019**, *160*, 51−58.

(114) Ng, W.; Malone, B. P.; Minasny, B. Rapid Assessment of Petroleum-Contaminated Soils with Infrared Spectroscopy. *Geoderma* **2017**, *289*, 150−160.

(115) Okparanma, R. N.; Mouazen, A. M. Visible and Near-Infrared Spectroscopy Analysis of a Polycyclic Aromatic Hydrocarbon in Soils. *Sci. World J.* **2013**, *2013*, e160360.

(116) Pyo, J.; Hong, S. M.; Kwon, Y. S.; Kim, M. S.; Cho, K. H. Estimation of Heavy Metals Using Deep Neural Network with Visible and Infrared Spectroscopy of Soil. *Sci. Total Environ.* **2020**, *741*, 140162.

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

(117) Liu, J.; Xie, J.; Han, J.; Wang, H.; Sun, J.; Li, R.; Li, S. Visible and Near-Infrared Spectroscopy with Chemometrics Are Able to Predict Soil Physical and Chemical Properties. *J. Soils Sediments* **2020**, *20* (7), 2749−2760.
(118) Xing, Z.; Du, C.; Tian, K.; Ma, F.; Shen, Y.; Zhou, J. Application of FTIR-PAS and Raman Spectroscopies for the Determination of Organic Matter in Farmland Soils. *Talanta* **2016**, *158*, 262−269.
(119) Zheng, L.; Lee, W. S.; Li, M.; Katti, A.; Yang, C.; Li, H.; Sun, H. Analysis of Soil Phosphorus Concentration Based on Raman Spectroscopy. *Multispectral, Hyperspectral, and Ultraspectral Remote Sensing Technology, Techniques and Applications IV* **2012**, 203−210.
(120) Zhang, K.; Hu, Y.; Li, G. Diazotization-Coupling Reaction-Based Selective Determination of Nitrite in Complex Samples Using Shell-Isolated Nanoparticle-Enhanced Raman Spectroscopy. *Talanta* **2013**, *116*, 712−718.
(121) Gulati, K. K.; Gambhir, V.; Reddy, M. N. Detection of Nitro-Aromatic Compound in Soil and Sand Using Time Gated Raman Spectroscopy. *Def. Sci. J.* **2017**, *67* (5), 588−591.
(122) Feng, Y.; Zhang, T.; Zhao, M.; Zhang, X.; Tang, H.; Sheng, Q. Raman-Infrared Spectral Fusion Combined with Partial Least Squares (PLS) for Quantitative Analysis of Polycyclic Aromatic Hydrocarbons in Soil. *Anal. Methods* **2020**, *12* (9), 1203−1211.
(123) Ferreira, E. C.; Gomes Neto, J. A.; Milori, D. M. B. P.; Ferreira, E. J.; Anzano, J. M. Laser-Induced Breakdown Spectroscopy: Extending Its Application to Soil PH Measurements. *Spectrochim. Acta Part B At. Spectrosc.* **2015**, *110*, 96−99.
(124) Yang, J.; Gong, W.; Shi, S.; Du, L.; Sun, J.; Y-Y, M.; S-L, S. Accurate Identification of Nitrogen Fertilizer Application of Paddy Rice Using Laser-Induced Fluorescence Combined with Support Vector Machine. *Plant Soil Environ.* **2016**, *61* (11), 501−506.
(125) Erler, A.; Riebe, D.; Beitz, T.; Löhmannsröben, H.-G.; Gebbers, R. Soil Nutrient Detection for Precision Agriculture Using Handheld Laser-Induced Breakdown Spectroscopy (LIBS) and Multivariate Regression Methods (PLSR, Lasso and GPR). *Sensors* **2020**, *20* (2), 418.
(126) Gu, Y.; Zuo, Z.; Shi, C.; Hu, X. Feasibility Study for Spatial Distribution of Diesel Oil in Contaminated Soils by Laser Induced Fluorescence. *Appl. Sci.* **2020**, *10* (3), 1103.
(127) Thakur, D.; Kumar, Y.; Kumar, A.; Singh, P. K. Applicability of Wireless Sensor Networks in Precision Agriculture: A Review. *Wirel. Pers. Commun.* **2019**, *107* (1), 471−512.
(128) Ojha, T.; Misra, S.; Raghuwanshi, N. S. Wireless Sensor Networks for Agriculture: The State-of-the-Art in Practice and Future Challenges. *Comput. Electron. Agric.* **2015**, *118*, 66−84.
(129) Rajasekaran, T.; Anandamurugan, S. Challenges and Applications of Wireless Sensor Networks in Smart Farming—A Survey. In *Advances in Big Data and Cloud Computing*; Peter, J. D., Alavi, A. H., Javadi, B., Eds.; Advances in Intelligent Systems and Computing; Springer: Singapore, 2019; pp 353−361.
(130) Arvidsson, Å. O.; Westberg, L. Transport Bottlenecks of Edge Computing in 5G Networks. *J. Commun. Softw. Syst.* **2019**, *15* (1), 59−65.
(131) Esfahani, S.; Rollins, P.; Specht, J. P.; Cole, M.; Gardner, J. W. Smart City Battery Operated IoT Based Indoor Air Quality Monitoring System. *2020 IEEE Sensors* **2020**, 1−4.
(132) Chen, J.; Ran, X. Deep Learning With Edge Computing: A Review. *Proc. IEEE* **2019**, *107* (8), 1655−1674.
(133) Mekala, M. S.; Viswanathan, P. A Survey: Smart Agriculture IoT with Cloud Computing. *IEEE Xplore* **2017**, 1−7.
(134) Azar, J.; Makhoul, A.; Barhamgi, M.; Couturier, R. An Energy Efficient IoT Data Compression Approach for Edge Machine Learning. *Future Gener. Comput. Syst.* **2019**, *96*, 168−175.
(135) Nasif, A.; Othman, Z. A.; Sani, N. S. The Deep Learning Solutions on Lossless Compression Methods for Alleviating Data Load on IoT Nodes in Smart Cities. *Sensors* **2021**, *21* (12), 4223.
(136) Akhtar, M. N.; Shaikh, A. J.; Khan, A.; Awais, H.; Bakar, E. A.; Othman, A. R. Smart Sensing with Edge Computing in Precision Agriculture for Soil Assessment and Heavy Metal Monitoring: A Review. *Agriculture* **2021**, *11* (6), 475.
(137) Murshed, M. G. S.; Murphy, C.; Hou, D.; Khan, N.; Ananthanarayanan, G.; Hussain, F. Machine Learning at the Network Edge: A Survey. *ACM Comput. Surv.* **2021**, *54* (8), 1−37.
(138) Nikhil, R.; Anisha, B. S.; Kumar P, R. Real-Time Monitoring of Agricultural Land with Crop Prediction and Animal Intrusion Prevention Using Internet of Things and Machine Learning at Edge. *IEEE Xplore* **2020**, 216368678.
(139) Prakash, S.; Sharma, A.; Sahu, S. S. Soil Moisture Prediction Using Machine Learning. *IEEE Xplore* **2018**, 1−6.
(140) Emadi, M.; Taghizadeh-Mehrjardi, R.; Cherati, A.; Danesh, M.; Mosavi, A.; Scholten, T. Predicting and Mapping of Soil Organic Carbon Using Machine Learning Algorithms in Northern Iran. *Remote Sens.* **2020**, *12* (14), 2234.
(141) Huang, F.; Chen, J.; Du, Z.; Yao, C.; Huang, J.; Jiang, Q.; Chang, Z.; Li, S. Landslide Susceptibility Prediction Considering Regional Soil Erosion Based on Machine-Learning Models. *ISPRS Int. J. Geo-Inf.* **2020**, *9* (6), 377.
(142) Serpen, G.; Li, J.; Liu, L. AI-WSN: Adaptive and Intelligent Wireless Sensor Network. *Procedia Comput. Sci.* **2013**, *20*, 406−413.
(143) Liu, Y.; Zhang, C.; Zhu, P. The Temperature Humidity Monitoring System of Soil Based on Wireless Sensor Networks. *International Conference on Electric Information* **2011**, 1850−1853.
(144) Al-Turjman, F.; Alturjman, S. Intelligent IoT for Plant Phenotyping in Smart-Cities' Agriculture. *Intelligence in IoT-enabled Smart Cities*; CRC Press, 2019.
(145) Jilani, M. T. Comparative Analysis of Wireless Technologies for Internet-of-Things Based Smart Farm. *Sci. Int.* **2017**, *29*, 373−378.
(146) Jiménez-Buendía, M.; Soto-Valles, F.; Blaya-Ros, P. J.; Toledo-Moreo, A.; Domingo-Miguel, R.; Torres-Sánchez, R. High-Density Wi-Fi Based Sensor Network for Efficient Irrigation Management in Precision Agriculture. *Appl. Sci.* **2021**, *11* (4), 1628.
(147) Augustin, A.; Yi, J.; Clausen, T.; Townsley, W. M. A Study of LoRa: Long Range & Low Power Networks for the Internet of Things. *Sensors* **2016**, *16* (9), 1466.
(148) Ertürk, M. A.; Aydın, M. A.; Büyükakkaşlar, M. T.; Evirgen, H. A Survey on LoRaWAN Architecture, Protocol and Technologies. *Future Internet* **2019**, *11* (10), 216.
(149) Vangelista, L.; Centenaro, M. Worldwide Connectivity for the Internet of Things Through LoRaWAN. *Future Internet* **2019**, *11* (3), 57.
(150) Alenezi, M.; Chai, K. K.; Chen, Y.; Jimaa, S. Ultra-Dense LoRaWAN: Reviews and Challenges. *IET Commun.* **2020**, *14* (9), 1361−1371.
(151) Zeitler, N.; Sowieja, F.; Gäbler, H.; Dommel, J.; Koerte, H.; Erben, S.; Konrad, T.; Kurth, M.; Sikora, A. Experimental Evaluation of NB-IoT Private Networks for Process Automation. *IEEE Xplore* **2022**, 405−410.
(152) Kullaa, J. Sensor Validation Using Minimum Mean Square Error Estimation. *Mech. Syst. Signal Process.* **2010**, *24* (5), 1444−1457.
(153) Camps-Valls, G.; Bruzzone, L. *Kernel Methods for Remote Sensing Data Analysis*; John Wiley & Sons, 2009.
(154) Maxwell, A. E.; Warner, T. A.; Fang, F. Implementation of Machine-Learning Classification in Remote Sensing: An Applied Review. *Int. J. Remote Sens.* **2018**, *39* (9), 2784−2817.
(155) Ahmad, S.; Kalra, A.; Stephen, H. Estimating Soil Moisture Using Remote Sensing Data: A Machine Learning Approach. *Adv. Water Resour.* **2010**, *33* (1), 69−80.
(156) Heung, B.; Ho, H. C.; Zhang, J.; Knudby, A.; Bulmer, C. E.; Schmidt, M. G. An Overview and Comparison of Machine-Learning Techniques for Classification Purposes in Digital Soil Mapping. *Geoderma* **2016**, *265*, 62−77.
(157) Padarian, J.; Minasny, B.; McBratney, A. B. Machine Learning and Soil Sciences: A Review Aided by Machine Learning Tools. *SOIL* **2020**, *6* (1), 35−52.
(158) Hong, J.; Liu, J. Rapid Estimation of Permeability from Digital Rock Using 3D Convolutional Neural Network. *Comput. Geosci.* **2020**, *24* (4), 1523−1539.

(159) Rodríguez, J. P.; Montoya-Munoz, A. I.; Rodriguez-Pabon, C.; Hoyos, J.; Corrales, J. C. IoT-Agro: A Smart Farming System to Colombian Coffee Farms. *Comput. Electron. Agric.* **2021**, *190*, 106442.
(160) Ben Yagouta, A.; Jabberi, M.; Ben Gouissem, B. Impact of Sink Mobility on Quality of Service Performance and Energy Consumption in Wireless Sensor Network with Cluster Based Routing Protocols. *IEEE Xplore* **2017**, 1125−1132.
(161) Tseng, C. H.; Wang, S.-H.; Tsaur, W.-J. Hierarchical and Dynamic Elliptic Curve Cryptosystem Based Self-Certified Public Key Scheme for Medical Data Protection. *IEEE Trans. Reliab.* **2015**, *64* (3), 1078−1085.
(162) Pouryazdanpanah, K. M.; Anjomshoa, M.; Salehi, S. A.; Afroozeh, A.; Moshfegh, G. M. DS-VBF: Dual Sink Vector-Based Routing Protocol for Underwater Wireless Sensor Network. *IEEE Xplore* **2014**, 227−232.
(163) Ghormare, S.; Sahare, V. Implementation of Data Confidentiality for Providing High Security in Wireless Sensor Network. *IEEE Xplore* **2015**, 1−5.
(164) Ahmad, S. S.; Camtepe, S.; Jayalath, D. Understanding Data Flow and Security Requirements in Wireless Body Area Networks for Healthcare. *IEEE Xplore* **2015**, 621−626.
(165) Alotaibi, M. Security to Wireless Sensor Networks against Malicious Attacks Using Hamming Residue Method. *EURASIP J. Wirel. Commun. Netw.* **2019**, *2019* (1), 8.
(166) Gill, M. K.; Asefa, T.; Kemblowski, M. W.; McKee, M. Soil Moisture Prediction Using Support Vector Machines1. *JAWRA J. Am. Water Resour. Assoc.* **2006**, *42* (4), 1033−1046.
(167) Song, X.; Zhang, G.; Liu, F.; Li, D.; Zhao, Y.; Yang, J. Modeling Spatio-Temporal Distribution of Soil Moisture by Deep Learning-Based Cellular Automata Model. *J. Arid Land* **2016**, *8* (5), 734−748.
(168) Tian, Y.; Xu, Y.-P.; Wang, G. Agricultural Drought Prediction Using Climate Indices Based on Support Vector Regression in Xiangjiang River Basin. *Sci. Total Environ.* **2018**, *622−623*, 710−720.
(169) Rhee, J.; Im, J. Meteorological Drought Forecasting for Ungauged Areas Based on Machine Learning: Using Long-Range Climate Forecast and Remote Sensing Data. *Agric. For. Meteorol.* **2017**, *237−238*, 105−122.
(170) Zhang, J.; Zhu, Y.; Zhang, X.; Ye, M.; Yang, J. Developing a Long Short-Term Memory (LSTM) Based Model for Predicting Water Table Depth in Agricultural Areas. *J. Hydrol.* **2018**, *561*, 918−929.
(171) Sorenson, P. T.; Small, C.; Tappert, M. C.; Quideau, S. A.; Drozdowski, B.; Underwood, A.; Janz, A. Monitoring Organic Carbon, Total Nitrogen, and PH for Reclaimed Soils Using Field Reflectance Spectroscopy. *Can. J. Soil Sci.* **2017**, *97* (2), 241−248.
(172) Blackford, C.; Heung, B.; Baldwin, K.; Fleming, R. L.; Hazlett, P. W.; Morris, D. M.; Uhlig, P. W. C.; Webster, K. L. Digital Soil Mapping Workflow for Forest Resource Applications: A Case Study in the Hearst Forest, Ontario. *Can. J. For. Res.* **2021**, *51* (1), 59−77.
(173) Geissen, V.; Kampichler, C.; López-de Llergo-Juárez, J. J.; Galindo-Acántara, A. Superficial and Subterranean Soil Erosion in Tabasco, Tropical Mexico: Development of a Decision Tree Modeling Approach. *Geoderma* **2007**, *139* (3), 277−287.
(174) Märker, M.; Pelacani, S.; Schröder, B. A Functional Entity Approach to Predict Soil Erosion Processes in a Small Plio-Pleistocene Mediterranean Catchment in Northern Chianti, Italy. *Geomorphology* **2011**, *125* (4), 530−540.
(175) Wu, G.; Kechavarzi, C.; Li, X.; Wu, S.; Pollard, S. J. T.; Sui, H.; Coulon, F. Machine Learning Models for Predicting PAHs Bioavailability in Compost Amended Soils. *Chem. Eng. J.* **2013**, *223*, 747−754.
(176) Jia, X.; Cao, Y.; O'Connor, D.; Zhu, J.; Tsang, D. C. W.; Zou, B.; Hou, D. Mapping Soil Pollution by Using Drone Image Recognition and Machine Learning at an Arsenic-Contaminated Agricultural Field. *Environ. Pollut.* **2021**, *270*, 116281.
(177) Goktas, R. K.; Aral, M. M. Integrated Dynamic Modeling of Contaminant Fate and Transport within a Soil−Plant System. *Vadose Zone J.* **2011**, *10* (4), 1130−1150.
(178) Vereecken, H.; Schnepf, A.; Hopmans, J. W.; Javaux, M.; Or, D.; Roose, T.; Vanderborght, J.; Young, M. H.; Amelung, W.; Aitkenhead, M.; Allison, S. D.; Assouline, S.; Baveye, P.; Berli, M.; Brüggemann, N.; Finke, P.; Flury, M.; Gaiser, T.; Govers, G.; Ghezzehei, T.; Hallett, P.; Hendricks Franssen, H. J.; Heppell, J.; Horn, R.; Huisman, J. A.; Jacques, D.; Jonard, F.; Kollet, S.; Lafolie, F.; Lamorski, K.; Leitner, D.; McBratney, A.; Minasny, B.; Montzka, C.; Nowak, W.; Pachepsky, Y.; Padarian, J.; Romano, N.; Roth, K.; Rothfuss, Y.; Rowe, E. C.; Schwen, A.; Šimůnek, J.; Tiktak, A.; Van Dam, J.; van der Zee, S. E. A. T. M.; Vogel, H. J.; Vrugt, J. A.; Wöhling, T.; Young, I. M. Modeling Soil Processes: Review, Key Challenges, and New Perspectives. *Vadose Zone J.* **2016**, *15* (5), vzj2015.09.0131.
(179) Azar, A. T.; Ammar, H. H.; de Brito Silva, G.; Razali, M. S. A. B. Optimal Proportional Integral Derivative (PID) Controller Design for Smart Irrigation Mobile Robot with Soil Moisture Sensor. In *The International Conference on Advanced Machine Learning Technologies and Applications (AMLTA2019)*; Hassanien, A. E., Azar, A. T., Gaber, T., Bhatnagar, R., Tolba, M., Eds.; Advances in Intelligent Systems and Computing; Springer International Publishing: Cham, Switzerland, 2020; pp 349−359.
(180) Ajay, M.; Rakesh, M.; Roshan, M. H.; Revathy, G. PLC Based Smart Farming System with Scada. *IEEE Xplore* **2020**, 1−2.
(181) Kirkels, F. M. S. A.; Cammeraat, L. H.; Kuhn, N. J. The Fate of Soil Organic Carbon upon Erosion, Transport and Deposition in Agricultural Landscapes — A Review of Different Concepts. *Geomorphology* **2014**, *226*, 94−105.
(182) Heinen, M.; Assinck, F.; Groenendijk, P.; Schoumans, O. Soil Dynamic Models. *Biorefinery of Inorganics*; John Wiley & Sons, Ltd., 2020; pp 405−435.
(183) Daly, K. R.; Roose, T. Homogenization of Two Fluid Flow in Porous Media. *Proc. R. Soc. Math. Phys. Eng. Sci.* **2015**, *471* (2176), 20140564.
(184) Chavez Rodriguez, L.; Ingalls, B.; Schwarz, E.; Streck, T.; Uksa, M.; Pagel, H. Gene-Centric Model Approaches for Accurate Prediction of Pesticide Biodegradation in Soils. *Environ. Sci. Technol.* **2020**, *54* (21), 13638−13650.
(185) Jansson, J. K.; Hofmockel, K. S. Soil Microbiomes and Climate Change. *Nat. Rev. Microbiol.* **2020**, *18* (1), 35−46.
(186) Karimi, B.; Karimi, N.; Shiri, J.; Sanikhani, H. Modeling Moisture Redistribution of Drip Irrigation Systems by Soil and System Parameters: Regression-Based Approaches. *Stoch. Environ. Res. Risk Assess.* **2022**, *36* (1), 157−172.
(187) Mahmoudi, E.; Fakhri, H.; Hajian, A.; Afkhami, A.; Bagheri, H. High-Performance Electrochemical Enzyme Sensor for Organophosphate Pesticide Detection Using Modified Metal-Organic Framework Sensing Platforms. *Bioelectrochemistry* **2019**, *130*, 107348.
(188) Berardi, D.; Brzostek, E.; Blanc-Betes, E.; Davison, B.; DeLucia, E. H.; Hartman, M. D.; Kent, J.; Parton, W. J.; Saha, D.; Hudiburg, T. W. 21st-Century Biogeochemical Modeling: Challenges for Century-Based Models and Where Do We Go from Here? *GCB Bioenergy* **2020**, *12* (10), 774−788.
(189) Ren, D.; Leslie, L. M.; Karoly, D. J. Sensitivity of an Ecological Model to Soil Moisture Simulations from Two Different Hydrological Models. *Meteorol. Atmospheric Phys.* **2008**, *100* (1), 87−99.
(190) Su, Z.; Wu, J.; He, X.; Elumalai, V. Temporal Changes of Groundwater Quality within the Groundwater Depression Cone and Prediction of Confined Groundwater Salinity Using Grey Markov Model in Yinchuan Area of Northwest China. *Expo. Health* **2020**, *12* (3), 447−468.
(191) Goodchild, M.; Kühn, K.; Burek, A.; Jenkins, M.; Dutton, A. A Method for Precision Closed-Loop Irrigation Using a Modified PID Control Algorithm. *Sens. Transducers* **2015**, *188*, 61−68.
(192) Sheikh, S. S.; Javed, A.; Anas, M.; Ahmed, F. Solar Based Smart Irrigation System Using PID Controller. *IOP Conf. Ser. Mater. Sci. Eng.* **2018**, *414*, 012040.
(193) Abdelkerim, A. I.; Eusuf, M. M. R. S.; Salami, M. J. E.; Aibinu, A.; Eusuf, M. A. Development of Solar Powered Irrigation System. *IOP Conf. Ser. Mater. Sci. Eng.* **2013**, *53*, 012005.

(194) Patil, P.; Desai, B. L. Intelligent Irrigation Control System by Employing Wireless Sensor Networks. *Int. J. Comput. Appl.* **2013**, *79* (11), 33−40.
(195) Gerba, C. P.; Pepper, I. L.; Whitehead, L. F., III. A Risk Assessment of Emerging Pathogens of Concern in the Land Application of Biosolids. *Water Sci. Technol.* **2002**, *46* (10), 225−230.
(196) Diaz-Mendez, S. E.; Patiño-Carachure, C.; Herrera-Castillo, J. A. Reducing the Energy Consumption of an Earth−Air Heat Exchanger with a PID Control System. *Energy Convers. Manag.* **2014**, *77*, 1−6.
(197) Yubin, Z.; Zhengying, W.; Lei, Z.; Weibing, J. The Control Strategy and Verification for Precise Water-Fertilizer Irrigation System. *2018 Chinese Automation Congress (CAC)* **2018**, 4288−4292.
(198) Tesfahunegn, G. B.; Vlek, P. L. G.; Tamene, L. Management Strategies for Reducing Soil Degradation through Modeling in a GIS Environment in Northern Ethiopia Catchment. *Nutr. Cycl. Agroecosystems* **2012**, *92* (3), 255−272.
(199) Minasny, B.; McBratney, A. B. Digital Soil Mapping: A Brief History and Some Lessons. *Geoderma* **2016**, *264*, 301−311.
(200) Rutgers, M.; van Leeuwen, J. P.; Vrebos, D.; van Wijnen, H. J.; Schouten, T.; de Goede, R. G. M. Mapping Soil Biodiversity in Europe and the Netherlands. *Soil Syst.* **2019**, *3* (2), 39.
(201) McBratney, A. B.; Mendonça Santos, M. L.; Minasny, B. On Digital Soil Mapping. *Geoderma* **2003**, *117* (1−2), 3−52.
(202) Arrouays, D.; Lagacherie, P.; Hartemink, A. E. Digital Soil Mapping across the Globe. *Geoderma Reg.* **2017**, *9*, 1−4.
(203) Zeraatpisheh, M.; Ayoubi, S.; Jafari, A.; Tajik, S.; Finke, P. Digital Mapping of Soil Properties Using Multiple Machine Learning in a Semi-Arid Region, Central Iran. *Geoderma* **2019**, *338*, 445−452.
(204) Arrouays, D.; Poggio, L.; Salazar Guerrero, O. A.; Mulder, V. L. Digital Soil Mapping and GlobalSoilMap. Main Advances and Ways Forward. *Geoderma Regional* **2020**, *21*, e00265.
(205) Minai, J. O.; Libohova, Z.; Schulze, D. G. Spatial Prediction of Soil Properties for the Busia Area, Kenya Using Legacy Soil Data. *Geoderma Regional* **2021**, *25*, e00366.
(206) Chen, S.; Arrouays, D.; Leatitia Mulder, V.; Poggio, L.; Minasny, B.; Roudier, P.; Libohova, Z.; Lagacherie, P.; Shi, Z.; Hannam, J.; Meersmans, J.; Richer-de-Forges, A. C.; Walter, C. Digital Mapping of GlobalSoilMap Soil Properties at a Broad Scale: A Review. *Geoderma* **2022**, *409*, 115567.
(207) Arrouays, D.; Poggio, L.; Salazar Guerrero, O. A.; Mulder, V. L. Digital Soil Mapping and GlobalSoilMap. Main Advances and Ways Forward. *Geoderma Reg.* **2020**, *21*, e00265.
(208) Zhang, G.-l.; Liu, F.; Song, X.-d. Recent Progress and Future Prospect of Digital Soil Mapping: A Review. *J. Integr. Agric.* **2017**, *16* (12), 2871−2885.
(209) Assami, T.; Hamdi-Aissa, B. Digital Mapping of Soil Classes in Algeria − A Comparison of Methods. *Geoderma Reg.* **2019**, *16*, e00215.
(210) Zhou, W.; Xu, Z.; Ross, D.; Dignan, J.; Fan, Y.; Huang, Y.; Wang, G.; Bagtzoglou, A. C.; Lei, Y.; Li, B. Towards Water-Saving Irrigation Methodology: Field Test of Soil Moisture Profiling Using Flat Thin Mm-Sized Soil Moisture Sensors (MSMSs). *Sens. Actuators B Chem.* **2019**, *298*, 126857.
(211) Kuang, B.; Mahmood, H. S.; Quraishi, M. Z.; Hoogmoed, W. B.; Mouazen, A. M.; van Henten, E. J. Chapter Four - Sensing Soil Properties in the Laboratory, In Situ, and On-Line: A Review. In *Advances in Agronomy*; Sparks, D. L., Ed.; Advances in Agronomy; Academic Press, 2012; Vol. *114*, pp 155−223.
(212) Rogovska, N.; Laird, D. A.; Chiou, C. P.; Bond, L. J. Development of Field Mobile Soil Nitrate Sensor Technology to Facilitate Precision Fertilizer Management. *Precis. Agric.* **2019**, *20* (1), 40−55.
(213) Horta, A.; Malone, B.; Stockmann, U.; Minasny, B.; Bishop, T. F. A.; McBratney, A. B.; Pallasser, R.; Pozza, L. Potential of Integrated Field Spectroscopy and Spatial Analysis for Enhanced Assessment of Soil Contamination: A Prospective Review. *Geoderma.* **2015**, *241-242*, 180.
(214) United States EPA. Guidance on Systematic Planning Using the Data Quality Objectives Process EPA QA/G-4, 2006; https://www.epa.gov/quality/guidance-systematic-planning-using-data-quality-objectives-process-epa-qag-4 (accessed 2022-09-15).
(215) Zhang, Y.; Chen, M.; Zhao, Y.-Y.; Zhang, A.-Y.; Peng, D.-H.; Lu, F.; Dai, C.-C. Destruction of the Soil Microbial Ecological Environment Caused by the Over-Utilization of the Rice-Crayfish Co-Cropping Pattern. *Sci. Total Environ.* **2021**, *788*, 147794.
(216) Conforti, M.; Buttafuoco, G.; Leone, A. P.; Aucelli, P. P. C.; Robustelli, G.; Scarciglia, F. Studying the Relationship between Water-Induced Soil Erosion and Soil Organic Matter Using Vis−NIR Spectroscopy and Geomorphological Analysis: A Case Study in Southern Italy. *CATENA* **2013**, *110*, 44−58.
(217) Akbari, A.; Kasprzyk, A.; Galvez, R.; Ghoshal, S. A Rhamnolipid Biosurfactant Increased Bacterial Population Size but Hindered Hydrocarbon Biodegradation in Weathered Contaminated Soils. *Sci. Total Environ.* **2021**, *778*, 145441.
(218) Kiefer, J.; Radzuan, M. N.; Winterburn, J. Infrared Spectroscopy for Studying Structure and Aging Effects in Rhamnolipid Biosurfactants. *Appl. Sci.* **2017**, *7* (5), 533.
(219) Wu, H.; Hao, H.; Lei, H.; Ge, Y.; Shi, H.; Song, Y. Farm Size, Risk Aversion and Overuse of Fertilizer: The Heterogeneity of Large-Scale and Small-Scale Wheat Farmers in Northern China. *Land* **2021**, *10* (2), 111.
(220) Mahmood, I.; Imadi, S. R.; Shazadi, K.; Gul, A.; Hakeem, K. R. Effects of Pesticides on Environment. In *Plant, Soil and Microbes: Implications in Crop Science*; Hakeem, K. R., Akhtar, M. S., Abdullah, S. N. A., Eds.; Springer International Publishing: Cham, Switzerland, 2016; Vol. 1, pp 253−269.
(221) Keating, B. A.; Herrero, M.; Carberry, P. S.; Gardner, J.; Cole, M. B. Food Wedges: Framing the Global Food Demand and Supply Challenge towards 2050. *Glob. Food Secur.* **2014**, *3* (3−4), 125−132.
(222) Ravindranath, S. P.; Mauer, L. J.; Deb-Roy, C.; Irudayaraj, J. Biofunctionalized Magnetic Nanoparticle Integrated Mid-Infrared Pathogen Sensor for Food Matrixes. *Anal. Chem.* **2009**, *81* (8), 2840−2846.
(223) Francesconi, W.; Srinivasan, R.; Pérez-Miñana, E.; Willcock, S. P.; Quintero, M. Using the Soil and Water Assessment Tool (SWAT) to Model Ecosystem Services: A Systematic Review. *J. Hydrol.* **2016**, *535*, 625−636.
(224) Katerji, N.; Mastrorilli, M.; Cherni, H. E. Effects of Corn Deficit Irrigation and Soil Properties on Water Use Efficiency. A 25-Year Analysis of a Mediterranean Environment Using the STICS Model. *Eur. J. Agron.* **2010**, *32* (2), 177−185.
(225) Schlesinger, W. H.; Amundson, R. Managing for Soil Carbon Sequestration: Let's Get Realistic. *Glob. Change Biol.* **2019**, *25* (2), 386−389.
(226) Farrelly, D. J.; Everard, C. D.; Fagan, C. C.; McDonnell, K. P. Carbon Sequestration and the Role of Biological Carbon Mitigation: A Review. *Renew. Sustain. Energy Rev.* **2013**, *21*, 712−727.
(227) Oertel, C.; Matschullat, J.; Zurba, K.; Zimmermann, F.; Erasmi, S. Greenhouse Gas Emissions from Soils—A Review. *Geochemistry* **2016**, *76* (3), 327−352.
(228) Barthès, B. G.; Kouakoua, E.; Clairotte, M.; Lallemand, J.; Chapuis-Lardy, L.; Rabenarivo, M.; Roussel, S. Performance Comparison between a Miniaturized and a Conventional near Infrared Reflectance (NIR) Spectrometer for Characterizing Soil Carbon and Nitrogen. *Geoderma* **2019**, *338*, 422−429.
(229) Kemper, J. Biomass and Carbon Dioxide Capture and Storage: A Review. *Int. J. Greenh. Gas Control* **2015**, *40*, 401−430.
(230) Tenenbaum, D. J. Biochar: Carbon Mitigation from the Ground Up. *Environ. Health Perspect.* **2009**, *117* (2), A70−A73.
(231) Osman, A. I.; Hefny, M.; Abdel Maksoud, M. I. A.; Elgarahy, A. M.; Rooney, D. W. Recent Advances in Carbon Capture Storage and Utilisation Technologies: A Review. *Environ. Chem. Lett.* **2021**, *19* (2), 797−849.
(232) Mol, G.; Keesstra, S. Soil Science in a Changing World. *Curr. Opin. Environ. Sustain.* **2012**, *4*, 473−477.

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX

(233) Barrera-Bassols, N.; Zinck, J. A. Ethnopedology: A Worldwide View on the Soil Knowledge of Local People. *Geoderma* **2003**, *111* (3), 171−195.
(234) Ebitu, L.; Avery, H.; Mourad, K. A.; Enyetu, J. Citizen Science for Sustainable Agriculture − A Systematic Literature Review. *Land Use Policy* **2021**, *103*, 105326.
(235) Zhou, W.; Xu, Z.; Ross, D.; Dignan, J.; Fan, Y.; Huang, Y.; Wang, G.; Bagtzoglou, A. C.; Lei, Y.; Li, B. Towards Water-Saving Irrigation Methodology: Field Test of Soil Moisture Profiling Using Flat Thin Mm-Sized Soil Moisture Sensors (MSMSs). *Sens. Actuators B Chem.* **2019**, *298* (June), 126857.
(236) Mittelbach, H.; Casini, F.; Lehner, I.; Teuling, A. J.; Seneviratne, S. I. Soil Moisture Monitoring for Climate Research: Evaluation of a Low-Cost Sensor in the Framework of the Swiss Soil Moisture Experiment (SwissSMEX) Campaign. *J. Geophys. Res. Atmospheres* **2011**, DOI: 10.1029/2010JD014907.
(237) Appenfeller, L. R.; Lloyd, S.; Szendrei, Z. Citizen Science Improves Our Understanding of the Impact of Soil Management on Wild Pollinator Abundance in Agroecosystems. *PLoS One* **2020**, *15* (3), e0230007.
(238) Dickinson, J. L.; Zuckerberg, B.; Bonter, D. N. Citizen Science as an Ecological Research Tool: Challenges and Benefits. *Annu. Rev. Ecol. Evol. Syst.* **2010**, *41* (1), 149−172.
(239) Zhang, J.; Xu, Z.; Shan, M.; Zhou, B.; Li, Y.; Li, B.; Niu, J.; Qian, X. Synergetic Effects of Oxidized Carbon Nanotubes and Graphene Oxide on Fouling Control and Anti-Fouling Mechanism of Polyvinylidene Fluoride Ultrafiltration Membranes. *J. Membr. Sci.* **2013**, *448*, 81−92.
(240) Qian, X.; Ravindran, T.; Lounder, S. J.; Asatekin, A.; McCutcheon, J. R. Printing Zwitterionic Self-Assembled Thin Film Composite Membranes: Tuning Thickness Leads to Remarkable Permeability for Nanofiltration. *J. Membr. Sci.* **2021**, *635*, 119428.
(241) Fan, Y.; Qian, X.; Wang, X.; Funk, T.; Herman, B.; McCutcheon, J. R.; Li, B. Enhancing Long-Term Accuracy and Durability of Wastewater Monitoring Using Electrosprayed Ultra-Thin Solid-State Ion Selective Membrane Sensors. *J. Membr. Sci.* **2022**, *643*, 119997.
(242) Sanjeevi, P.; Prasanna, S.; Siva Kumar, B.; Gunasekaran, G.; Alagiri, I.; Vijay Anand, R. Precision Agriculture and Farming Using Internet of Things Based on Wireless Sensor Network. *Trans. Emerg. Telecommun. Technol.* **2020**, *31* (12), e3978.
(243) Ullah, R.; Abbas, A. W.; Ullah, M.; Khan, R. U.; Khan, I. U.; Aslam, N.; Aljameel, S. S. EEWMP: An IoT-Based Energy-Efficient Water Management Platform for Smart Irrigation. *Sci. Program.* **2021**, *2021*, e5536884.
(244) Adebiyi, M. O.; Ogundokun, R. O.; Abokhai, A. A. Machine Learning−Based Predictive Farmland Optimization and Crop Monitoring System. *Scientifica* **2020**, *2020*, e9428281.
(245) Hong, Y.; Chen, S.; Zhang, Y.; Chen, Y.; Yu, L.; Liu, Y.; Liu, Y.; Cheng, H.; Liu, Y. Rapid Identification of Soil Organic Matter Level via Visible and Near-Infrared Spectroscopy: Effects of Two-Dimensional Correlation Coefficient and Extreme Learning Machine. *Sci. Total Environ.* **2018**, *644*, 1232−1243.
(246) Gbangou, T.; Sarku, R.; Slobbe, E. V.; Ludwig, F.; Kranjac-Berisavljevic, G.; Paparrizos, S. Coproducing Weather Forecast Information with and for Smallholder Farmers in Ghana: Evaluation and Design Principles. *Atmosphere* **2020**, *11* (9), 902.
(247) Wolfert, S.; Ge, L.; Verdouw, C.; Bogaardt, M.-J. Big Data in Smart Farming − A Review. *Agric. Syst.* **2017**, *153*, 69−80.

https://doi.org/10.1021/acs.est.2c03562
Environ. Sci. Technol. XXXX, XXX, XXX−XXX