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REVIEW

Dynamic Soil Health Monitoring: Early Warning Thresholds of Pollution and Structural Failure Based on Data

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ABSTRACT

The health of soil is a vital factor in the ecology of the ecosystem, the use of agriculture, and the stability of infrastructure. The conventional soil evaluation techniques, which are mainly based on periodical sampling and laboratory analysis, are usually unable to provide the dynamic variability of chemical, physical, and biological soil properties. The recent sensor network, remote sensing, and data analytics innovations have allowed the creation of dynamic soil health monitoring systems that deliver high-resolution and continuous data. The review paper summarizes the existing information on the application of chemical, physical, and biological indicators to the assessment of soils, with a focus on how these indicators are used as early warning indicators of pollution and structural damage. We critically assess sensor technologies, Internet of Things (IoT) platforms, remote sensing strategies, and the integration of labs and fields, with an emphasis on their strong aspects, limitations, and opportunities to use them in real-time. The review goes on to discuss data-driven modeling approaches, such as statistical modeling, machine learning, and sensor fusion, for predicting soil degradation, contaminant accumulation, and structural instability. The main issues, including the heterogeneity of the soils, the reliability of the sensors, the fusion of the data, and the tailored thresholds, are presented, as well as the new opportunities in adaptive monitoring, the development of biosensors, and predictive analytics. Dynamic soil health monitoring can provide evidence-based interventions proactively in advance through the integration of multi-dimensional pointers with real-time data and predictive modeling, and through the implementation of soil management programs based on anticipation instead of remedies. It is a framework that provides a means of sustainability in the management of soil and infrastructure, which

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increases resilience to man-made pressures and environmental uncertainty.

Keywords: Dynamic Soil Monitoring; Early Warning Thresholds; Pollution; Structural Failure; Data-Driven Modeling

1. Introduction

Soil is a key element of the terrestrial ecosystem, and therefore it plays essential roles in sustaining agriculture, water, nutrient cycling, and infrastructural stability [1]. Soil health has become a key issue of concern that is widely acknowledged to determine ecosystem services, food security, and environmental sustainability [2]. Conventionally, soil testing has been based on periodic sampling and laboratory testing of chemical, physical, and biological characteristics [3]. Although these approaches can give fine snapshots, they are limited in nature to describe the spatiotemporal variability of soil systems. Dynamic processes like nutrient transfers, contaminant transport, moisture fluctuations, and structural erosion may take place in a short period, and in most cases, they may not be detected using traditional methods of monitoring [4]. Therefore, there is an increased need for advanced approaches that would be able to constantly observe the health of soil, identify the initial signs of its deterioration or pollution, and offer practical thresholds that would avoid ecological and infrastructural breakdowns.

Increased pressure on soil systems has been triggered by recent environmental issues, such as increased industrialization, urbanization, and intensive agriculture [5]. The heavy metals, persistent organic pollutants, and the excessive use of fertilizers may chemically pollute the earth and interfere with the biogeochemical processes, diminishing the diversity of microorganisms and lowering the productivity of soil [6]. Physical degradation, such as compaction, erosion, and subsidence, undermines the structural integrity of the soils and poses a risk to the stability of structures like roads, embankments, and buildings. The interaction of these stressors tends to go into complex feedback, which the traditional methods of monitoring cannot effectively handle. Here, dynamic soil health monitoring concept, where soil health is assessed on a continuous or near real-time basis through a combination of chemical, physical, and biological indicators, has become a pioneer concept of soil management and mitigating risks [7].

Dynamic monitoring is new because it allows examination of the early warning signs before it is too late to reverse the process of soil degradation [8]. Early warning thresholds refer to the quantitative levels of soil systems that are based on empirical data, predictive models, or regulatory standards and warn that the soil systems are moving toward dangerous contamination or structural instability. As an example, the slight metal heavy metal rises, changes in microbial activity, or even progressive compaction may signal the approach of ecological stress or subsidence. With such thresholds, managers will be able to take the necessary interventions at the right time through changing the irrigation patterns, implementing remedial measures, or strengthening the vulnerable infrastructure to avoid the costly effects on the environment as well as the economy. In contrast to the conventional methods used to assess the environment, dynamic monitoring considers the temporal dynamics, the spatial variability and the environmental interactions, thus allowing the proactive management of the environment as opposed to the remedial process that restores it [9,10].

The recent developments in sensor technologies, remote sensing, and data analytics have provided opportunities to operationalize dynamic soil monitoring as never before [11]. Internet of Things (IoT) platforms and wireless sensor networks enable real-time measurements of soil moisture, temperature, pH, nutrient levels, and compaction with a high level of temporal resolution [12]. Remote sensing imaging (unmanned aerial vehicles (UAVs), satellites, hyperspectral imaging, etc.) can be used to monitor the surface properties, erosion, and distribution of pollutants in large areas of land [13]. Such technologies, together with powerful data management systems, offer access to multidimensional soil data in real time. Notably, the incorporation of chemical, physical, and biological streams of information improves the precision and sensitivity of early warning systems. As an example, a heavy metal sensor in conjunction with the microbial diversity index and the soil drying out or wetting can help identify the risks of contamination that the monitoring of one indicator alone would not show.

In addition to technological innovations, data-driven modeling is also one of the essential innovations in the dynamic evaluation of the health of the soil [14]. Predictive analytics, machine learning algorithms, and various statistical models can be used to extract meaningful patterns from big heterogeneous data. Non-linear interdependence between soil properties and environmental stressors can be detected using machine learning algorithms, including random forests and neural networks, which would allow predicting both pollution and structural failures with high confidence. A further method of predictive ability involves sensor fusion, whose different indicators are combined to form composite risk indices[15]. Through their flexibility, adaptive threshold models provide the opportunity to consider the variation in the soils and climate of the region and land-use patterns, based on historical trends and environmental context. These strategies taken in combination bring the paradigm of descriptive soil monitoring to the predictive and prescriptive soil management and this is just a major stride forward in the realms of environmental science and infrastructural engineering.

Although these have been made, there are still many knowledge gaps that justify the need to revise dynamic soil health monitoring in depth. To begin with, there exists no commonized structure for incorporating multi-source soil data into practical early warning parameters. Current regulatory boundaries usually address individual contaminants or individual physical parameters, without evaluating the synergies of interaction between chemical, physical, and biological characteristics[16]. Second, there are still difficulties in the translation of high-resolution sensor and remote sensing data into viable management decisions. The variability of the environment and the different types of soils, as well as the technical constraints of sensors, may complicate the interpretation of data and risk assessment[11]. Third, the synthesis of the emerging methods of identifying structural failure in soils, such as compaction, subsidence, erosion, and aggregate breakdown, is limited, even though they have serious implications for infrastructure and land management[17]. To solve such gaps, a comprehensive model is needed that incorporates technological innovation, modeling based on data, and ecological and engineering concepts.

The present review will attempt to offer such a framework by summarizing the existing knowledge on the topic of dynamic soil health monitoring and emphasizing the importance of early warning thresholds in identifying both pollution and structural failure[18]. The goals are three and they include: (1) to review the chemical, physical, and biological indicators of the dynamic monitoring, (2) to outline the technological platform and data-driven models allowing continuous assessment of soil, and (3) to address the challenge, knowledge gaps, and prospects of integrating early warning systems into sustainable soil management. This review offers a new dimension of understanding soil health monitoring, which goes beyond the traditional, non-dynamic methods of assessment by focusing on the integration of multi-dimensional data streams and predictive modeling. It also indicates the opportunities of dynamic methods to assist in proactive efforts, minimize the environmental risk, and protect the agricultural performance, as well as the resilience of infrastructure[19].

Finally, the originality of dynamic soil health monitoring is that it is integrative in nature, real-time, and predictive, thus making soil management a proactive rather than a reactive science[10]. With integrated sensor networks, remote sensing, and machine learning, it is possible to create early warning levels that notice slight changes in soil status before it is too late and the degradation process cannot be reversed (**Figure 1**)[20]. These are the strategies that are essential in solving the modern environmental issues, such as pollution, soil degradation, and climate unpredictability, and provide a way of achieving sustainable and resilient soil management practices. This review offers a thorough synthesis of the existing body of knowledge and offers potential directions for future research, which can be seen as transformative due to the potential offered by data-driven soil health monitoring.

2. Soil Health Indicators

Soil health is the capacity of soil to perform as an important living ecosystem to support plants, animals, and people[18]. Its evaluation should be based on a thorough comprehension of various related properties, including chemical, physical, and biological levels. Although conventional assessment is typically conducted in terms of single parameters, there is emerging evidence of incorporating the indicators to reflect the multifactorial dynamics of the soil systems. All types of indicators offer different understandings of the functioning of the soil and its resilience, and yet the indicators are related, and changes in one aspect are frequently reflected in other ones, which makes it clear that multi-dimensional monitoring structures are required[21].

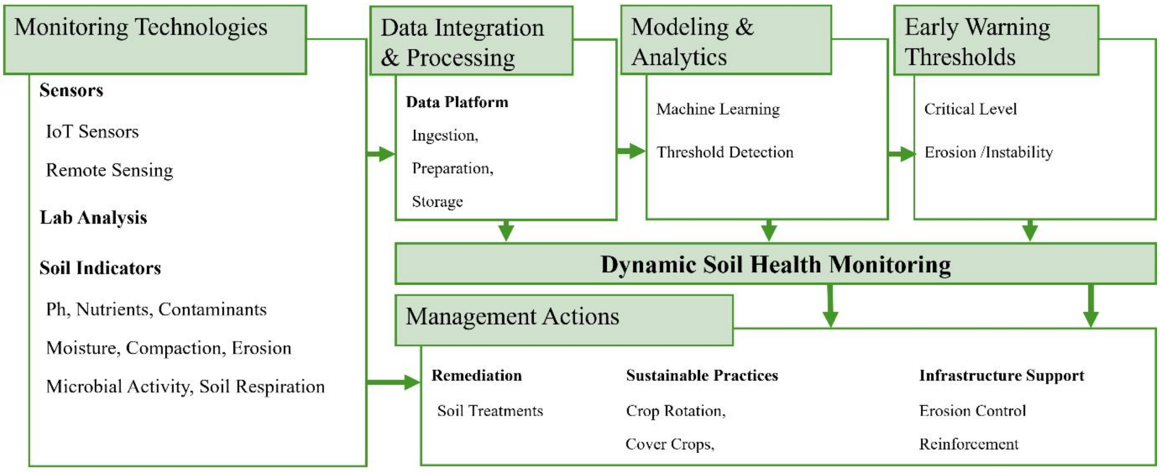

Figure 1. Conceptual framework of dynamic soil health monitoring.

Note: **Figure 1** illustrates the integration of chemical, physical, and biological soil indicators with monitoring technologies such as sensors, remote sensing platforms, and laboratory analyses. These data streams feed into analytical and modeling systems that establish early warning thresholds for pollution and structural degradation, supporting proactive soil management and intervention strategies.

2.1. Chemical Indicators

The most common measures of soil health are still chemical properties, since they directly relate to fertility, toxicity, and the cycling of nutrients[22]. Parameters (pH, salinity, nutrient contents, especially nitrogen, phosphorus, and potassium) are construction blocks where the functions of soils can be assessed. Sub and supersaturation of pH not only affect the growth of plants, but it also controls the bioavailability of micronutrients and heavy metals, and, consequently, microbial activity and mobility of contaminants. Of particular importance are the heavy metals such as lead, cadmium, and arsenic, which occur frequently in contaminated or industrialized soil and are likely to accumulate to toxic levels, affecting the microbial communities and leading to health hazards to humans[23]. Inorganic contaminants, e.g., the persistence of pesticides or hydrocarbons, also disrupt microbial metabolism and enzymatic functioning, producing permanent functional impairment[24]. My investigation of the existing studies shows that chemical indicators are not very difficult to measure, but their one-sided interpretations may be inaccurate. An example is the nutrient deficiencies that can be found in soils that have adequate total nutrient content, but as a result of adsorption, competing ions, or microbial immobilization. Thus, the indicators of chemical must be put into the framework of the bigger soil processes to enable a meaningful understanding of the health of the soil in general.

2.2. Physical Indicators

Water retention, aeration, root penetration, and erosion resistance are directly dependent on the physical properties of soil, such as texture, bulk density, porosity, aggregate stability and compaction[25]. Damage to the structure, which may be a result of intensive tillage, or traffic of heavy machinery and may be caused by natural processes like desiccation, can be a serious deterrent to soil functioning. Bulk density is used as a measure of compaction, with large values normally suggesting constrained root development and lower water absorption, and low bulk density may show poor aggregation and susceptibility to erosion. The measure of the resilience of groups of soil under the influence of water or mechanical forces, aggregate stability, indicates the presence of chemical binding, as well as biological activity. According to recent research findings, physical indicators are not simply descriptive; they predict soil behavior under stress. Indicatively, soils that have marginally low porosity levels can record disproportionate decline in hydraulic conductivity during episodic rainfall, triggering erosion or surface runoff[26]. Although they are crucial, the systematic assessment of physical indicators stands as a rather challenging issue because of the heterogeneity of space and variability with time. This constraint highlights the possibility of implementing dynamic monitoring technologies that are capable of recording real-time variations and correlating them to early warning levels of structural failure.

2.3. Biological Indicators

The biological properties give an insight into the living part of the soils, and they entrap the ability of microorganisms, animals, and biochemical reactions to continue soil functionality [27]. The resilience and nutrient cycling are indicated by such indicators as the biomass of the microbes, enzyme activity, rates of respiration, and diversity indexes [28]. Microbial communities are rather sensitive to chemical pollutants, compaction, changes in moisture, pH variations, and, as such, are one of the greatest indicators of early warning. The activities of enzymes, including dehydrogenase, urease, and phosphatase, can be used as integrative measures of the biochemical potential and nutrient turnover and can respond faster to environmental perturbations as compared to physical or chemical parameters. A critical review of the literature shows that despite its high information potential, the biological indicators have not been used in soil monitoring on a large scale because of the complexity of measurement and the confounding effect of seasonal variation and the availability of the substrate [29]. New developments in the field of metagenomics, metabolomics, and biosensor technology, though, are providing new possibilities to measure and quantify microbial activity on a real-time basis, and to this end, biological indicators are becoming more and more actionable with regard to early warning systems.

2.4. Composite Indices

Leveraging the shortcomings of single indicators, scientists have recently come to create composite measures of soil health, where chemical, physical, and biological data are combined into complete measures of soil health [30]. Other indices include the Soil Quality Index (SQI) or the Integrated Soil Health Index (ISHI), which uses a weighted aggregation scheme or multivariate statistical methodology to give a single measure that can be used to make a comparison across sites, time, or across management regimes [31]. The benefits of these composite indices are as follows: they are able to capture complicated interactions between soil properties, and they can directly relate soil health to ecosystem services or crop yield. Nevertheless, there are some difficulties in the creation of such indices. The weighting schemes tend to be based on skill or empirical associations and might not be applicable in heterogeneous soils or climatic conditions. Moreover, dynamic monitoring has an additional condition that composite indices are not simply reflective of static snapshots. New paradigms that integrate real-time data streams, sensor fusion, and machine learning are now trying to overcome these issues, and composite indices are becoming good predictors of early warning systems in not only pollution control, but also structural collapse [32]. **Table 1** summarizes the principal soil health indicators that are measured and used in dynamic monitoring, and the functional implications of these indicators.

Table 1. Major soil health indicators used in dynamic monitoring systems include chemical, physical, and biological parameters, measurement techniques, and functional relevance.

Indicator Type	Specific Parameters	Measurement Methods	Functional Relevance	Typical Thresholds/Notes
Chemical	pH, N, P, K, heavy metals, salinity, organic contaminants	Soil extraction, spectrometry, ion-selective electrodes	Nutrient availability, contamination, microbial activity	Varies by crop/soil type; regulatory limits for pollutants
Physical	Bulk density, porosity, aggregate stability, compaction, erosion susceptibility	Penetrometer, core sampling, water-stability tests	Root penetration, water retention, soil structure	Site-specific; thresholds for compaction and erosion risk
Biological	Microbial biomass, enzyme activity, respiration, diversity indices	Respiration assays, enzyme activity kits, metagenomics	Nutrient cycling, soil resilience, organic matter turnover	Sensitive to chemical stress and moisture variation

2.5. Integrative Perspectives

Combining chemical, physical, and biological indicators, a multidimensional approach to the measurement of soil health is created [33]. These categories are complementary, and their combination is necessary to get a clear picture of the dynamic processes under which soil functions. Notably, changes in one area frequently trigger changes in others, so the chemical contamination can cause a decline in microbial diversity, a decrease in enzyme activity, and a change in the aggregate stability. The major problem of soil monitoring is whether or not to capture these interactions in real-time and to translate them into predictive measures that result in a management decision. Data-driven, operationalizing such an integrative perspective can be achieved through dynamic operational means that combine high-frequency sensor data, remote sensing, and modeling. With the help of such innovations, scientists and operators can shift to active management of the soil instead of passive testing and come up with early warning signs that allow for maintaining the ecological and structural stability of the soil [30].

3. Dynamic Soil Monitoring Technologies

Dynamic observation of soil health is a shift in paradigm from traditional, fixed measurements of soil health to continuous, high-resolution measurements of chemical, physical, and biological properties of soil [7,10]. Technological inventions are critical in the ability to capture the temporal variability, identify the initial indicators of degradation, and forecast the occurrence of imminent structural or chemical stress. In the last ten years, sensor networks, remote sensing, the integration of the laboratory and the field, and the management of data have all been developed to achieve the actual dynamic soil monitoring systems. These technologies do not just improve on the spatial and temporal precision of the soil assessment, but also emerge as invaluable inputs to data-informed early warning thresholds, predictive modelling, and decision structures [14].

3.1. Sensor Networks and the Internet of Things (IoT)

IoT platforms and wireless sensor networks (WSNs) have become the main technologies and foundation of real-time soil monitoring [34]. In situ sensors that can measure soil moisture, temperature, pH, electrical conductivity, nutrient concentrations, and bulk density may be used in agricultural fields, urban soils, or industrial locations [35]. These instruments are used to record high-frequency measurements that are continuous and affected by the occurrence of irrigations, rainfall, contaminant infiltration, or anthropogenic disturbance. Critical assessment of WSNs suggests that even though it offers unprecedented temporal resolution, there are still issues of sensor calibration, drift, energy efficiency, and spatial representativeness. An example is the soil heterogeneity on micro- to meso-scales that may lead to immense variability that cannot be captured using a single-point measurement. To solve this, there have been suggestions of dense sensor arrays and mobile sensor platforms, which allow fixed and adaptive monitoring [36]. Connection to IoT models is enabling data to be sent in real-time to cloud servers where complex analytics can be performed to detect anomalies, raise threshold warnings, and make predictive model forecasts. Although this has been achieved, the cost, maintenance, and standardization requirements are still obstacles to large-scale implementation, and this is one of the main areas that future research can focus on.

3.2. Remote Sensing Technologies

Remote sensing provides a complementary approach to ground-based sensors, which allows the analysis of surface soil properties and environmental drivers on a large scale [11]. Multispectral and hyperspectral imaging systems in satellites, unmanned aerial vehicles (UAVs), and manned aircraft can identify the changes in the vegetation cover, soil moisture, surface temperature, and contaminant signal [37]. Hyperspectral indices are helpful, especially in mapping soil organic matter, salinity, heavy metal contamination, and erosion patterns at very fine spatial resolution [38]. The remote sensing data are sharply criticized in regard to their capabilities to detect fine details on the surface; in fact, the technologies have a strong spatial coverage, but weak depth penetration, and they need calibration with ground-truth measurements most of the time. Additionally, atmospheric interference, seasonal vegetation alterations, and sensor resolution limitations may create uncertainties in the process of interpreting soil properties. However, sensor fusion, i.e., the combination of remote sensing and ground-based sensors, can help eliminate most of these constraints and offer a multiscale, multidimensional perspective of soil dynamics that would be needed to set up effective and trustworthy early warning levels [39]. **Table 2** outlines the major technologies that are currently used to do dynamic soil monitoring and their main features.

Table 2. Comparison of dynamic soil monitoring technologies.

Technology	Parameters Measured	Spatial/Temporal Resolution	Strengths	Limitations
Soil sensors/IoT	Moisture, temperature, pH, nutrients, bulk density	High temporal, point-scale	Real-time, continuous, integrative	Calibration, maintenance, spatial heterogeneity
Remote sensing (UAV, satellite)	Surface moisture, vegetation indices, salinity, contaminants	Large area, moderate temporal	Large-scale, non-invasive, multi-spectral	Limited depth, requires ground-truthing

Table 2. *Cont.*

Technology	Parameters Measured	Spatial/Temporal Resolution	Strengths	Limitations
Laboratory/ portable devices	Heavy metals, organic contaminants, enzyme activity	Point-scale, episodic	High accuracy, multi-parameter	Labor-intensive, not continuous

Note: The comparison includes sensor networks, remote sensing platforms, and laboratory-based methods, highlighting their measured parameters, spatial and temporal resolution, strengths, and limitations.

3.3. Laboratory and Field Integration

Although in situ sensors and remote platforms can offer real-time data, laboratory-based analyses are necessary to make high-accuracy measurements, especially on complex chemical and biological indicators. The portable spectrometers, microfluidic equipment and automated soil analyzers enable the near real-time evaluation of heavy metals, nutrients, organic contaminants, and microbial activities in the field [40,41]. The ability of the system to combine laboratory-grade precision and field-deployed flexibility improves coverage and reliability. Moreover, recent advances in biosensors and enzyme-based probes make it possible to directly measure the biological activity, including microbial respiration or enzyme inhibition, which can give dynamic information on the state of soil functional health [42]. Critical assessment suggests that these kinds of technologies are generally not robust, sensitive to environmental conditions, and require standardization for calibration procedures. However, the combination of field sensors, remote platforms, and laboratory validation is an all-encompassing strategy of dynamic soil monitoring.

3.4. Data Management and Analytical Platforms

The resulting expansion of high-frequency, multidimensional soil measurements requires complex data management, processing, and analysis structures. Real-time aggregation, storage, and processing of chemical, physical, and biological data are possible based on cloud-based platforms, edge computing, and sensor fusion algorithms [43]. Higher-order analytics, such as statistical models, multivariate analysis, and machine learning, assist in discovering the patterns, anomalies, and predictive features of pollution or structure collapse. One of the crucial observations is that the value of dynamic monitoring lies not in data acquisition, but in the ability to convert the complex and heterogeneous datasets to actionable knowledge. The difficulties still lie in the process of reconciling the data between different sources, addressing the uncertainty, and converting the results into meaningful early warning indicators for managers. New strategies, including adaptive thresholding, predictive modeling, and integrated decision support systems, are starting to deal with these shortcomings, offering a model in which dynamic monitoring is closely connected with intervention and risk reduction [14].

3.5. Integrative Perspective

All these technologies of dynamic soil monitoring allow shifting towards proactive soil management rather than a reactive one. With the integration of real-time sensors, remote sensing platforms, field-laboratory integration, and superior data analytics, the spatial-temporal heterogeneity of the soil systems and the early signs of contamination or structural breakdown can be recorded [11,44]. The critical analysis of the literature implies that the combination of numerous technological layers will strengthen the system and increase the predictability, whereas the use of the single platform may lead to wrong interpretations. In addition, the methodological standardization, calibration protocols, and site-specific understanding of soil properties should accompany the technological innovation in order to achieve the highest level of reliability. In the end, such dynamic monitoring solutions are the basis of defining the early warning threshold, evidence-based intervention, and sustainable management of soil and infrastructure under the pressure of the growing environmental demands.

4. Early Warning Thresholds and Data-Driven Risk Assessment

The resulting dynamic soil monitoring produces large volumes of chemical, physical, and biological data, but the question of whether the observations can be converted into environmental and infrastructure management insights is highly critical [10,45]. Early warning thresholds are a fundamental idea of this translation; they define some quantitative values beyond which the functioning of soil is likely to be impaired, or some damage might be irreversible. These thresholds are not fixed, and instead, they are dynamic, context-oriented, and usually predictive and combine and amalgamate historical data, environmental circumstances, as well as mechanistic knowledge of the soil processes. Combined with data-driven modeling methods, early warning thresholds can be used to implement proactive responses to avert the growth of pollution, structural collapse, or the loss of an ecosystem service.

4.1. Pollution Thresholds

Soil pollution is one of the most widespread risks to soil health, and chemical pollutants of soil, such as heavy metalloorganic compounds and nutrient imbalances, have long-term ecological and human-health risks [46]. Drawing early warning levels of pollution entails setting the critical levels of the contaminants at which they start to interfere with the microbial communities, nutrient cycling, or plant growth.

Cadmium, lead, and arsenic are of particular concern because they are persistent and bioaccumulative. Studies have shown that even low levels of these metals may cause changes in the composition of microbial communities, diminish enzyme activities, and undermine soil resilience well before regulatory levels are achieved [47]. In the same way, the organic pollutants, such as the long-lasting pesticides and industrial hydrocarbons, have the potential to produce unnoticeable but accumulating effects on the metabolism and structure of the soil. Excessive nutrients, especially nitrogen and phosphorus, cause eutrophication in neighboring water systems and alter the biogeochemistry of soils. It can be critically stated that traditional regulatory thresholds do not tend to consider the time dynamics of the process, its synergies, and site-specific variability, and adaptive thresholds based on data are desirable to consider not a fixed limit of a chemical concentration but real-time soil functioning [14].

4.2. Structural Failure Thresholds

In addition to chemical contamination, the soil's structural integrity is also necessary to support vegetation, sustain hydrological activity, and infrastructure [48]. Examples of processes included in structural failure are compaction, aggregate breakdown, erosion, subsidence, and landslides. Early warning criteria in this field tend to be expressed in terms of critical bulk density, porosity, moisture content, or shear strength values, above which the soil cannot perform its load-bearing or erosion-resistance duties any longer [49]. Compaction, such as will lower the pore connectivity and hydraulic conductivity, augmenting the chance of surface runoff, root stress, and desiccation cracks, and aggregate instability may lead to localized collapse or erosion during rainfall. The critical evaluation of the available literature shows that structural thresholds are very site-dependent and depend on soil type, land use, climatic conditions, and antecedent stressors. Also, cross-coupling of chemical and physical degradation processes, e.g., metal contamination, enhances the destabilization of the aggregate, highlighting the integration of thresholds to reflect multi-dimensional soil vulnerability as opposed to structural and chemical risks separately [50]. **Table 3** summarises representative values of early warning thresholds of indicators of pollution and structural degradation.

Table 3. Representative early warning thresholds for selected soil chemical, physical, and biological indicators used to detect pollution risks and structural degradation.

Indicator Type	Parameter	Threshold Value/Risk Level	Early Warning Signal	Reference/Source
Chemical	Cadmium	3 mg/kg (soil guideline)	Decline in microbial biomass	Yu et al. [51]
Chemical	Nitrogen (N)	>200 kg/ha	Nutrient leaching potential	Cannavo et al. [52]
Physical	Bulk density	>1.6 g/cm^3	Compaction risk	Alosnos [53]
Physical	Shear strength	<25 kPa	Erosion/slope instability	Huang et al. [54]
Biological	Enzyme activity (dehydrogenase)	<30% baseline	Soil functional stress	Asensio et al. [55]

4.3. Data-Driven Modeling Approaches

The declivity of soil systems and the variety of systems require the use of advanced modeling to identify efficient early warning levels. The basis of the insight relates to statistical models, such as multivariate regression and principal component analysis, which correlate the soil indicators with the environmental stressors or the results of degradation.

Nevertheless, these methods might be restricted in their ability to represent non-linear interactions, high-dimensional dependencies, or dynamics. Machine learning algorithms, including random forests, support vector machines, and artificial neural networks, also provide better predictive features, being able to determine intricate patterns and thresholds within heterogeneous data [56]. Sensor fusion also enhances predictive performance by combining chemical, physical, and biological data streams that embody cross-domain interactions, which can be an early warning of imminent failure. Predictive modeling frameworks that integrate multi-source soil data enable the development of adaptive early warning systems (**Figure 2**).

Adaptive thresholding is a new idea, and in it, predictive models constantly revise threshold values using real-time data, environmental factors, and past trends [57]. These methods go beyond fixed, one-fit limits, providing context-dependent early warnings, both as to the current condition of the soil and the direction it takes when subjected to environmental stress. Critical analysis points to the fact that thresholds based on data are successful when there is high-quality data, data density, and sound models are developed. Predictive thresholds can either give false positive or false negative results without proper calibration and integration, and hence, the reliability of early warning systems is compromised.

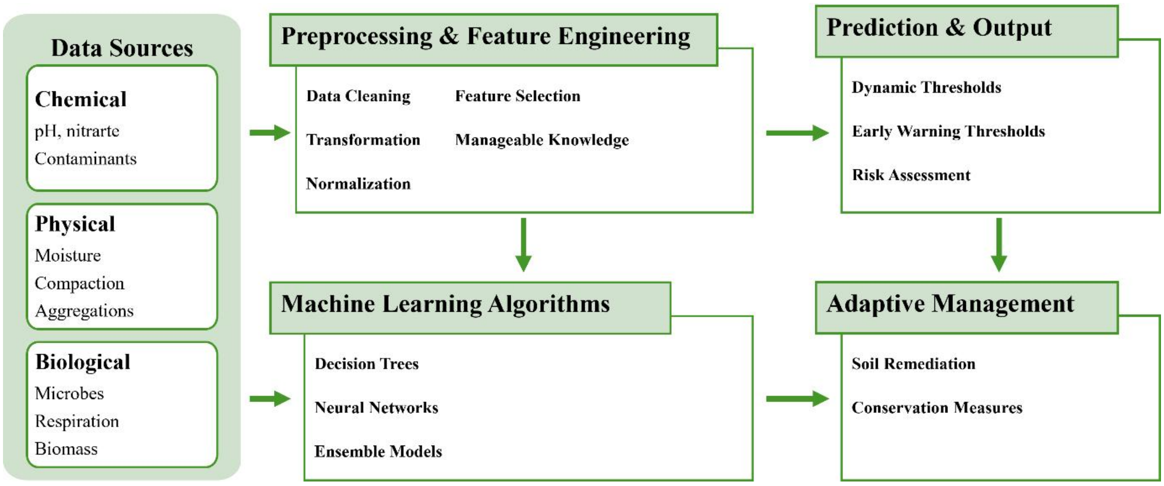

Figure 2. Workflow of data-driven soil health prediction.

Note: **Figure 2** illustrates the integration of chemical, physical, and biological datasets through preprocessing, machine learning algorithms, and predictive modeling to generate dynamic early warning thresholds and risk assessments.

4.4. Integrative Perspective

The combination of pollution and structural thresholds with data-driven modelling constitutes a complete scheme for proactive management of soil [14]. Maintaining a balance between the chemical, physical, and biological attributes, as well as inoculating predictive algorithms to create dynamic thresholds, enables soil health evaluation to be proactive instead of reactive. This method can be used to detect at-risk soils at an early stage so that corrective measures, such as remedial measures, structural reinforcements, or management practices, can be implemented before it is too late. Importantly, evolving early warning systems not only enhance ecological and agricultural resilience but also have useful inputs towards infrastructure planning, climate adaptation policies, and environmental policy. Recent research suggests that synergistic deliveries of real-time monitoring, predictive modelling, and adaptive thresholding are the future of soil health management, as they contain the potential to balance between productivity, sustainability, and risk reduction [58].

4.5. A Structured Framework for Defining, Calibrating, Validating, and Transferring Early Warning Thresholds

We suggest a four-stage process to shift the focus from concept to operation, one that enables systematic definition, calibration, validation, and transfer of early warning thresholds across soils and regions. The framework is an iterative and data-driven approach that allows thresholds to be updated as additional monitoring data becomes available [59].

Stage 1—Definition sets initial candidate thresholds with two complementary approaches. The top-down values are first compiled from existing regulatory limits (e.g., soil quality guidelines for heavy metals), ecotoxicological benchmarks (EC_{10} or EC_{25} for microbial endpoints), and literature-based critical ranges for physical parameters (bulk density or shear strength). Second, baseline monitoring data from non-stressed conditions are used in a bottom-up approach to calculate specific percentiles (such as the 90th percentile for pollutants and the 10th percentile for enzyme activities), with bootstrap confidence intervals. A hybrid candidate threshold (e.g., the 85th percentile of background cadmium concentrations, not exceeding the regulatory guideline) is then chosen to ensure ecological relevance and legal defensibility while meeting the threshold.

Stage 2—Calibration fine-tunes thresholds for candidates based on high-frequency time series data from sensor networks. In quantile regression, the 10th, 50th, and 90th quantiles of a biological or physical response are modeled as functions of the indicator; the threshold is the indicator value that corresponds to the 10th quantile of the response being below a given function. Changepoint detection algorithms can independently detect statistically significant changes in the mean or variance of an indicator over time. A changepoint detection algorithm, such as Pruned Exact Linear Time (PELT), can detect statistically significant changes in the mean or variance of an indicator over time without relying on other algorithms. The first changepoint before degradation is observed (degradation here means either decreased crop yields or increased erosion) is chosen as the calibrated threshold. For example, if the soil's bulk density has a changepoint at 1.58 g/cm^3 and structural failure consistently occurs when the bulk density exceeds 1.62 g/cm^3, then the calibrated early warning threshold is set to 1.58 g/cm^3 with a safety margin. Calibration should be done for every soil type, land use, and climate zone, and should take anywhere from 6 to 12 months of daily or sub-daily data [60].

Stage 3—Validation is the stage where the calibrated threshold is quantified in terms of how well it distinguishes between safe and impending-failure conditions prior to irreversible damage. The time series is divided into two sets: a calibration set (the first 70% of the data) and a testing set (the last 30%), using temporal cross-validation. The true positive rate (TPR, the proportion of degradation events that are detected at least 48 h before their onset), the false alarm rate (FAR, the proportion of warnings for which no degradation is actually observed before the onset), and the lead time (LT, the mean time between threshold violation and visually noticed degradation onset) are calculated for each threshold. The acceptable early warning threshold is a true positive rate of at least 0.80, or a false alarm rate of less than 0.20, with a lead time of at least 24–72 h, depending on the process. Spatial validation is also carried out by calibrating thresholds on a representative sample of monitoring sites, testing them on independent sites, and assessing the level of agreement by calculating the Kappa coefficient and the area under the receiver operating characteristic curve (AUC-ROC). If the AUC is below 0.10, an attempt is made to return to Stage 2 for recalibration.

Stage 4—Transfer allows thresholds to be applied to areas with no existing historical data via pedotransfer functions and covariate-adjusted transfer matrices. A random forest or gradient boosting machine is trained on a meta-dataset from multiple sites with previously validated data, using soil texture, organic carbon, cation exchange capacity, mean annual precipitation and temperature, and land-use intensity as input variables. The model gives the prediction of the local threshold for each indicator. An adjustment matrix gives multipliers when model runs are not available to use in the field quickly, such as when applying to a different soil or rainfall amount (e.g., 2% organic carbon and 800 mm rainfall). The values of clay content (30–35%) and organic carbon (3–3.5%) are between 1.2 and 1.4, while the values of heavy use of agricultural land (intensive agriculture) and annual rainfall (1,000–1,500 mm) are 0.8–0.9. The final transferred threshold is the product of relevant multipliers times the reference threshold. Thus, for a region of high organic carbon content (3.5%) and high rainfall (1,200 mm) and in a heavily cultivated area (HOC), a Cd reference level of 3.0 mg/kg on loam is carried over to a clay rich highly organic carbon and high rainfall (HOC) area as $3.0 \times 1.3 \times 1.2 \times 0.8 \times 0.85 = 3.18$ mg/kg, rounded to 3.2 mg/kg for operational use.

The framework is iterative, and thresholds should be recalibrated every 2–3 years or after extreme climatic events. Each threshold is reported along with 90% confidence intervals and validation metrics and given as traffic light bands: green (less than 0.8 × threshold, normal), yellow (0.8–1.0, watch), orange (1.0–1.2, early warning), and red (above 1.2, imminent failure). This is a structured approach that brings the early warning thresholds concept to life and makes it transferable, expressing the need for a concrete contribution beyond a simple summary [61–65].

5. Challenges and Future Perspectives

The dynamic monitoring of soil health has a transformational potential in addressing pollution, structural stability, and resilience of the entire ecosystem [66,67]. Nevertheless, in spite of the high technological and methodological development, the common usage of such monitoring systems is characterized by a range of interdependent challenges. These issues are technical, ecological, and socio-political because the nature of soil systems and the characteristics of soil health assessment are multidisciplinary. These limitations have to be mitigated to realize the potential of proactive and data-driven management of soils to the fullest and develop reliable, robust, and broadly applicable early warning systems. Several statistical and machine learning methods have been recommended to convert intricate soil data to predictive risk scores **(Table 4).**

Table 4. Data-driven modeling approaches are used for soil health prediction and early warning systems, including statistical models, machine learning algorithms, and sensor-fusion methods.

Approach	Input Data	Output/Prediction	Strengths	Limitations
Statistical regression	Chemical, physical, and biological indicators	Soil property trends, contamination risk	Interpretable, widely used	Limited for non-linear interactions
Multivariate analysis	Multi-indicator datasets	Composite indices, correlation patterns	Handles multi-dimensional data	Requires assumptions on linearity
Machine learning (RF, SVM, ANN)	Multi-source real-time data	Predictive thresholds, early warning	Captures non-linear relationships, adaptive	Data-intensive, less interpretable
Sensor fusion/adaptive models	Integrated chemical, physical, and biological data	Context-specific dynamic thresholds	Real-time, predictive, integrative	Complex implementation requires calibration

Note: RF: Random Forest; SVM: Support Vector Machine; ANN: Artificial Neural Network.

The first problem is the heterogeneity of soils in nature. There is a wide range of soil properties depending on both the spatial scale, due to parent material, topography, land use, and climatic conditions [68]. This heterogeneity makes the data collection and interpretation more difficult because local variations may cause misleading measurements in case monitoring networks that are not dense enough. Micro differences in texture, moisture, and microbial community can lead to significant changes in important indicators even in a single field. This form of variation poses challenges to sensor positioning, calibration, and threshold values. Although these problems are addressed to some degree by high-density sensor arrays and mobile monitoring platforms, they pose extra costs and maintenance demands and also complicate data. Further, remote sensing, though useful in large-scale observations, may not be fine enough to measure the micro-scale heterogeneity, which requires multi-scale, multi-method solutions to guarantee a complete assessment of soil health [30].

Sensor reliability and standardization are another formidable problem. The sensors of soil, whether in terms of chemical levels, moisture, or structural parameters, tend to drift, suffer environmental interference, and mechanical damage [35]. Data accuracy can be compromised by inconsistent calibration, and standardized protocols have not been adopted by them, so they cannot depend on early warning thresholds. Among the biological indicators, such as microbial activity and enzyme function are especially susceptible to the temporal and environmental changes, and incorporating such measurements into real-time monitoring systems is a technically challenging task. To solve these problems, technological development, including self-calibrating sensors and strong biosensors, is needed, along with standard procedures of deployment, calibration, and validation in different types of soils and climatic conditions.

Information merging and handling are other challenges. Dynamic soil monitoring generates multidimensional datasets of large size that consist of heterogeneous data, such as ground-based sensors, remote sensing platforms, and laboratory tests [69]. It is not easy to harmonize these datasets to make meaningful analysis and model predictions. Problems in this case include a lack of consistent temporal resolutions, data gaps, imprecision of measurement of the variables, and variance in units or scales among indicators. Real-time data aggregation and processing can be enabled by more sophisticated data management systems, cloud computing environments, and edge computing, but these solutions demand large computing resources and expertise. Also, more complex data outputs should be translated into useful early warning indicators by using advanced analytic models and communicated to stakeholders in a clear manner, which is why interdisciplinary community involvement of soil scientists, data engineers, and decision-makers is necessary.

The other major problem is that early warning thresholds are context-dependent. Thresholds obtained under a single soil type, climatic regime, or land-use situation may not be generalizable and thus could be specific to that location. Field dynamics also pose greater challenges to the definition of the threshold because the soil properties change over time depending on seasonal changes, weather conditions, and management activities [70]. The adaptive thresholds, which use real-time values, proactive models, and historical patterns, have a potential solution but are still in the development and verification process. The combination of chemical, physical, and biological indicators into one context-specific threshold system is a current research boundary area that needs both empirical and mechanistic knowledge of soil processes.

In the future, the prospect is promising with the new technologies and innovations in the field of methodology, which would help to overcome these obstacles. Nanotechnology and biosensor development could allow for high sensitivity, selectivity, and low maintenance of the chemical and biological soil properties [71]. Machine learning and artificial intelligence can be used to improve predictive modeling, whereby adaptive early warning thresholds are achieved by taking into consideration complex interactions between soil indicators and environmental variables [20]. Combining these technologies with Internet of Things (IoT) systems and remote sensing systems will enable multi-scale, real-time monitoring that will provide field-level detail with regional-level assessment [72]. Also, active dynamic soil monitoring coupled with climate forecasting, hydrological modeling, and land-use planning may offer proactive information on sustainable soil and infrastructure management.

Lastly, the socio-political and institutional relations will have a conclusive role in the adoption of dynamic soil monitoring systems [73]. Smart data monitoring means infrastructure, training, and administrative structures with the purpose of promoting the number of standardized data collection, analysis, and distribution. The integration of early warning levels into environmental policies, agricultural management, and infrastructure development needs policy structures that would adjust technological opportunities into concrete impact. Interdisciplinary collaboration, stakeholder engagement, and public-private partnerships will be essential in making sure that dynamic monitoring systems are scientifically sound and even socially and economically feasible.

To sum up, dynamic soil health monitoring faces significant difficulties but can still be overcome. The interdisciplinary collaboration will be necessary to address the issues of soil heterogeneity, sensor reliability, data integration, adaptive threshold development, and socio-political implementation. Perspectives The future is very bright: due to new technologies and integrative methods, it is possible to turn soil health assessment into a reactive, static, and predictive management. The accomplishment of such obstacles will ensure that dynamic soil monitoring protects soil activity, reduces the risk of pollution, structural collapse, and, eventually, sustainable and robust ecosystems.

6. Conclusions

Dynamic soil health monitoring is a paradigm shift in soil assessment and management, where traditional, fixed measures of soil are replaced by continuous, integrative, and predictive measures. Whether it is chemical, physical, or biological indicators, this framework, combined with real-time data acquisition, remote sensing, and advanced analytics, allows for detecting soil degradation, contamination, and structural failure early. The synthesis provided in this review points to the critical role of developing context-specific and adaptive early warning thresholds that can enable proactive responses that preserve ecosystem functions, ensure agricultural productivity, and protect infrastructure.

The combination of sensor networks, IoT-based platforms, remote sensing, and laboratory-based measurements offers the spatial and temporal resolution that has never been achieved before, and shows dynamic trends and interactions that would otherwise be obscured during conventional measurements. Statistical methods and machine learning are instances of data-driven modeling that can be used to increase the predictive ability of a monitoring system by being able to detect non-linear dependencies, multifaceted relationships, and indicators of impending failures. A combination of chemical, physical, and biological measurements into composite indices further enhances the capacity to convert raw data into actionable information, which is effective in supporting decision-making at various levels.

Although these advances have taken place, there are still several challenges. Heterogeneity in the soil, reliability of the sensors, data integration, as well as the dependence of the thresholds on the context, require further methodological developments. Adaptive and predictive models should be validated with caution and standardized to be reliable and applicable to a variety of soils, climatic conditions, and land-use situations. In addition, technological and analytical capacity translation into an efficient process of soil management needs interdisciplinary development, strong governance systems, and incorporation of the monitoring output in policy and planning.

In perspective, the new technology, such as nanotechnology sensors, biosensors, and artificial intelligence, has the potential to overcome these restrictions and advance dynamic soil monitoring further. These techniques can convert high-resolution data acquisition to predictive modeling, which will help operationalize early warning thresholds and proactively manage soil health and resilience. This way, dynamic monitoring not only responds to urgent environmental and infrastructural issues but also provides measures for sustainability in land use, climate change, and ecosystem maintenance in the long term.

To conclude, dynamic soil health monitoring through the use of data-driven early warning thresholds is an innovative and radical methodology for learning and managing soil systems. The uptake can radically change the paradigm of soil management practices, which rely on reactive remediation, into proactive stewardship to ensure ecological, agricultural, and infrastructural sustainability in the wake of increased anthropogenic and environmental demands. The future research and technology should be used to perfect the monitoring procedures, to combine multi-source data, and to establish powerful predictive models that can make the most of the potential of this paradigm.

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