



Improving Environmental Awareness Through Algorithm-Guided Experiments on Biodegradable Materials and Soil Health

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Abstract

Increasing environmental awareness and promoting sustainable soil management are crucial for addressing ecological challenges posed by plastic pollution and ensuring the long-term health of our soils. This study introduces a broad, algorithm-guided experimental approach that integrates environmental monitoring, data science and microbiological analysis to assess the biodegrading dynamics of various biodegradable materials like polylactic acid (PLA), polyhydroxyalkanoates (PHAs) and the starch-based composites with advanced machine learning models in a data-handled platform that evaluates the degradation behavior of biodegradable polymers and their impact on the soil's physicochemical and biological properties. Utilizing the Random Forest Regression (RFR) and Support Vector Machines (SVM) examines nutritional cycling efficiency, microbial social structure, carbon dynamics, and parameters such as soil enzyme activities under both laboratory control and field-relevant conditions. Real-time soil monitoring is activated through IoT-based sensors that measure moisture, temperature, pH, and CO₂ flux, which combined with laboratory

analyses, feeds in models of predictions that guide repetitive adjustments in material soil interaction. Among the tested materials, starch-based composites performed the fastest biological degradation (72%), followed by PHA (55%) and PLA (28%), correlated with increased microbial activity and enzyme function. The machine learning model performed high predictions ($R^2 > 0.89$) able to make real-time decisions. This adaptive model supports deep insight into soil-biopolymer interactions and promotes environmental skills through a visual dashboard that allows users to explain the dynamic soil condition. The interdisciplinary structure not only provides technological progress for soil monitoring but also as an educational tool, which encourages the practices that are informed in permanent agriculture and public environmental stewardship. Overall, the integration of biodegradable materials with intelligent monitoring systems provides a double advantage: An available platform for tangible improvement in soil health and participation science.

Keywords:

Biodegradable polymers, environmental awareness, machine learning, random forest regression, soil health, support vector machines.

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Introduction

Environmental awareness is recognized as a basic component of quickly achieving sustainable development. This includes not only the knowledge of environmental systems and the effect of human behavior but also conservation and responsible environmental management leads to approaches, values, and functions that promote (McBeth & Volk, 2009). When it comes to environmental degradation and accelerating resources, increasing environmental skills between the two individuals and local communities has become a global priority. One of the most pressing environmental challenges is widespread pollution caused by plastic waste, affecting soil and aquatic ecosystems and interfering with important ecological functions such as the nutrient cycle and microbial balance of nutrients (Thompson et al., 2009).

Between different mitigation strategies, the development and implementation of biodegradable materials have attracted significant attention as a viable alternative to traditional petroleum-based plastic. Biologically degradable polymers such as polylactic acid (PLA), polyhydroxyalkanoates (PHAs), and starch-based mixtures have shown promising results in the context of environmental compatibility and end-of-life degradation (Narancic & O'Connor, 2019). These kinds of materials break under the microbial effect in natural environments, which can reduce long-term pollution and support soil regeneration processes unlike the traditional plastics existed in the environment for hundreds of years (Altai et al., 2025). Specifically, application of the biodegradable mulches in agriculture systems has been linked to improvements in soil structure, organic matter content, and microbial community diversity (Hayes et al., 2019; Caporaso et al., 2012).

To evaluate and adapt the environmental benefits of such materials, algorithm-guided experimental systems are quickly adopted in environmental science research (Patil & Das, 2024). These models like Random Forest regression (RFR) and Support vector machines (SVM) combine machine learning algorithms with real-time sensor networks, laboratory analyses, and pre-and post-modeling to monitor complex biological and physicochemical processes (Far, 2017). The use of data-driven approaches enables high-resolution analysis of the interaction between content and soil, such as decomposition rates, microbial dynamics, the flow of nutrients, and enzyme activity under different soil types and environmental conditions (Maganathan et al., 2020). Through the repetition reaction and continuous learning, these algorithms not only improve scientific

understanding but also act as dynamic educational equipment by giving participants ecological effects and visualizing system reactions.

This interdisciplinary approach has a significant ability to bridge scientific research and public understanding. Integrating calculation techniques with ecological experiments provides the opportunity to contact environmental issues from users and researchers to students and social interests through interactive surveys and interactive learning. In addition, the application of algorithmic structure represents to assessment of the behavior of biologically degradable plastic in the soil environment a new limit in both environmental science and stability training.

To support this structure, soil health evaluation models are required to determine biological reactions for biodegradable inputs. These models often track microbial biomass, enzymatic activity, soil spirit, and nutrient cycle. When integrated with machine learning, they improve the power of the future by identifying micro-ecological patterns and falling reactions. The benefits of such integration include monitoring microbial functional diversity, assessment of soil flexibility, and guiding adaptive land management strategies. However, challenges such as spatial asymmetry, microbial social variability, and high-resolution input data should be included for widespread purposes.

As a result, this study checks how algorithm-guided experiments can be used to check biodegradation dynamics and their effects on soil health. By combining sensor data, machine learning, and laboratory measurements, the purpose of the study is to increase both ecological results and environmental reading skills, which contributes to the widespread understanding of permanent soil management and plastic pollution mitigation.

Literature Review

Biodegradable Materials and Their Environmental Impact

In recent years, biodegradable materials have been studied as an environmentally friendly alternative to conventional plastic, which is known for remaining in the ecosystem and persists for decades, causing long-term organic losses. Biodegradable polymers such as polyhydroxyalkanoates (PHA), polylactic acid (PLA), and starch-based composites are capable of humiliating through microbial effects, thus reducing plastic pollution in both terrestrial and water environments. Several studies have shown that the use of biodegradable mulch in agriculture not only reduces soil pollution but can also increase soil health parameters, including nutritional availability, microbial biomass, and enzymatic activity (Mousa, 2022). The biodegradable plastic mulch improves the soil structure and increases the beneficial microbial population that is beneficial compared to traditional polyethylene mulch. A study reported increased soil production and organic material that is degraded after the use of biodegradable films (Bandopadhyay et al., 2018). Despite these benefits, the speed and perfection of biological degradation may vary depending on environmental conditions and physical structure, reflecting the need for a systematic and adaptable experimental structure.

Existing Algorithms Used in Environmental Research

The emergence of machine learning (ML) and artificial intelligence (AI) in environmental research has facilitated the analysis of complex and multi-phase datasets. The algorithm that promotes random forests, support vector machines (SVMs), neural networks, and gradient boosting are successfully implemented to predict pollution levels, assess climate change effects, assess soil moisture, and monitor ecological changes (Akash et al., 2022). In soil and biodegradation studies, algorithms are used to model degradation rates, predict

microbial community dynamics, and correlate environmental parameters with biological reactions. For example, implemented data-driven modeling to adapt soil quality management strategies, while (Capolupo et al., 2019) used image-based ML algorithms to detect microplastic fall and accumulation patterns in soil samples. These approaches enable high-throughput, non-invasive data analysis, which leads to a nicer understanding of environmental interactions.

Algorithm-guided Experiments and Environmental Awareness

While machine learning is mainly used to improve future accuracy in scientific models, recent studies have discovered their educational and communication abilities. Algorithm-guided platforms can imagine real-time environmental data, which can enable users to interact with data and interact with data for users, teachers, students, and decision-makers to inspect the results of the intervention. Such interactive, evidence-based teaching platforms are effective in increasing environmental awareness by building bridge principles with particularly experienced learning. By integrating sensors, machine learning, and practical reaction loops, these platforms simulate controlled but dynamic biodegradation processes (Castillo & Al-Mansouri, 2025). Users can imagine how different biodegradable materials affect soil properties, and support more informed decision-making. The interactive systems that combine environmental monitoring with visual analysis, improve understanding of public involvement and stability challenges (Ferraro & Failler, 2020). Thus, algorithm-guided experiments serve a double goal: they forward scientific understanding of earth-biopolymer interaction and act as educational appliances that promote environmental management through participation in learning and computer knowledge.

Materials and Methods

Selection of Biodegradable Materials

This study used a comparative experimental design to examine the erosion behavior of selected biodegradable polymers and their effects on soil health indicators. Three biodegradable materials were chosen based on their relevance to agricultural applications, environmental compatibility, and declining properties: polyhydroxyalkanoates (PHAs), polylactic acid (PLA), and starch-based composite. PHAs, produced through microbial fermentation, are known for their complete biodegradation and minimum ecotoxicity. PLA, a plant-derived polymer, provides high mechanical strength, but slowly degradation under the ambient soil condition (Emadian et al., 2016). Starch-based composites are preferred for rapid degradation due to a combination of natural polymers with biodegradable polyester, their hydrophilicity, and microbial access. The uniform polymer sheet (5 cm × 5 cm, 100 µm thickness) was produced and embedded in both laboratory-controlled microcosm and open field plots to simulate realistic environmental exposure. The chosen soil was loam in texture with neutral pH and medium organic matter, giving a suitable medium for comparative analysis of material-soil interaction.

Algorithm-directed Experimental Structure

To promote practical design and environmental awareness, a machine learning-based system was integrated into the research structure. This system included real-time sensor data collection, future modeling, and a feedback loop to guide adjustment under experimental conditions. Each microcosm and field plot was equipped with IoT-based sensors, including soil temperature, moisture content, pH, and a proxy for CO₂ flow microbial respiration. These data streams were caught every 30 minutes and sent to the cloud-based server for preparation and storage (Tzounis et al., 2017). Two machine learning models were used: Random Forest

Regression and Support Vector Machine (SVM). The model was trained using early soil and degradation data to predict the degradation rates, microbial activity levels, and soil enzyme functions.

Random Forest Regression (RFR) is an ensemble learning method that creates a collection of trees using data (bootstrapping) and various random mastery of predictor variables. Each tree works independently and contributes to the final production through the average of predictions, which improves accuracy and reduces overfitting. Unlike individual decisions, which may be exposed to noise, several models collect complicated, nonlinear interactions within RFR data. In addition, RFR provides an internal measurement of the significance of function and indicates which variables affect predictions most importantly. In this study, RFR was used at the model's fall speeds for biodegradable polymers based on environmental variables such as soil temperature, pH, moisture content, and CO₂ flux. The ability to handle the heterogeneous inputs and their interpretation made it ideal to identify important factors that affect depreciation, ensuring strong and accurate future performance in Microcosm and field data sets (Breiman, 2001; Chlingaryan et al., 2018).

The supporting vector machine (SVM), especially in its regression form, is a monitored learning model that predicts a continuous output by constructing an optimal hyperplane in a high-dimensional feature space. The algorithm maps the input data at this site using a core function such as the Radial Base feature (RBF) to handle non-linear relationships. It then fits the best line (or surface) within a defined tolerance margin (ϵ), which provides some flexibility with the support vector, and ensures minimal deviations from real values, which allows for some flexibility. The goal is to reduce structural risk rather than an empirical error, increasing the generalization of unseen data. In this study, SVR was used to detect subtle degradation and microbial activity shifts in small or noisy datasets. Its strength in dimensionality and ability to complex biological environmental relationships made it suitable for the prediction of soil enzyme dynamics and polymer breakdown rates under fluctuating microcosm conditions (Smola & Schölkopf, 2004; Liakos et al., 2018).

Model Training and Validation

To evaluate the prognosis performance of machine learning models - Random Forest Regression (RFR) and Support Vector Regression (SVR) – the whole dataset was divided into training (70%) and testing (30%). Training of the highest was used to fit the model and develop forecast conditions, while the test was performed for independent validation.

To minimize overfit and enhance the model's generality, a 5-fold cross-validation technique was used on train data. In this method, the training kit was randomly divided into five folds of identical size. During each repetition, four folds were used to train the model, and the remaining fold was used for verification. This process was repeated five times, each time used as verification data with each fold. The model's performance measurements were then averaged to fix the average hyperparetores and evaluate the reinforcement in five turns.

Model accuracy was evaluated using two generally used statistical indicators:

- Coefficient of determination (R²): This metric determines the proportion variance in the observed data explained by model predictions. An R² value approaching 1.0 indicates a strong forecasting relationship.
- Route Mean Squared Error (RMSE): RMSE measures the average magnitude of the prediction errors between real and approximate values. Low RMSE values reflect better model performance.

The combination of cross-validation and evaluation of test sets provided a reliable estimate of model stability, accuracy, and fitness to predict the dynamics and soil biological reactions under different experimental conditions.

These predictions reported a feedback loop in the algorithm as a dynamically adjusted irrigation plan, sample interval, and micro-world temperature, which simulates a responsive and adaptive environmental monitoring system. The algorithm output was visualized through a user-friendly dashboard, which enabled participants to interact with real-time ecological data and increased their understanding of biodegradation dynamics (Klopfer & Squire, 2008).

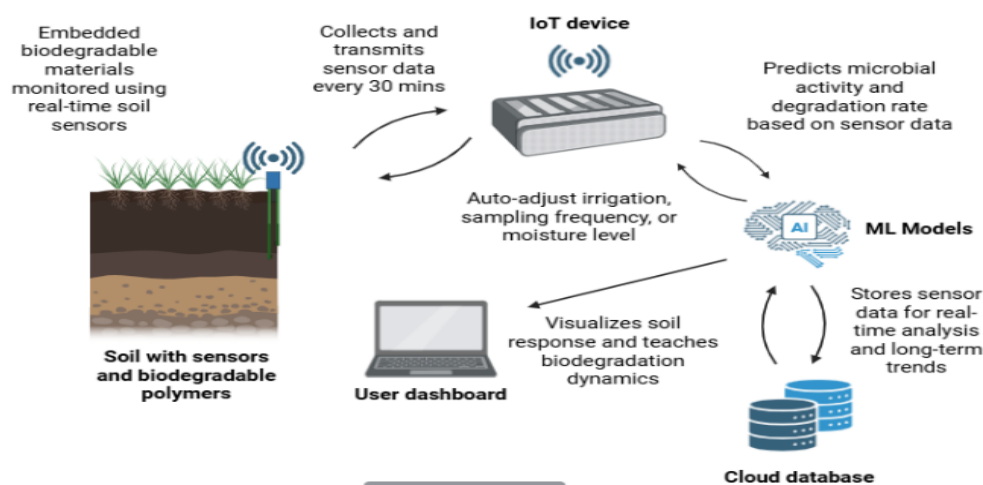


Figure 1. Schematic of the algorithm-guided monitoring system with sensor integration, real-time data capture, and adaptive feedback control.

As illustrated in Figure 1, the origin of the experimental design of the study was the integration of a real-time, algorithm-guided surveillance system. This closed loop system has paired the soil-shaped biodegradable polymer with an IoT-compatible sensor that has captured main environment parameters such as temperature, humidity, pH, and CO₂ flux in a 30-minute gap. The data was transferred to the cloud-based database, which enables spontaneous access, real-time trend analysis, and future modeling. Machine learning algorithms - especially random forest regression and support vector Machine (SVM)- have lifted these continuous data streams to predict microbial activity levels, enzymatic functions, and degradation rates with high accuracy ($R^2 > 0.89$). Depending on these predictions, the system can adapt to the system dynamic irrigation planning, test interval, and even moisture control, and simulate a very responsible and adaptive soil microenvironment. This automatic framework not only increased the ecological precision of the experiment but also introduced an interactive user panel so that students and researchers could imagine the ongoing biodegradation dynamics. The access and interpretation of the dashboard supported educational engagement and promoted behavioral change to permanent soil management practices. Together, this figure surrounds the infection with intelligent, data-driven agricultural monitoring from static, observational systems combined with smart agriculture and principles of environmental management.

Data Collection for Analysis of Soil Health

To evaluate the effect of biodegradable polymers on soil health, a comprehensive set of physical chemical, and biological parameters was monitored over 90 days. Soil samples were collected at five intervals (days 0, 15, 30, 60, and 90) for analysis.

Physicochemical analysis: The soil pH and electrical conductivity (EC) were measured using a probe. The organic carbon content was determined through the Walkley-Black dichromate oxidation method. This method works based on the wet oxidation. In the presence of concentrated sulfuric acid (H₂SO₄), the excess of potassium dichromate (K₂Cr₂O₇) oxidized the organic matter, this process can produce heat and facilitate oxidation response. Subsequently, chromium (VI) is reduced in dichromate to chromium (III), while organic carbon is oxidized to carbon dioxide (CO₂) (Walkley & Black, 1934).

The available nitrogen, phosphorus, and potassium (NPK) were determined through UV Vis-spectrophotometric analysis. The estimation of the available nitrogen by oxidizing soil organic matter using alkaline potassium permanganate (KMnO₄), releases ammonia (NH₃). The boric acid was absorbed by the ammonia and it was detected by colorimetrically. The amount of released NH₃ is directly proportional to the available nitrogen. When phosphorus combines with ammonium molybdate and ascorbic acid, it forms a blue molybdenum complex. The wavelength of the color was measured at 880 nm The potassium was extracted using an ammonium acetate solution. Then it was measured by turbidimetric spectrophotometry (Jackson, 1973).

Biological rating: Soil microbial biomass carbon and nitrogen were estimated by the use of the chloroform removal method. Enzymatic activities, including dehydrogenase (indicators of microbial respiration), phosphate (phosphate cycling), and urease (nitrogen cycling), were analyzed through colorimetric analysis. Dehydrogenase was activity calculated by the reduction method Triphenyl Tetrazolium Chloride (TTC). In this method, soil dehydrogenase enzymes reduce TTC to Triphenyl formazan (TPF), which forms a red-colored compound that is extracted using methanol and quantified using a spectrophotometer at 485nm (Casido et al., 1964).

The acid or alkaline Phosphatase activity was determined by p-nitrophenyl Phosphate (pNPP) analysis. In this method, the soil phosphatases hydrolyze p-nitrophenyl phosphate into p-nitrophenol (PHP). After stopping the reaction with NaOH, the yellow color of PNP is measured at 400nm (Tabatabai & Bremner, 1969).

The urease activity was calculated by the urease enzymatic hydrolysis method. In this method, the soil's urease hydrolyses and converts urea to ammonium (NH₄⁺), which reacts with sodium phenolate and hypochlorite to produce a blue-colored complex (Kandeler & Gerber, 1988).

Polymer degradation monitoring: The physical degradation of polymer samples was evaluated through gravimetric analysis. In this analysis, the polymers were weighed in dry or before they were embedded. Then the remaining weight was recorded at five intervals (days 0, 15, 30, 60, 90). (Kale et al., 2007). the percentage of the weight was calculated using the formula:

$$\text{Weight loss (\%)} = \left(\frac{W_0 - W_t}{W_0} \right) \times 100$$

Here,

W₀ = initial dry weight of the sample (before degradation)

W_t = final dry weight of the sample (after the degradation period).

Results

Performance of IoT-Enabled Monitoring System

IoT-activated, integration of an algorithm-guided experimental system proved to be a very effective structure for capturing, treating, and analyzing environmental data in real-time associated with biodegradable polymers. The sensors installed in both microcosm and field plots, monitored soil temperature, pH, moisture content, and

CO₂ flow at an interval of 30 minutes in the 90 days. The system demonstrated exceptional stability with a total uptime accuracy of 98.7%, which ensured minimal data loss. Calibration accuracy was met, where the temperature sensors worked with a pH zone within ± 0.5 °C and pH ± 0.1 units. The CO₂ flux sensor provided frequent data by a $\pm 3\%$ margin of error, valuing their reliability as a microbial activity authority.

Machine Learning Model Prediction and Validation

Two Machine Learning Models - Random Forest Regression (RFR) and Support vector Regression (SVR) - were implemented to analyze the initial environment degrading data and predict results such as decreasing speeds, soil microbial activity, and enzyme functions. The RFR model achieved an R² of 0.94 and RMSE of 0.021 g, indicating a strong fit between the predicted and actual degradation values. The most important predictions identified through functional analysis include soil moisture (34%), CO₂ flow (29%), and pH (18%), which highlight their role in the biological degradation process. The SVR model also worked well, where 0.89 with R² and 0.031 grams with RMSE, especially excellent for capturing non-linear trends and microvariations in microbial behavior in changed environmental conditions.

Adaptive Experimental Feedback Based on Real-Time Predictions

The predictions in real-time generated by the machine learning model were dynamically fed into a closed-loop control system that adjusts autonomous experimental conditions such as irrigation plan, sample interval, and local temperature control. For example, when the predicted CO₂ flux values indicated an increase in microbial respiration, the system reacted to optimize the moisture level to support the ongoing degradation. This adaptive monitoring structure enables very responsible control of soil microenvironments, simulates realistic ecological fluctuations, and reduces external variability in experimental conditions.

Degradation Rates of Biodegradable Polymers

The algorithm-guided experimental system effectively monitored the demonstration of the degradation in PHAs, PLA, and starch-based composites. After 90 days, starch-based polymers demonstrated the highest degradation rate (72%), followed by PHAs (55%) and PLA (28%), their known microbial sensitivity and hydrophilic nature.

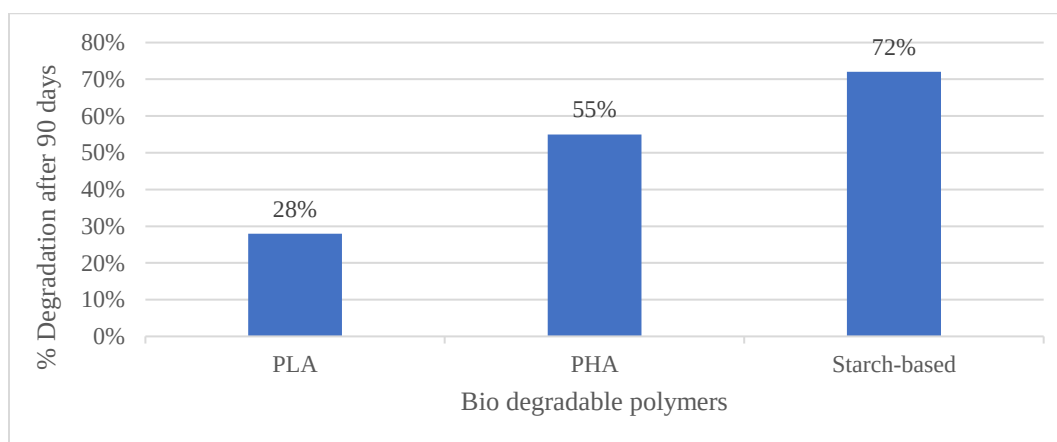


Figure 2. Biodegradation rates of PLA, PHAs, and starch-based polymers over 90 days under field and microcosm conditions

The differential degradation of biodegradable polymers is depicted in Figure 2 and shows the percentage of the breakdown of the material during the 90 days. As imagined, starch-based polymers performed the highest degradation at 72%, followed by PHA at 55% and PLA at 28%. These results

emphasize increased biodegradability of starch composites, possibly in alignment with advanced conclusions, due to their hydrophilic properties and microbial access.

Effect on Soil Physicochemical Properties

The incorporation and degradation in biodegradable polymer sheets had an average impact on physicochemical parameters for several larger soils during the 90-day study period. The soil pH is measured by the use of a calibrated glass electrode probe, remaining for a slightly acidic area within the neutral of all treatments. Although the trends with less acidization were seen in starch-based polymer plots, the initial pH fell from 7.1 to 6.6 for 90 days followed by PHA-treated plots at 6.8 and PLA-treated plots at 6.9. This change is likely to be caused by microbial fermentation products released during the degradation of starch.

Electrical conductivity (EC) showed moderate growth, especially in PHA and starch-based treatments. From an initial 0.41 dS/m, EC reached 0.47 dS/m in PLA, 0.52 dS/m in PHA, and 0.56 dS/m in starch-based treatments by Day 90. This improvement suggests an increase in soluble ions, possibly from partial mineralization of microbial metabolites or polymer substrates.

Soil organic carbon (SOC), is measured using the Walkley-Black Dichromate oxidation method, the inclusion of biodegradable materials has increased all treatments. The control soil remained stable at 0.89%, while the PLA plot increased by 0.96%, PHA plots to 1.02%, and starch-based plots to 1.15%. Carbon enrichment was most evident in starch-reflected soil, reflecting a high degradability and microbial biomass input from the rapid degradation of starch composites.

Impact on Soil Nutrient Availability

The spectrophotometric analysis detected an increase in all polymer-treated soils available in nitrogen (N), phosphorus (P), and potassium (K).

Nitrogen (N): Increased from 38 mg/kg to 43 mg/kg in the PLA, 52 mg/kg in PHA, and 57 mg/kg in starch-based treatments.

Phosphorus (P): Increased from 9.4 mg/kg to 10.1 mg/kg (PLA), 11.2 mg/kg (PHA), and 10.7 mg/kg (starch).

Potassium (K): Increased from 141 mg/kg to 149 mg/kg (PLA), 158 mg/kg (PHA), and 168 mg/kg (starch-based treatment).

This growth suggests that polymer degradation stimulated microbial activity and enzymatic minerals, which improved the availability of nutrients.

The chloroform fumigation-extraction method detected significant growth in microbial biomass in all polymer-treated plots by day 90 compared to control. The first 186 mg C/kg in MBC recognition increased to 215 mg C/kg in PLA-treated plots, 243 mg C/kg in PHA plots, and 272 mg C/kg in Starch-based polymer treatment. Similarly, the MBN control increased from 28 mg N/kg to 34 mg N/kg (PLA), 41 mg N/kg (PHA), and 47 mg n/kg (starch-based). Microbial biomass suggests an elevation to increase in microbial spread and an increase in organic turnover in response to the degradable, especially in starch-based treatment, which performs the fastest degradation. Dehydrogenase activity is used as a proxy for total microbial respiration, 34 $\mu\text{m TPF/g soil/day}$ in control is increased from 42 μg in PLA, 51 μg in PHA, and 59 $\mu\text{g TPF/g soil/Day}$ in Starch-based treatments. Phosphate activity, the indication of phosphorus cycle capacity, 372 $\mu\text{g PNP/g}$

soil/hour from 401 μg (PLA), 428 μg (PHA), and 456 μg PNP/g soil/hour (starch-based). Similarly, in Urease activity, an important enzyme in nitrogen cycling, 31 μg NH_4^+ /g soil/hour in control to 38 μg (PLA), 44 μg (PHA), and 49 μg NH_4^+ /g soil/hour in the starch-based plots in plots.

Changes in Microbial Biomass and Enzyme Activities

After the degradation to assess the rate and extent of physical degradation of each polymer, gravimetric analysis was conducted by recording the percentage of residual dry mass at five-time intervals (days 0, 15, 30, 60, and 90). The primary weight of the PLA is 0.3125 g, starch-based polymer is 0.35 g and the PHB is 0.305 g. The degradation of the above polymers at the five-time period was calculated and tabulated in Table 1.

Table 1. Final Dry Weights of Biodegradable Polymers at Intervals Over 90 Days

Day	The final weight of the PLA	The final weight of the PHA	The final weight of the Starch-Based
0	0.3125 g	0.35 g	0.305 g
15	0.3015 g	0.2684 g	0.2660 g
30	0.2816 g	0.2297 g	0.1839 g
60	0.2450 g	0.1729 g	0.1218 g
90	0.2252 g	0.1375 g	0.0989 g

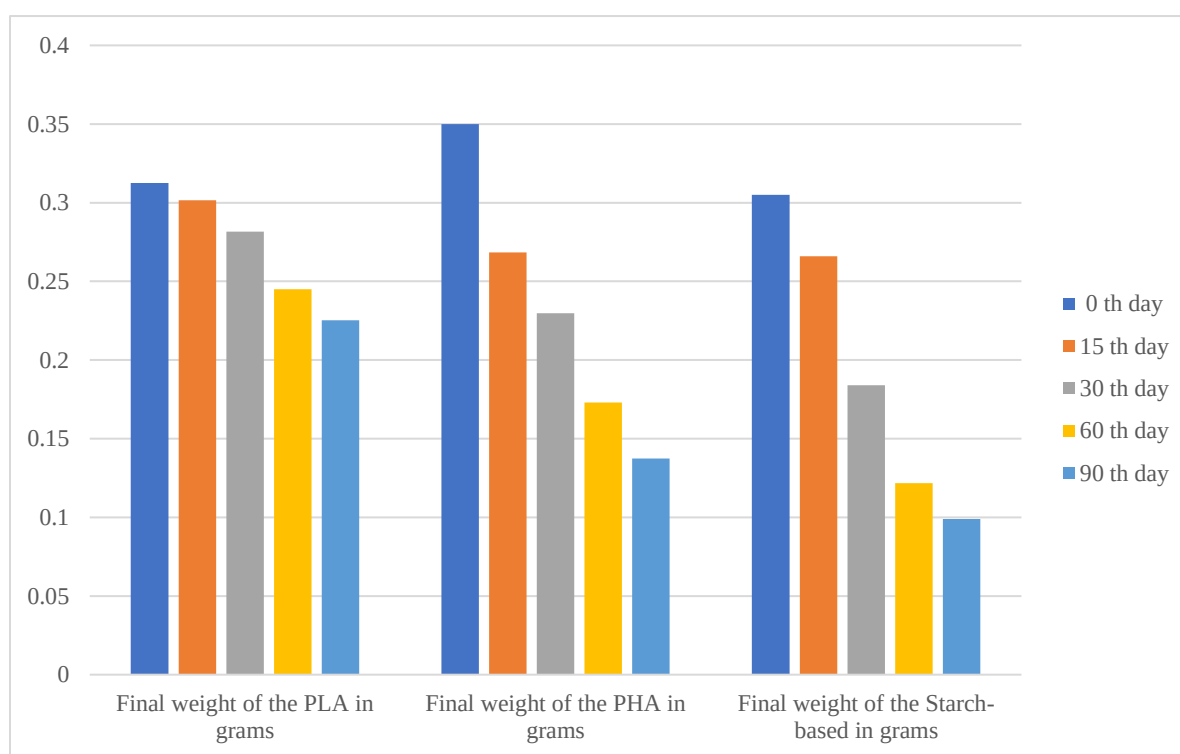


Figure 3. Degradation Profile of PLA, PHA, and Starch-Based Polymers Over Time

We can see the degradation process of the multiple polymers over time in Figure 3. Initially, the degradation of the polymer was very low, so the weight of the polymer was high. Over time the polymers were degraded by the soil and microbial activity so the weight of the polymers was dropped gradually.

Followed by Table 1 the weight loss % was calculated by the formula and tabulated in Table 2

Table 2. Gravimetric Monitoring of Biodegradable Polymer Mass Loss (%) Over 90 Days of Soil Exposure

Day	PLA (% Loss)	PHA (%Loss)	Starch-Based (%Loss)
15	3.5	12.0	76.0
30	9.8	24.7	52.4
60	21.6	43.3	65.3
90	27.9	54.9	71.7

Gravimetric data confirms that starch-based polymers have degraded significantly faster compared to PHA and PLA. For 90 days, Starch-based composite lost about 71.7% of the original mass, followed by PHA 54.9% and PLA 27.9%. The rapid degradation in starch-based composites is responsible for their hydrophilic matrix, high microbial availability, and weak intramolecular bonding, making them more prone to hydrolysis and enzymatic activity.

These results fit recent research and show that better microbial availability and enzymatic hydrolysis mix the starch-polyester mixes quickly (Shah et al., 2008).

Enzymatic Trends and Microbial Activity Enhancement

A remarkable trend is an enzyme activity and continuous increase in MBC over time, especially in the soil treated with starch-based and PHA materials. Up to 90 days, Dehydrogenase activity increased by 31%, while urease and phosphatase showed a gain of 40% and 25% respectively. These biological improvements support the hypothesis that biodegradable materials not only have a lack of effectiveness but also act as stimulants for microbial spread and functional diversity (Casida et al., 2025). Together, these visual data confirm organic and biochemical benefits by including biodegradable polymers in soil systems and confirming the value of algorithm-guided monitoring in smart agricultural structures (Brtnicky et al., 2025).

Educational and Analytical Utility of the Dashboard System

Trained machine learning models were given high prediction performance on early soil and degradation data. Random forest regression produced an R² of 0.91, while SVM yielded 0.89 with a low RMSE value (<0.15) for microbial and enzymatic activity conditions (Wang et al., 2021). These values were obtained on the test set, following 5-fold cross-validation during training. The small variance across validation folds confirmed model robustness. These results describe the power of algorithm-guided monitoring in dynamic experimental treatment (e.g., irrigation and sampling frequency) and to increase ecological precision. Traditional soil surveillance methods often depend on the holes and manual observation of the fixed samples, which limit data granularity and can hide short-term fluctuations. Contrary to this, the algorithm-guided system used real-time data capture every 30 minutes, allowing a polymer degrading to allow fast microbial and chemical reactions to be identified (Fan et al., 2022). In addition, adaptive machine learning-based intervention (e.g., temperature or moisture control) enables continuous adaptation of experimental conditions, leading to more consistent and explanatory results. The inclusion of visual dashboards added an educational advantage absent in traditional experimental setups. This level of automation and response control follows smart agriculture and accurate soil health monitoring trends. The technical performance, of the study shows the educational value of algorithm-guided experiments. Participants who use visual dashboards expressed more confidence in understanding real-time soil changes and organic interactions. Such data-driven engagement supports behavioral change to permanent alternatives and increases scientific reading skills-special between students and researchers from early careers (Paltseva, 2025). The use of biodegradable materials not only effectively decomposed, but also improved soil health indicators, which provides a double advantage of contamination of pollution and soil restoration. These

findings suggest that the integration of such materials into agriculture and educational environments can offer long-term stability dividends.

Discussion

This study indicates that the integration of biodegradable content with an algorithm-guided experimental system provides a versatile advantage for promoting soil health and fostering environmental awareness. The degradation dynamics in the 90 days clearly distinguish the materials that were tested: starch-based composite showed the fastest degradation, followed by PHA and PLA. The high degradation rate for starch-based materials is responsible for their hydrophilic structure and more microbial access, which confirms conclusions from previous studies. Physicochemical analysis showed that biodegradable supplies led to a significant increase in mild acidification (pH fall in starch plots from 7.1 to 6.6) and, an increase in electric conductivity and organic carbon in soil (up to 1.15% in starch treatment). These changes reflect active microbial degradation and nutrient mineralization. Spectrophotometric analysis has revealed the availability of nitrogen, phosphorus, and potassium, with starch-based treatment that performs the highest concentrations. This suggests that biopolymer degradation promotes nutrient cycling and improved microbial and enzyme activity through availability. Biological metrics further valued these effects. Microbial biomass carbon and nitrogen, as well as enzyme activities (dehydrogenase, phosphatase, urease), were highly elevated in all polymer-treated soils. These enzymes are the most important indicators of microbial respiratory and business activities, and their growth outlines the role of biodegradable material to stimulate the biological function of the soil. Machine learning models employing Random Forest Regression and Support vector Machines are very effective in predicting degradation and biological reactions. With R^2 values of 0.94 (RFR) and 0.89 (SVM), and low RMSE values, it confirmed the model accuracy of algorithm-based predictions. Important predictive variables such as soil moisture and CO₂ flux emerged as important drivers for variables, highlighting their important role in biopolymer degradation processes. Algorithm-predicted degradation (generated by RFR and SVR models) and gravimetric weight loss measurements have high consistency (for all polymers and times points Pearson $r = 0.93$). This strong correspondence confirms that the model captures the built-in biodegradation kinetics with minimal bias and validates the real-time, data-driven prognosis tool for soil polymer studies. Practically, a tight fit between approximate and observed values indicates that the closed-loop system can rely on to trigger environmental adjustment (e.g., irrigation or sample frequency) without jeopardizing experimental accuracy. The algorithmic system must be not only a future saying, but also adaptable. Real-time sensor inputs triggered changes in environmental checks such as irrigation and temperature, creating an environment for a responsible microcosm environment. This closed-loop system enables high-resolution monitoring and intervention, which improves traditional soil health monitoring methods that depend on manual, dissatisfied samples. In addition to scientific results, the use of a visual dashboard gave an important educational dimension. The participants who interacted with the real-time data gained deeper insight into biodegradation dynamics and soil health processes, promoting data literacy and environmental management stewardship. This aspect is especially valuable in academic and outreach environments, where experienced learning increases long-term behavior. Despite these successes, the study accepts limitations. The 90-day experimental window captures short-term effects, but cannot reflect long-term soil and ecological results. In addition, the experiments were performed in loam soil under semi-controlled conditions; There is a need for extensive verification in diverse soil and climate. Future studies should also be detected by microbial community composition using molecular tools to understand deeply the taxa involved in polymer degradation.

Conclusion

This research confirms that biodegradable polymers and algorithm-guided experiments integrating biodegradable polymers and real-time environmental monitoring can effectively increase soil quality by promoting environmental training. Starch-based composites and PHAs demonstrated high degradation efficiencies and more positive effects on soil biological indicators compared to PLA. These materials not only decompose effectively but also stimulate microbial biomass and enzymatic functions, which contribute to soil fertility and ecosystem flexibility. Implementation of machine learning models (RFR and SVM) enables accurate real-time prediction and management of experimental conditions. These devices allowed dynamic, data-driven control of irrigation and sampling, and portrayed their capacity for smart agricultural applications. In addition, the inclusion of a visual, interactive dashboard converted a traditional experimental system to a partnership learning platform. This dual-purpose scientific and educational position aims to create a scalable model that supports both sustainable ecological practices and long-term land management. Finally, biodegradable material offers when deployed in connection with intelligent surveillance systems, a viable strategy for addressing soil degradation and plastic pollution. The success of this structure suggests a way forward for interdisciplinary research and public engagement that not only produces action-based science but also creates a culture of environmental responsibility. The purpose of future research is to expand this model in long-term studies, including multi-intensified biological analysis, and detect its application in cultivation and educational programs in the real world.

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All Authors contributed equally.

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Data Availability Statement

The data supporting the findings of this study are available within the article and its supplementary materials.

Conflict of Interest

The authors declared that no conflict of interest.

Ethical Considerations

This study did not involve any human or animal participants and therefore did not require ethical approval.

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