In-situ Decomposition Sensor Output Correlates with Soil Health Indicators

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Abstract

Monitoring of soil microbiological processes can inform strategies to improve soil health and agricultural productivity. Biological soil health measurements are currently difficult to make in-situ and in real time, usually involving manual sampling and laboratory analysis. This is costly, time consuming, resource intensive, and cannot measure changes at high temporal and spatial resolution, limiting the ability to make prompt informed land management decisions. Low-cost soil sensors manufactured using printing techniques offer a potential scalable solution to these issues. Here, we tested the use of novel sensors for the proxy evaluation of soil microbial processes, hypothesizing that sensor decomposition rates may be related to manual soil sampling measurements. This is the first multi-plot field deployment of sensors which use a biodegradable composite conductor to transduce microbial decomposition of substrates to a change in electrical resistance, providing time-series decomposition rate data. Sensors were installed for 50 days across 44 experimental plots of a long-term grassland experiment with varying historical treatments and significant differences in soil microbial activity. Early failures and unresponsive substrates reduced the included sensor count to 31. Measurements commonly used as soil health indicators, including microbial biomass and enzymatic activities related to nutrient cycling, were determined using standard laboratory methods and compared to sensor responses. Three statistical approaches found positive correlations between the sensor signal and laboratory measurements of microbial biomass carbon and soil organic carbon, and some approaches found weaker correlations with enzymatic measurements. Although this experiment is limited in scope to a single experimental field and season, these initial findings show promise for enabling the proxy measurement of soil microbial processes in-situ using low-cost, scalable printed sensors.

Keywords

Printed Electronics, In-situ Sensing, Soil Biological Activity, Soil Health, Soil Sensing

1. Introduction

High spatial and temporal resolution monitoring of soils is required to accurately manage soil resources [1], but currently we have limited capability beyond the monitoring of soil water, temperature, and some chemical parameters.

Soil health refers to a broad set of metrics and methodologies that relate to a soil's ability to provide ecosystem services [2]. Soil health indicators are usually broken into three categories: physical, chemical, and biological [3,4], with biological indicators receiving relatively less attention in soil health assessments [5,6]. This is due in part to difficulties in both the measurement and integration of biological parameters into soil health models [7]. There is broad agreement that more comprehensive soil health models would place greater weight on biological measurements [8,9]. Conventional laboratory methods for assessing soil biological properties that are key to soil health (Table 1) are typically carried out on samples taken from the field and analyzed in the laboratory. This means that the conditions of the sample may no longer reflect those in the field. Additionally, lab analyses can be expensive and time consuming, do not provide the benefits of continuous, in-situ monitoring [10], and in the case of microbial biomass carbon (MBC) and genetic sequencing, do not differentiate between currently active microbes and relic materials from the microbial necromass [11]. Techniques involving the burial of organic matter such as litter bags, wood, cotton strips, or tea bags, are advantageous due to their simplicity and the fact that they represent the rate of organic matter decomposition in-situ [12]. However, they require retrieval, drying, and weighing, limiting their utility at identifying short-term changes in decomposition rates or critical change points. Similarly, nitrogen mineralization techniques can capture in-situ effects with the use of soil buried in gas permeable containers [13], but require retrieval and laboratory analysis. As such, there is a need for better ways to evaluate the biological components of soil health at scale, including the implementation of continuous monitoring to evaluate changing trajectories.

Table 1: Comparison of methods commonly used for determining microbial activity in soils.

	PHBV:C Decomp. Sensor (this work)	**Litter Bag / Wood / Standard Decomp.** [12,14,15]	**CO_2 Chamber Methods** [16]	**Nitrogen Mineraliz-ation** [13,17]	**MBC Lab Test** [18]	**Enzyme Activity** [19]	**PLFA Lab Test** [20]	**Genetic Sequencing** [21,22]
In-Situ?	Yes	Yes / episodic	Yes / episodic	Yes	No	No	No	No
Continuous Signal?	Yes	No	Yes	No	No	No	No	No
Sensed property	Substrate -specific decompo -sition	Mass change of organic matter	Soil respiration (plant and microbial)	Rate of Nitrogen species conversion	Total microbial biomass	Enzymatic functional	Fatty acid across taxa	Broad microbial composition
Living organisms only?	Yes	Yes	Yes	Yes	No	Yes	Yes	No
Time Integration	Long-term time series	Long-term time series	Short-term time series	Snapshot / Short-term time series	Snapshot	Snapshot	Snapshot	Snapshot
Relative Sample Costs	$	$	$$$$	$$	$$	$$	$$	$$$

Continuous monitoring of soil microbiological activity has been primarily restricted to measuring soil CO_2 fluxes [23], manual measurement of tea bag, cotton, or wood decomposition during burial [12], controlled laboratory analysis, or small-scale applications of prototype sensors [24]. Fine-scale CO_2 flux measurements rely on either regular visits to the field to take gas samples from chambers or the use of expensive automated chamber systems; neither can differentiate root and soil respiration or provide truly continuous measurements. Real-time monitoring of soil biological activity would enable precise and sustainable management of this key component of soil. This is particularly important given the fundamental importance of the soil microbiome for maintaining soil health and ecosystem functioning [25,26]. These critical soil functions include nutrient cycling, decomposition, plant growth, and mediation of soil carbon fluxes due to respiration and sequestration [27–29]. Microorganisms in the soil affect the fate and transport of carbon in the largest terrestrial carbon pool on the planet [30]. In addition, they contribute to critical ecosystem services from the provisioning of food and safe drinking water to the regulation of pathogenic organisms [31].

Emerging technologies have shown promise in supporting programs to restore soil health, including remote sensing, mobile applications, and in-situ sensors [32]. However, monitoring systems have challenges to overcome, including energy efficiency constraints, cost, response time, accuracy, and ease of use [33]. Due to their heterogeneity, soils can be particularly hard to meaningfully monitor without high spatial coverage, with soil microbial communities and soil properties showing high spatial and temporal variability [11,34]. Print-based fabrication of electronic devices offers a potential solution to several of these limitations, as the low cost of manufacturing allows for large-scale deployment with high sensor counts, enabling high spatial and temporal resolution for soil monitoring. Others have demonstrated the utility of a variety of printed electronic sensors applied in the continuous monitoring of soil physical and chemical properties, including moisture [35–37], relative humidity [38], pH [39–41], nitrate [42–45], and chloride [46,47]. We have previously demonstrated printed electronic sensors which transduce microbial decomposition activity into electrical resistance changes as soil microbes degrade a poly(hydroxybutyrate-co-valerate) (PHBV)/carbon composite conductor [24]. In this approach, the PHBV biopolymer (which is degraded in both aerobic and anaerobic conditions [48]), is blended with carbon flake to form a printable ink. Using a stencil-printing process, the ink is deposited onto a surface and dried to create a resistor which is responsive to microbial activity. As the resistor is decomposed in the soil, it swells more effectively, leading to an increase in resistance over time with a gradient which dynamically corresponds to the level of microbial activity. Controlled experiments comparing sensor response in active and sterilized compost tea showed a sensor response only in the non-sterile case. In relatively sterile environments, such as autoclaved sand or deionized water, the resistor showed a negligible change in resistance over time, further suggesting microbial activity as the primary contributor to sensor response. The resistance changes that are provided by the sensor are trivially simple to measure using conventional low-cost electronics, thereby supporting high-density deployments that can help keep instrumentation costs low.

The goal of this work was to determine whether PHBV/carbon decomposition sensor signals mirrored more conventional measurements from various soil plots. Here, the performance of and methods for use and analysis of these sensors is evaluated in a first multi-plot field deployment within a long-term grassland biodiversity restoration experiment in northern England. This site includes experimental treatments of different agricultural management practices, which have led to significant differences in soil properties and plant productivity over the site. We compared signals from the sensors and related them to standard measures of soil microbial biomass and function across 44 experimental plots over 50 days during the summer of 2023. Previous studies at this deployment site have demonstrated significant shifts in microbial communities, including their biomass and activity in response to management treatments [49]. As such, this experiment provided an excellent basis for examining the function of these novel sensors and the relationship between their response and traditional laboratory soil measurements.

This new sensing modality provides real-time information about rates of decomposition of a biodegradable substrate. This process is downstream of various drivers of decomposition in soils, including soil temperature, moisture and pH. Rather than considering these confounders separately, these sensors directly measure substrate decomposition. We hypothesized that these decomposition sensors could correlate to soil health-related laboratory measurements within the scope of this study, enabling useful proxy soil biological measurements in the case of a single historical field site. Successful correlation to existing biological soil health indicators would suggest possible future utility of the technology.

2. Materials and Methods

2.1. Sensor Fabrication

The deployed sensors were prepared according to previous reports [24]. A single loop microbe responsive resistor (width 3 mm, length 75 mm) composed of a PHBV/carbon flake composite was printed using a laser-cut tape stencil on to a glass substrate. A conductive epoxy (*MG Chemicals 8331D*) was used to connect two leads at either side of the trace, followed by dipping in a weatherizing adhesive (*FlexSeal*) to waterproof the connections. This left a large portion conductive polymer trace exposed (Figure 1b). Roughly 60mm of trace is left exposed following the epoxy process, resulting in a sensing area of roughly 33mm^2. Each sensor has a waterproof connector at the end of a signal wire. 82 sensors were initially fabricated with an average resistance of 2.88 kΩ ± 0.43 kΩ (standard deviation). Seven outliers were removed to yield a final average sensor resistance of 2.95 kΩ ± 0.22 kΩ.

Sensor readout was achieved using custom made data loggers, where each logger supports up to six channels though which individual sensors can be read. Loggers were produced using low-cost electronics, including an SD-card enabled microcontroller (*Arduino, Inc.*), a lithium polymer battery, a watertight enclosure, and a timing circuit which provided power to the microcontroller every 30 minutes.

2.2. Experimental Site

The study took place in Colt Park Meadows, located in the Ingleborough National Nature Reserve (Latitude 54°12’N, Longitude 2°21’W, 350 m.a.s.l.) in the United Kingdom. The test site is part of a long-term grassland biodiversity restoration experiment established in 1989 on agriculturally improved, species-poor mesotrophic grasslands [50]. It has provided a variety of management-relevant experimental restoration treatments on a field scale. The soil at this site is a moderate to high residual fertility clayey Brown Earth over limestone bedrock (clay + silt ≈ 60–70%), belonging to the Malham series of Eutric Endoleptic Cambisols, with an average soil organic carbon content of about 8.3% and a pH of ~5.8 [51,52]. These grasslands have been targeted by various environmental land management schemes aimed at enhancing botanical diversity and soil health [53,54]. The experiment includes four main treatments with their

respective controls, using a full factorial and split-plot design to provide 16 different management treatment combinations. These treatments include periodic applications of inorganic fertilizer (nitrogen: phosphorus: potassium = 20:10:10) at 25 kg nitrogen ha^{-1} y^{-1}; starting in 1990. Another involves the annual addition of farmyard manure at 12 t ha^{-1}, beginning in 1998. Efforts to enhance plant diversity began in 1990 with the addition of mixed seeds from 19 species. Furthermore, the promotion of the nitrogen-fixing leguminous herb, *Trifolium pratense* (red clover), began with seed additions in 2004, with a repeat in 2011. Each treatment combination is replicated across three blocks, resulting in a total of 48 sampling plots (each 3 × 3 m). These interventions have been shown to affect multiple soil health indicators, such as microbial biomass, enzymatic activity, and soil carbon storage [49,55–58]. As a result of these historical treatments, the Colt Park site now comprises plots that differ in plant community composition and soil microbiomes, creating a useful diverse test bed for evaluating sensor performance under different soil microbial conditions.

2.3. Deployment

Sensor deployment occurred between June 19th and August 7th, 2023, coinciding with the end of a national drought in the UK. Sensors were installed within 44 plots, across the southern portions of all three blocks. Sensors were installed at the center of each instrumented plot, with signal lines running out to loggers (Figure 1). Within each plot, sensors were installed by cutting a slit in the soil surface, excavating a small cubic hole at the top of the slit to house the wider epoxied housing, and inserting the sensing surface containing the printed resistor taking care to minimize disturbance. Soil was then loosely packed back into the excavated space and allowed to rebound, closing the slit around the sensor. This placed the center of the sensing loop roughly 35cm below the surface. In total, 44 sensors were installed in the various experimental plots. Ultimately, 31 were determined to provide usable information following a filtering algorithm which removed sensors whose response showed rapid failure or no response.

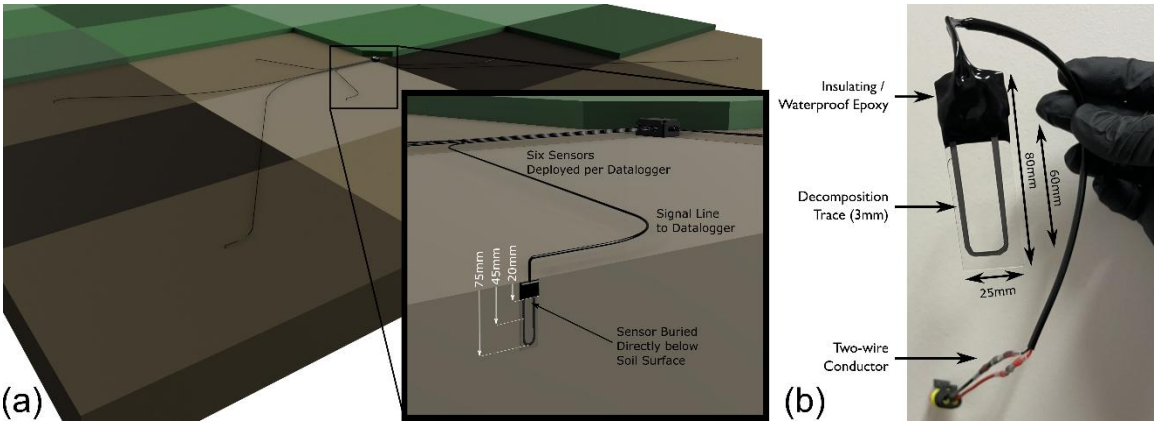

Figure 1. (a) Diagram showing the placement of printed decomposition sensors and loggers in the field, including sensing surface depths. (b) Image of a single decomposition sensor as fabricated for this field deployment.

The state of the sensors was continuously monitored over the course of 50 days using custom waterproof data loggers each capable of interrogating up to 6 individual sensors through wired connections, as depicted in Figure 1. As Colt Park is located in a field at some distance from reliable internet connection, data loggers collected data via SD card rather than using WiFi or other telemetry options.

2.4. Lab Analysis

Within each plot, soil sampling methods were used to obtain laboratory measurements for a variety of chemical and biological parameters near the mid-point of the deployment period, in mid-July. At least three soil cores were collected approximately 30 cm from the sensors. This proximity was selected to balance two factors: it is sufficiently close to ensure that laboratory soil health indicators remain spatially representative of the sensor data, yet distant enough to prevent sampling-induced disturbances, such as altered water infiltration or oxygen diffusion caused by macropores, from potentially interfering with the sensor readings. The cores from each plot were then composited prior to laboratory analysis.

Lab measurements included soil organic content (SOC), determined by an elemental analyzer (Elementar Vario EL CN analyzer) as no detectable inorganic carbon was found in the samples. Additionally, three extracellular enzyme activities were measured by standard colorimetric analysis [59]: glucosidase (GLC), glucosaminidase (NAG), and phosphatase (PHO), which represent carbon, nitrogen, and phosphorus decomposition or acquisition enzymes, respectively. Microbial biomass carbon (MBC) was obtained using the fumigation-extraction method [60].

2.5. QC and Filtering

The soil decomposition sensors generally show an increasing resistance over time in response to microbial activity in the soil (Supplemental Figures S1, S2). Resistances are normalized by dividing all readings by the initial resistance of each sensor (Supplemental Figure S3). At some point – typically weeks after installation for this materials set and sensor design – the resistor material is sufficiently damaged by microbial activity and the resistance rapidly increases indicating that the device has reached the end of its useful lifetime. After an initial settling time and prior to this failure point, the sensor signal defines a decomposition window in which useful data can be extracted. In some cases, likely due to variability related to the fabrication process or issues which occur during installation, a sensor will either be non-responsive or will fail very rapidly in comparison to other devices. These devices are identified through data filtering. Our first step in the data analysis pipeline was to use a polynomial fitting algorithm to remove these anomalous signals. Devices with a low correlation coefficient ($R^2 < 0.5$) from a second-order

polynomial regression were removed from the analysis, along with two additional sensors which had spuriously high initial resistance, likely caused by trace damage on soil insertion (Supplementary Figure S2). This filtering approach shows sensitivity to the selection of the pre-analysis filter threshold (Supplementary Table S6). We chose the 0.5 R^2 threshold because the results most closely aligned with our visual examination of sensor signals, and this threshold maintained just over 70% of the installed sensors. The 0.5 R^2 threshold left 31 sensors for inclusion in the analysis. Totals for each sensor category are shown in Table 2 below.

Table 2: Sensor counts included and removed from the analysis, with failure modes identified.

	Included	Removed (Rapid Response)	Removed (No Response)	Removed (Trace Damaged)
Sensor n	31	5	2	6
Sensor %	70.5%	11.4%	4.5%	13.6%
Total by Category	31 / 70.5%	Removed: 13 / 29.5%		

2.6. Statistical Approaches

To understand how various analytical approaches impact correlation to other field measurements within the remaining data set, three analyses (Figure 2) were then evaluated: a global decomposition window approach (Analysis 1), an individual sensor approach with two varying decomposition phases (Analysis 2), and a sensor signal changepoint count analysis (Analysis 3). In all analysis approaches described here, a single time-integrated measurement results from processing time series data, either by taking the slope of the sensor's normalized resistance or by counting the number of changepoints detected in the signal. In other words, all analyses depend on a structured dataset in which the base sampling unit is the soil plot; for each plot, a single slope or changepoint count total is compared to mid-experiment traditional laboratory measurement. The correlations between the time-integrated measurements and the laboratory measurements are then investigated to establish the connection between sensor signals and soil microbial activities.

Analysis 1 evaluated all 31 sensor responses using a single decomposition window. To define a decomposition window for analysis, all filtered sensor signals were averaged, and changepoint detection was used to define the point at which the average sensor signal changes significantly (Supplemental Figure S4). In this case, changepoint detection was performed by looking for the location of change in variance in the first-order difference time series using the Binary Segmentation method with a maximum of 3 changepoints. This defined the end of the decomposition window and the beginning of the sensor failure phase. The signal following this

sensor failure time was removed from the dataset. Next, the same changepoint detection algorithm was applied to the remaining data to define the beginning of the decomposition window following sensor settling in the soil. A short buffer of three days was applied at the beginning and end of the window to isolate the region in which sensor responses are well-defined (Supplemental Figure S5). Each sensor's slope within the decomposition window was calculated using a second-order polynomial regression, and we took the linear coefficient to be the slope. On a per-sensor basis, sensor slopes were then calculated and compared to laboratory measurements within the plots.

Analysis 2 differs from Analysis 1 in two primary ways: first, we considered individual decomposition windows on a per-sensor basis, varying the beginning and end of the period included in the analysis by sensor signal. Second, visual examination of the sensor signals suggested two distinct phases of decomposition, with the slope increasing more rapidly in a phase prior to total sensor failure, so we aimed to investigate the relationship between the rate of decomposition and the soil parameter measurements in two phases. In this analysis, two changepoint analyses were applied to each individual sensor signal iteratively. First, the pruned exact linear time (PELT) method with manually selected penalty [61] was applied to each individual sensor signal to identify changes in variance in the first-order difference time series. The time of failure is defined as the changepoint where the ratio of variance before and after the changepoint reaches the maximum. A minimum decomposing time of 10 days was used to avoid the identification of unrealistic early time of failure due to the division of a moderate variance by a very small variance in the segment before the changepoint. The signal beyond this point was removed from the analysis. A second changepoint detection, assuming there is at most one change (AMOC, estimated using likelihood ratio test-based method) in the slope of the linear regression model, was then used to differentiate phase 1 and phase 2 within the remaining decomposition signal. Finally, a linear regression model was applied to each phase. The estimated slope parameters from the two phases were correlated to soil parameter measurements respectively (Supplementary Figure S6).

Analysis 3 focused on the number of significant changepoints observed in a given sensor's signal, rather than the rate of sensor decomposition. This analysis does not require the definition of any specific decomposition window, looking instead at the total number of changepoints detected in a particular sensor's signal during deployment prior to sensor failure. For this approach the failure time of each sensor signal is detected in the same way as described for Analysis 2. Whereas the previous two analyses considered a polynomial or linear regression model for the data within the decomposition windows, we instead continued with the changepoint approach and allowed the number of changepoints to be estimated (Supplementary Figure S7). The changepoint model finds structural breaks in the decomposition time series due to changes in linear and/or quadratic trend to model more local features and is fitted using the optimal pruned exact linear time (PELT) changepoint search algorithm [50], with manually selected penalty. The number of detected changes was then correlated to soil parameter

measurements (Figure 2, Analysis 3). A table summarizing the statistical methods used in the three analyses and the derived metrics is given in supplemental Table S3.

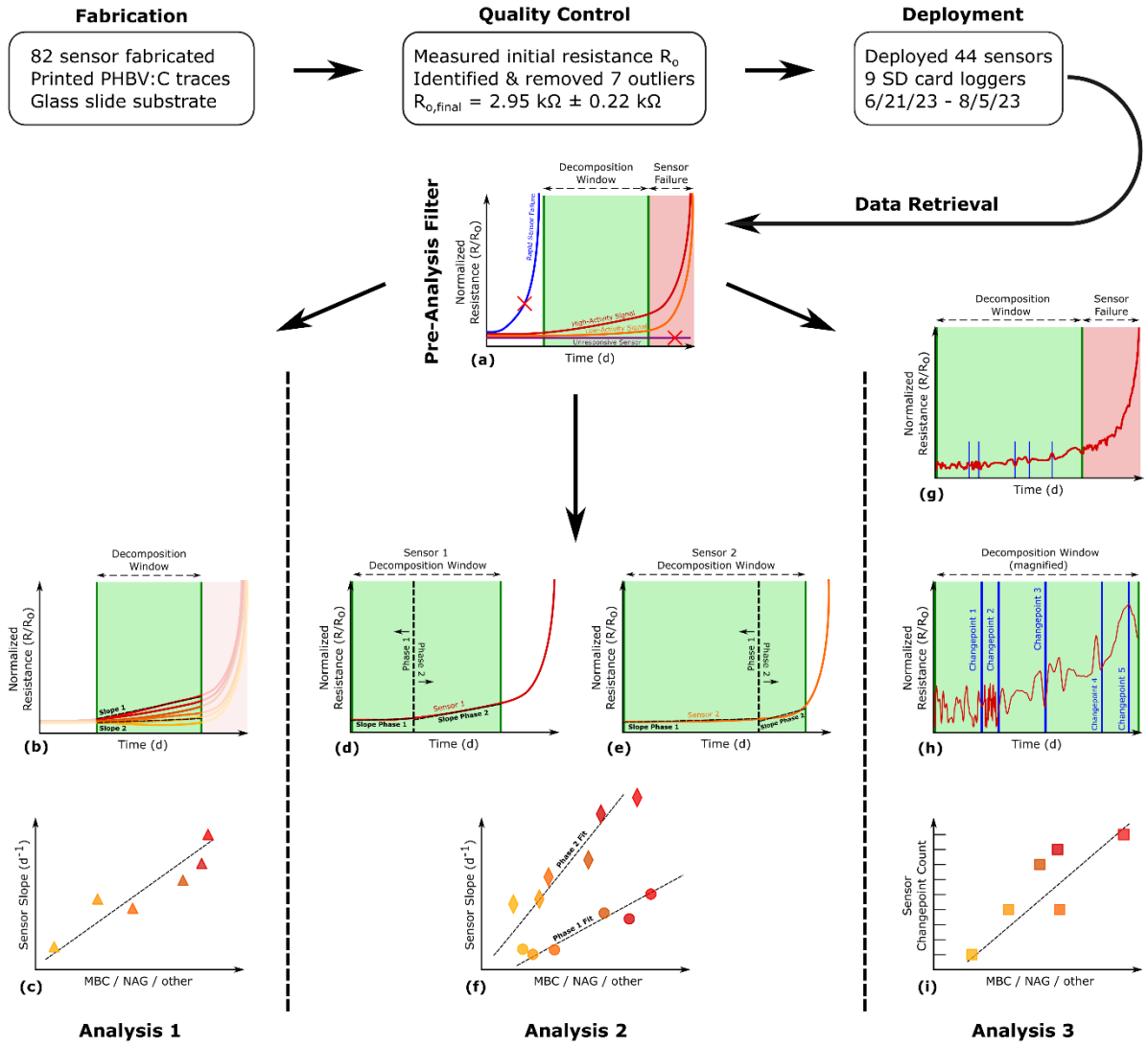

Figure 2. Illustration of the data pipeline for the three analysis approaches. Following fabrication, deployment, and data retrieval, stochastic sensor signals were removed by the pre-analysis filter prior to all correlation analyses (a). For Analysis 1, slopes within the decomposition window were extracted and correlated to laboratory measurements (b, c). Analysis 2 broke each sensor signal into two sensor-specific decomposition windows (d, e). On a per-sensor basis, correlations were then taken between the measured parameter and slopes within each phase (f). Analysis 3 used the number of decomposition function changepoints as a proxy for microbial activity and stability, breaking each sensor signal into sensible changepoints (g, h). On a per-sensor basis, the number of changepoints was then correlated to each measured parameter (i).

To determine whether the sensor signal mirrored biogeochemical differences in instrumented plots, we carried out a series of regression analyses of sensor signals against measured soil attributes and present these analyses with estimated correlation coefficients and p values. Tests of the validity of model assumptions are presented in Supplemental Table S2. It should be noted that based on the focus of the study, sufficient sensors were not available to replicate a standard randomized design for evaluation of treatment differences, but we have visualized treatment effects over our primary findings (Supplementary Figure S14). The statistics extracted from the regression and changepoint analyses are time-integrated measures which are hypothesized to reflect the level of soil microbial activities during the monitoring window. The soil microbial parameters obtained from the fieldwork, despite being one-off measurements, are expected to be stable over the monitoring period [62]. Here we investigated the relationship between these measurements and the extracted statistics to gain insight into the sensor responses to soil microbial activities.

All data analysis was carried out with R version 4.3.2. utilizing R packages changepoint for implementing the binary segmentation and the PELT methods for identifying changes in variance and R package EnvCpt for detecting changes in trend in the linear or polynomial regression models [63,64]. The tests on regression model assumptions were carried out using the R package lmtest [65].

2.7 Interference Experiments

Because this experiment did not include the co-deployment of traditional in-situ sensors in each soil plot, ambiguity exists in the signal. Resistance changes in the sensor substrate can be the result of abiotic processes including changes in soil moisture and temperature. Rainfall and air temperature data from a nearby weather station (Ribblehead Station, ~1.7 km from Colt Park [66]) were collected and visualized alongside minimum, maximum, and median sensor signals in supplementary figure S15.

To more fully characterize the impacts of local soil conditions, we conducted a set of interference experiments over short time periods to isolate impacts on the signal from microbial decomposition. New sensors were produced and installed in soil in the lab. Varying one parameter at a time, continuous resistance outputs were collected. Temperature was varied by installing the soil sample in a heating coil within a refrigerator; a temperature controller swept across a range from 5.4 to 23.5 °C. Volumetric water content was varied from 18.9% to 46.4%, and soil conductivity was modified by alternating between DI water and dissolved NaCl application, giving a range from 437 to 1120 μS/cm. Soil moisture, temperature, and conductivity were measured simultaneously using a TDR-310H (Acclima) with data collected with a DataSnap logger (Acclima). Readings were collected every 5 minutes.

3. Results and Discussion

3.1. Soil indicators

As expected, due to differing soil conditions originating from combinations of historical management treatments, lab measurements of soil parameters show a wide range of values across the experimental plots. These indicators are used in current soil health measurements [5,67–69], and are commonly known as key factors controlling soil organic matter decomposition rates. SOC is one of the most widely used soil health indicators [5], given its role in enhancing soil physical stability, improving water retention, and carbon sequestration. The SOC content ranges from 6.65% to 10.58% across all plots, indicating generally high but variable substrate availability for microbial decomposition. MBC represents a small yet active carbon pool in this study, comprising approximately 2.1% of the total SOC on average, consistent with findings from other studies [70]. It has been suggested as dominant factor that controls the overall decomposition rate of soil organic matter [71]. Microbial biomasss is considered a conservative indicator of soil biological status, showing lower short-term variability than more labile indicators, such as extracellular enzymes [72]. Similarly, SOC is well-established as a slowly changing pool, typically requiring years to decades of altered management to detect significant changes [62]. Although MBC tends to show higher temporal dynamics than SOC, there was no significant environmental perturbation during the sampling period, and evidence indicates that C-rich and low-pH soils, such as the ones at our study site, tend to dampen the temporal variability of microbial biomass [73].

Extracellular enzymes in the soil, mainly produced by microbes, are directly involved in the breakdown of certain organic materials and nutrient cycling (e.g., carbon, nitrogen, phosphorus cycling), thereby directly affecting plant growth and soil fertility [74], and can be used to indicate substrate-specific decomposition processes. The enzymes measured here also exhibit high spatial variability (Figure 3), highlighting their sensitivity to management differences. Monitoring these parameters helps in understanding the impacts of ecosystem management practices and environmental changes on soil health and guides sustainable soil management strategies. For the purposes of this study, these measurements demonstrate that a wide range of soil conditions exist at this test site (Supplementary Figure S16).

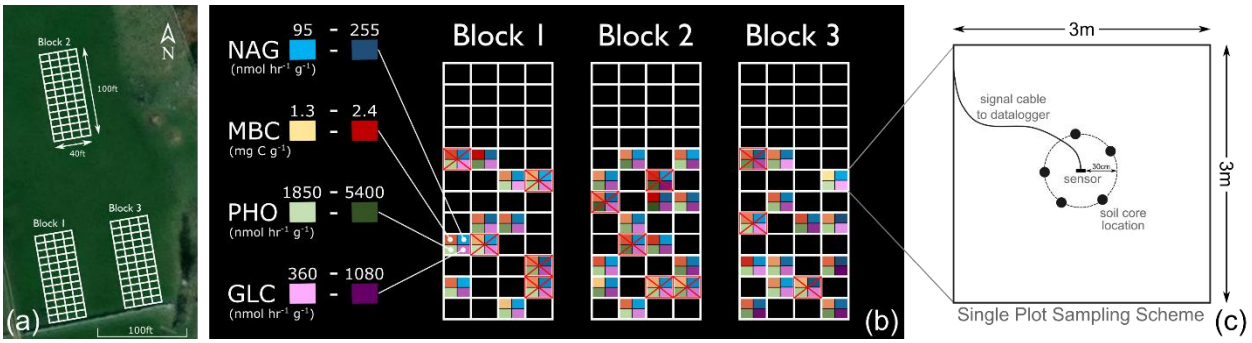

Figure 3. (a) Satellite image of Colt Park Meadows, showing the positions of the 3 replicate experimental blocks, each of which contain 48 plots (*EarthSat image courtesy of the U.S. Geological Survey).* (b) Colors show relative results from biological soil enzyme measurements taken from within instrumented plots. Sites where sensors failure led to removal from the final analysis are indicated with red X icons. (c) At each plot, the sensor was installed at the middle of the plot, and soil samples were taken at a distance of ~30cm from the sensor.

3.2. Sensor Data Analysis

3.2.1 Analysis 1: Global Decomposition Window

The results of Analysis 1 indicate that the rate of resistance change recorded by the sensor is correlated with conventional measures of microbial biomass and activity, with significant variability due to the hardware constraints of the deployed sensors. A positive correlation was observed with MBC ($r = 0.70$, $p = 1.9 \times 10^{-5}$). Fitting a linear regression model between MBC and the rate of resistance change (i.e., the polynomial regression coefficient) results in a coefficient of determination of $R^2 = 0.50$, slope of 20.54, and 95% CI [12.10, 29.06] (Figure 4). We also observed a weaker negative correlation with the ratio GLC:NAG ($r = -0.40$, $p = 0.03$, slope=-47.66, 95% CI [-92.75, -2.58]), which has been considered as an index for early chitin decomposition processes [75]. A significant but weak correlation is also observed with SOC ($r = 0.40$, $p = 0.03$, slope=52.51, 95% CI [6.59, 98.42]). We should note that these correlations are not meant to serve as a calibration curve but rather indicate a strong pattern relating sensor decomposition rate to associated measurable parameters. Two apparent visual outliers occurring at higher MBC contents and having higher sensor slopes were examined in an outlier analysis, where we determined their inclusion is appropriate after examining the sensor signals (see the supplementary information for discussion, with Table S1 and Figures S8-S13). Removing these signals from the analysis results in a weaker but still-significant correlation with MBC ($r = 0.48$, $p = 0.03$, 95% CI [2.9×10^{-3}, 2.1×10^{-2}]).

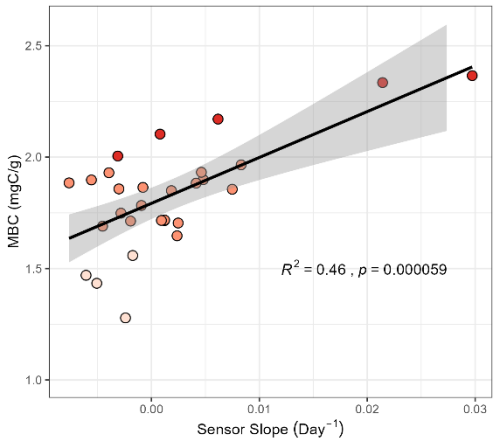

Figure 4. A single decomposition window analysis showed a strong correlation between measured plot-wise MBC values and sensor slopes. 95% CI shown in grey.

To test the impact of decomposition window selection on these results, a sensitivity analysis was carried out by modifying window start and end dates and re-calculating correlations with MBC. Four tests were carried out, expanding and contracting the decomposition window by 40% and 160% respectively, and moving the window 3 days left or 3 days right. All tests resulted in statistically significant but lower correlation coefficients compared to the baseline test (Supplementary Table S5).

3.2.2 Analysis 2: Sensor-specific decomposition windows in two phases

Considering two sensor-specific decomposition windows determined by changepoint analysis, Phase 1 and Phase 2 slopes positively correlated to MBC ($r = 0.52$, $p = 0.003$, and $r = 0.526$, $p = 0.0041$ respectively). Weaker, yet still-significant correlations were found with SOC ($r = 0.37$, $p = 0.043$, and $r = 0.424$, $p = 0.0222$ respectively). This suggests that there is utility to both Analysis 1 and Analysis 2, with useful biological information extractable from the fleet as a whole or from individual sensors, even at this early stage of sensor development.

3.2.3 Analysis 3: Sensor-specific changepoint analysis

This approach found correlations between the number of significant changepoints in the time series data and laboratory measurements within plots. Statistically significant correlations were found with a number of measurements (SOC $r = 0.53$, $p = 0.001$; PHO $r = 0.46$, $p = 0.006$; MBC $r = 0.37$, $p = 0.033$, GLC $r = 0.36$, $p = 0.038$). It is worth noting that in the sites with higher numbers of detected change points, we see a high number of detectable events over a relatively short deployment period, suggesting that useful information can be gleaned by monitoring at this relatively high frequency. It is also interesting that the more static carbon-related measurement, SOC, correlates more strongly with the sensor signal in this approach than MBC does.

All of the data analysis approaches described here resulted in statistically significant correlations with MBC and SOC, indicating a robust correlation to these soil properties. All statistically significant results ($p < 0.05$) are shown below (Table 3). Results from fitting the linear regression models to the laboratory measurements that have a significant correlation with the derived metrics from Analysis 2 and Analysis 3 are presented in the supplemental Table S2.

Table 3: Decomposition sensor signal correlations to laboratory measurements (Pearson correlation coefficient), all significant at $p < 0.05$. n.s. indicates no statistically significant correlation was detected.

Soil health parameter

Method	MBC	GLC	NAG	PHO	GLC:NAG	SOC
Analysis 1	0.70	n.s.	n.s.	n.s.	-0.40	0.40
Analysis 2, Phase 1	0.52	n.s.	n.s.	n.s.	n.s.	0.37
Analysis 2, Phase 2	0.52	n.s.	n.s.	n.s.	n.s.	0.42
Analysis 3	0.37	0.36	n.s.	0.46	n.s.	0.53

438

439 *3.2.3 Interference Experiments*

440 The interference experiments showed repeatable and reversible responses of measured resistance
441 as a function of soil moisture, temperature, and conductivity. Varying temperature between 5.4
442 and 23.5 °C resulted in normalized sensor resistances from 1.06 to 0.86, showing an inverse
443 relationship with temperature. Varying soil moisture between 18.9% and 46.4% VWC resulted in
444 normalized resistances between 0.83 and 1.44, and varying soil conductivity between 437 and
445 1120 μS/cm showed an inverse relationship with normalized resistances between 0.6 and 1.0.
446 Timeseries plots showing normalized resistance changes across these conditions are shown in
447 Supplementary Figure S17.

448 These results suggest that while field conditions do impact the resistivity of the substrate and
449 therefore logged resistance readings, these impacts are predictable, temporary and reversible.
450 Moreover, it is important to note that since all sensors in this experiment were co-located in the
451 same field, the impacts of rain and diurnal temperature variations are shared across the fleet,
452 constituting a background signal shared by all sensors.

453 **3.3. Potential Application and Implications for Environmental Monitoring**

454 The sensor described here shows initial promise in enabling scalable, in-situ data collection that
455 relates to widely used soil biological properties related to soil health. Low-cost printed microbial
456 sensors could support efforts to track and verify the rehabilitation of degraded land and
457 contribute to food security-related environmental monitoring. We have shown here that several
458 statistical approaches suggest a robust relationship between the sensor signal and measurements
459 of microbial biomass carbon and soil organic carbon, important indicators of soil health. The
460 other analysis approaches described here found weaker but still significant correlations with
461 other important field measurements, including GLC, PHO, and the GLC:NAG ratio. With
462 improvements to the fabrication and interrogation of these decomposition sensors, scalable, low-
463 cost deployments could help overcome current limitations in soil biological health monitoring
464 programs.

Prominently, all three analysis approaches found significant correlations between the sensor signal and measured MBC and SOC values in instrumented plots. Prior studies have shown a positive correlation between MBC and organic matter mineralization [76,77], and have, in fact, posited it as a more useful indicator when compared with other forms of SOC, including particulate organic carbon (POC) and mineral associated organic carbon (MAOC) [78]. MBC is also often used as a biological indicator of soil health, showing promise as an early indicator of ecological change following land use change and changes in agricultural practices [79–82]. A low-cost and easily distributable solution for MBC-proxy tracking could offer a new high-spatiotemporal resolution window into these dynamics.

A potential application for this sensing approach is to continuously monitor proxy signals for the soil microbiome's metabolism and activity immediately following environmental perturbations. This could yield useful insights into the resilience of the microbial community in the face of shocks including droughts or agricultural practices like pest fumigation. A more mature instantiation of these decomposition sensors could help to determine whether critical nutrient cycling capacity is impacted by such events and help to characterize the resilience of the soil microbiome by monitoring changes in microbial activity over time.

3.4. Strengths and Limitations

This sensing modality offers new opportunities to monitor decomposition activity in real time and at low cost. Significant opportunities might lie in the exploration of other conductor formulations, applied to a similar deployment platform but targeting other decomposition pathways by selecting alternate binders. Some applicable binder materials might include lignin, cellulose, or location-specific plant litter.

Another valuable aspect of the sensor response is that the signal should be related only to living microbes, avoiding issues associated with relic DNA and enhancing the sensor's specificity. This might be especially important for environments where the soil microbiome changes seasonally.

A primary challenge in interpreting this sensor data and making the results useful is the stochastic response of individual sensors, both initially on installation and as decomposition rates increase and sensors begin to fail. Upon insertion, the resistor can be damaged, rendering the sensor useless; even with great care taken during installation, one sensor's initial resistance in this study indicated that physical damage had immediately occurred. Furthermore, if sensor failure is rapid, the useful life of the sensor can be meaningfully reduced. In this experiment, using sensors with a single loop of substrate, the rate of sensor failure was high: 13 of 44 total installed sensors (29.5%) were removed from the final analysis due to rapid failure, high initial resistance, or a non-response signal. Time to failure was not found to have a statistically significant correlation to measured soil parameters. To address these issues, ongoing work is examining approaches to control the degradation process through material and hardware modifications to improve reliability and reduce sensor-to-sensor variability. One approach may

be to combine multiple sensing surfaces, decreasing the impact of any individual sensor trace failure.

Another challenge lies in the time-integrated nature of the readings derived in this research. While we have stressed the intensive nature of traditional laboratory measurements in yielding actionable data for soil health, one limitation of this technology is that a usable reading requires ongoing monitoring of the sensor signal. Future work must quantify the deployment time required for a sensor which uses this modality to produce readings, which may be a function of biological and physical characteristics at deployment sites. Tied to this, design decisions related to deployment platforms need to be considered. Local logging systems like the one used here can function continuously with extremely low power consumption, but a sensor network that enables more active management decisions would likely need to incorporate telemetry solutions which bring with them significant logistical challenges and higher deployment costs and complexity.

This experiment deployed sensors across plots at one outdoor site and across a single season. Therefore, the extensibility of these results is not yet clear. Experiments across various soil types and weather conditions are necessary in the future to establish the contexts in which these sensors can serve as a proxy for biological soil health. Additionally, no co-located in-situ sensors were deployed in this experiment, limiting our ability to examine sources of interference in the sensor signal. These novel sensors are directly measuring substrate decomposition, rather than the upstream drivers, which include both microbial processes and abiotic drivers like changes in soil moisture and temperature. Ultimately, we are primarily interested in measuring decomposition rates, which are driven by complex soil dynamics including physical and chemical processes. These drivers must be examined in future research to decouple biotic and abiotic influence. While we have started to characterize immediate environmental impacts on sensor signals here, observing significant but reversible resistance changes due to changes in soil moisture, temperature and conductivity, future work should include co-located soil temperature, moisture, pH, and respiration sensors.

In this work, we evaluate sensor signals which are the result of changes to a biodegradable substrate. These changes are downstream of primary drivers including microbial community composition and dynamic soil conditions like moisture, pH and temperature. Significant future work must be undertaken to characterize the sensor's response to other abiotic drivers, and to establish what microbial communities are responsible for the sensor signal. This work should include genetic analysis and expanded testing, including quantification of sensor signals in a wider range of live and sterilized soils and analysis of the impacts of abiotic drivers.

4. Conclusion

This report describes the first field deployment of a novel soil sensor designed to determine microbial decomposition activity through a unique transduction mechanism based on a soil degradable resistor. These low-cost sensors, manufactured from readily available materials using

printing approaches and addressable by simple electronics, are a step towards spatially dense data collection of parameters related to biological soil health. This study analyzed the signal from 31 sensors over 50 days at an experimental field site with varying soil properties. Three approaches for extracting data from the sensor signal were evaluated, with the principal finding that all analyses demonstrated a robust correlation to microbial biomass carbon and soil organic carbon.

Future work will focus on improving manufacturing quality control and decreasing sensor failure rates by mitigating the impacts of individual decomposition trace failure. Multiple traces will be printed on each sensing surface and their signals multiplexed or smoothed. Controlled interference experiments with co-located soil sensors are needed to help to characterize biotic and abiotic drivers of the sensor signal, and genetic analysis of instrumented soil samples can identify what microbes are responsible for trace decomposition. Multiple soils and seasons must be instrumented to establish generalizability of this sensing modality, along with larger-scale deployments across diverse sites. Logger hardware development will focus on field telemetry, enabling long-distance data collection via radio or satellite signal.

This experiment is a first step towards validating a new sensing modality which shows promise as a proxy for soil biological processes. The results described here suggest potential future applications for these in-situ transient decomposition sensors to help characterize soil health trajectories at high resolution and low cost, aligning with the need for larger spatial and temporal scales of soil microbiome monitoring.

Data Availability Statement

Raw datalogger datasets, a plot lookup table, and soil property measurement data are hosted on the Open Science Framework. These resources are openly available at the following DOI: https://doi.org/10.17605/OSF.IO/K98Q4

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